SELF-POLICING IN ENVIRONMENTAL REGULATION:

AN EMPIRICAL APPROACH

by

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STATEMENT BY AUTHOR

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Abstract

We study the effects of self-policing environmental regulations on the quantity of air pollutants released to the environment, as well as on the number of inspections that the regulatory agencies conduct. We find that audit privilege and self-policing policies have a negative and significant impact on the number of inspections, while immunity increases inspections in a significant way. Emissions are increased by immunity laws and decreased by audit privilege regulations. We find evidence that self-policing policies support what the theory predicts: self-policing regulations reduce inspections and, therefore, decrease enforcement costs (Kaplow and Shavell, 1994; Malik, 1993; Innes, 1999a: Innes, 1999b; Innes, 2000; Innes, 2001). We also find that audit privilege and immunity laws that apply to administrative and civil penalties have a more significant effect on inspections, compared to audit privilege and immunity laws that apply to administrative, civil and criminal penalties.

Chapter 1. Introduction

Over the last decade, several US states have adopted environmental regulations that provide incentives for self-policing.[1] As more states in the country enact environmental laws that protect voluntary environmental audits, the concern of environmentalists and of the Environmental Protection Agency (EPA) about their effects on the environment is also growing.[2] As of today, forty four US states have adopted some kind of regulation that protects environmental audits. Although the popularity of these regulations has grown in the last ten years, the empirical literature that analyzes their consequences to the environment and to the enforcement effort of regulatory agencies is quite limited.[3]

Environmental audit regulations are of three types: self-policing policies, audit immunity laws and audit privilege laws. Self-policing policies and audit immunity reduce the penalties for voluntarily disclosed violations, whereas audit privilege protects the information contained in the environmental audits from any legal action. The existing theory is fairly comprehensive in the analysis of self-policing regulations that grant penalty reductions, such as immunity laws and self-policing policies; nevertheless, to our knowledge, there is no theoretical work that analyzes the effects of audit privilege laws on the environment and on the enforcement level of the regulator.

According to the theoretical literature on self-policing, when an adequate set of incentives is in place to encourage firms to self-police, enforcement resources will be saved, since the regulator does not have to invest in enforcement resources to inspect firms that voluntarily disclose their violations (Kaplow and Shavell, 1994). According to

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[1] As used in Stafford (2006a), the term self-policing refers to the voluntary reporting of environmental violations to the regulator, through an environmental audit.
[2] In its Audit Policy, EPA opposes to the environmental audit regulations adopted by some states. See Chapter 2 for a detailed discussion.
[3] Main empirical work has been conducted by Stafford (2004), Stafford (2005), Stafford (2006b), Stretesky & Gabriel (2005) and Pfaff and Sanchirico (2004).

Kaplow and Shavell (1994), an adequate set of incentives is assured by setting the maximal feasible penalty for those firms that do not self-police and a penalty equal or less than the expected fine self-policing firms would face if caught in violation.[4] Other theoretical studies stress the effectiveness of environmental audit regulations beyond saving in enforcement resources (Innes, 1999a: Innes, 1999b; Innes, 2000; Innes, 2001).

The objective of this thesis is to estimate the effects of self-policing regulations on the environment and on the enforcement level of the regulatory agencies. Previous empirical studies use facility-level data to analyze the impact of these regulations on the probability of self-policing, the probability of violation and on the probability of being inspected in the future (Stafford, 2005; Stafford, 2006b; Stretesky and Gabriel, 2005). Our approach is different in that, rather than investigate the effects of environmental audit regulations on the probability of violation or inspection, we analyze the effects of environmental audit regulations on the number of inspections and the amount of pollutants released to the air from 1989 to 2003, using a panel dataset at the industry-state-level. In order to test the effects of environmental audit regulations on the environment, we estimate an emissions equation, using quantity of air pollutants released to the environment as the dependent variable. We also estimate an inspection equation to measure the effects of these regulations on the enforcement level of the regulatory agencies, using the number of inspections conducted by the state and by EPA as the dependent variable. We control for industry, policy and state specifics in each equation.

Since audit privilege, immunity and self-policing policies vary across states, we estimate an emissions and an inspection equation using a broader classification of the three regulations. More specifically, every regulation is divided into two different regulations. Audit privilege is divided into audit privilege that grants legal protection for

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[4] According to Kaplow and Shavell (1994), the maximal feasible penalty equals the firm’s wealth.

administrative and civil offenses and audit privilege that grants protection for administrative, civil and criminal offenses. Immunity is divided the same as audit privilege, whilst self-policing policies is divided in self-policing policies that apply to all business and self-policing policies that apply to business with less than 20 employees. Tables 3 and 4 present the differences and years of adoption of the environmental audit regulations that are in place in several US states. We find that there are significant differences between state regulations. In particular, audit privilege and immunity laws that apply to administrative and civil penalties have a more significant effect on inspections than those that apply to administrative, civil and criminal penalties.

We also consider two specifications for the inspection equation: a non-dynamic and a dynamic model. In the dynamic model we introduce inspections lagged one period as a regressor to control for autocorrelation. Our results show that past inspections have a significant and positive effect on contemporaneous inspections.

The outline of the thesis is as follows. The literature review is presented in Chapter 2, it includes two sections: a section on theoretical work and a section on empirical research. Chapter 3 presents a brief summary of the environmental audit regulations, their provisions and their differences between and within each other. Chapter 4 summarizes the data and the expected effects of the independent variables on the emissions and on the inspection equations. Chapter 5 presents the models and the methods used to estimate both equations. Chapter 6 presents the results. In Chapter 7 we present conclusions and, finally, in the Appendix we present tables with all our results.

Chapter 2. Literature Review

In the 1990s, the EPA published its Audit Policy, entitled "Incentives for Self-Policing: Discovery, Disclosure, Correction and Prevention of Violations," that provides incentives for firms that self-police their environmental violations. Besides the Federal Audit Policy, several US states have adopted laws and policies that encourage firms to self-police. Although the implementation of these policies has spread nationwide, the literature concerning the empirical analysis of such laws and policies is quite limited.

This chapter presents a literature review on self-policing in environmental regulation. The first section reviews theoretical treatments of self-policing and the second section reviews existing empirical studies.

2.1 Theoretical Studies

With the exception of Stafford (2006a) and Livernois and McKenna (1999), the theoretical models developed so far to analyze self-policing are static. The static models presented in this section are Kaplow & Shavell (1994), Malik (1993), Innes (1999b), Innes (1999a), and Innes (2001) and Innes (2000).

The first model that analyzes the implications of self-policing regimes on the enforcement effort of environmental agencies was developed by Kaplow and Shavell (1994).

By establishing an expected penalty for firms caught in violation which is equal to the penalty they would face if they disclose their violations, Kaplow & Shavell (1994) show that enforcement costs can be saved. Since this penalty structure maintains the same level of deterrence as regimes without self-policing incentives, self-policing assures that firms that have committed a violation will report them to the regulator. Thus, the regulatory agency does not have to invest resources to inspect self-policing firms.

Moreover, when firms are risk-averse, additional costs are saved since the penalty for self-policing firms is certain, rather than probabilistic.

In his model, Malik (1993) introduces stochastic pollution, social costs associated with the imposition of sanctions and errors in the monitoring technology used by regulators. In his model, self-policing is mandatory rather than voluntary, which is commonly referred as self-reporting. Self-reporting is only desirable when the regulator can not set the penalty at the maximum feasible level and when the quality of monitoring technology is erratic. In particular, in the presence of self-reporting, the regulator faces fewer incentives to improve its monitoring technology.

These two studies stress the idea that enforcement costs are saved under self-policing and self-reporting schemes, via less inspections. Kaplow & Shavell (1994) and Malik (1993) also state that under administrative costs, self-policing and self-reporting schemes could impose higher social costs.

Innes (1999b) shows that when remediation is valuable,[5] self-policing regimes are more efficient than non self-policing regimes since remediation can be achieved immediately after violation and enforcement resources are saved. According to Innes (1999b), by setting the expected fine that a firm would face if caught in violation equal to the remediation cost it would incur if it is self-policing, the same level of deterrence is achieved, remediation is promptly made and the monitoring effort can be set to a minimum yielding to an optimal level of remediation.

In self-policing regimes remediation is assured *ex-ante*, which produces clean-up benefits. Innes (1999a) analyzes the social benefits of regimes with self-policing in the presence of positive *ex-post* gains of clean-up (when *ex-post* damages are greater than the cleaning costs plus the *ex-ante* damages). With self-policing, clean-up is assured, while

[5] Remediation is valuable when there are economic gains obtained from the remediation of harm.

without self-policing, clean-up is only achieved with the probability of detection (when a firm is caught). Self-policing also saves enforcement costs, since the government can lower its monitoring effort and increase the penalty for non-reporters without altering the level of deterrence.

Aside from the benefits identified when remediation is valuable in self-policing regimes, Innes (2001) analyzes the benefits of these regimes when violators engage in avoidance activities to reduce the probability of being caught. According to Innes (2001), enforcement costs, avoidance costs and deterrence costs are each saved under self-policing schemes. Enforcement and avoidance costs are saved because violators are encouraged to self-police their violations, since the sanction they face if they self-police is less or equal to the expected costs they would face if caught.[6] As stated before, deterrence costs can also be saved because the government can lower the monitoring costs and obtain the same level of deterrence by increasing the sanction for non-reporters.

In another study, Innes (2000) examines the advantages of self-policing schemes when violators face heterogeneous probabilities of apprehension. In his model, the probability of detection depends on the government monitoring effort, denoted by $r(g)$, and the "detectability" of a firm, denoted by δ; the latter one is exogenous and does not depend on firm characteristics. In a regime without self-policing, firms with high δ are overpenalized and firms with low δ are underpenalized, since the expected fine depends on the detectability factor. In a self-reporting scheme, the government sets a fine for self-policing firms that equals the expected sanction that they would face if caught. In doing so, firms that have a high detectability will self-report; overcompliance by those firms will be reduced and efficiency will be enhanced overall.

[6] In his model the expected costs comprise the expected fine as well as the avoidance costs.

The models presented so far restrict the interaction between the regulator and the firm to one period. Dynamic models analyze strategic behavior of the regulator and the firms through time. In a dynamic setting, some firms will self-police because that will decrease the frequency of inspections in the future (Stafford, 2006a; Pfaff and Sanchirico, 2004). There are two basic works concerning dynamic interactions reviewed here: Livernois and McKenna (1999) and Stafford (2006a).

In the context of self-reporting, Livernois and McKenna (1999) analyze the paradox of high compliance rates and low expected fines, which are commonly observed in the real world. According to their model, setting the penalty for non-compliance to a minimum and the penalty for false reporting to its maximum carries the effect that some firms in the continuum will find non-compliance more cost effective. These firms will then report truthfully and the compliance rate will be higher, since detection is promptly made.

Stafford (2006a) analyzes the effects of self-policing regulations using Harrington's targeting enforcement model (Harrington, 1988).[7] In Stafford's model, there are two sources of non-compliance: probabilistic events and deliberate events, and there is a trade-off between policies that enhance pollution abatement and those that increase audits and disclosures. Whether self-policing regimes improve environmental protection depends on setting the proper combination of fines and on the policy objectives of the regulator.

[7] In Harrington's model, the regulator classifies and targets firms according to past compliance. "Good" firms are those ones that have complied with environmental regulations in the past, while "bad" firms have a history of violations. Firms can switch groups with a given probability, depending on recent inspections and the level of cooperation with the regulator through voluntary disclosures.

2.2 Empirical Studies

The articles presented in this section are Stafford (2005), Stafford (2006b), Stretesky & Gabriel (2005), Pfaff and Sanchirico (2004) and Stafford (2004).

Stafford (2005) studies the effects of EPA Audit Policy and state regulations on the probability of being inspected, as well as on the probability of violating hazardous waste regulations. Using a panel dataset for the period 1992-2001 from EPA's Resource Conservation and Recovery Act (RCRA) database, Stafford estimates a Probit model for the inspection equation and a censored Probit model for the violation equation.

According to her results, all environmental audit regulations are significant determining the probability of inspection. Those facilities that are located in states that adopted self-policing policies or audit privilege laws are less likely to be inspected. In contrast, there is a higher probability that facilities located in states that adopted immunity laws are inspected with more frequency. After the implementation of EPA's Audit Policy, facilities are also more likely to be inspected. Interestingly, the effects of environmental audit regulations on the violation equation are similar to the effects they had on the probability of inspection: self-policing policies and privilege laws decrease the probability of violation, while immunity laws increases it. Except for EPA's Audit Policy, the rest of the regulations were significant. Another relevant result is that facilities that were inspected more intensely in the past five years are more likely to be inspected in the present. This result indicates that EPA uses a targeting strategy to inspect facilities, according to Harrington's hypothesis.

If privilege laws and self-policing policies are used by the regulatory agencies as substitutes for inspections, one would expect that they have a positive effect on the probability of disclosure. Using RCRA data, Stafford (2006b) shows that self-policing policies and immunity laws have a significant and positive effect on the probability of disclosure, while privilege laws have a positive but insignificant effect. She also shows that those facilities that self-disclose a violation and are located in states that enacted audit privilege or self-policing policies are "rewarded" with a lesser probability of inspection. As in the inspection case, inspection history plays an important role in determining the probability of disclosure: facilities that were inspected more frequently in the past five years have a higher probability of disclosure.

According to Stafford (2005 & 2006b) the fact that some facilities are inspected more often than others is based on past inspections and past environmental performance. Whether or not this targeting strategy is based upon industry and company specifics is addressed by Stretesky and Gabriel (2005). In their study, they compare a control group (companies that were found in violation by EPA) with an event group (companies that under EPA's Audit Policy disclosed a violation) to study the motivation for a company to disclose its violations. After controlling for company size, market structure, credit performance, property regime (public or privately owned) and past enforcement actions taken against the company, the probability of disclosure is positive and significantly explained by past inspections, variety of laws violated in the past and regional inspection levels. Neither company size nor market concentration are significant in explaining the probability of disclosure.

The fact that company specifics do not affect the probability of disclosure might be influenced by the nature of the violations disclosed to EPA. If disclosed violations are related to filing oversights rather than failing to comply with emissions standards, an audit can be done at a reasonably low cost, regardless of the size of the company. On the other hand, if disclosed violations are related to failure to comply with emissions standards, it is more likely that an audit to detect such a violation will require investing in more advanced monitoring equipment, which only larger companies are willing to do.

Pfaff and Sanchirico (2004) compare the differences between violations self-disclosed under EPA's Audit Policy and violations found as a result of an inspection. The majority of the violations disclosed to EPA from 1994 to 1999 are related to failure to report required information relating to substances transported or failure to record and keep track of hazardous materials. In contrast, the violations most commonly found by EPA are associated with non-compliance with emission standards. This fact supports the results found by Stretesky and Gabriel (2005), in which company size is not significant in determining the probability of disclosure.

Using fines as a proxy for the severity of violations, Pfaff and Sanchirico (2004) also find that, in general, violations disclosed to EPA are less severe than violations found as a result of an inspection.[8]

In another study, Stafford (2004) analyzes the political, environmental and institutional factors that influence states decision to adopt a given environmental audit regulation; namely, audit privilege, immunity or self-policing policies. The probabilities of adoption of a given regulation are influenced by different factors. For the adoption of self-policing policies, only the political context is significant; for immunity, political factors as well as the nature of the relationship between the state and the Federal government are important in determining its adoption; for audit privilege, a combination of political, environmental and institutional elements are relevant. This might explain the fact that some states adopted a combination of regulations

The differences found by Stafford (2004) on the factors that cause the adoption of different environmental audit regulations indicate that there are significant differences between these regulations. In the next Chapter, we summarize the different

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[8] This is not surprising since EPA's Audit Policy explicitly limits the application of the policy to violations that do not "[…] resulted in serious actual harm, or may have presented an imminent and substantial endangerment, to human health or the environment." For a further discussion, see Chapter 3.

environmental audit regulations that are in place at the federal and state level. The resulting comparison is the basis for the classification of regulations that is used in the empirical model.

Chapter 3. Environmental Audit Regulations

The Federal Government published its Audit Policy for the first time in 1986. This was the first attempt to promote the implementation of environmental audit programs on a national basis. Since the first publication, the Audit Policy has been revised twice. The first revision, in 1995, lead to increased incentives for firms to conduct audits by reducing penalties for entities that voluntarily disclose a violation. The 1995 EPA's Audit Policy reduces the gravity-based penalty up to 100% of a violation found as a result of an internal audit. There are nine requirements that an entity must meet in order to qualify for the benefits of the policy.[9] In general terms, the Audit Policy Conditions are as follows:

1. The violation must be discovered as a result of an environmental audit.
2. The environmental audit must be conducted voluntarily.
3. The violation must be disclosed in a period of ten days after discovery.
4. The violation was not found by a third party.
5. The violation must be corrected no later than 60 days after the discovery.
6. The firm must take preventive steps to avoid the recurrence of the violation.
7. A similar or related violation must not have occurred in the past three years.
8. The violation does not "result in serious actual harm" or represents an "imminent and substantial endangerment to public health or the environment."
9. The firm must cooperate with EPA to establish the application of the Policy.

After an evaluation of its Policy in 1998, EPA amended its 1995 Audit Policy. In the third version of its Policy, the period of disclosure of a violation was extended from 10 to

[9] See EPA's "Incentives for Self-Policing: Discovery, Disclosure, Corrections and Prevention of Violations."

21 days and the application of the Audit Policy Conditions when a firm is transferred to other owners was made explicit.

Some authors claim that EPA's Audit Policy does not give the proper incentives to disclose violations, since the information obtained from the audits is not legally protected and can be used to the detriment of the disclosing firm (Hawks, 1998; Stafford, 2005). The current legislation provides limited protection for self-audits in the form of privilege. Firms can get protection from three legal sources: the attorney-client privilege, the attorney-work product privilege and the privilege of self-critical analysis (Hawks, 1998). The principal limitation of these privileges is that they do not protect the information disclosed in the audit (Hawks, 1998; Frey and Johnson, 2000). Although companies might find some legal resources to protect disclosed information, this protection is rather limited.

In 1993, Oregon enacted its Environmental Audit Privilege, which aims to give protection to the information disclosed as a result of a self-audit. Since then, half of the states in the country have adopted similar laws. Moreover, some states took an additional step and enacted audit immunity laws.

An environmental audit, as defined by EPA, is a "[…] systematic, documented, periodic and objective review by regulated entities of facility operations and practices related to meeting environmental requirements." In general, states that adopted environmental audit laws use a similar definition in their statutes. While audit privilege laws prohibit the use of environmental audit reports as evidence in any administrative, civil, and criminal or enforcement action, immunity laws waive the penalty resulting from a violation voluntarily disclosed to the environmental agency. Although environmental audit state laws are similar in their provisions (Hawks, 1998), they differ in the type of penalties for which the privilege and the immunity apply (see Table 3). In only eight states, environmental audit laws protect audits from administrative, civil and criminal legal actions. For the remaining states, environmental audit laws are more limited in the sense that they only apply to administrative and civil proceedings (see Table 3). Thus, we might expect a higher number of disclosures in states that also protect audits from criminal acts.

In its third version of its Audit Policy, EPA explicitly declares its opinion regarding state environmental audit laws:

> The Agency remains firmly opposed to statutory and regulatory audit privileges and immunity […]. Audit privilege and immunity laws are unnecessary, undermine law enforcement, impair protection of human health and the environment, and interfere with the public's right to know of potential and existing environmental hazards.

In response to EPA's opposition to privilege and immunity regulations, some of the states have made some amendments to their legislation regarding their environmental audit regulations. For example, audit privilege laws in Texas, South Carolina, Mississippi and Oregon were changed to only provide evidentiary privilege to administrative and civil penalties, excluding criminal offenses (see Table 3).

Given the strong opposition of EPA to audit privilege and immunity laws and the growing interest of the public and the government in promoting self-policing regulations, the policies and laws that that some states have adopted so far differ in their applicability as well as in their scope (see Tables 3 and 4).

In general, the self-policing policies that some states have incorporated to their environmental regulations are very similar to EPA's Audit Policy in terms of definitions, conditions and incentives (Frey and McCollough, 2003). However, a relevant distinction comes from the scope of the policy in place. Maine and New York are the only US states where self-policing policies are valid for small businesses (with 20 or less employees) alone (see Table 4). Since it is possible that administrative costs of inspecting small firms are higher compared to the benefits of deterring them from committing a violation, it is possible that these two states are using self-policing policies as direct substitutes for inspections.

In the next Chapter we present the data and the variables used in our estimations.

Chapter 4. The Data and the Variables

This thesis uses a panel dataset from the period 1989-2003 to test the implications of self-policing policies. Table 2 presents a description of the variables, their sources, class and level of aggregation.[10] Data on emissions and inspections, which are the dependent variables, are aggregated at the industry-state-level.[11] These variables were obtained from EPA's Toxics Release Inventory (TRI) and the Integrated Data for Enforcemet Analysis (IDEA) databases, respectively. *Emiss* contains total onsite air emissions registered in the TRI.[12] *Inspec* measures the total number of inspections conducted by EPA and state environmental agencies related to air programs.

The independent variables are classified as policy, industry or state variables. Industry variables were obtained from Compustat, a database with financial information on publicly traded companies. The industry pool contains expenses on R&D (*randt*), age of the assets (*age*), Herfindahl Index (*hfin*), annual sales growth (*growth*), number of employees (*emplsc*) and sales (*salesct*). These variables are intended to control for industry characteristics, such as market structure and size. Unfortunately, there is no information industry-state-level for a large number of companies recorded in Compustat, therefore, all of the industry variables are at the industry-level with the exception of *salesc* and *emplscale*, which were scaled by the ratio

$$S_{ij} = \frac{f_{ij}}{\sum_{j=1}^{N} f_{ij}}, \qquad 4.1$$

[10] All prices are real (100=1995).
[11] The level of aggregation of the industry variables is at the three-digits SIC code.
[12] Individuals for which total on site air emissions are less than one pound or more than ten million pounds were eliminated from the sample.

where the ith and jth indexes refer to industry and state, respectively and *f* denotes number of facilities.[13]

randt is expected to have a negative impact on emissions and inspections, since part of the R&D expenses might be intended to develop cleaner technologies. As argued by Innes and Bial (2002), firms competing in oligopolistic markets overcomply with environmental regulations to pressure the government to tighten environmental standards. Tighter environmental standards impose a higher cost on their rivals. On the inspections equation, *randt* is expected to have a negative impact since the government expects overcompliance in industries with high R&D expenses. To measure industry concentration, we calculated a Herfindahl Index by adding up the squared sales shares of the companies for each industry.[14] We expect *hfin* to have a negative impact on emissions since higher levels of market concentration imply higher incentives for innovation in cleaner technologies (Innes and Bial, 2002).

On the inspections side, the sign of *hfin* can go either way. On one side, concentrated industries provide more incentives to overcomply with environmental standards (Innes and Bial, 2002). Since the regulators expect concentrated industries to incur fewer violations, regulators will inspect these industries less frequently. On the other side, concentrated industries are easier to target for the regulator since they are composed of only one or two firms. Thus, these firms can expect higher inspection frequencies. *Age* was calculated by dividing net assets by gross assets, where gross assets is the sum of net assets plus depreciation.[15] *Growth* measures annual growth in sales in a

[13] In order to have industry variables at the industry-state-level we decided to adjust the number of employees and total sales by the scale factor S_{ij}, since those variables measure economies of scale.
[14] The sale share was computed by taking the percentage of sales made by the ith company with respect to the sales made by the four companies with more sales obtained in a given year.
[15] In the estimations where we control for endogeneity, we use age as the instrument for emissions, since we expect it to increase emissions (Helland, 1998), but not to have any impact on the number of inspections.

given industry.[16] We do not expect any particular sign on this variable. On one hand, following the Environmental Kuznets Curve hypothesis, companies in early stages of economic expansion might disregard environmental performance, while companies that have passed the expansion stage overcomply with environmental regulations to take advantage of "green" markets (Arora and Gangopadhyay, 1995). *Emplsc* measures the number of employees. It is expected to have a positive impact on emissions since it is a proxy for the physical size of a company. Following Gray and Dely (1996), the physical size of a company also determines the political power of the firm. Bigger companies expect fewer inspections since the regulator wants to assure political support from them. As a result, *emplsc* is expected to impact negatively to the number of inspections. *Salesct* is expected to have a negative impact on emissions since wealthier companies might expend more resources in pollution abatement (Henriques and Sadorsky, 1996). On the inspection side, we expect *salesct* to have a negative impact since it can also be a proxy for political influence.

State variables are intended to control for state specifics. Variables on population and income per capita were obtained from Economagic.[17] *Popt* measures the population of a given state and is expected to decrease emissions and increase the number of inspections. Industries located in highly populated states might be exposed to higher levels of public scrutiny, as well as to a higher likelihood of being sued for environmental crimes. Regulators in those states might also be subject to more public pressure to make industries comply with environmental standards through more frequent inspections rates. *Inpercapt* measures income per capita. It is expected to decrease emissions and to increase the number of inspections since people in wealthier states might place more

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[16] Industries for which growth in sales was greater that 8000% were eliminated from the sample.
[17] See http://www.economagic.com/

value on the environment (Helland, 1998). In order to control for state expenses in environmental programs, we include the variable *nrexpt*, which captures state expenditures in natural resources. This variable was obtained from *US Statistical Abstracts*. It is expected to decrease emissions and increase inspections, since it captures environmental preferences. Another variable that intends to capture environmental public awareness is *sierraper*, which measures Sierra Club members per capita. It is expected to decrease emissions and increase inspections. To control for state economic activity related to polluting sectors in the economy, we include *gsp_m_mt*, which measures gross state product of mining and manufacturing sectors. It is expected to increase emissions and increase inspections. *Repvot* measures the ratio of popular vote cast for the republican candidate to total votes in the most recent presidential election. It is intended to capture people's political preferences and is expected to increase emissions and decrease inspections.[18]

Policy variables are dummy variables that indicate whether or not a state has a particular environmental regulation in place. Data used to create these variables were obtained from several State Codes and Frey and McCollough (2003). Although audit privilege and immunity laws are similar on their conditions and provisions, their scope varies from state to state. In some states, audit privilege and immunity laws only apply to civil and administrative penalties, while in some others, these laws also apply to criminal penalties. According to the theory, immunity laws encourage firms to disclose their violations and therefore, they have a negative impact on the number of inspections. *I_ac* is a dummy variable that takes values of '1' if a state has an immunity law that waives civil and administrative penalties. *I_ac_o* takes a value of '1' if the immunity law waives

[18] Alberini and Austin (2002) find that the percentage of votes for the democratic candidate decreases the occurrence of hazardous waste accidents.

civil, administrative and criminal penalties. Since *i_ac_o* also waives criminal penalties, we expect it to have a greater impact on the number of inspections. We expect immunity laws to have a positive effect on emissions. *Imm* is a variable that accounts for any kind of immunity (or *i_ac_o* or *i_ac*). *P_ac* is a dummy variable for audit privilege laws that apply to civil and administrative penalties, while *p_ac_o* is a dummy that indicates whether the audit privilege applies to criminal penalties as well. *Priv* is a dummy that accounts for any kind of audit privilege (or *p_ac_o* or *p_ac*). Whereas the theory predicts that immunity laws will decrease the number of inspections, to our knowledge, there is no theoretical framework that predicts the impacts of audit privilege laws on inspections or on emissions. According to past empirical research (Stafford, 2005, 2006a), audit privilege has shown to reduce the probability of inspections and violations of environmental regulations. However, since there is no theoretical work regarding the impact of audit privilege on the environment or on the number of inspections, there is no anticipated effect of audit privilege variables.

Like immunity and audit privilege laws, self-policing policies are similar in their provisions, but they vary in their applicability. *Sp_ab* is a dummy variable that takes the value of '1' if the self-policing policy applies to all business, regardless of their size. *Sp_sb* is a dummy that takes vales of '1' if the self-policing policy is only applicable to small business (with less than 20 employees). *Selfpol* is a dummy variable that accounts for both types of self-policing policies (*sp_ab* or *sp_sb*). Given that self-policing policies are a special case of immunity,[19] we expect these variables to have a negative effect on inspections and to have a significant and positive effect on emissions.

[19] In general terms, self-policing policies waive the gravity-based part of a penalty, which is the part of the penalty that goes beyond the economic benefit.

Sliab is a dummy variable that indicates whether a state has a law that makes parties strictly liable for accidental hazardous waste spills. We expect this variable to have a negative effect on emissions and inspections, since it is intended to increase company's care in managing hazardous waste.

Chapter 5. Models and Methods

We estimate two equations: an emissions equation and an inspection equation. The emissions equation is intended to capture the effects of environmental audit regulations on the environment, while the inspection equation is intended to pinpoint the impacts of these regulations on the enforcement level of the environmental agencies.

Given that inspections is a count variable, standard OLS cannot be implemented since it generates biased estimates (Winkelmann, 2000). Poisson and Negative Binomial models are more adequate to deal with this kind of dependent variables. By using a panel dataset, we control for unobserved heterogeneity, arising from industry and state specifics that are not captured by the exogenous variables. In order to control for those unobservable characteristics, we estimated fixed and random effects for Poisson and Negative Binomial models.

We also conduct t tests for differences in means of inspections and emissions, before and after the implementation of the different regulations.[20] Table 5 presents the results of the t tests. According to the results, for almost all of the regulations inspections were decreased after the implementation of the policies. On the emissions side, immunity and self-policing policies decrease them, while audit privilege increases them.

Although simple t tests can provide us with a preliminary criterion to evaluate the effects of environmental audit regulations, we still have to control for industry, state and policy characteristics to get a more accurate measure of the impacts of the environmental audit regulations.

[20] We detrended emissions by fitting a regression of emissions on a trend variable.

5.1 The Emissions Equation

We have an unbalanced panel data of 22,408 observations and 2,489 cross-sectional individuals. In order to account for unobserved heterogeneity usually present on panel data models, we estimate a fixed effects model specified by[21]

$$\begin{aligned}
Emiss_{ijt} &= \alpha_{ij} + \beta_1 salesct_{ijt} + \beta_2 emplsc_{ijt} + \beta_3 facility_{ijt} + \beta_4 age_{it} + \beta_5 hfin_{it} + \beta_6 growth_{it} + \\
&\beta_7 randt_{it} + \beta_8 popt_{jt} + \beta_9 inpercapt_{jt} + \beta_{10} gsp_m_mt_{jt} + \beta_{11} nrexpt_{jt} + \beta_{12} repvot_{jt} + \\
&\beta_{13} sierraper_{jt} + \delta T_t + \beta_{14} priv_{jt} + \beta_{15} imm_{jt} + \beta_{16} selfpol_{jt} + \beta_{17} sliab_{jt} + e_{ijt}
\end{aligned} \qquad 5.1$$

where the ith and jth indexes refer to industry and state, respectively.

All of the variables and their expected signs were discussed in Chapter 4, except for T_t which is a vector of time dummies.

5.2 The inspection equation

We estimate fixed effects and random effects Poisson and Negative Binomial models for the inspection equation. In order to compute the fixed effects models, we deleted observations with only one cross-section and individuals for which the sum of the total inspections across time equals cero, $\Sigma_t y_{ij}$=0.[22] The dataset for the fixed effects model has 16,918 observations and 1,714 cross-sectional individuals. The inspection equation is specified by

$$\begin{aligned}
Inspec_{ijt} &= f(salesct_{ijt}, emplsc_{ijt}, facility_{ijt}, hfin_{it}, growth_{it}, randt_{it}, popt_{jt}, inpercapt_{jt}, \\
&gsp_m_mt_{jt}, nrexpt_{jt}, repvot_{jt}, sierraper_{jt}, \delta T_t, priv_{jt}, imm_{jt}, selfpol_{jt}, sliab_{jt})
\end{aligned} \qquad 5.2$$

[21] We conducted a Hausman specification test to test fixed effects appropriateness and we could not reject the null at 5% of significance level.
[22] *Infra*, p. 33.

where the ith and jth indexes refer to industry and state, respectively. The variables and their effects were discussed in Chapter 4.

5.2.1 Fixed Effects and Random Effects

In our model, the number of inspections is distributed as a Poisson

$$y_{ijt} \mid x_{ijt} \sim Poisson\{\lambda_{ijt}\alpha_{ij}\}$$

or as Negative Binomial

$$y_{ijt} \mid x_{ijt} \sim \text{Negative Binomial}\{\lambda_{ijt}\theta_{ij}, \lambda_{ijt}\theta_{ij}(1+\theta_{ij})\}$$

where $\theta_{ij} = \dfrac{\alpha_{ij}}{\phi_{ij}}$

In both models λ_{ijt}=exp($x_{ijt}\beta$), α_{ij} is the source of unobserved heterogeneity and $ø_{ij}$ is the dispersion parameter. In general, Negative Binomial models are less restrictive than Poisson models since they allow for overdispersion (variance greater than the mean).

As in linear models, instead of estimating n different individual effects, we can get rid of the α_{ij}'s and still be able to estimate β. There are several ways in which this can be done.[23] The one we will briefly summarize here is the conditional maximum likelihood proposed by Hausman, Hall and Griliches (1984). It consists of conditioning the probability function of the ith individual on the individual sum of the dependent variable over time, $\Sigma_t y_{ij}$. By doing so, the α_{ij}'s are canceled out and the maximum likelihood can be maximized. The shortcomings of the conditioned maximum likelihood method is that we cannot have individuals in our sample for which $\Sigma_t y_{ij} = 0$, since it will produce divisions by zero in the conditioned maximum likelihood function, and that time invariant regressors can not be used.

[23] See Winkelmann (2000) for a detailed discussion.

An alternative is to estimate a random effects model, where the disturbances α_{ij}'s enter in the model as a random variable.[24] As long as the distribution of the α_{ij}'s is correctly specified, random effects is more efficient than fixed effects, since the former uses the full maximum likelihood function instead of a conditioned maximum likelihood (Winkelmann, 2000). Problems of random effects arise when the unobservable α_{ij}'s are correlated with regressors x_{ij}'s, in which case fixed effects models are preferable. Given that both models have advantages and disadvantages, we decided to estimate both for the inspection equation.

5.3 Econometric Issues

There are two econometric issues that we consider in our estimations. The first one is that emissions and inspections might be determined simultaneously, which indicates that we have to account for endogeneity. The second one is that past inspections might be correlated with present and future inspections, which violates the assumption of no autocorrelation.

We use two econometric estimation techniques to account for endogenous variables and autocorrelation: two-stage Poisson and Negative Binomial models and dynamic models.[25] On the next sections we provide their methodologies, advantages and disadvantages.

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[24] In our Poisson Random Effects estimations, each α_{ij} has a gamma distribution.

[25] We also estimated a Linear Feedback Model by Generalized Method of Moments (GMM), as proposed by Blundell, R., R. Griffith and F. Windmeijer (2002). This model is intended to correct for autocorrelation and endogenous variables and it was estimated using ExpEnd Gauss program (Windmeijer, 2002). We discarded the results of this model because of two reasons: first, for none of our specifications past inspections resulted significant explaining contemporaneous inspections and, second, since the program does not allow for gaps in the individual time-series, the sample got reduced from 17,857 observations to only 9,382, which barely represents all of the industries and the US states.

5.3.1 Two-Stage Model

One approach to deal with endogenous variables in this context is to estimate a two-stage regression model. In the first stage one of the endogenous variables is regressed on a set of instruments that includes the instruments and all of the exogenous variables. In the second stage the other dependent variable is regressed on the exogenous variables and on the predicted values of the dependent variable used in the first stage. This approach produces consistent estimates, although the standard errors need to be corrected (Mullahy, 1997).[26]

Since we could find a good instrument for emissions, but not for inspections, in the first stage we estimate the emissions equation and in the second stage, we estimate the inspections equation. The instrument for emissions is age of the assets, which is correlated with emissions, but uncorrelated with inspections.[27]

Given that we did not find significant coefficients in the two-stage models for the variable *instrumented emissions*, the results of the two-stage method are not reported. Instead, Tables 13 and 14 report the *instrumented emissions* bootstrapped and non-bootstrapped t-statistics for each model specification, respectively.[28]

5.3.2 Dynamic Model

In order to control for autocorrelation we estimate a dynamic specification for the inspection equation, where the variable $\ln(inspec_{ijt-1}+0.5)$ is included as a regressor. Since

[26] In order to correct the Standard errors each model was bootstrapped 500 times.
[27] Our basic argument to use age as instrument for emissions is that regulators will inspect more regularly plants with older assets because they expect those plants to pollute more.
[28] The specifications we estimated were dynamic and non-dynamic models with contemporaneous or lagged emissions instrumented. The reason for which emissions instrumented is not significant explaining inspections might be that other scale variables such as sales or employees are capturing its effect.

inspec is a count variable, it is more appropriate to include the logarithm of the lagged variable, instead of the lagged variable itself (Hill, Rothchild and Cameron, 1998).[29]

Tables 8 and 10 show the results for the dynamic models.

5.4 Extensions

Since the environmental audit regulations vary from state to state, we also estimate an emissions and an inspection equation using a broader classification of audit regulations in the regressors set: *p_ac* and *p_ac_o* are included in place of *priv*, *i_ac_o* and *i_ac* in place of *imm*, and *sp_ab* and *sp_sb* in place of *selfpol*. Tables 6, 9 and 10 show the results for the models with six regulations.

A reduced model is also estimated for the emissions and the inspection equations, where the only explanatory variable included, besides policy variables, is the number of facilities. Table 11 presents the results of the reduced model for the inspection equation and Table 6 presents the results of the reduced specification for the emissions equation.

[29] The constant 0.5 is added to avoid infinity values.

Chapter 6. Results

6.1 The Emissions Equation

Table 6 presents the results for the emissions equation. First, as expected, industries with older assets pollute more. Second, concentrated industries and industries that expend more in R&D pollute less. This result is consistent with the rival's cost hypothesis (Innes and Bial, 2002), which states that competing firms in oligopolistic markets expend more in R&D to overcomply with environmental standards, in order to prompt the government to tighten environmental standards thus gaining an advantage over their rivals. Third, the physical size of the industry, as measured by *emplsc* has a positive and significant impact on the level of pollutants released to the air. Fourth, industries with more facilities have fewer emissions. Two reasons underpin this result: first, those industries are subject to a stronger scrutiny as can be noticed by the results on the inspection equation and, second, industries with more facilities might have larger companies, which usually have better technologies to control emissions. Fifth, income per capita and percentage vote for the republican candidate have a significant and positive impact on emissions. Income per capita captures the extent of industrial activity in the state, while percentage vote for the republican candidate reveals the effects of people's political preferences on the environment. Sixth, states that have strict liability also have higher emissions levels, which suggest that states that adopted strict liability face tougher environmental problems (Alberini and Austin, 2002). Finally, our results show that privilege and immunity have a significant impact on emissions, while self-policing has a non-significant effect. On one hand, audit privilege encourages firms to conduct audits that reduce emissions. On the other hand, audit immunity increases emissions, which suggest that violations disclosed under immunity raise the level of emissions. More specifically, states with audit privilege reduced their emissions in 94,000 pounds, whilst states with immunity increased their emissions in 69,000 pounds.

When we disaggregate the effects of the three environmental audit regulations into six, we obtain that self-policing policies for small business is significant and negative determining emissions. This result implies that self-policing policies have significant differences between each other.

6.2 The Inspection Equation

Results for the different models specified for the inspection equation are presented in Tables 7 to 12. In general, our results are consistent for the different specifications of the inspection equation. In order to tests the robustness of our results, we estimated the inspection equation excluding regions that are conformed by states with relatively small industrial activity. We created five regions: the first region was Arizona, New Mexico, Colorado, Utah and Wyoming; the second region was conformed by Louisiana, Mississippi, Arkansas and Oklahoma; the third one was North Carolina, South Carolina, Georgia and Alabama; the fourth one was Vermont, Maine, New Hampshire, Massachusetts and Rhode Island; and the fifth one was conformed by North Dakota, South Dakota, Minnesota, Wisconsin, Nebraska and Iowa. Our results showed to be very consistent excluding one region at a time: the signs and significance of the independent variables did not change.

More evidence of the robustness of our results comes from the fact that dynamic models produce similar outcomes than non-dynamic ones. For all our dynamic models, lagged inspections resulted positive and significant determining contemporaneous inspections. This result suggests that contemporaneous errors in non-dynamic models are correlated with past errors.

On the industry variables, the variables that are consistently significant through all the specifications are number of facilities, size of the industry as measured by number of employees, membership to the Sierra Club, income per capita and ratio of republican votes to total votes in the most recent presidential election. Number of facilities and size of the industry have a positive impact on the number of inspections. Contrary to what we expected, we do not find evidence of the political influence of larger industries, as evidenced from the effect of the variable *emplsc*. Another interesting result is that variables that measure industry concentration and expenses in R&D, which have a significant impact on emissions, do not have a consistent and significant impact in the different specifications for the inspection equation.

On the state variables, there are several interesting results. First, membership to Sierra Club, as measured by the variable *sierraper*, has a consistent negative and significant effect on inspections. This result indicates that environmental organizations are used as indirect substitutes for enforcement by regulatory agencies. Second, income per capita has a consistent negative and significant impact on inspections. This may be due to the fact that wealthier states use prevention pollution programs, rather than direct enforcement to reduce pollution. Third, percentage of republican votes is also negatively consistent and significant, reflecting the effect of people's political preferences on the environment.

On the policy side, we also find interesting results. When controlling for three regulations, our results are similar to what we obtain on the emissions equation. Audit privilege and self-policing policies have a consistent negative and significant impact on inspections, while immunity has a consistent positive and significant effect on inspections. These results suggest that self-policing policies are consistent to what the theory predicts: they decrease the number of inspections. Our results also suggest that the incentives that immunity laws provide for self-policing firms are decreasing the level of deterrence, which, ultimately, raises inspection rates. Since regulatory agencies have to verify that violations disclosed under immunity are indeed corrected, inspections are increased in states that adopted audit immunity laws. Audit privilege has a negative impact on inspections, implying that the regulatory agencies use it as a direct substitute for inspections (Stafford, 2005).

In order to have a more accurate measure of the effect of these regulations on the number of inspections, we calculate the marginal effects for the models specified in Table 8. Table 12 shows the marginal effects. Depending on the model, privilege reduces the average inspection from 0.24 to 0.67;[30] self-policing reduces it from 0.21 to 0.44; and immunity increases it from 0.32 to 0.77.

Tables 9 and 10 present the results for models with 6 regulations. In general, environmental regulations that apply to administrative and civil penalties alone have stronger impacts than those that also apply to criminal sanctions.

[30] The average inspection is 4.48 and was calculated from the original sample (see Table 2).

Chapter 7. Conclusions

This thesis analyzes the effects of environmental audit regulations on the number of inspections conducted by the regulatory agencies, as well as on the level of air pollutants released to the environment.

Using state, industry and policy controls we find that audit privilege has a negative and significant effect on emissions and inspections; immunity is positive and significant explaining emissions and inspections; and self-policing policies have a significant and negative effect on inspections, though a non-significant effect on emissions.

Our findings regarding self-policing policies support the hypothesis we were testing: self-policing regimes save enforcement resources through decreasing inspections. The fact that immunity reduces the number of inspections and raises emissions suggests that the incentives that immunity laws place for self-policing affect the level of deterrence. The results for the audit privilege variable imply that is used by the regulators as an efficient substitute for inspections (Stafford, 2005).

Industry characteristics have significant effects on inspections and emissions. We find consistent evidence supporting the raising rival's cost hypothesis (Innes and Bial, 2002): firms in oligopolistic markets invest in cleaner technologies to prompt regulatory agencies to stiffen environmental standards.

This work also shows that membership in environmental organizations, as measured by per capita membership to Sierra Club, is used by the regulatory agencies as an indirect substitute for enforcement.

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Appendix

Table 1. Description of Variables

Level of aggregation	Variable	Description	Source
Sic-state	emiss	Millions of pounds of total on site air emissions	TRI (www.epa.gov/tri/)
Sic-state	inspec	State and EPA inspections	IDEA Database
Sic-state	facility	Number of facilities registered in the IDEA Database	IDEA Database
State	popt	Population (millions)	Economagic (www.economagic.com)
State	inpercapt	Income per capita (millions of dollars)	Economagic (www.economagic.com)
State	nrexpt	State Expenditures in Natural Resources (trillions of dollars)	US *Statistical Abstracts*, various years
State	gsp_m_mt	Mining and manufacturing Gross State Product (millions of dollars)	Bureau of Economic Analysis (www.bea.gov/bea/regional/gsp/)
State	sierraper	Per capita members of Sierra Club	Sierra Club
State	repvot	Ratio of popular vote cast for republican candidate to total votes in the most recent presidential election	US *Statistical Abstracts*, various years
Sic	randt	Expenses in R&D (billions of dollars)	Compustat
Sic	age	Age of assets calculated as (Net assets/Gross Assets)	Compustat
Sic	hfin	Herfindahl Index (Σ(Si)^2)/1000, where Si is the share of the ith company with respect to the total sold by the 4 companies with more sales in a given year	Compustat
Sic	growth	Growth in sales	Compustat
Sic-state	emplsc	Number of employees scaled by fac_sic (thousand)	Compustat and IDEA
Sic-state	salesct	Total sales scaled by fac_sic (millons of dollars)	Compustat and IDEA
State	sliab	Dummy variable indicating Strict liability	Environmental Law Institute (ELI)
State	p_ac_o	Dummy variable indicating Privilege applicable to administrative, civil and criminal penalties	State Codes, various years
State	p_ac	Dummy variable indicating Privilege applicable to administrative and civil penalties	State Codes, various years
State	i_ac	Dummy variable indicating Immunity applicable to administrative and civil penalties	State Codes, various years
State	i_ac_o	Dummy variable indicating Immunity applicable to administrative, civil and criminal penalties	State Codes, various years
State	sp_sb	Dummy variable indicating Selfpolicing Policies only valid for small business	State Codes, various years
State	sp_ab	Dummy variable indicating Selfpolicing Policies applicable to all business	State Codes, various years
State	selfpol	Dummy variable indicating Self policing Policies (sp_sb or sp_ab)	State Codes, various years
State	imm	Dummy variable indicating Immunity (i_ac or i_ac_o)	State Codes, various years
State	priv	Dummy variable indicating Privilege (p_ac or p_ac_o)	State Codes, various years

Table 2. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
inspec	4.4830	10.3853	0	281
emiss	0.5896	1.2387	0.000001	9.9918
sliab	0.7393	0.4390	0	1
popt	7.1721	6.5033	0.4537	35.4845
nrexpt	0.3251	0.3848	0.0233	2.8944
gsp_m_mt	0.0370	0.0314	0.0007	0.1720
repvot	0.4578	0.0899	0.1062	0.6789
sierraper	0.0019	0.0026	0.0003	0.0525
inpercapt	0.0233	0.0036	0.0153	0.0369
age	0.7639	0.1161	0.0736	1
facility	5.8297	9.4531	1	224
growth	0.2773	1.9820	-0.9748	29.3739
hfin	5.8939	2.3239	2.5139	10
salesct	0.0006	0.0024	0.00000000312	0.0722
emplsc	0.0018	0.0066	0.0000000345	0.2023
randt	0.6849	2.5698	0	18.1656
selfpol	0.1961	0.3970	0	1
imm	0.2168	0.4121	0	1
priv	0.2829	0.4504	0	1
p_ac_o	0.1341	0.3408	0	1
p_ac	0.1488	0.3559	0	1
i_ac	0.1408	0.3478	0	1
i_ac_o	0.0760	0.2650	0	1
sp_sb	0.0113	0.1059	0	1
sp_ab	0.1848	0.3881	0	1
Obs	22408			

Table 3. Audit Privilege and Immunity Laws Provisions and Years of Adoption

State	Year of adoption	Privilege	Immunity	Provisions: Administrative and Civil Penalties	Provisions: Other legal actions
Alaska	1997	x	x	x	
Arkansas	1995	x		x	x
Colorado	1994	x	x	x	x
Idaho	1996*	x	x	x	x
Illinois	1995	x		x	x
Indiana	1994	x		x	Criminal penalties removed in the 1999 amendments
Iowa	1998	x	x	x	
Kansas	1995	x	x	x	x
Kentucky	1996	x	x	x	
Michigan	1996	x	x	x	Criminal penalties removed in the 1997 amendments
Minnesota	1995	x	x	x	x
Mississippi	1995	x	x	x	Criminal penalties removed in the 2003 amendments
Montana	1997**	x	x	x	
Nebraska	1998	x	x	x	x
Nevada	1997	x	x	x	x
New Hampshire	1996	x	x	x	
New Jersey	1995		x	x	
Ohio	1997	x	x	x	
Oregon	1993	x		x	Criminal penalties adopted in 1997 amendments and removed in 2000
Rhode Island	1997		x	x	
South Carolina	1996	x	x	x	Criminal penalties removed in the 2000 amendments
South Dakota	1996	x	x	x	
Texas	1995	x	x	x	Criminal penalties removed in the 1997 amendments
Utah	1996	x	x	x	
Virginia	1995	x	x	x	
Wyoming	1995	x	x	x	

Source: Frey and McCollough (2003)
*In sunset since 1997
**In sunset since 2001

Table 4. Self-policing Policies Provisions and Years of Adoption

State	Year of adoption	Applies only to Small Business	Applies to All Business
Arizona	2002		x
California	1996		x
Connecticut	1996		x
Delaware	1994		x
Florida	1996		x
Hawaii	1998		x
Indiana	1999		x
Maine	1996	x	
Maryland	1997		x
Massachusetts	1997		x
Minnessota	1995		x
New Mexico	1999		x
New York	1999	x	
North Carolina	1995		x
Oregon	2002		x
Pennsylvania	1996		x
Tennessee	1996		x
Vermont	1996*		x
Washington	1994		x

Source: Frey and McCollough (2003)

* In sunset from 1998 to 2000

Table 5. t Test of Mean Differences: Before and After Regulation Implementation

Self-Policing Policies

	Emissions		Inspections	
	Before	Alter	Before	Alter
Mean	0.0085	-0.0349	4.4304	4.6987
Variante	1.6241	1.0981	93.1877	167.9552
Observations	18014	4394	18014	4394
t Stat	2.0976		-1.53	
P one-tail	0.018		0.9376	

Immunity

	Emissions		Inspections	
	Before	Alter	Before	After
Mean	0.0087	-0.0314	4.8603	3.1202
Variante	0.000075	0.0009	124.6923	44.6625
Observations	17550	4858	17550	4858
t Stat	2.0091		10.3596	
P one-tail	0.0223		0.0000	

Audit Privilege

	Emissions		Inspections	
	Before	Alter	Before	After
Mean	-0.0102	0.0258	4.6865	3.9674
Variante	1.5932	1.3384	120.1936	76.2218
Observations	16068	6340	16068	6340
t Stat	-1.9736		4.6713	
P one-tail	0.0242		0.0000	

Table 6. Emissions Equation

Variables		6 Regulations	3 Regulations	Reduced Model
cons		0.3927*	0.3641*	0.9738**
		(0.2181)	(0.2164)	(0.0158)
age		-0.1352**	-0.1348**	-
		(0.0488)	(0.0488)	
hfin		-0.0111**	-0.0111**	-
		(0.0034)	(0.0034)	
salesct		4.9251	5.0424	-
		(7.4479)	(7.4477)	
randt		-0.0441**	-0.0441**	-
		(0.0044)	(0.0044)	
growth		0.0027	0.0027	-
		(0.0019)	(0.0019)	
emplsc		4.8491**	4.8367**	-
		(2.4489)	(2.4489)	
sierraper		-0.0927	-0.1375	-
		(1.7006)	(1.6975)	
popt		-0.0354**	-0.0360**	-
		(0.0110)	(0.0109)	
inpercapt		38.4315**	39.3325**	-
		(8.3012)	(8.2016)	
nrexpt		0.0187	0.0290	-
		(0.0619)	(0.0615)	
gsp_m_mt		0.1734	0.5131	-
		(1.1811)	(1.1457)	
repvot		0.2625**	0.2582**	-
		(0.1175)	(0.1152)	
sliab		0.0415**	0.0401**	-
		(0.0197)	(0.0196)	
facility		-0.0052**	-0.0052**	-0.0046**
		(0.0011)	(0.0011)	(0.0010)
priv	p_ac	-0.1088**		
		(0.0267)	-0.0940**	-0.0937**
	p_ac_o	-0.0825**	(0.0202)	(0.0201)
		(0.0252)		
imm	i_ac	0.0819**		
		(0.0289)	0.0691**	0.0769**
	i_ac_o	0.0616**	(0.0215)	(0.0214)
		(0.0300)		
selfpol	sp_ab	-0.0034		
		(0.0178)	-0.0140	-0.0199
	sp_sb	-0.1103**	(0.0163)	(0.0159)
		(0.0562)		
R-2		0.1075	0.1073	0.0999
F		70.44	77.12	122.65
P>F		0.0000	0.0000	0.0000
Obs		22408	22408	22408

Table 7. Inspection Equation: Non-Dynamic Model with 3 Regulations

	Random Effects		Fixed Effects	
Variable	Poisson	NB	Poisson	NB
hfin	0.0150**	0.0162**	0.0151**	0.0166**
	(0.0032)	(0.0040)	(0.0033)	(0.0042)
salesct	-14.3032**	-7.2687	-14.8978**	-6.9437
	(5.0221)	(6.5200)	(5.0831)	(6.7777)
randt	-0.0046	-0.0060	-0.0035	-0.0050
	(0.0047)	(0.0057)	(0.0050)	(0.0061)
growth	0.0008	0.0003	0.0006	0.0003
	(0.0015)	(0.0021)	(0.0015)	(0.0021)
facility	0.0424**	0.0327**	0.0408**	0.0309**
	(0.0006)	(0.0007)	(0.0006)	(0.0007)
emplsc	17.0205**	16.3181**	17.1779**	16.1973**
	(1.7499)	(2.1981)	(1.7668)	(2.2662)
sierraper	-7.1231**	-3.9748**	-6.2033**	-5.0078**
	(1.5648)	(1.8972)	(1.5556)	(1.9279)
popt	0.0167**	-0.0551**	0.1495**	-0.0370**
	(0.0077)	(0.0078)	(0.0136)	(0.0085)
inpercapt	-53.2179**	-20.7077**	-45.7642**	-13.0388
	(6.9219)	(7.1357)	(9.6078)	(8.7038)
nrexpt	0.0693	0.0701	-0.2393**	-0.2435**
	(0.0627)	(0.0792)	(0.0698)	(0.0873)
gsp_m_mt	4.7978**	14.6289**	5.5524**	15.0708**
	(0.9809)	(1.0551)	(1.0763)	(1.1353)
repvot	-0.7756**	-0.7446**	-0.8032**	-0.7801**
	(0.1427)	(0.1704)	(0.1481)	(0.1775)
priv	-0.0592**	-0.1658**	-0.0719**	-0.1950**
	(0.0168)	(0.0227)	(0.0169)	(0.0231)
imm	0.1052**	0.1668**	0.1585**	0.1979**
	(0.0201)	(0.0262)	(0.0204)	(0.0268)
selfpol	-0.0944**	-0.0569**	-0.1267**	-0.0580**
	(0.0155)	(0.0199)	(0.0160)	(0.0204)
sliab	-0.0081	-0.0541**	-0.0046	-0.0387
	(0.0199)	(0.0236)	(0.0209)	(0.0251)
cons	2.0088**	2.6876**	-	2.4261**
	(0.1957)	(0.2111)		(0.2423)
Wald chi2(30)	14114.1	8279.63	13692.78	7563.06
Prob>chi2	0.0000	0.0000	0.0000	0.0000
Log likelihood	-39276.277	-38023.619	-29760.645	-28425.409
Obs	22408	22408	16918	16918

Note: Standard Errors in parenthesis. **Statistically significant at the 5% level. *Statistically significant at the 10% level. Time Dummies included.

Table 8. Inspection Equation: Dynamic Model with 3 Regulations

Variable	Random Effects Poisson	Random Effects NB	Fixed Effects Poisson	Fixed Effects NB
inspec(t-1)	0.4575**	0.4635**	0.3561**	0.2936**
	(0.0088)	(0.0116)	(0.0083)	(0.0110)
Hfin	0.0037	0.0061	0.0056	0.0096**
	(0.0034)	(0.0040)	(0.0036)	(0.0045)
salesct	-5.3347	1.1922	-6.2245	1.4147
	(5.4629)	(6.5556)	(5.5850)	(7.0328)
randt	-0.0114**	-0.0090	-0.0115**	-0.0067
	(0.0049)	(0.0056)	(0.0055)	(0.0065)
growth	0.0006	0.0001	0.0006	0.0003
	(0.0017)	(0.0021)	(0.0017)	(0.0022)
facility	0.0315**	0.0250**	0.0328**	0.0260**
	(0.0007)	(0.0008)	(0.0007)	(0.0008)
emplsc	12.1973**	11.0670**	12.7119**	12.1883**
	(1.9093)	(2.2315)	(1.9492)	(2.3694)
sierraper	-7.2232**	-4.7333**	-6.8770**	-5.7850**
	(1.5960)	(1.8333)	(1.5985)	(1.9140)
popt	0.0153**	-0.0323**	0.1945**	-0.0253**
	(0.0072)	(0.0081)	(0.0175)	(0.0100)
inpercapt	-28.9897**	-26.3935**	-25.7811**	-28.2731**
	(6.5735)	(6.7733)	(10.6851)	(9.9367)
nrexpt	-0.0004	0.2361**	-0.5460**	-0.1972**
	(0.0654)	(0.0751)	(0.0809)	(0.0923)
gsp_m_mt	-0.3216	5.6126**	-0.2957	10.5026**
	(0.9960)	(1.1616)	(1.1853)	(1.3258)
repvot	-0.9978**	-1.0487**	-1.0342**	-1.1587**
	(0.1544)	(0.1772)	(0.1659)	(0.1948)
priv	-0.0572**	-0.1187**	-0.0713**	-0.1623**
	(0.0178)	(0.0218)	(0.0181)	(0.0231)
imm	0.0710**	0.1119**	0.1323**	0.1596**
	(0.0215)	(0.0259)	(0.0222)	(0.0274)
selfpol	-0.0645**	-0.0496**	-0.1044**	-0.0621**
	(0.0168)	(0.0201)	(0.0174)	(0.0212)
sliab	0.0058	-0.0299	0.0192	-0.0124
	(0.0216)	(0.0243)	(0.0237)	(0.0275)
cons	1.3251**	2.7080**	-	1.4685**
	(0.1932)	(0.2107)		(0.3104)
Wald chi2(30)	14181.6	10201.48	13036.81	8287
Prob>chi2	0.0000	0.0000	0.0000	0.0000
Log likelihood	-31446.018	-31002.022	-23514.7	-22968.595
Obs	17857	17857	13473	13473

Table 9. Inspection Equation: Non-Dynamic Model with 6 Regulations

	Random Effects		Fixed Effects	
Variable	Poisson	NB	Poisson	NB
hfin	0.0150**	0.0162**	0.0151**	0.0166**
	(0.0032)	(0.0040)	(0.0033)	(0.0042)
salesct	-15.1184**	-7.7622	-15.7423**	-7.5010
	(5.0410)	(6.5426)	(5.0938)	(6.8044)
randt	-0.0042	-0.0058	-0.0031	-0.0047
	(0.0047)	(0.0057)	(0.0050)	(0.0061)
growth	0.0007	0.0003	0.0006	0.0003
	(0.0015)	(0.0021)	(0.0015)	(0.0021)
facility	0.0425**	0.0328**	0.0408**	0.0310**
	(0.0006)	(0.0007)	(0.0006)	(0.0007)
emplsc	16.9265**	16.2510**	17.1832**	16.1373**
	(1.7558)	(2.2050)	(1.7701)	(2.2739)
sierraper	-6.3324**	-3.5109*	-5.8367**	-4.6051**
	(1.5699)	(1.9059)	(1.5608)	(1.9398)
popt	0.0106	-0.0575**	0.1448**	-0.0394**
	(0.0077)	(0.0078)	(0.0142)	(0.0086)
inpercapt	-52.3815**	-20.7923**	-40.6229**	-11.8785
	(6.9956)	(7.1963)	(9.8221)	(8.8134)
nrexpt	0.0703	0.0712	-0.2374**	-0.2463**
	(0.0629)	(0.0793)	(0.0701)	(0.0876)
gsp_m_mt	5.3630**	14.9220**	5.7351**	15.4227**
	(0.9921)	(1.0673)	(1.0910)	(1.1495)
repvot	-0.5727**	-0.6490**	-0.6155**	-0.6516**
	(0.1463)	(0.1750)	(0.1516)	(0.1826)
p_ac	-0.1709**	-0.2297**	-0.1296**	-0.2577**
	(0.0272)	(0.0350)	(0.0280)	(0.0362)
p_ac_o	-0.0088	-0.1311**	-0.0447**	-0.1607**
	(0.0192)	(0.0263)	(0.0194)	(0.0267)
i_ac	0.2744**	0.2577**	0.2812**	0.2953**
	(0.0310)	(0.0397)	(0.0313)	(0.0410)
i_ac_o	-0.0187	0.1029**	0.0397	0.1239**
	(0.0254)	(0.0334)	(0.0259)	(0.0342)
sp_ab	-0.0412**	-0.0285	-0.0951**	-0.0312
	(0.0176)	(0.0220)	(0.0184)	(0.0227)
sp_sb	-0.2851**	-0.1642	-0.1329	-0.0383
	(0.0967)	(0.1104)	(0.1006)	(0.1161)
sliab	-0.0198	-0.0564**	-0.0120	-0.0405
	(0.0200)	(0.0236)	(0.0210)	(0.0251)
cons	1.9065**	2.6499**	-	2.3432**
	(0.1978)	(0.2137)		(0.2460)
Wald chi2(33)	14154.68	8340.58	13721.75	7621.7
Prob>chi2	0.0000	0.0000	0.0000	0.0000
Log likelihood	-39240.466	-38017.8	-29731.367	-28419.217
Obs	22408	22408	16918	16918

Note: Standard Errors in parenthesis. **Statistically significant at the 5% level. *Statistically significant at the 10% level. Time Dummies included.

Table 10. Inspection Equation: Dynamic Model with 6 Regulations

Variable	Random Effects Poisson	Random Effects NB	Fixed Effects Poisson	Fixed Effects NB
inspec(t-1)	0.4562**	0.4626**	0.3549**	0.2949**
	(0.0088)	(0.0115)	(0.0083)	(0.0109)
hfin	0.0036	0.0060	0.0057	0.0095**
	(0.0034)	(0.0040)	(0.0036)	(0.0044)
salesct	-6.2205	0.2684	-7.1984	0.3360
	(5.4844)	(6.5824)	(5.5963)	(7.0708)
randt	-0.0109**	-0.0086	-0.0109	-0.0062
	(0.0049)	(0.0056)	(0.0055)	(0.0065)
growth	0.0005	0.0001	0.0005	0.0002
	(0.0017)	(0.0021)	(0.0017)	(0.0022)
facility	0.0316**	0.0251**	0.0328**	0.0261**
	(0.0007)	(0.0008)	(0.0007)	(0.0008)
emplsc	12.0388**	10.9740**	12.6732**	12.0810**
	(1.9155)	(2.2391)	(1.9519)	(2.3799)
sierraper	-6.5185**	-4.2128**	-6.6456**	-5.2848**
	(1.6015)	(1.8397)	(1.6038)	(1.9282)
popt	0.0130**	-0.0332**	0.1930**	-0.0278**
	(0.0072)	(0.0081)	(0.0183)	(0.0100)
inpercapt	-28.9529**	-26.7532**	-20.8362*	-27.6153**
	(6.6195)	(6.8161)	(10.8685)	(10.0457)
nrexpt	-0.0061	0.2269**	-0.5437**	-0.2044**
	(0.0656)	(0.0754)	(0.0813)	(0.0927)
gsp_m_mt	-0.0851	5.7270**	-0.3493	10.8249**
	(1.0064)	(1.1742)	(1.2012)	(1.3392)
repvot	-0.8319**	-0.9287**	-0.8751**	-0.9875**
	(0.1578)	(0.1815)	(0.1693)	(0.2001)
p_ac	-0.1574**	-0.1956**	-0.1096**	-0.2401**
	(0.0286)	(0.0341)	(0.0297)	(0.0364)
p_ac_o	-0.0136	-0.0810**	-0.0525**	-0.1225**
	(0.0201)	(0.0248)	(0.0206)	(0.0263)
i_ac	0.2175**	0.2232**	0.2319**	0.2850**
	(0.0328)	(0.0390)	(0.0333)	(0.0416)
i_ac_o	-0.0320	0.0337	0.0255	0.0620*
	(0.0273)	(0.0328)	(0.0281)	(0.0347)
sp_ab	-0.0148	-0.0123	-0.0811**	-0.0253
	(0.0192)	(0.0226)	(0.0203)	(0.0239)
sp_sb	-0.2656**	-0.2015*	-0.0492	-0.0468
	(0.1048)	(0.1170)	(0.1140)	(0.1290)
sliab	-0.0039	-0.0335	0.0160	-0.0148
	(0.0218)	(0.0243)	(0.0239)	(0.0276)
cons	1.2525**	2.6739**	-	1.3778**
	(0.1947)	(0.2125)		(0.3139)
Wald chi2(33)	14196.37	10269.82	13042.27	8352.37
Prob>chi2	0.0000	0.0000	0.0000	0.0000
Log likelihood	-31422.405	-30992.57	-23493.666	-22957.899
Obs	17857	17857	13473	13473

Note: Standard Errors in parenthesis. **Statistically significant at the 5% level. *Statistically significant at the 10% level. Time Dummies included.

Table 11. Inspection Equation: Reduced Model

Variable	Random Effects Poisson	Random Effects NB	Fixed Effects Poisson	Fixed Effects NB
facility	0.0446**	0.0346**	0.0433**	0.0325**
	(0.0005)	(0.0007)	(0.0006)	(0.0007)
priv	-0.0682**	-0.1658**	-0.0841**	-0.1949**
	(0.0166)	(0.0232)	(0.0167)	(0.0241)
imm	0.1022**	0.1565**	0.1239**	0.1829**
	(0.0198)	(0.0265)	(0.0199)	(0.0274)
selfpol	-0.0606**	-0.0338*	-0.0586**	-0.0359*
	(0.0148)	(0.0195)	(0.0149)	(0.0201)
cons	0.8334**	2.0894**	-	2.0027**
	(0.0325)	(0.0350)		(0.0344)
Wald chi2(18)	13656.42	7782.36	13177.49	7009.43
Prob>chi2	0.0000	0.0000	0.0000	0.0000
Log likelihood	-39464.658	-38227.301	-30006.077	-28622.429
Obs	22408	22408	16918	16918

Note: Standard Errors in parenthesis. **Statistically significant at the 5% level. *Statistically significant at the 10% level. Time Dummies included.

Table 12. Marginal Effects with Respect to the Average Inspection

Variable	Random Effects Poisson	Random Effects NB	Fixed Effects Poisson	Fixed Effects NB
lninspeclag	2.0498	2.0766	1.5952	1.3153
facility	0.1413	0.1119	0.1468	0.1163
emplsc	54.6438	49.5802	56.9494	54.6035
sierraper	-32.3597	-21.2053	-30.8090	-25.9170
inpercapt	-129.8737	-118.2429	-115.4992	-126.6634
repvot	-4.4702	-4.6982	-4.6333	-5.1908
priv*	-0.2493	-0.5014	-0.3081	-0.6712
imm*	0.3299	0.5302	0.6339	0.7753
selfpol*	-0.2797	-0.2166	-0.4442	-0.2696

Note: Marginal Effects were computed using results in Table 8. The average inspection is 4.48 and was calculated from the original sample. *Discrete Marginal Effects: ($\exp(b_i)$-1).

Table 13. Bootstrapped t Statistics for Emissions Instrumented in the Inspection Equation

	Random Effects		Fixed Effects	
Model Specification	Poisson	NB	Poisson	NB
Dynamic with lagged instrumented emissions	0.1717	0.1166	0.1859	0.1718
	(17857)	(17857)	(13473)	(13473)
Dynamic with contemporaneous instrumented emissions	0.1125	0.0716	0.1660	0.1177
	(17857)	(17857)	(13473)	(13473)
Inspections with lagged emissions instrumented	0.2812	0.2152	0.2395	0.3127
	(17857)	(17857)	(13473)	(13473)
Inspections with contemporaneous emissions instrumented	0.1714	0.2349	-0.1502	-0.0393
	(22408)	(22408)	(16918)	(16918)
Reduced Model with contemporaneous emissions instrumented	0.1831	0.2307	0.1855	0.1799
	(22408)	(22408)	(16918)	(16918)

Note: Number of observations in parenthesis

Table 14. Non-Bootstrapped t Statistics for Emissions Instrumented in the Inspection Equation

	Random Effects		Fixed Effects	
Model Specification	Poisson	NB	Poisson	NB
Dynamic with lagged instrumented emissions	1.1237	0.5740	0.5769	0.5341
	(17857)	(17857)	(13473)	(13473)
Dynamic with contemporaneous instrumented emissions	1.1237	0.5740	0.5934	0.5240
	(17857)	(17857)	(13473)	(13473)
Inspections with lagged emissions instrumented	1.9115*	1.2362	1.0759	0.8271
	(17857)	(17857)	(13473)	(13473)
Inspections with contemporaneous emissions instrumented	0.4342	0.3592	-0.2594	-0.0643
	(22408)	(22408)	(16918)	(16918)
Reduced Model with contemporaneous emissions instrumented	0.8112	0.6499	0.4188	0.2238
	(22408)	(22408)	(16918)	(16918)

Note: * Statistically significant at the 10% level. Number of observations in parenthesis.