IMPLEMENTING ENVIRONMENTAL REGULATION: AN INTER-INDUSTRY ANALYSIS

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INTRODUCTION

Over the last thirty years public interest in the environmental issues, and subsequent environmental regulation, has grown in importance both in the U.S. and abroad. The importance of this issue has led to a substantial economics literature wherein researchers apply the tools of economics to design socially efficient emission taxes, technology standards, tradable emission permit mechanisms, etc., all with the ultimate goal of making policy recommendations.

Regardless of the policy prescription adopted, recognition of the objectives of the various players and the various institutions involved is required in order to evaluate any regulatory regime. For instance, it is obvious that enforcement issues should be taken into consideration when designing and appraising any environmental regulatory structure. This is particularly relevant given the manner in which environmental policies are structured in the United States. Reduced to its simplest characteristics, environmental regulation can essentially be characterized as a type of regulatory federalism [Goldstein, 1995, 242-259; List and Gerking, 2000]. While most environmental regulations, such as the Clean Air Act or Clean Water Act, are enacted at the federal level by the United States Congress, it is largely the responsibility of state environmental protection agencies to implement these policies through their respective environmental plans. In most instances, states have authority to grant environmental operating, discharging, and/or construction permits and are principally responsible for enforcing the pollution requirements of those permits.

This basic structure, however, can generate a type of moral hazard potentially leading to a significant agency problem. That is, the objective of the principal, or policy designer (in this case, the U.S. Congress), may be significantly different from that of the agent, or policy implementer (in this case the state regulatory authority).[1] This type of administrative hierarchy has various implications such as recent developments in federal-state enforcement cooperation as well as industry location patterns.

Arguably, the primary goal of the policy designer is full compliance on the part of regulated entities with environmental law [Keeler, 1995]. However, policy implementers may be influenced by other considerations, such as local employment considerations and the desire to attract capital. As a matter of policy then, it seems a worthy research

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effort to address the behavior of these policy implementers.[2] This paper is an attempt to shed light on such regulatory behavior by investigating how industry-level characteristics influence environmental monitoring strategies.

There are compelling theoretical (as well as some empirical) reasons why we should *not* expect policy implementation to be politically neutral. While there are many theories of regulatory behavior, one prominent construct is the "External Signals" model attributed to Joskow [1974], Noll [1989], and Magat, Krupnick, and Harrington [1986], which can be thought of as an extension of Stigler's [1971] "Economic Theory of Regulation." This external signals theory asserts that regulators respond to various groups (or stakeholders) outside the agency, such as labor unions, environmental groups, or industry trade associations. The primary objective of the regulator in this model is to minimize negative feedback (complaints) from each of these stakeholders. This feedback often manifests itself in political actions, product boycotts, bad publicity, etc.

The nature of this theory suggests that the relative influence each group can exert on a regulator will ultimately determine regulatory intensity. Hence, we might expect that larger firms exert more influence on environmental inspection authorities and, thereby, receive more favorable regulatory conditions (i.e., fewer inspections). However, we also would expect that powerful industry interests should be able to do the same and realize similar benefits. However, this last group may be comprised of some smaller firms that also would realize more favorable enforcement.

There is a small but growing empirical literature that offers various insights into what influences monitoring and enforcement activity.[3] Deily and Gray [1991] and Helland [1998], for instance, find that enforcement is weaker when there is a higher likelihood that a given inspected plant will shut down in response. Dion, Lanoie, and Laplante [1998] find that inspections are more frequent at production facilities whose pollution byproducts are more harmful to the surrounding environment. All studies find that a plant's historical compliance record influences subsequent monitoring activity.

However, there are a number of inconsistencies in these studies as well. For instance, Deily and Gray [1991] find that plants that employ a larger share of the local labor force are monitored less frequently. Helland [1998] finds a similar result. Yet Dion, Lanoie, and Laplante [1998] find that inspections increase with plant employment. Larger plants, they argue, are more visible and therefore an informed public might view inspections here as mitigating potential environmental harm. Nadeau [1997] also finds that larger plants (measured as plant production capacity) also receive more regulatory scrutiny. Finally, Decker [2002] investigates three separate industries and finds mixed results with respect to the relationship between employment and enforcement. In the pulp and paper and iron and steel industries, for instance, he finds that plants that employ more workers are inspected less frequently. However, he finds that just the opposite effect is true for chemical plants.

Common to all of the above studies is the fact that they are all intra-industry analyses. That is, each looks at regulatory sensitivity to plant- (or firm-) level characteristics *within* a given industry. However, given the inconsistencies identified above, some additional insight into regulatory behavior may be gained by focusing empirically on inter-industry effects. Indeed, the nature of the External Signals model suggests that it is the relative influence that each *group* has on the regulator that will ultimately determine monitoring and enforcement.

Within this context I study environmental monitoring and enforcement activity and its sensitivity to industry-level characteristics. I find that firms competing in those industries that garner a larger share of a state's manufacturing employment are, *ceteris paribus*, subject to less regulatory scrutiny. Moreover, the effect is not limited to employment. Indeed, firms operating in industries that garner a larger share of a state's manufacturing gross state product (value added) are, *ceteris paribus*, subject to less regulatory scrutiny as well.

It is important to note at this juncture that, although there are a fair number of similarities, this study is not directly comparable to the ones cited above since those tended to deal with the U.S. EPA as the regulator [Deily and Gray, 1991] or provincial government [Dion, Lanoie, and Laplante, 1998]. This study focuses on states as the primary regulator and as such, we might expect more regulatory influence by local industry patterns.

This paper is organized as follows. In the next section I discuss the basic model to be estimated, the data, and the various data sources. I then discuss the econometric methodology adopted in the study and certain econometric issues that need to be addressed. Primary results are then discussed and finally I conclude and offer some avenues of future research.

THE EMPIRICAL MODEL AND DATA

Most of the data for this study comes from the U.S. Environmental Protection Agency's (EPA's) Office of Enforcement and Compliance Assurance's (OECA's) Integrated Data for Enforcement Analysis (IDEA) data system. These data contain information on inspection and enforcement activity, compliance records, and the total number of facilities inspected by state and industrial sector. To these data, state- and industry-level employment and gross state product data are added, as well as other state-level economic and demographic data, the sources for which are discussed in the text.

The basic form of the empirical model is taken from a variety of studies, most notably Deily and Gray [1991] and Dion, Lanoie, and Laplante [1998], and is specified as follows:

$$\begin{aligned}
&\log(IN98) = \alpha + \beta_1 \log(\#FAC) + \beta_2 \log(EN97) + \beta_3 \log(EN96) + \\
&\beta_4 \log(EN95) + \beta_5 \log(FEN97) + \beta_6 \log(FEN96) + \beta_7 \log(FEN95) + \\
&\beta_8 \log(ENMAJ97) + \beta_9 \log(EMANS97) + \beta_{10} \log(GMANS97) + \\
&\beta_{11} \log(TRIAIR96) + \beta_{11} \log(TRIWAT96) + \beta_{11} \log(TRILAN96) + \\
&\beta_{12} \log(TRI96 / TRI90) + \beta_{13} \log(DENSITY) + \beta_{14} \log(ENVEXP) + \\
&\beta_{15} GREENINDEX + \beta_{16} DMY26 + \beta_{17} DMY28 + \beta_{19} DMY29 \\
&+\beta_{20} DMY33 + \sum_{r=reg1}^{reg9} \beta_r EPA_r + e
\end{aligned} \tag{1}$$

The variables are measured in log form so that the estimated coefficients can be conveniently interpreted as elasticities.[4] As discussed in detail below, this model is estimated using both standard OLS and maximum likelihood treating IN98 as a count variable.[5]

The dependent variable considered in this study, IN98, obtained from OECA, measures the total number of inspections conducted in 1998 by state environmental authorities for combined Clean Air Act (CAA), Clean Water Act (CWA) and Resource Conservations and Recovery Act (solid and hazardous waste regulation - RCRA) compliance broken down by two-digit Standard Industrial Classification (SIC).[6] The analysis conducted here focuses only on those sectors comprising the U.S. manufacturing sector, encompassing Standard Industrial Classifications (SICs) 20-39 (see Table 1).

The variable #FAC, from OECA, represents for each state and industry the number of facilities (plants) subject to environmental inspections. It stands to reason that the estimated effect should be positive since, *ceteris paribus*, more facilities will necessarily result in more inspections. In fact, we might expect an elasticity close to one, indicating a ten percent increase in regulated facilities within a particular industry should, *ceteris paribus*, lead to a ten percent increase in inspections.

TABLE 1
Inspections and Employment

SIC code	Industrial category	Ratio of inspections to facilities	Industry's share of total manufacturing employment
33	Primary Metal Industries	0.919	0.037
32	Stone, Clay, Glass, and Concrete Products	0.810	0.027
26	Paper and Allied Products	0.762	0.033
28	Chemicals and Allied Products	0.760	0.045
24	Lumber and Wood Products	0.744	0.040
29	Petroleum Refining and Related Industries	0.740	0.006
20	Food and Kindred Products	0.629	0.083
25	Furniture and Fixtures	0.613	0.028
21	Tobacco Products	0.590	0.001
22	Textile Mill Products	0.568	0.028
37	Transportation Equipment	0.465	0.084
30	Rubber and Miscellaneous Plastic Products	0.452	0.054
31	Leather and Leather Products	0.432	0.003
34	Fabricated Metal Products	0.372	0.083
36	Electronic and Other Electrical Equipment and Components	0.351	0.082
39	Miscellaneous Manufacturing	0.320	0.021
27	Printing, Publishing, and Allied Industries	0.301	0.081
35	Industrial and Commercial Machinery and Computer Equipment	0.281	0.105
38	Measuring, Analyzing, and Controlling Instruments; Photographic, Medical, and Optical Goods, Watches and Clocks	0.279	0.044
23	Apparel and other Finished Products made from Fabrics	0.205	0.045

EN97, EN96, and EN95, again provided by OECA, measure the total number of enforcement actions levied by state enforcement officials for a given industry in 1997, 1996, and 1995, respectively. FEN97, FEN96, and FEN95, also from OECA, measure the total number of enforcement actions levied by federal enforcement officials (primarily U.S. EPA and U.S. Department of Justice officials) for a given industry in 1997, 1996, and 1995, respectively.[7] While this action may or may not involve a penalty, it will almost certainly require the violator to undertake some remedial action.

These variables are included to control for reputation effects. One would expect those industries that have performed poorly in the past to be inspected more frequently. The additional years are included to analyze the possibility of a reputation effect (that is, whether or not regulators are more concerned with recent historical compliance than with the longer-term record of the industry). The data is broken down between state and federally levied enforcement actions to test whether or not inspection behavior is sensitive to such a classification difference. We should expect the estimated coefficients on both state and federal enforcement in equation (1) will be positive but it is an empirical question as to whether or not state inspectors are more concerned with the local enforcement or national enforcement.

While providing information on historical noncompliance, this enforcement data gives no information as to the relative severity of noncompliance associated with each enforcement action. This presents some difficulty since instances of violations in, say, the petrochemical industry may represent greater threat to human health and the environment than violations in the printing and publishing industries. We might expect, then, that inspectors, if indeed concerned with human health and the environment, would concentrate more monitoring effort on the petrochemical industry than the printing and publishing industry even if there are fewer violations in the former.

To control for this possibility, I include several variables in my regressions. First, I include the variable ENMAJ97. This variable, compiled from the OECA's *Enforcement and Compliance Assurance Accomplishments Report, FY 1997*, counts the number of what the U.S. EPA classifies as significant administrative and judicial actions levied in fiscal year, 1997. In compiling this data, I focused attention only on those cases involving manufacturing companies (i.e., SIC's 20 through 39) located in the United States for CAA, CWA, and RCRA violations.[8] If inspectors are sensitive to such information, the estimated coefficient should be positive and significant.

Secondly, dummy variables DMY26, DMY28, DMY29, and DMY33, are included in the model specification. Also in its annual enforcement and compliance assurance accomplishments reports, OECA identifies several priority industries that are earmarked as requiring particular enforcement attention. Factors considered in selecting these industries include: compliance history, regional and state concerns, size of the industrial sector, and the potential environmental and human heath risk posed by industrial releases. Priority industries are the industries within SICs 26 (pulp and paper), 28 (chemical manufacturing), 29 (petroleum refining), and 33 (iron and steel). Each variable DMY_i equals 1 if the industry is classified as industry i (i = 26, 28, 29, and 33), and is 0 otherwise. We should see more inspection activity directed towards these priority sectors, *ceteris paribus*.

EMANS97 and GMANS97 measure, respectively, for each state a given industry's *share* of total manufacturing and value added (i.e., gross state product or GSP) in 1997. The one-year lag relative to inspections accounts for the fact that this data is usually released with about a one-year lag by the U.S. Bureau of Economic Analysis.[9] Also, by avoiding contemporaneous values for these variables in the estimated equations we can reasonably avoid any potential endogeneity problems that may arise. Consistent with the External Signals model of regulatory behavior, I expect industries that contribute more to a state's economy will wield greater influence over regulatory activity. Hence, those industries should be inspected less frequently than others.[10]

Before continuing with the formal econometric analysis, it is worthwhile to investigate the raw data to see if it offers any clues as to the expected effect described above (see Table 1). The first data column reports, by industry, the ratio of inspections in 1998 to number of facilities and the second data column reports a given industry's share of total U.S. manufacturing employment. The columns are ordered from largest to smallest based on the inspections ratio data. For instance, SIC 33 (primary metals) was the most frequently inspected industry in 1998. The average plant could have expected to be audited for compliance just less than one time that year. The least frequently inspected industry in 1998 was SIC 23 (apparel). Two features of this table are noteworthy. First, the inspections column highlights observations made by Russell [1990] and others that inspections are relatively infrequent but it also indicates that inspections vary considerably by industry. Second, when compared to the employment share data, it does appear that the more frequently inspected industries have a relatively smaller share of manufacturing employment. Plants in SICs 33 (primary metals), 32 (stone, clay and glass), 28 (chemicals), and 29 (petroleum refining) can expect to be audited .7 to .9 times per year. Yet their employment shares are relatively low (between 2 and 4 percent). Plants in SIC 36 (electronics), 27 (printing, publishing), and 35 (industrial equipment) are inspected much less frequently, yet their employment shares are much higher (8 and 10 percent).

Because there tends to be a high correlation between employment and gross state product, it may be difficult for the regression to correctly differentiate the partial effect each variable has on inspections. Therefore, I will estimate (1) in three different ways. First, I will include employment and GSP together (equation (1) in Table 5). Given the potential for multicollinearity, I estimate a second equation with just employment (equation (2)) and a third with just GSP (equation (3)).

There are several other control variables used in this analysis. DENSITY represents state population in 1998 (taken from estimates provided by the U.S. Department of Commerce's *Regional Economic Information System* (REIS) database, per 1000 acres of a given state's land area [see *Statistical Abstract of the United States*, 1997].[11] One would expect a positive effect since a denser population means a greater number of people are exposed to potentially harmful emissions.

ENVEXP measures the total expenditures by states for air quality, water quality, and hazardous waste disposal, as a percent of total state expenditures. This attempts to measure a state's aggressiveness directed towards environmental compliance. The data comes from the Council of State Governments' publication *Resource Guide to State Environmental Management, 4th ed.* [1996] and captures state expenditures on air quality, water quality, and hazardous waste management for fiscal year 1994. The estimated coefficient should be positive.

An additional necessary control variable is industry pollution emissions by state. There are a number of different measures of pollution but most are specific to a particular media (such as CO or SO_2 air emissions), and few allow for a detailed breakdown by both state and industry. One reasonably detailed pollution database, used by several authors, is the EPA's Toxic Release Inventory (TRI). By way of background, the TRI program was established as part of the EPA's Emergency Planning and Community Right to Know Act. Under this legislation, plants meeting certain criteria are required to report their releases into the air, water, land or underground, and report any off-site transfers, of some 640 toxic chemicals. While the truthful nature of the data might be subject to some question because it is self-reported, it is the case that plants face severe penalties for failure to report and report truthfully. Hence, like others who have used this data, I will assume that the level of reported TRI release is credible. Furthermore, in spite of the fact that most of the chemicals listed in the TRI are not subject to restrictions under other environmental statutes, for the purposes of this paper, I follow King and Lenox [2000] and others, and use TRI releases aggregated by state and industry as a general measure of industrial emissions.

While the self-reported nature of this data may be of some concern, there are several advantages of using this data. First, the data is readily available at zero cost to everyone such as activist groups, communities, researchers, and, indeed, regulators. Second, because the data is self-reported and most of the chemicals released are not subject to limitations under other statutes, there is little reason to suspect any causal relationship between TRI releases and historical enforcement actions. Therefore, possible endogeneity problems can be avoided. Third, there does seem to be good reason to believe that enforcement agencies are using the TRI data in an effort to at least target inspection activities. The U.S. EPA asserts that the TRI data is often used to provide a rough indication of sector compliance over time.[12] Hence, it appears to be the case that environmental regulators do care about TRI releases to the point that they may use it to target regulated plants. Finally, TRI data provide pollution releases by media. Since the inspection data for CAA, CWA, and RCRA compliance is combined, TRI can provide aggregate release data for all media; air, water, and ground.

Specifically then, the variables used in my estimated equations, TRIAIR96, TRIWAT96, and TRILAN96 measure (in pounds) air, water, and land (including underground injections) TRI releases by state and industry, per capita.[13] Using the 1996 TRI and population data is necessary because this data is available at an eighteen-month to two-year lag. Therefore, inspections in 1998 should be sensitive to TRI release information as of 1996, the latest year of data that would have been available at that time. Moreover, controlling for environmental media-specific pollution can provide some information as to the relative importance of air, water, and solid waste pollution in the total inspection effort (an importance attribute given the limitation of IN98 described above). One would expect higher releases per capita to prompt increased regulatory attention.

One might also conjecture that regulators might reward sectors for pollution reductions. To capture this, TRI96/TRI90 is included in the equations where TRI96 and

TRI90 measure total per capita TRI releases in 1996 and 1990 respectively. Since the variable enters in log form, this variable captures the growth rate of per capita TRI releases. One would expect a positive effect on 1998 inspections since increases in TRI releases over this period represent increases in emissions. Conversely, reductions in emissions should result in fewer inspections, *ceteris paribus*.

In an effort to control for general state regulatory attitudes toward environmental concerns, GREENINDEX is included in the model. This variable, constructed by Hall and Kerr [1991], is an index ranking states' records on environmental policy initiatives, natural resource policy initiatives, and spending on environmental quality.[14] This index encompasses a large array of environmental programs, including sixty-seven policy indicators ranging from recycling, solid waste, and Superfund programs to pesticide regulations and specific state programs directed at protecting and improving groundwater resources. Once the index is constructed, states are ranked from fifty to one with fifty being the most pro-environment state (in this case, California).[15] Since the index is designed to capture state attitudes toward the environment, it seems reasonable to expect, *ceteris paribus*, more inspections in those states that are more highly ranked. Hence, we should observe a positive coefficient.

Finally, a set of regional dummy variables, delineated by U.S. EPA region, is included (see Table 2). Each EPA-delineated region comprises a certain set of states and serves largely as an intermediary between state environmental agencies and the U.S. EPA. Moreover, regional EPA offices have certain enforcement responsibilities as well as some limited authority to develop and institute special environmental programs that apply only to that region. It is conceivable that certain regional offices have differing attitudes toward monitoring and enforcement or that certain regional offices are able to influence state environmental agencies to differing degrees. Therefore, included are nine different dummy variables where EPA_r equals one if a state belongs to region r, and zero otherwise.[16] For convenience, Table 2 provides a summary of model variables and each variable's expected effect on inspection behavior. Table 3 provides summary statistics for each variable as well.

THE ECONOMETRIC ESTIMATION

In principle, the inspection data could be analyzed using ordinary least squares (OLS) in much the same way as Deily and Gray [1991] proceed. However, as can be seen in Table 1, the low averages and the preponderance of zeros in the inspection variables highlight the discrete nature of the data. This suggests that we could improve on OLS by using a count model that specifically accounts for these characteristics. In this paper I will employ both techniques.

The most basic count model utilizes the Poisson density function to perform maximum likelihood estimation of the β coefficients. This density function, however, has the defining characteristic that the conditional mean of the outcome is equal to the conditional variance, a characteristic rarely exhibited in applied analysis. It is most

TABLE 2
Model Variables

Variable	Definition	Expected sign
IN98	1998 state conducted inspections - CAA, CWA, RCRA by 2 digit SIC for each state	dependent variable
#FAC	number of facilities subject to inspection as of 1998	+
EN97, EN96, EN95	1997, 1996, and 1995 state enforcement actions – CAA, CWA, RCRA by 2 digit SIC for each state	+
FEN97, FEN96, FEN95	1997, 1996, and 1995 federal enforcement actions – CAA, CWA, RCRA by 2 digit SIC for each state	+
ENMAJ97	major administrative and civil enforcement actions – CAA, CWA, RCRA by 2 digit SIC for each state	+
EMANS97	Industry's share of total state manufacturing employment	-
GMANS97	Industry's share of total state value added (GSP)	-
TRI96, TRI90	1996 and 1990 total releases of toxic chemicals into the air, water, land, by state and industry (per capita)	+
TRIAIR96	1996 air releases of toxic chemicals by state and industry (per capita)	+
TRIWAT96	1996 water releases of toxic chemicals by state and industry (per capita)	+
TRILAN96	1996 land (and underground) releases of toxic chemicals by state and industry (per capita)	+
DENSITY	1998 state population per 1000 acres of state land area	+
ENVEXP	1994 total expenditures ($millions) by state for air quality, water quality, and hazardous waste disposal per facility	+
GREENINDEX	1988 index ranking U.S. state's records on environmental policy initiatives (1 (lowest) to 50 (highest))	+
DMY26	dummy variable - equals 1 for pulp and paper manufacturing, 0 otherwise	+
DMY28	dummy variable - equals 1 for chemical manufacturing, 0 otherwise	+
DMY29	dummy variable - equals 1 for petroleum refining manufacturing, 0 otherwise	+
DMY33	dummy variable - equals 1 for iron and steel chemical manufacturing, 0 otherwise	+
EPA1	CT, MD, ME, NH, RI, VT	?
EPA2	NY, NJ	?
EPA3	DE, MA, PA VA, WV	?
EPA4	AL, FL, GA, KY, MS, NC, SC, TN	?
EPA5	IL, IN, MI, MN, OH, WI	?
EPA6	AR, LA, NM, OK, TX	?
EPA7	IA, KS, NE, MO	?
EPA8	CO, MT, ND, SD, UT, WY	?
EPA9	AZ, CA, HI, NV	?
EPA10	AK, ID, OR, WA	?

often the case that the data is over-dispersed; that is, the conditional variance exceeds the conditional mean. Failure of the equi-dispersion assumption inherent in the Poisson distribution has consequences for the estimated standard errors on the coefficients similar to those that result when heteroskedasticity is present in standard linear regression models. That is, the estimated variances on the vector of coefficient estimates will be biased estimators of the true variance of these estimated parameters, thus making statistical inference unreliable.[17] Under such a scenario, the Poisson model is usually rejected in favor of the Negative Binomial (NB) regression model whose distributional properties allow for over-dispersion.[18]

TABLE 3
Summary Statistics

Variable	Mean	Median	Std. Dev.
IN98	32.11	8.00	67.72
#FAC	56.80	25.00	82.67
EN97	1.74	0.00	5.45
EN96	1.76	0.00	6.10
EN95	2.00	0.00	6.34
FEN97	0.26	0.00	1.31
FEN96	0.20	0.00	0.99
FEN95	0.27	0.00	1.40
ENMAJ97	0.05	0.00	0.23
EMANS97	0.05	0.03	0.06
GMANS97	0.05	0.03	0.07
TRIAIR96	0.30	0.04	1.28
TRIWAT96	0.05	0.00	0.34
TRILAN96	0.17	0.00	1.93
DENSITY	343.45	69.53	1361.65
ENVEXP	19.56	4.66	86.82
GREENIND	25.00	25.00	14.73
DMY26	0.05	0.00	0.22
DMY28	0.05	0.00	0.22
DMY29	0.05	0.00	0.22
DMY33	0.05	0.00	0.22
EPA1	0.12	0.00	0.32
EPA2	0.04	0.00	0.19
EPA3	0.12	0.00	0.32
EPA4	0.16	0.00	0.36
EPA5	0.12	0.00	0.32
EPA6	0.10	0.00	0.30
EPA7	0.08	0.00	0.27
EPA8	0.12	0.00	0.32
EPA9	0.08	0.00	0.27

There are several ways of testing for over-dispersion. Here, I employ a simple technique suggested by Cameron and Trivedi [1990]. To carry out the test, I first estimate each equation under the Poisson distribution restriction, i.e., that the conditional mean and variance are equal, and obtain fitted values for the dependent variable $\breve{y}$ (number of inspections, called IN98F in Table 4). The over-dispersion test is based on an auxiliary OLS regression of the squared residuals minus the actual values of the dependent variable on the squared fitted values of the dependent variable (without a constant):

$$(y - \breve{y})^2 - y = \lambda \breve{y}^2 + u \tag{2}$$

where $u \sim N(0,1)$. A standard one-tailed t-test is conducted on the estimated coefficient, $\breve{\lambda}$, under the null hypothesis that no over-dispersion exists in the model: $H_0{:}\lambda = 0$. The alternative hypothesis is over-dispersion: $H_a{:}\lambda > 0$. Failure to reject the null indicates a failure to reject the Poisson whereas rejection of the null suggests evidence of over-dispersion in the sample.

Table 4 presents the results of the over-dispersion tests. In all three equations there is strong evidence of over-dispersion in the data. Hence, I will estimate each equation using the NB density function. Moreover, because there seems to be over-dispersion in the data, in the OLS regressions I will correct for unobserved heteroskedasticity using White's Heteroskedasticity-Consistent GMM estimator [Greene, 1993, 377].

TABLE 4
A Test for Overdispersion

LHS Variable: $(\text{IN98-IN98F})^2$-IN98
RHS Variable: IN98^2

	Eq. 1	**Eq. 2**	**Eq. 3**
Est. Coeff.	0.066***	0.067***	0.065 ***
standard error	(0.003)	(0.003)	(0.003)

*** Significant at 1 percent, one-tailed test.

ESTIMATION RESULTS

Significance and Goodness of Fit

The regression results are presented in Table 5. While the sign and significance of each independent variable's coefficient is most important from the standpoint of the hypotheses discussed earlier, it is desirable to test the overall significance of the estimated models. First, note that as far as overall "fit" of the data is concerned, the reported adjusted R^2's are in line with what one might expect using industry-level data. About eighty-six percent of the variation in inspection activity is explained by the estimated equations.

Often for maximum-likelihood estimation, a likelihood ratio test provides additional valuable information regarding the explanatory power of models using count data techniques. As is well understood, under the joint null hypothesis that all slope coefficients except the constant are zero, the L-R statistic is asymptotically distributed χ^2, with degrees of freedom equal to the number of restrictions (i.e., number of independent variables) under the test.

Table 5 reports, for each maximum likelihood regression, the appropriate L-R statistic and the associated degrees of freedom. Since all of the reported L-R statistics are well in excess of any reasonable critical value for any level of uncertainty, I can safely reject the null hypothesis that all the slope coefficients in the estimated equations are jointly zero.[19]

Sign and Significance

Before continuing, it is important to re-iterate that for both the OLS and maximum likelihood results, the estimated coefficients can be interpreted as elasticities. In OLS equations, this is obvious since the equation is estimated in double-log form. For the maximum likelihood equations estimated assuming the negative binomial distribution, note that all of the independent variables are measured in log form and the dependent variable, IN98, is measured as a numerical count. The matrix of independent variables typically enters the density function as

$$m(\mathbf{x},\beta) = E(y|\mathbf{x},\beta) = \exp(\mathbf{x}'\beta) \tag{3}$$

where m(.) is the conditional mean of the distribution, the matrix **x** is an NxL array of independent variables that describe the conditional mean, and β is a 1xL vector of coefficients to be estimated via maximum likelihood. Refer to Greene [1993] or Cameron and Travedi [1998] for detailed discussions of count models.

Given the definition of the conditional mean, equation (3), it is easy to see that one can interpret the effect a given variable in **x** has on the number of inspections as a semi-elasticity; i.e., a one unit increase in (i.e., variable l in matrix **x**) will change inspections by β percent. However, since all the independent variables are transformed into log form, the resulting β 's will be elasticities.

As far as point estimates are concerned, most of the coefficients come through as expected. In every equation, the estimated elasticity on #FAC is positive and significant. The elasticity is also close to one in all equations; for the OLS specifications the estimates are about 0.88 and for the MLE specifications its between 1.1 and 1.3.[20]

Moreover, the results indicate that, as expected, there is a reputation effect in that in every equation, the estimated coefficient on EN97 is positive and significant with the elasticities ranging from 0.09 to 0.15. Thus, industries with a poorer environmental record, as evidenced by more state levied enforcement actions in the (recent) past, should expect more subsequent inspection activity.

It is interesting to note, however, that the effect past noncompliance has on current inspection behavior is short-lived. EN96 is rarely significant (and when it is, the estimated elasticity is on the order of 0.06), and EN95 is never significant. The results seem to suggest that regulators care little about an industry's longer-term performance but rather emphasize recent performance when designing their environmental monitoring strategies. Moreover, FEN97, FEN96, and FEN95 are never significant. This is somewhat surprising since one might expect that federally levied enforcement actions might garner greater public and media attention, which would presumably foster greater subsequent inspections. However, the results here seem to suggest that local enforcement actions weight more heavily on local inspections officials. This notion is further evidenced by the fact that ENMAJ97 proves insignificant as well.[21]

Turning attention to the primary variables of interest in this study, EMANS97 and GMANS97, in each equation where EMANS97 appears, it is highly significant and has a negative effect on current inspections with elasticities ranging from -0.09 to -.14. For instance, consider equation (2) estimated via maximum likelihood (column 5). A 10 percent increase in an industry's share of total manufacturing employment reduced inspection behavior by 1.4 percent. *Ceteris paribus*, regulators seem to reward firms operating in those industries that are more important (in terms of employment) to a given state's economy with fewer inspections.

In equation (1), an industry's contribution to total manufacturing value added (GMANS97) is not significant regardless of whether OLS or maximum likelihood is applied. However, this is likely due to the fact that GSP and employment tend to be highly correlated. In equation (2) GMANS97 is dropped. Notice that the employment variable still has a negative and significant impact on current inspection behavior. In equation (3), GMANS97 is retained and EMANS97 is dropped. In this case GMANS97's effect on inspections is both negative and highly significant in both the OLS and maximum likelihood procedures. While the estimated elasticities are slightly smaller (-0.078 and -0.097) relative to those estimated for EMANS97, the effect is still qualitatively the same. Industries that contribute more to a state's manufacturing value added are, *ceteris paribus*, inspected less frequently than other industries. Therefore, regardless of how economic contributions are measured, there seems to be broad evidence that regulators favor those sectors that contribute more to their state's economic welfare.

As far as general pollution is concerned, the results indicate that, *ceteris paribus*, more per capita emissions lead to more inspection activity. This is true irrespective of the type of release. While the estimated elasticities are relatively small, ranging from 0.02 to 0.06 for air releases, roughly 0.03 for water releases, and roughly 0.02 for land releases, in all equations the pollution effect has a positive and significant impact on inspections. For the MLE equations, air releases have the largest effect on inspections while land releases have the smallest. This result seems reasonable since most of the total per capita TRI releases are injected into the air (see Table 3), perhaps garnering greater inspection attention. It is interesting that the air release effect is the largest only in the maximum likelihood estimations where IN98 is treated as a count. This might suggest that deference be given to the count data models over OLS. However, given that statistical significance obtains in all cases under both estimation techniques, the OLS results may still be reasonable.

However, while per capita pollution levels matter, there is no evidence that regulators respond to changes in per capita emissions. In no equation is TRI96/TRI90 significant.[22]

There is some evidence that environmental budgets matter. In every equation the estimated elasticity on ENVEXP is positive, as expected, and significant. For instance, focusing on equation (2) (column 5 in Table 5), a 10 percent increase in a state's per facility environmental management budget will increase inspections by 0.94 percent.

Quite surprisingly, we find that GREENINDEX has a negative effect on inspections. That is, more inspections are conducted in states that scored more poorly on pro-environment policy issues. There may be a couple of possible rationales for this counter-intuitive result. One possibility is the quality of inspections differs across

TABLE 5
REGRESSION RESULTS

Variable	Eq. 1 OLS[1]	Eq. 1 Max. Likelihood[2]	Eq. 2 OLS[1]	Eq. 2 Max Likelihood[2]	Eq. 3 OLS[1]	Eq. 3 Max. Likelihood[2]
	dep. var. LOG(IN98)	dep. var. IN98	dep. var. LOG(IN98)	dep. var. IN98	dep. var. LOG(IN98)	dep. var.: IN98
C	-0.180	-0.744***	-0.172	-0.742***	-0.125	-0.616***
	(0.213)	(0.215)	(0.212)	(0.215)	(0.211)	(0.211)
LOG(#FAC)	0.879***	1.129***	0.878***	1.129***	0.870***	1.105***
	(0.047)	(0.050)	(0.047)	(0.050)	(0.047)	(0.049)
LOG(EN97)	0.155***	0.091**	0.153***	0.090**	0.160***	0.098***
	(0.037)	(0.038)	(0.037)	(0.038)	(0.037)	(0.038)
LOG(EN96)	0.065*	0.013	0.066*	0.013	0.059	0.006
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
LOG(EN95)	-0.016	-0.041	-0.016	-0.040	-0.014	-0.038
	(0.041)	(0.038)	(0.041)	(0.038)	(0.041)	(0.038)
LOG(FEN97)	-0.020	-0.025	-0.019	-0.025	-0.026	-0.038
	(0.072)	(0.064)	(0.072)	(0.063)	(0.073)	(0.064)
LOG(FEN96)	0.065	0.012	0.065	0.012	0.065	0.009
	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)	(0.075)
LOG(FEN95)	0.018	0.003	0.017	0.003	0.020	0.007
	(0.062)	(0.063)	(0.062)	(0.063)	(0.062)	(0.063)
LOG(ENMAJ97)	-0.132	-0.128	-0.131	-0.126	-0.122	-0.115
	(0.167)	(0.130)	(0.168)	(0.130)	(0.165)	(0.131)
LOG(EMANS97)	-0.087**	-0.142***	-0.096***	0.139***	———	———
	(0.041)	(0.050)	(0.025)	(0.031)	———	———
LOG(GMANS97)	-0.013	0.002	———	———	-0.078***	-0.097***
	(0.039)	(0.045)	———	———	(0.024)	(0.028)
LOG(TRIAIR96)	0.020**	0.059***	0.020**	0.060***	0.020**	0.060***
	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
LOG(TRIWAT96)	0.032***	0.027***	0.031***	0.027***	0.033***	0.027***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)
LOG(TRILAN96)	0.025***	0.022***	0.025***	0.022***	0.025***	0.022***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)
LOG(TRI96/TRI90)	0.003	0.007	0.003	0.007	0.005	0.009
	(0.009)	(0.012)	(0.009)	(0.012)	(0.009)	(0.012)
LOG(DENSITY)	0.039*	0.025	0.039*	0.025	0.043**	0.030
	(0.020)	(0.022)	(0.021)	(0.022)	(0.020)	(0.022)
LOG(ENVEXP)	0.084*	0.093**	0.085*	0.094**	0.092**	0.101**
	(0.046)	(0.046)	(0.046)	(0.046)	(0.045)	(0.046)
GREENINDEX	-0.007**	-0.012***	-0.006**	-0.012***	-0.006**	-0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
DMY26	0.105	0.157	0.102	0.156	0.129	0.200**
	(0.085)	(0.099)	(0.085)	(0.099)	(0.084)	(0.098)
DMY28	-0.115	-0.143	-0.120	-0.141	-0.040	-0.013
	(0.105)	(0.109)	(0.102)	(0.105)	(0.098)	(0.099)
DMY29	0.102	0.169	0.094	0.171	0.253*	0.437***
	(0.167)	(0.143)	(0.165)	(0.138)	(0.147)	(0.110)
DMY33	-0.136	-0.039	-0.133	-0.039	-0.113	-0.010
	(0.098)	(0.100)	(0.098)	(0.100)	(0.098)	(0.100)
EPA1	-0.126	-0.087	-0.129	-0.086	-0.109	-0.064
	(0.117)	(0.114)	(0.115)	(0.114)	(0.115)	(0.114)
EPA2	-0.462***	-0.683***	-0.461***	-0.681***	-0.433***	-0.622***
	(0.104)	(0.131)	(0.104)	(0.130)	(0.103)	(0.129)

TABLE 5—*Continued*
REGRESSION RESULTS

Variable	Eq. 1 OLS[1]	Eq. 1 Max. Likelihood[2]	Eq. 2 OLS[1]	Eq. 2 Max Likelihood[2]	Eq. 3 OLS[1]	Eq. 3 Max. Likelihood[2]
	dep. var. LOG(IN98)	dep. var. IN98	dep. var. LOG(IN98)	dep. var. IN98	dep. var. LOG(IN98)	dep. var.: IN98
EPA3	0.081	0.080	0.082	0.081	0.097	0.114
	(0.122)	(0.117)	(0.122)	(0.117)	(0.122)	(0.117)
EPA4	0.064	-0.165	0.066	-0.163	0.090	-0.102
	(0.107)	(0.110)	(0.107)	(0.110)	(0.105)	(0.108)
EPA5	-0.370***	-0.672***	-0.370***	-0.672***	-0.338***	-0.609***
	(0.109)	(0.109)	(0.109)	(0.109)	(0.106)	(0.107)
EPA6	-0.299**	-0.576***	-0.296**	-0.575***	-0.306**	-0.551***
	(0.124)	(0.128)	(0.124)	(0.128)	(0.124)	(0.128)
EPA7	-0.083	-0.376**	-0.081	-0.375***	-0.057	-0.323***
	(0.112)	(0.122)	(0.112)	(0.122)	(0.111)	(0.121)
EPA8	-0.047	-0.194	-0.052	-0.197	-0.037	-0.168
	(0.117)	(0.124)	(0.116)	(0.123)	(0.116)	(0.124)
EPA9	-0.046	-0.070	-0.050	-0.070	-0.030	-0.045
	(0.120)	(0.125)	(0.118)	(0.124)	(0.118)	(0.125)
ADJ R^2	0.862		0.862		0.862	
L-R STATISTIC		59,984		59,997		59,976
n	879	879	879	879	879	879

Note: *standard errors are reported* in parentheses.
1 White Heteroskedasticity-Consistent Standard Errors & Covariance.
2 Negative Binomial Distribution Count.
* Significant at 10 percent, one-tailed test.
** Significant at 5 percent, one-tailed test.
*** Significant at 1 percent, one-tailed test.

states. Perhaps more pro-environment states conduct more thorough, higher quality inspections and therefore fewer inspections are conducted in a year's time. Secondly, perhaps plants located in more pro-environment states are more concerned about getting caught out of compliance and therefore may be more inclined to self-police their environmental performance and indeed self-report findings of noncompliance. This might subsequently reduce the need for greater inspections.

The dummy variables for the four EPA delineated priority industries are rarely significant in determining inspections. When statistically significant, we find that it appears to be so only in the petroleum refining and pulp and paper industries.[23] At least when it comes to inspections, there seems little support for the notion that facilities classified in sectors that the EPA had targeted as priority receive more attention simply because of their classification. Historical compliance, pollution levels, and employment (value added) seem to be the primary determinants of inspections.

There is some evidence of regional variation in inspections. EPA Regions 2, 5, 6, which are primarily industrial regions, as well as 7, which is primary agricultural, are systematically lower relative to EPA Region 10. This is a potentially interesting result in that it suggests that, while the analysis conducted here focuses attention on states, there may be some evidence that regional regulators are sensitive to the industrial characteristics of their jurisdictions. Finally, a state's population density (DENSITY), while generally having a positive impact on inspections is only barely significant in the OLS regressions and not significant in the MLE regressions.

CONCLUSION

This paper has investigated the implementation of environmental regulations through monitoring and enforcement and how such enforcement is influenced by inter-industry characteristics. Controlling for other effects, I found evidence that firms competing with those industries that garner a larger share of a state's manufacturing employment are, *ceteris paribus*, subject to less regulatory scrutiny. Moreover, the effect is not limited to employment. Firms operating in industries that garner a larger share of a state's manufacturing gross state product (value added) are, *ceteris paribus*, subject to less regulatory scrutiny as well.

Consistent with other studies, I find that larger polluting sectors are inspected more frequently as are those industries that have poorer environmental compliance records. However, this effect seems to come through only when considering recent historical compliance records and only when enforcement is levied locally. Moreover, inspections tend to be more frequent in more densely populated states and in states with larger per-facility budget resources. Interestingly, inspections are less frequent in states with better records on environmental policy initiatives, a result that might be illustrating variance in inspection quality. Finally, there is little evidence suggesting that regulators respond favorably to pollution reductions.

There are a number of implications of this research. For instance, as described in the introduction, with federal legislators primarily responsible for regulatory design and states primarily responsible for monitoring and enforcement, a potential agency problem exists. As is well understood, there are several solutions to agency problems, such as incentive-based contracts. Since the evidence presented here suggests that state regulators favor certain sectors, then, to the extent that federal regulators would find this result detracting from its primary objective, we might be observing efforts by federal regulators to offer incentives for states to more aggressively monitor and enforce environmental regulation.

As a potential example, consider the National Environmental Performance Partnership System, spearheaded by U.S. congressional and administrative officials in 1995. This is an agreement between U.S. EPA and state environmental officials to improve local environmental conditions and protection efforts.[24] As part of this partnership, Performance Partnership Grants (PPGs) were established to help states fund new pollution prevention programs and defray monitoring, enforcement and other administrative costs. Moreover, the U.S. EPA has recently established the Environmental Finance Program (EFP) to provide local communities with both financial and technical assistance in an effort to improve and maintain compliance with environmental regulations.[25] In light of the results shown here, we might consider programs like PPGs and EFPs to be analogous to incentive-based contracts developed to solve principal-agent problems. If, for the moment, we were to consider the U.S. EPA as the "principal", then we might infer that one reason for the increased prevalence of such programs is that federal regulators are attempting to offer incentives for states to improve their environmental compliance records.

In addition, the results presented here may have implications for industrial location patterns. A number of studies have attempted to test the effect that state environmental regulation has on plant location but with little success [Gray, 1997]. Most of this work has centered on using pollution abatement expenditures, state environmental budgets, or clean air inspections as measures of regulatory effort. However, since the inspection data aggregates across all environmental statues and there is strong evidence that state inspection authorities do favor certain industries over others, perhaps a broader measure of inspection and enforcement activity would prove more fruitful in testing the effect environmental enforcement has on industrial location.

There are several other research extensions as well. For instance, this paper focused on state-conducted inspections. It would be interesting, for example, to construct a similar model for federally-conducted inspections to test whether or not federal regulators are sensitive to local economic conditions. Also, it would be beneficial to estimate statute-specific equations where inspections for air, water, and solid waste compliance are analyzed separately. Finally, it would be interesting to estimate the model using different measures of regulatory influence, such as PAC money spent in a state by industry.

NOTES

The author thanks the editor and two anonymous referees for their helpful comments.

1. It is important to note, however, that the U.S. EPA and its regional offices conduct a fair amount of enforcement, encompassing both inspections and punitive actions for noncompliance. Therefore, this type of agency problem might potentially exist even if the U.S. EPA were the sole enforcement agency. To the extent, however, that U.S. or regional EPA inspectors and enforcement officials are as sensitive to local economic conditions as, say, state regulators, is an open question. Indeed, it would be useful as a research extension to apply the empirical model developed here to federal inspection activity to investigate this question.
2. It is important to note that there is a fair amount of evidence suggesting enforcement generates compliance, despite the generally accepted belief by many economists that inspections for environmental noncompliance are infrequent and enforcement is weak [Harrington, 1988; Russell, 1990; Cohen, 1998]. Laplante and Rilstone [1996] for instance find that both inspections and the threat of inspections by regulatory authorities result in lower emissions. Gray and Deily [1996] find that inspections positively influence compliance rates for plants in the U.S. steel industry. Nadeau [1997] finds that monitoring and enforcement activities reduce the duration of noncompliance for plants in the pulp and paper industry. Weil [1996] finds that inspections for compliance with the Occupational Safety and Health Administration's (OSHA's) machine guarding standards in custom woodworking establishments significantly improve compliance rates.
3. See Cohen [1998] and Heyes [2000] for surveys of this literature.
4. Transforming the data into log form does generate some problems for IN98, EN97, EN96, and EN95 since, in a few instances (particularly for the enforcement data) there were no recorded actions. Following Gray and Deily [1996] and others, I scaled these data up by one. This avoids losing a number of observations and generating results that are conditional on only those industries for which some historical enforcement was observed.

5. As such, IN98 will enter in level, rather than log, form. As we will see later however, the estimated coefficients will still be elasticities.
6. One of the limitations of this analysis is that I do not observe statute-specific inspections in this particular dataset. I do attempt to account for variation across statute by including in my regression analysis pollution releases broken down by environmental media (see below). Nevertheless, not having data broken out by statute can be problematic since there have been some recent studies that have found some evidence that the U.S. EPA and the U.S. Department of Justice treat *enforcement* differently across statutes (see, e.g., Firestone [2002]). Perhaps, then there might be differences across inspections as well. It would be interesting, therefore, to extend the empirical model here to investigate statute-specific inspection behavior. Before doing so, however, it should be noted that, at least when it comes to inspections, what little evidence exists suggests that there may not be much variation in how certain economic, statutory and demographic variables influence inspections across statutes (see Decker [2002]). Moreover, as Russell, Harrington, and Vaughan [1986] report based on their survey of inspection and enforcement costs, "The differences between mean audit costs...across the media are not statistically significant at the 5 percent level...This implies that there is no point is speculating about reasons for the differences in discharge measurement costs across media..." (p. 56). Nonetheless, more work must be done to more completely ascertain whether or not certain variables impact inspection behavior systematically across statutes.
7. By definition, an enforcement action is any formal administrative or judicial action taken against a violating plant. It is possible that an inspection that discovers noncompliance may result in a referral or an informal enforcement action where the plant will be required to correct any discovered problems within some mutually agreed upon time frame. It will not, however, be recorded as an enforcement action against the violating plant. While this suggests that the number of recorded enforcement actions may not be a perfect indicator of environmental non-compliance, informal enforcement actions are simply not observed. Hence, from an empirical perspective, I will assume that the enforcement actions serve as an indicator of the plant's historical proclivity to violate environmental law.
8. I compiled this data only for fiscal year 1997 since all of my preliminary regression analyses indicate that inspections are most sensitive to recent noncompliance information (i.e., EN97).
9. This data can be queried at http://www.bea.doc.gov. Note that there is actually roughly a two-year lag in the availability of the GSP data. However, it turns out that using GMANS96 instead of GMANS97 makes no substantive difference to the results presented below.
10. There are many examples of empirical models that utilized employment levels as political influence variables such as Deily and Gray [1991] cited in this paper. In addition, Olsen [1997] includes information on firm-level employment in analyzing what determines the Food and Drug Administrations (FDA) review times for new pharmaceuticals to proxy for a company's political clout with FDA regulators. None-the-less, it would be interesting as part of a research extension to investigate other political influence variables, such as campaign contributions by industry, and test their potential impact on inspections.
11. The REIS data can be found at http://www.bea.doc.gov/bea/regional/reis/.
12. Interested readers should see http://www.epa.gov/tri/whatis.htm for additional information on TRI.
13. The population data comes from REIS.
14. Given that this index includes environmental expenditures, it is reasonable to assume some correlation between this index and ENVEXP. Since such correlation would have the effect of biasing the standard errors in my regressions, I attempted to control for this possibility by regressing GREENINDEX on ENVEXP and utilize the resulting residuals as a substitute for GREENINDEX. However, this auxiliary regression proved to have little explanatory power. This may be in part because the Hall and Kerr index was developed based on 1986 state environmental expenditure data and my ENVEXP data is more current. At any rate, since the two-stage approach proved to have no negligible effect on my results, I report those regressions utilized the Hall and Kerr index directly.
15. In the actual publication, the ranking goes from one to fifty with one being the most pro-environmental state. I have chosen to reverse the scale since doing so makes interpreting the regression results easier. Moreover, this ranking only includes the fifty U.S. states and does not include Washington D.C., Puerto Rico, or other U.S. provinces.

16. For EPA region 10, the dummy variable was omitted since each regression was estimated with a constant term.
17. In fact, Cameron and Trivedi [1998] illustrate that the magnitude of the standard error bias in a count model that fails to correct for over-dispersion can be much larger than a standard regression model that fails to correct for heteroskedasticity.
18. In fact, it can be shown that the Poisson density function is a special case of the NB density (see Cameron and Trivedi [1998]).
19. For instance, the critical value for the at one percent significance is 23.2. Note that all of the reported L-R statistics are well in excess of this critical value.
20. The MLE results are somewhat surprising since in theory we would have expected an elasticity equal to one. Here, estimated elasticities are not only greater than one in all specifications, but statistically significantly greater than one as well. This would imply that a ten percent increase in the number of regulated facilities generates a greater than ten percent increase in inspections, suggesting some spillover effects in inspections.
21. This result might suggest that there is some collinearity between the federal actions and ENMAJ97 making statistical inference unreliable. To test this, I estimated each equation without ENMAJ97. In each case, the federal actions still proved highly insignificant. These results, not reported here, are available from the author upon request.
22. This variable may benefit from further refinement in future work in this area. First, as currently measured, the variable does not account for new listing or de-listing of certain chemicals over the period 1990 to 1996. Selecting a consistent set of chemicals over the period may generate different results (however, this is not likely since, arguably, regulators would still care about aggregate emissions anyway). Furthermore, the question arises: Which set of chemicals to use? Answering this question, in and of itself, would be a complicated and interesting study. Perhaps more importantly, however, the chemical aggregations used in my TRI measures treat chemicals as homogenous in nature. In principal, it may be useful to test whether or not regulators would be sensitive to a toxicity-weighted measure of TRI releases per capita. I leave these considerations to future research.
23. It should be noted that the p-values for DMY26 and DMY29 are relatively small (on the order of 15 to 20 percent) in equations 1 and 2 for both the OLS and MLE estimations. Moreover, significance is little affected when the federal and major enforcement variables are dropped.
24. For further information, the reader is referred to http://www.epa.gov/ocir/nepps/.
25. For further information, please see www.epa.gov/efinpage/efp.htm.

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