Statutory Rewards to Environmental Self-Auditing: Do They Reduce Pollution and Save Regulatory Costs? Evidence from a Cross-State Panel

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Abstract

State-level statutes provide firms that engage in environmental self-audits, and that self-report their environmental violations, with a variety of different regulatory rewards, including "immunity" from penalties and "privilege" for information contained in self-audits. This paper studies a panel of State-level industries from 1989-2003, in order to determine the effects of the different statutes on toxic pollution and government inspections. We find that, by encouraging self-auditing, privilege and limited immunity protections tend to reduce pollution and government enforcement activity; however, more sweeping immunity protections, by reducing firms' pollution prevention incentives, raise toxic pollution and government inspection oversight.

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I. Introduction

Recent changes in environmental law enforcement encourage polluters to self-report their violations to government authorities. Across U.S. States, self-reporting inducements vary from promises of modest reductions in sanctions to complete immunity from sanctions and privilege protections for information uncovered in a firm's environmental self-audit. Environmental groups argue that many of these protections amount to a free pass for polluters that negates incentives for firms to avoid pollution violations and requires increased government oversight of firms' environmental practices (EPA, 2000). Proponents argue instead that these protections are necessary for firms to audit their own environmental performance, audits that in turn yield environmental dividends in the form of quick detection and remediation of pollution violations and potentially the identification and avoidance of pollution outbreaks before they occur (Weaver, Martineau, and Stagg, 1997). Moreover, because self-auditing firms can uncover and self-report pollution violations, enforcement of environmental laws can be achieved with less government investment in oversight and monitoring (Kaplow and Shavell, 1994; Malik, 1993).

These two perspectives offer competing empirical predictions, one that self-policing statutes raise pollution and government environmental monitoring activity, and the other that they lower them. The objective of this paper is to test these predictions, distinguishing between cross-state differences in self-policing policies in a panel of State-level industries. We estimate two equations, one for total toxic emissions and the other for the number of government environmental inspections, both aggregated across facilities to the level of State-specific industries. In doing so, we find some merit in the arguments of both environmentalists and proponents of self-policing protections. Some protections, by promoting environmental self-auditing, are found to lower levels of toxic pollution even though they also prompt lower rates of government environmental monitoring, while others deplete firms' pollution avoidance incentives to such an extent that they raise pollution and prompt compensatory increases in government oversight.

Despite the controversy surrounding self-policing policies, and a burgeoning theoretical literature on the subject,[1] there is surprisingly little empirical work studying their impact. A notable exception is a key paper by Stafford (2005), who estimates the impact of self-policing policies on the probabilities of facility-level inspection and violation using a panel of RCRA (Resource Conservation and Recovery Act) data. There are a number of crucial differences between our analysis and Stafford's (2005) that motivate our work. First, Stafford (2005) controls for overall State-level inspections in estimating her facility-level inspection equation. Hence, she implicitly controls for the effects of self-policing policies that are our primary focus, namely, impacts of self-policing statutes on government inspection *policy*. In order to capture State-specific inspection policy as targeted to different industries, we use data that is at a State-specific industry (vs. facility) level. Second, we study a more direct measure of environmental performance: total toxic emissions, rather than the occurrence of a RCRA violation. Although RCRA violations may have a relationship to ultimate toxic emissions, this relationship is not clear-cut. Many violations are not directly related to emissions, including those that concern reporting and record-keeping. Those that do concern practices that affect emissions are not weighted in Stafford's (2005) violation measure. Rather, this measure is a zero-one variable that equals one if any violation occurs and

[1] See the initial papers of Kaplow and Shavell (1994) and Malik (1993), and recent papers by Pfaff and Sanchirico (2000), Mishra, Newman and Stinson (1997), Friesen (2006), Livernois and McKenna (1999), and Innes (1999a, 1999b, 2000, 2001a). See also the related literature on self-regulation (e.g., Maxwell, Lyon and Hackett, 2000; Maxwell and Decker, 2006).

does not capture effects of multiple or more serious violations. Hence, it is possible that self-policing policies yield less frequent technical violations of RCRA, even though they lead to increased toxic emissions. Third, beyond our different data and longer study period are a number of key differences in estimation method, including (for example) our accounting for fixed individual and time effects.[2]

Other related papers include Pfaff and Sanchirico (2004), who compare and contrast self-disclosed and government-detected violations; Stretsky and Gabriel (2005) and Short and Toffel (2005), who estimate an equation to explain the probability of self-disclosure; Helland (1998), who estimates a joint model explaining facility-level self-reporting and inspections; and Stafford (2006), who estimates the impact of self-policing policies on the probability of self-disclosure (generally positive). However, none of this excellent work seeks to identify the effect of self-policing policies on pollution and government inspection activity, our objective.

To frame the empirical issues addressed in this paper, we begin with an illustrative theoretical model that embeds a number of policy trade-offs relevant here but absent in prior work (see Section II below). In particular, we model effects of privilege protections; care-based sanctions that are prevalent in practice and can motivate government monitoring of self-reporting violators as a counter to weak precautionary incentives; and heterogeneous costs of environmental self-auditing programs that imply plausible marginal effects of policy on the extent of self-auditing. The resulting theory yields analytically ambiguous policy effects on average harm (our theoretical proxy for emissions) and government inspections, but also identifies specific opposing influences. Based on educated conjectures about which opposing influences dominate, we posit three

[2] Stafford (2005) controls for state effects, but not industry or time effects. In addition, we consider a variety of time-varying industry forces and State variables omitted in Stafford's analysis, including measures of industry scale, concentration, growth and R&D, and State population and political composition that can be important in driving environmental regulatory policy.

Hypotheses on the effects of self-policing policies, which we proceed to test in our empirical work (Sections III-IV below).

II. An Illustrative Model

Properly designed enforcement regimes that elicit self-reporting enjoy a number of potential efficiency advantages. They can yield direct enforcement economies (Kaplow and Shavell, 1994; Malik, 1993), indirect enforcement economies (such as saving on costs of imprisonment, Kaplow and Shavell, 1994), more frequent remediation / cleanup (Innes, 1999a), better tailoring of penalties to heterogeneous violators (Innes, 2000), and savings of wasteful avoidance expenditures (Innes, 2001a). To obtain benefits of self-reporting, firms must generally adopt costly environmental self-auditing programs that not only reveal pollution violations, but enable quick remediation and potentially the prevention of accidents that would otherwise occur. In doing so, self-audits also provide much cleaner and clearer documentation of a firm's environmental practices. Legal scholars have argued that this documentation can provide a roadmap for regulatory enforcement that makes prosecution of violations much easier (Hawks, 1998).

To enable self-reporting, by encouraging self-auditing, State laws variously provide two types of protections. First is a reduction in sanctions to self-reporters vis-à-vis violators who are discovered by government inspectors. Extant theory generally argues for self-reporting sanctions equal to the expected non-reporter sanction, thereby motivating firms to self-report without sacrificing incentives for the prevention of accidents / violations. Accounting for costs of self-audit programs, however, firms must be offered somewhat lower self-reporting sanctions so that they enjoy strictly positive benefits of self-reporting that can compensate for costs of self-auditing (Pfaff and Sanchirico, 2000; Mishra, et al., 1997; Innes, 2001b). Some State statutes provide self-reporters with reductions in gravity-based penalties that may or may not be in line with those advanced by economic theorists;[3] others provide self-reporters with complete immunity from sanction.

The second type of protection afforded to self-reporters is "privilege." Many States protect the information contained in self-audits and self-reports from regulatory use beyond the narrow confine of the self-reported violation.[4] Privilege can deny regulators the enforcement economies made possible by self-audit documentation. However, privilege can also encourage firms to adopt self-auditing programs.

Both forms of protection have effects on deterrence (firms' incentives to prevent violations) and firms' adoption of self-audit programs, both of which in turn affect government enforcement incentives and environmental performance. To illustrate the trade-offs, we consider a simple model of self-auditing, deterrence, and enforcement. [5]

Firms engage in activities that can cause pollution "accidents." Due to rapid detection and pro-active management, a self-auditing / self-reporting program leads to lower harm from an accident, with h_S denoting accident harm with self-auditing and h_N ($>h_S$) denoting harm otherwise. Firms reduce accident risk by spending x on "care," which yields the probability of an accident, p(x), where $p'<0$ and $p''>0$. To engage in environmental self-auditing, a firm must invest i. i is heterogeneous across firms, distributed with density (distribution) g(i) (G(i)) on $[0, \bar{i}]$ in the population of regulated firms. Without a self-auditing program, a firm does not observe when it has an accident.

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[3] To obtain these benefits, firms must satisfy various technical requirements, including: disclosing the violation within 21 days of discovery; correcting the violation within 60 days; taking steps to avoid a recurrence of the violation. In addition, the violation must not have been found by a third party and must not be an "imminent and substantial endangerment to public health or the environment" (EPA, 1995).

[4] Privilege makes environmental audit reports inadmissible as evidence in administrative, civil, and sometimes criminal proceedings, including those for environmental enforcement actions. However, privilege does not exclude documentation that is part of an audit report, but also contained in other reports required by law. Although States differ in the breadth of their statutes, privilege is typically voided when a violation is not diligently corrected (Weaver, et al., 1997).

[5] We make a number of stylized assumptions for simplicity; the tradeoffs that we identify extend to more complicated environments, including more involved enforcement regimes, additional benefits of self-auditing in reducing costs of care or cleanup, or firms' observation of some accidents without self-auditing.

Regulatory inspections examine two environmental outcomes: (i) accidents, and (ii) care. An inspection occurs with an endogenous probability r common to all firms. When an (unreported) accident is discovered, the firm is fined f. In addition, if a firm's level of care is found to fall below a given standard, a distinct sanction is imposed. However, this process is imperfect (as in Kolstad, Ulen and Johnson, 1990, for example); observed care is subject to error, $x+\varepsilon$, where ε is random. With an assumed (exogenous) high standard of care, the expected care sanction is a continuous function of true care x that depends upon the presence (or absence) of a self-auditing roadmap. Formally, we assume the expected sanction is $s(x;\eta)$ where η is an information parameter (positive if the firm self-audits and does not enjoy privilege, zero otherwise), $\partial s/\partial x<0$, $\partial s/\partial \eta>0$, and $\partial^2 s/\partial x\partial\eta<0$. Thus, the expected sanction falls with higher care (and hence, a lower probability of falling below the standard) and rises with government information about the firm's environmental practices.[6] Finally, if a firm self-reports an accident, it is fined f_S; however, an inspection remains necessary to sanction insufficient care.

The order of play is as follows. State statutes first dictate privilege protection ($\eta=0$) or not, and the self-reporting sanction parameter $\alpha\in[0,1]$, $f_S=\alpha f$ (where f is exogenous). Second, firms adopt self-auditing programs or not. Third, the government chooses its inspection rate r. Fourth, firms select their care levels. Fifth, accidents occur (or not). Finally, inspections occur and sanctions are levied.

In this model, firms self-report if they self-audit. Formally, a self-auditing (SA) / self-reporting firm faces the expected cost,

$$J_S(x;\alpha,\eta,r) = x + p(x)\, f_S + r\, s(x;\eta) \ , \ f_S = \alpha f,$$

[6] For example, suppose the "care sanction" is f_c; ε is uniformily distributed on [-b,b]; self-auditing improves the precision of the government's observation by narrowing the ε distribution to $[-b+\eta,b-\eta]$, with $b>\eta$; and the "care standard" $\underline{x}$ is set high in a sense to be made precise in a moment. Then

$$s(x;\eta) = f_c\, H(\underline{x}-x;\eta)\ ,\ H()=(\underline{x}-x+b-\eta)/[2(b-\eta)]$$

$$\leftrightarrow\ \partial s/\partial x<0,\ \partial s/\partial\eta=\{f_c/[2(b-\eta)]\}[2H()-1)] > 0,\ \partial^2 s/\partial x\partial\eta=[f_cH_x()]/(b-\eta) < 0,$$

where $\underline{x}$ is sufficiently high that $H()>.5$ for relevant x.

the sum of the care cost (x), expected sanctions from an accident ($p(x)\ f_S$), and the expected care sanction, equal to the probability of inspection r times the expected care sanction if inspected (s). A non-auditing (NA) firm faces the expected cost,

$$J_N(x;r) = x + r\ (p(x)f + s(x;0)).$$

Note that an SA firm will self-report provided the sanction from doing so, f_S, is no greater than the expected accident sanction otherwise faced, rf. Moreover, if $f_S \geq rf$, then (with $\eta \geq 0$), $J_S(x;.) > J_N(x;.)$ and, hence, a firm with positive costs of self-auditing (i>0) will not self-audit. In order to induce self-auditing, f_S must therefore be strictly less than rf, implying that self-auditors self-report.

SA and NA firms choose care to minimize costs,

(1a) $J^*_S(\alpha,\eta,r) = \min J_S(x;.) \quad , \quad x_S(\alpha,\eta,r) = \text{argmin } J_S(x;.)$

(1b) $J^*_N(r) = \min J_N(x;.) \quad , \quad x_N(r) = \text{argmin } J_N(x;.)$

Comparing minimal costs with and without self-auditing, a firm self-audits provided

$$i + J^*_S \leq J^*_N,$$

implying the critical firm (indifferent between SA and NA),

(2) $i^*() = J^*_N - J^*_S \rightarrow q_S$ = proportion of firms that self-audit = $G(i^*(\alpha,\eta,r))$.

Finally, taking q_S as parametric, the government chooses its inspection rate to minimize the expected social costs,

(3) $\min_r \quad q_S\ \{x_S(\alpha,\eta,r) + p(x_S())h_S\} + (1-q_S)\{x_N(r) + p(x_N())h_N\} + rc,$

where c is the cost of an inspection.[7]

This model illustrates a number of tradeoffs involved in self-auditing and policies that prompt this practice. First, self-auditing reduces post-accident harm (to h_S vs. $h_N > h_S$)

[7] The equilibrium r satisfies the first order condition for problem (3) with q_S taken as parametric, but evaluated at $q_S = G(i^*())$ from equation (2).

but also reduces deterrence (with $f_S<rf$) for given government monitoring effort (r) and information ($\eta=0$). The former benefit implies:

Remark 1. An optimal policy involves some immunity protection ($\alpha<r$) that elicits some self-auditing ($i^*>0$). (See Appendix for proof.)

Intuitively, consider setting the self-reporter sanction f_S marginally below the non-reporter sanction rf, with privilege attaching ($\eta=0$). The marginal ($i=0$) firm then self-audits; for this firm, post-accident harm is thereby lowered (to $h_S<h_N$), while deterrence is (approximately) preserved. Hence, welfare costs are lowered. Because it is thus possible to improve welfare by eliciting some (vs. no) self-auditing, there must be some self-auditing in an optimum, which requires some immunity protection ($\alpha<r$).

Remark 2. In a self-auditing optimum (vis-à-vis policies that elicit no self-auditing), there are lower average costs of harm and harm prevention ($x+p(x)h$), lower monitoring costs (rc), or both.

Because self-auditing involves costs of program implementation (i), it must improve welfare by lowering costs of harm and/or monitoring, and most likely both.

Second, we can see effects of immunity and privilege protections on both incentives to self-audit and incentives for care, for given government monitoring effort.

Remark 3. Increased immunity and privilege protections both raise incentives to self-audit ($\partial q_S/\partial\alpha<0$ and $\partial q_S/\partial\eta<0$) and lower incentives for self-auditors to undertake care (reducing deterrence, with $\partial x_S/\partial\alpha>0$ and $\partial x_S/\partial\eta>0$).

In view of these properties, we can identify opposing effects of privilege and/or immunity on average harm and government inspection rates. For each policy that we consider, we expect one effect to dominate, giving us speculative empirical hypotheses that we test in this paper. In our testing, we use toxic emissions of State-level industries as our measure of "average harm," and relevant (air-related) government environmental inspections of State-level industries as our measure of monitoring intensity.

First consider the effects of privilege protection (η=0) when there is some immunity for self-auditors (α<r, so that there is some self-auditing). The social benefit of privilege is that, by eliciting more self-auditing, average accident harms across self-auditors and non-auditors may be lowered. The opposing costs are two: reduced deterrence of self-auditors (thus raising average harm from self-auditors' accidents) and voiding the information economies of self-auditing to government regulators, thus requiring higher monitoring investments in order to achieve the same incentive benefits of care sanctions. Effects of privilege on average harm are thus unclear analytically, even controlling for government inspections: average harm is lowered due to more self-auditors and raised due to reduced deterrence. Effects on government inspections (r) are also unclear. On one hand, reduced deterrence motivates a compensatory increase in government inspections. On the other hand, privilege reduces the effectiveness of government inspections on self-auditors, motivating less monitoring. We conjecture that the self-audit promotion (and harm reduction) effects of privilege dominate in practice:

Hypothesis 1. Privilege lowers both emissions and government inspections.

Consider next the potential consequences of complete immunity when privilege obtains (as it does in all immunity States except two). Let us compare this policy to one with no immunity protection, and hence, no self-auditing. Complete immunity exempts self-reporters from accident sanctions, so that f_S is reduced to only costs of cleanup and correction (with α at a minimum). However, immunity does not exempt self-auditors from sanctions for deficient care, which (given privilege) remain the same as far non-auditors. Controlling for government inspections, immunity thus lowers average accident harm by prompting more self-auditing, but raises it by reducing deterrence.

Immunity also has opposing effects on government monitoring. Reduced deterrence raises incentives for government monitoring of self-auditors' "care." However, monitoring yields less deterrence benefit than without self-auditing; whereas non-auditors face both the average accident sanction p(x)f and the care sanction s() when they are monitored, self-auditors only face the care sanction (paying the negligible "accident sanction" f_S regardless of government monitoring). As a result, with immunity and correspondingly many self-auditors, the average deterrence-promoting effectiveness of inspections declines, favoring less monitoring.

We expect the large deterrence depletion effects of immunity to dominate, implying increased net harms and heightened levels of government inspection scrutiny:

Hypothesis 2. Complete immunity (with privilege) raises both emissions and government inspections.

Finally, many States have enacted an intermediate policy that provides limited immunity protection, but not "complete" immunity. These "self-policing" statutes essentially mimic the U.S.E.P.A.'s guidance on reducing the "gravity based" penalties of self-reporting violators. As with privilege, we expect that these protections spur increased self-auditing that lowers average harm, an effect that may dominate the resulting deterrence depletion. Hence, comparing the "self-policing" policy to one of no self-auditing inducements, we posit the testable speculation:

Hypothesis 3. "Self-policing" statutes lower emissions and government inspections.

III. The Data and the Econometric Model

We construct a panel dataset over the period 1989-2003 where the cross-section units are State-level industries measured using three-digit SIC codes. Due to missing observations and omission of outliers, this gives us an unbalanced panel of 93 industries in the fifty states for a total of 22,408 observations. A given industry's emissions for a given State are obtained by summing the reported toxic releases from facilities that are located in the State and report the industry (three digit SIC) as their primary line of business. The release data is obtained from the EPA's Toxic Release Inventory (TRI). We measure government enforcement activity with the number of State and Federal inspections under the Clean Air Act (CAA).[8] State and industry specific inspections numbers are obtained by summing across each industry's facilities in each State. The source for inspections data is the EPA's IDEA database.

For these two endogenous variables, we posit the following structural model:

(4) $$E_{it} = X_{Eit}\, \beta_E + I^*_{it}\, \alpha_E + \varepsilon^*_{Eit},$$

(5) $$I^*_{it} = X_{Iit}\, \beta_I + E_{it}\, \alpha_I + \varepsilon^*_{Iit},$$

where E_{it} denotes emissions, $I^*_{it} = \ln(I_{it}+k)$ represents inspection intensity (with $k>0$ and I_{it} denoting inspection counts), and $(\varepsilon^*_{Eit}, \varepsilon^*_{Iit})$ are disturbances with zero conditional mean. In principle, inspection activity can promote emission reductions (as documented by Gray and Deily, 1996, and Deily and Gray, 2007, among others). In addition, the anticipation of higher emissions may spur more government enforcement scrutiny.

The structural model can be solved for the reduced form:

(6) $$E_{it} = X_{it}\, \delta + \varepsilon_{Eit},$$

(7) $$I^*_{it} = X_{it}\, \gamma + \varepsilon_{Iit},$$

where X_{it} is the union of X_{Eit} and X_{Iit}.

In what follows, we estimate the reduced form equations (6)-(7), rather than the structural forms (4)-(5), for two reasons. First, our interest ultimately is to measure the overall impact of self-policing statutes on emissions and inspections, including indirect

[8] TRI pollutants are predominantly air pollutants; hence, we focus on CAA inspections.

effects of altered enforcement strategies (on emissions) and of changed emissions (on inspections). Second, as a practical matter, identification of inspections is problematic; for any instrument, a case can be made for direct relevance to emissions.[9]

Explanatory Variables. We have five general classes of independent variables: (1) individual and time effects, (2) measures of industry scale within each State, (3) State attributes, (4) industry attributes, and (5) self-policing policy variables. In both equations, we incorporate fixed time effects and fixed individual effects for all cross-section (industry-State) units. This treatment accounts for unobserved heterogeneity and any time trends. For the inspection equation, we also consider random individual effects.

We construct three measures of industry scale: the number of industry facilities in each state (*Facility*), and measures of State-level industry output (*Sales*) and employment (*Empl*).[10] To obtain State-level sales and employment, we use facility numbers to allocate nationwide sales and employment numbers (constructed from the financial database for publicly traded companies, COMPUSTAT).[11] We expect larger industries to have higher emissions and greater inspection scrutiny, implying positive coefficients on *Empl* or *Sales*. However, controlling for industry size, we have no prior expectation on the effects of facility numbers, whether industries with more (and hence smaller) facilities will tend to produce more or fewer emissions and be subject to more or fewer inspections.

We include a number of State attributes. First, *Pop* measures the State's population. More populous States are expected to be more sensitive to toxic pollution

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[9] For the inspections equation, we experimented with an identification strategy for emissions in the structural equation (5). See note 19 below for details.

[10] All financial variables in our analysis are real (1995=100).

[11] Specifically, we scale nationwide industry sales and employment by the proportion of industry facilities belonging to each state,

$$S_{ijt} = n_{ijt} / \{ \sum_{j} n_{ijt} \},$$

where the ith and jth indexes refer to industry and State, respectively, and n denotes number of facilities.

and, hence, due to heightened public and regulatory pressure, to elicit lower levels of pollution and higher rates of inspection. Second, *Gspmm* measures gross State product in mining and manufacturing industries. Following Alberini and Austin (1999, 2002), we include this measure of output in the more polluting activities even though we control for individual effects; the reason is that higher *Gspmm* may serve to focus regulatory efforts on pollution, potentially raising inspection activity and reducing releases. Third, we include two measures of political attitudes. *Repvote* is the ratio of votes cast for the Republican candidate to total votes in the most recent presidential election. And *Sierra* is the State's per capita Sierra Club membership, a measure of the State's environmentalist constituency. We expect *Repvot* to favor a pro-business regulatory environment, leading to higher emissions and fewer inspections. Conversely, *Sierra* may yield more public scrutiny of industry environmental performance, spurring fewer emissions and either fewer or more inspections as public scrutiny either spurs or substitutes for regulatory enforcement. Fourth, *Income* is per capita income, reflecting overall economic activity and potentially intensifying either pro-business impulses or environmental preferences. Fifth, *Nrexp* measures State expenditures on natural resource programs, including conservation and regulation of exploitive industries. We include this variable to proxy for competition in State environmental budgeting between natural resource services and enforcement of clean air laws; for example, *Nrexp* may crowd out air-related enforcement expenditures and thus lead to fewer environmental inspections.[12] Last, *Strict* is a dummy variable indicating whether or not a State imposes strict environmental liability. Strict (vs. negligence) liability can favor higher emissions if firms are predominantly smaller

[12] Potential effects on emissions are unclear. By lowering inspections, higher *Nrexp* may lead to higher emissions. However, higher *Nrexp* may also indicate public sensitivity to environmental issues and, due to generalized community and political pressure, promote pollution abatement.

(and can thus escape liability) or lower emissions if firms have deep pockets (Alberini and Austin, 1999), and may substitute or complement government enforcement efforts.[13]

We include four industry variables. *RD* is industry research and development expenditure. *Age* represents the "newness" of industry assets, as measured by the ratio of net to gross assets (see Khanna and Damon, 1999); industries with newer assets (and hence, less accumulated depreciation) have *Age* values closer to one. *Herf* is the four-firm Herfindahl Index, a measure of industry concentration. And *Growth* is industry sales growth over the prior year. Newer assets contain more recent pollution abatement equipment and, hence, are expected to reduce toxic releases. Similarly, more research intensive and rapidly growing industries are expected to be more facile in abating pollution. More concentrated industries may be more heavily regulated because they are perceived to be more facile in adapting to tighter emission standards; on the other hand, concentrated industries may be more effective at lobbying for more lax regulation. Hence, expected effects of concentration (*Herf*) on emissions and inspections are unclear.

Finally, our key self-policing policy variables are dummies indicating whether or not a state has a particular statute in place.[14] Three general classes of self-policing statutes are indicated. First, does a State provide privilege protections to information contained in environmental self-audits? If so, our *Privelege* variable takes a value of one. Second, does a State explicitly provide reductions in gravity-based penalties to qualified self-reported violators, consistent with the EPA's 1995 Audit Policy?[15] If so, our *Self-Police* variable takes a value of one. Third, alternatively, does a state provide complete

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[13] If strict liability substitutes for government oversight – spurring fewer inspections and regulatory actions – it may also indirectly spur higher emissions. In our empirical work, however, we do not find evidence for this "enforcement substitution" effect. Any potential endogeneity issues associated with the adoption of strict liability statutes are mitigated by our fixed effects and the tiny shares of individual industries in overall State-level economic and environmental activity in our sample (see discussion below).
[14] These variables are constructed from data in Frey and McCollough (2003) and a review of State Codes.
[15] EPA (1995).

immunity from penalty for qualified self-reported violations? If so, our *Immunity* variable takes a value of one. For each of these variables, we also make finer distinctions. In some states, audit privilege and immunity laws only apply to civil and administrative penalties, while in others, these laws also apply to criminal penalties. Variables distinguishing these effects are denoted by the suffixes, *-ac* (for administrative and civil) or *–aco* (for administrative, civil, and other). Self-policing policies are similar in their provisions, but vary in their applicability. Some States apply self-policing benefits to all businesses (which we measure with the dummy, *Sp-ab*), while others apply only to small businesses (*Sp-sb*).

In practice, the distinction between "self-policing" and "immunity" statutes goes beyond language on the extent of immunity when it is granted (reducing gravity-based penalties versus waiving sanctions altogether). Immunity statutes are generally less restrictive in terms of the eligibility requirements for relief. Following EPA guidelines, "self-policing" policies are much more specific and encompassing with regard to the information that a firm must provide, including self-audit material that goes beyond the initial disclosure.[16] Unlike immunity statutes, these policies also stipulate specific timelines for disclosure and correction (note 3).

Like Stafford (2005), we treat our self-policing policy variables as exogenous. Inclusion of fixed effects mitigates any potential for endogeneity. Moreover, our industries are individually very small contributors to overall State pollution; the average

[16] The EPA requires, at a minimum, "access to all requested documents; access to all employees of the disclosing entity; assistance in investigating the violation, any noncompliance problems related to the disclosure, and any environmental consequences related to the violations; access to all information relevant to the violations disclosed, including that portion of the environmental audit report or documentation from the compliance management system that revealed the violation; and access to the individuals who conducted the audit or review" (EPA, 1995). In contrast, immunity statutes do not define what cooperation is specifically required for relief (with the exception of Rhode Island) and in almost all cases, limit required cooperation to the investigation of the self-reported violation. Ohio's statute is typical, requiring cooperation in "investigating the cause, nature, extent, and effects of the non-compliance" (Frey and McCollough, 2003).

industry share of State emissions in our data is less than one-fifth of one percent (.0019).[17]

Table 1 describes our endogenous and explanatory variables. Table 2 gives corresponding sample statistics. Table 3 describes which States have adopted environmental privilege and/or complete immunity for self-reported violations. Table 4 describes which States have officially adopted a "self-policing" policy following EPA guidance. Note that 22 States have adopted immunity laws, and all but two of these States (New Jersey and Rhode Island) have also enacted privilege protections. Four additional States have enacted privilege statutes, but not any immunity protections. Among the 26 States offering immunity or privilege statutes, all but eight limit the protections to administrative and civil proceedings. In addition, 19 states have enacted EPA-sanctioned "self-policing" statutes, with seventeen of these offering no additional (privilege or immunity) protections to environmental self-auditors. In all but two of these states, the enacted "self-policing" benefits apply to all regulated businesses. In all, 43 States have enacted some form of policy inducement to environmental self-auditing.

IV. Methods and Models

A. The Emission Equation. For the reduced form emission equation (6), we estimate three models by OLS, all with fixed cross section and time effects.[18] Two models include all of our posited explanatory variables, the first with all six self-policing policy variables and the second with our three aggregated policy variables (*Privilege*,

[17] Although individual industries are small – thus motivating our exogeneity premise – collectively they contribute the large majority of measured TRI releases in each State. Accounting for the broader set of industries included in the TRI after 1998, industries included in our analysis account for an average of approximately 64 percent of all State-level TRI emissions; excluding these industries (pre-1998), our included industries account for an average of 99 percent of State-level TRI emissions.

[18] Estimating with fixed effects implicitly accounts for heterogeneity across cross-section units (STATA reference). In addition, we construct heteroskedasticity-robust standard errors.

Immunity, and *Selfpolice*). The third model is a parsimonious specification that includes only the three key policy variables and a measure of industry scale (*Sales*).

Due to evidence of autocorrelation, we also estimate dynamic analogs to our two full models that incorporate an emission lag. To account for potential endogeneity of the lag (due to serial correlation), we instrument it with lagged exogenous data (Greene, 2003) and adjust the standard errors in the resulting two-step estimator to ensure their consistency (following Gujarati, 2003).[19]

Table 5 presents our estimates for these five models of the emission equation.

B. The Inspection Equation. Two central issues arise when estimating the inspection equation (7). First, our inspection data takes a count form, with no negative values, a large number of zeros (34 percent of our sample) and predominantly small integer values (with 74 percent of our observations having values of four and below). To avoid bias in estimation (Winkelman, 2000), we account for the count structure of the data using standard linear exponential models of the equation (2) form (Cameron and Trivedi, 1998). Because Poisson fixed effects models suffer from an equi-dispersion constraint that we reject in statistical tests, we present three models that do not impose the constraint: Negative Binomial fixed and random effects, and Poisson random effects.[20]

Second, we estimate both non-dynamic and dynamic inspection equations. Finding evidence of autocorrelation in the former and a significant lag in the latter, we only present our dynamic estimations in this paper (see Table 6).[21] In these estimations, we follow Hill, Rothschild and Cameron (1998) by including the lagged regressor,

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[19] Note that, with dynamics in emissions and inspections equations, the counterparts to our reduced form equations (6)-(7) include lags in the exogenous data. For both equations, we have also estimated with lagged data, finding that first lags are jointly significant and second lags are not. With first lags included in the models, qualitative effects on our key policy variables are the same as those reported in Tables 5-6.

[20] Negative Binomial and Poisson random effects models allow for over-dispersion. We estimated Poisson fixed effects models as well (results available upon request); however, in all cases, we test for over-dispersion and reject the null of equi-dispersion (with p values below .001).

[21] Non-dynamic analogs, with bootstrapped errors to account for autocorrelation, are available from the authors. Results of these estimations are qualitatively similar to those presented here.

$\ln(I_{it}+.5)$, to account for the assumed linear exponential form of inspections. Following Cameron and Trivedi (1998, p. 229), we construct a test statistic for the null of no serial correlation; asymptotically distributed as a standard normal, we find that this statistic (as reported in Table 6) is not significantly different from zero in any of our models (at the ten percent level). Hence, we proceed under the null of no serial correlation, implying that our estimated coefficients and standard errors are consistent.[22]

In Table 7, we also present a (non-dynamic) parsimonious inspection model. For one of the estimations (negative binomial fixed effects), we reject the null of zero serial correlation at the ten percent level. Although our coefficient estimates are consistent despite autocorrelation (Brannas and Johansson, 1994), the standard errors are not; therefore, for this last model, we present (consistent) bootstrapped standard errors.

V. Results

A. The Emission Equation. Key qualitative results from Table 5 are as follows:

1. Self-policing and privilege protections lead to reduced toxic emissions, while complete immunity leads to increased toxic pollution. Estimated effects of privilege are negative and statistically significant in all models, and arise both when *Privilege* applies

[22] We also estimated the structural form for inspections, equation (5). To do so, we used our asset *Age* variable to identify emissions. Based on the first two (OLS) emission models of Table 5, this variable is highly correlated with emissions with the predicted negative sign, although the F-statistics for this variable (6.3-6.6) are not as high as one might like. There is no reason (to our knowledge) to believe that asset *Age* affects government enforcement policy other than via its impact on anticipated industry emission performance. To estimate, Windmeijer and Santos Silva (1997) provide a GMM procedure for a count panel model with an endogenous regressor, like ours. However, we chose not to use this estimator because required data restrictions compel us to sacrifice almost half of our observations. Instead, we appealed to a simple estimator proposed by Mullahy (1997) that also accounts for an endogenous regressor in a count model, provided the regressor has a linear generating process. For our non-dynamic models, the generating process is indeed linear (equation (6)). In all of these models (twelve of them, Poisson and Negative Binomial, random and fixed effects, contemporaneous and lagged emissions, plus the four parsimonious models of Table 7), the bootstrapped t-statistics on instrumented emissions are insignificant, ranging from .039 to a high of only .313. For the dynamic models, the true reduced form for emissions is linear in an infinite series of lags in the exogenous data. Finding that once-lagged exogenous variables are jointly significant in the emissions equation, and twice-lagged variables are jointly insignificant, we used contemporaneous and once lagged exogenous variables (including the identifying *Age* variable) to instrument emissions. In resulting estimations of the dynamic inspections equation, qualitative effects of the key self-policing policy variables are the same as reported in our reduced form (Table 6) estimations, and instrumented emissions has a significant positive coefficient (consistent with theory).

only to administrative and civil proceedings, and when it applies also to criminal cases. The estimated impacts are large. In the three policy Models 2 and 5, *Privilege* is estimated to reduce emissions by approximately 15.7 percent (in Model 2) and 8.1 percent annually (the long-run effect in Model 5), both as a proportion of sample average emissions.[23]

Estimated effects of "self-policing" are also negative in all models, but statistical significance varies. The provision of self-policing protections only to small businesses appears particularly effective in reducing emissions; statutes that offer these protections to all businesses are estimated to be less effective, perhaps because the more liberal coverage also yields greater depletion of self-auditors' pollution prevention incentives.[24] Small business protections are estimated to reduce toxic emissions by approximately 8.7 percent (Model 1) and 11 percent annually (the long run effect in Model 4).

In contrast, complete immunity for self-reporters is estimated to have positive and statistically significant effects on toxic pollution, regardless of the breadth of application for the immunity protections. In the three-policy models, *Immunity* is estimated to raise toxic emissions by 11.7 percent (Model 2) and 4.5 percent annually (Model 5), again as proportions of the sample average.

2. Toxic emissions tend to be greater in larger industries that have fewer facilities, less R&D, and older assets, and in States that are less populous and more Republican. Emissions are estimated to rise with (State-specific) industry sales, significantly so in our dynamic models. When a State's industry has more facilities

[23] The "long-run" percentage effect is obtained by converting Model 5 into difference form (subtracting lagged emissions from both sides) and solving for the long-run impact of *Privilege* on the change in emissions.

[24] Coverage of all businesses may imply greater relative deterrence-depletion (vs. auditing promotion) effects either because fewer larger businesses are spurred to enact self-auditing programs as a result of the protections (in contrast to small businesses whose self-auditing practices may be more sensitive to the protections) and/or because the broader coverage is associated with somewhat more liberal immunity protections.

(controlling for scale), emissions tend to fall; there are at least two possible explanations for this effect. One, industries with more facilities are subject to more regulatory scrutiny (as revealed in our inspection results to follow). And two, smaller scales of operation may permit better control of environmental outcomes.

As expected, industries with newer assets and more R&D are more likely to benefit from modern pollution abatement techniques that lead to lower levels of pollution. Less populous States with more (pro-business) Republicans experience less public harm from pollution and more public concern for costs of pollution regulation, respectively; hence, they are associated with higher levels of toxic emissions.[25]

B. The Inspection Equation. Key qualitative results from the *Inspections* estimations are as follows (Tables 6-7).

1. Self-policing and privilege protections lead to reduced rates of government inspection, while complete immunity spurs increased government scrutiny of firms' environmental practices. The estimated coefficients on *Privilege* are negative and statistically significant in all models. Based on the three-policy results, *Privilege* is estimated to reduce average inspection rates by between 5 and 15 percent. With one exception, *Privilege* has a significant negative effect on government inspections whether it applies to only administrative and civil proceedings or to criminal cases as well.[26] However, the estimated impact of *Privilege* is greater when it applies more narrowly, indicating that the *addition* of privilege for criminal cases tends to raise inspection rates.

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[25] Table 5 reveals other statistically significant effects as well. Per capita income has a positive impact on emissions (likely as a proxy for overall economic activity). For our dynamic models, *Nrexp* has a negative impact on emission changes, likely as an indicator of community preference and pressure for environmental performance. *Growth* has a negative effect on emission changes, reflecting the improvements in pollution abatement technologies that rapidly growing industries can make. Greater industry concentration leads to reduced pollution (likely reflecting economies of scale in pollution abatement). Finally, *Strict* liability has a weakly significant positive effect on emission levels, and no significant effect on emission changes; the former impact is consistent with results of Alberini and Austin (1999), reflecting a positive effect of strict (vs. negligence) liability on emissions of smaller firms who can escape liability.

[26] The exception is in the six-policy random effects Poisson estimation, where *Priv-aco* has an insignificant (but negative) coefficient and *Priv-ac* has a significant negative coefficient.

Intuitively, criminal privilege (without criminal immunity) may deplete incentives for pollution prevention by more than does privilege for administrative and civil cases; to counter this deterrence depletion, the government may increase its monitoring of firms' environmental practices to ensure that they meet desired standards of "care."[27]

Self-policing policies that mimic EPA guidance are also estimated to reduce inspection rates in all cases, and by substantial amounts – between 5 and 10 percent in the three-policy models. However, in the random effects models, *Self-policing* protections afforded to small businesses are estimated to have much larger effects than those afforded all businesses; hence, offering limited immunity protections to larger businesses (in addition to small businesses) leads to more inspections, not fewer.[28]

Complete *Immunity* is estimated to increase government inspections by between 7 and 17 percent (in the three policy models). Estimated impacts on inspections are larger when immunity only applies to civil and administrative proceedings. Hence, in our sample, the *addition* of criminal immunity tends to spur reductions in inspections. In principle, this may be because criminal immunity is particularly important in spurring the adoption of self-auditing programs, even though (as a practical matter) it has less relevance to pollution prevention incentives than does immunity from civil and administrative sanctions.[29]

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[27] This logic is consistent with our results from the emission equation, where the addition of criminal privilege leads to slightly higher emissions, an increase that is tempered by the additional inspections brought about by the criminal privilege (Table 6).

[28] In principle, this may be because the self-auditing promotion effects of the limited immunity provided by State self-policing policies are much smaller for large businesses than for small; hence, for the large businesses, the principal effect of a self-policing statute is to reduce self-auditors' pollution prevention incentives, which tends to raise emissions (Table 5) and raise government monitoring as a counter.

[29] Fear of criminal prosecution, even if a remote possibility, may deter managers from enacting self-auditing programs. See Starr and Cooney (1996), for example. As discussed in Section II, self-auditing – with privilege and without reduced deterrence – negates the effect of government monitoring on accident sanctions and thereby reduces inspection incentives. This is the effect of adding criminal immunity claimed here.

In sum, if a State is going to enact a complete immunity protection, it may be advantageous to apply immunity broadly – to administrative, civil *and* criminal cases; the *addition* of criminal immunity appears to lower both toxic emissions and government inspection effort. However, *any* complete immunity statute – whether applying narrowly or broadly – has adverse effects on pollution and regulatory costs, *raising* both. In contrast, privilege and self-policing protections have salutary effects on pollution and requisite government inspections, *lowering* both. Our results thus support our initial Hypotheses 1-3. For *Privelege* and *Self-policing*, however, there appear to be benefits of circumscribing the breadth of application. Privilege is most effective in lowering pollution and inspections if it is only applied to civil and administrative cases. And self-policing appears most effective if only applied to small businesses.

2. Government inspection activity tends to be greater in larger industries with more employees and more facilities, and in States that have smaller environmental constituencies, lower incomes per capita, and fewer Republicans. As expected, larger industries with more facilities are subject to more inspections. Pro-business Republican constituencies promote less government regulatory intrusion in the lives of polluting firms. More surprising is that wealthier States with more environmentalists per capita (as measured by Sierra Club membership) tend to inspect less. Environmentalism may promote public scrutiny of firms' environmental conduct that substitutes for regulatory oversight. Higher incomes may tend to reinforce pro-business or environmental impulses or both, adding to their negative effects on government monitoring activity. These effects are also significant in their magnitudes. For example, a one percent change in average income is estimated to reduce inspection rates by approximately five to seven tenths of one percent. A one percentage point increase in Republican voting (approximately two percent of the average Republican vote percentage) is estimated to reduce inspections by approximately .83 to 1.15 percent. And increasing the share of population that is in the Sierra Club by one-fifth of one percent (approximately the mean per-capita Sierra Club membership) is estimated to reduce inspections by approximately .84 to 1.4 percent.[30]

VI. Conclusion

Regulators and environmental groups criticize State-level self-policing statutes because they enable firms to hide their environmental crimes (in the case of privilege) and deny them incentives to prevent pollution outbreaks (in the case of immunity). As a result, they argue, these policies lead to more pollution and require more government monitoring of regulated firms in order to ensure that appropriate pollution abatement activity takes place. In contrast, proponents of these statutes argue that they are necessary for firms to audit their own environmental practices, auditing programs that are costly but yield substantial dividends by identifying and correcting pollution outbreaks that would not otherwise be discovered, sometimes enabling prevention of outbreaks and other times enabling quick remediation. These pollution-reduction benefits of self-auditing are made possible by statutes that protect firms from thereby incriminating themselves and give regulatory rewards to the self-reporting of self-discovered violations. In addition, because firms audit themselves, the statutes may also permit environmental law enforcement to be done effectively with fewer government inspections.

[30] Table 6 reveals some other statistically significant effects. In most models, *Nrexp* is estimated to reduce inspections, consistent with our initial expectation that State expenditures on natural resource programs crowd out environmental enforcement investments. *RD* has a negative effect on inspections, significantly so in the Poisson models; the facility of research-intensive industries to better address pollution outbreaks may motivate less regulatory scrutiny. *Gspmm* has significant positive coefficients in the Negative Binomial models; positive effects are consistent with our initial expectation that States more exposed to the more polluting industries focus more regulatory effort on environmental enforcement. Finally, larger populations are estimated to spur more inspections in our Poisson model, but fewer inspections in the Negative Binomial models. Positive effects are consistent with out initial expectation that more populous States are more sensitive to pollution and, hence, seek to regulate pollution more strictly, including using the inspection tool more vigorously. Negative effects suggest that more populous States achieve reduced pollution (from Table 5) with more public scrutiny and suasion, rather than more regulatory scrutiny per se.

Theory confirms elements of both arguments. Immunity encourages firms to adopt self-auditing programs which can lower the harm from pollution outbreaks. However, immunity also reduces self-auditing firms' incentives to avoid pollution violations in the first place, thereby increasing average pollution and motivating more government monitoring of firms' pollution prevention activities. We conjecture that *complete* immunity has such powerful deterrence-depletion effects – because it gives firms no penalty at all from pollution violations, other than costs of correction – that the second (pollution raising) effect will dominate the first (self-auditing promotion) effect. Hence, we expect immunity to raise both toxic pollution and government inspections.

Similarly, there are competing effects of privilege. Privilege encourages firms to adopt self-auditing programs, but makes it more difficult for regulators to identify and sanction slovenly firm performance in pollution prevention (care). With less effective "care" regulation, firms have less incentive to exercise care and the government has less incentive to regulate it. In sum, privilege can lower pollution by eliciting more environmental self-auditing, but raise pollution by reducing deterrence. If the first effect dominates – as we conjecture – then pollution will fall and governmental monitoring is also likely to decline both because harm-reduction benefits of monitoring are smaller and because monitoring is less effective in spurring pollution prevention.

Our empirical results confirm both of our conjectures to varying degrees. Privilege protections and "self-policing" provisions that provide limited immunity (mimicking Federal guidelines) are estimated to reduce toxic emissions and government inspections. These results indicate salutary effects of these policies, spurring savings of both environmental costs and regulatory resources. In contrast, complete immunity is estimated to raise toxic emissions and government inspections. These effects tend to confirm environmentalists' criticism of self-reporting inducements, when they are too liberal, as protecting polluters to society's detriment. Overall, however, our results suggest that providing firms with positive incentives for environmental self-auditing, both by protecting their audits from capricious use by government prosecutors and by giving properly constructed breaks in sanctions for pollution violations, can be a valuable component of environmental law enforcement, reducing both pollution and enforcement costs. They also suggest the need for care in the design of self-auditing inducements, arguing against blanket immunity protections and instead in favor of more targeted and limited revisions in sanctions.

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Appendix

Proof of Remark 1. It suffices to show that welfare costs can be lowered by lowering α marginally below r (with η=0). Formally, welfare costs are:

$$\text{(A1)}\quad W(\alpha,\eta,r(\alpha,\eta)) = \int_0^{i^*} i\, g(i)\, di + q_S(\alpha,\eta,r(\alpha,\eta))\{x_S() + p(x_S())h_S\}$$

$$+ (1-q_S())\{x_N(r) + p(x_N())h_N\} + r(\alpha,\eta)\, c$$

where $i^*=i^*(\alpha,\eta,r(\alpha,\eta))$ from (2) and $r(\alpha,\eta)$ solves problem (3) (see note 6).

Differentiating:

$$\text{(A2)}\quad dW()/d\alpha\big|_{\alpha=r} = \partial W()/\partial\alpha + (\partial W()/\partial r)(\partial r/\partial\alpha)$$

$$= (di^*/d\alpha)\, i^*()g(i^*()) + (\partial q_S/\partial\alpha)\{x_S()-x_N() + p(x_S())h_S - p(x_N())h_N\}$$

$$+ q_S()\ \{(dx_S/d\alpha)(1+p'(x_S())h_S)\} + (\partial W()/\partial r)(\partial r/\partial\alpha)$$

$$= (\partial q_S/\partial\alpha)\big|_{\alpha=r}\ p(x_N())(h_S-h_N) > 0,$$

where the second equality substitutes from the first order condition for problem (2), and the third is due to the following at α=r: $i^*()=0$, $q_S()=0$, $\partial r/\partial\alpha=0$ and (with η=0), $x_S()=x_N()$. The inequality is due to $h_S<h_N$ and $(\partial q_S/\partial\alpha)\big|_{\alpha=r} = -g(0)p(x_S())f<0$. (A2) implies that welfare costs can be lowered by marginally lowering α below r. QED.

Proof of Remark 2. Follows from Remark 1 and (A1). QED.

Proof of Remark 3. Follows from equations (1) and (2). QED.

Table 1. Description of Variables

Level of aggregation	Variable	Description	Source
Sic-state	Emission	Millions of pounds of total on-site air emissions	TRI (www.epa.gov/tri/)
Sic-state	Inspection	State and Federal environmental inspections	IDEA Database
Sic-state	Facility	Number of facilities registered in the IDEA Database	IDEA Database
State	Pop	State population (millions)	Economagic (www.economagic.com)
State	Income	State income per capita (millions of dollars)	Economagic (www.economagic.com)
State	Nrexp	State Expenditures in Natural Resources (millions of dollars)	US *Statistical Abstracts*, various years
State	Gspmm	Gross State Product in mining and manufacturing (millions of dollars)	Bureau of Economic Analysis (www.bea.gov/bea/regional/gsp/)
State	Sierra	State Sierra Club membership per capita	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	RD	Industry R&D expenditures (billions of dollars)	Compustat
Sic	Age	Industry age of assets (Net assets/Gross Assets)	Compustat
Sic	Herf	Industry four-firm Herfindahl Index	Compustat
Sic	Growth	Industry growth in sales	Compustat
Sic-state	Empl	Industry number of employees by state (millions)	Compustat and IDEA
Sic-state	Sales	Industry total sales by state (trillons of dollars)	Compustat and IDEA
State	Strict	Dummy variable indicating strict liability	Environmental Law Institute (ELI)
State	Priv-ac	Dummy variable indicating Privilege applicable to administrative and civil penalties	State Codes, various years
State	Priv-aco	Dummy variable indicating Privilege applicable to administrative, civil and criminal penalties	State Codes, various years
State	Imm-ac	Dummy variable indicating Immunity applicable to administrative and civil penalties	State Codes, various years
State	Imm-aco	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 businesses	State Codes, various years
State	Sp_ab	Dummy variable indicating Selfpolicing Policies applicable to all businesses	State Codes, various years
State	Selfpolice	Dummy variable indicating Self policing Policies (Sp-sb or Sp-ab)	State Codes, various years
State	Immunity	Dummy variable indicating Immunity (Imm-ac or Imm-aco)	State Codes, various years
State	Privelege	Dummy variable indicating Privilege (Priv-ac or Priv-aco)	State Codes, various years

Table 2. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Inspection	4.4830	10.3853	0	281
Emission	0.5896	1.2387	0.000001	9.9918
Strict	0.7393	0.4390	0	1
Pop	7.1721	6.5033	0.4537	35.4845
Nrexp	0.3251	0.3848	0.0233	2.8944
Gspmm	0.0370	0.0314	0.0007	0.1720
Repvot	0.4578	0.0899	0.1062	0.6789
Sierra	0.0019	0.0026	0.0003	0.0525
Income	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
Herf	5.8939	2.3239	2.5139	10
Sales	0.0006	0.0024	0.00000000312	0.0722
Empl	0.0018	0.0066	0.0000000345	0.2023
RD	0.6849	2.5698	0	18.1656
Selfpolice	0.1961	0.3970	0	1
Immunity	0.2168	0.4121	0	1
Privelege	0.2829	0.4504	0	1
Priv-aco	0.1341	0.3408	0	1
Priv-ac	0.1488	0.3559	0	1
Imm-ac	0.1408	0.3478	0	1
Imm-aco	0.0760	0.2650	0	1
Sp-sb	0.0113	0.1059	0	1
Sp-ab	0.1848	0.3881	0	1
Observations	22408			

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

				Provisions	
State	Year of adoption	Privilege	Immunity	Administrative and Civil Penalties	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. Emissions Equation

Variables		6 Policies	3 Policies	Reduced Model	Dynamic 6 Policies	Dynamic 3 Policies
$Emission_{-1}$		-	-	-	0.4686**	0.4673**
					(0.0460)	(0.0460)
Age		-0.1352**	-0.1348**	-	0.0107	0.0104
		(0.0525)	(0.0525)		(0.0283)	(0.0283)
Herf		-0.0111**	-0.0111**	-	-0.0151**	-0.0151**
		(0.0044)	(0.0044)		(0.0018)	(0.0018)
Sales		4.9251	5.0424	2.1488	9.2035**	9.3167**
		(10.8524)	(10.8562)	(3.9408)	(3.7025)	(3.7020)
RD		-0.0441**	-0.0441**	-	-0.0083**	-0.0085**
		(0.0071)	(0.0071)		(0.0035)	(0.0035)
Growth		0.0027	0.0027	-	-0.0034**	-0.0034**
		(0.0024)	(0.0024)		(0.0011)	(0.0011)
Empl		4.8491	4.8367	-	0.1615	0.1749
		(3.4737)	(3.4746)		(1.2526)	(1.2525)
Sierra		-0.0927	-0.1375	-	-0.5401	-0.6171
		(1.0540)	(1.0504)		(0.8117)	(0.8100)
Pop		-0.0354**	-0.0360**	-	0.0058	0.0067
		(0.0156)	(0.0156)		(0.0669)	(0.0066)
Income		38.4315**	39.3325**	-	11.3917**	11.7377**
		(7.4274)	(7.4755)		(4.8986)	(4.8602)
Nrexp		0.0187	0.0290	-	-0.0557*	-0.0541*
		(0.0725)	(0.0719)		(0.0326)	(0.0324)
Gspmm		0.1734	0.5131	-	-1.5589**	-1.4588**
		(1.4090)	(1.4050)		(0.6287)	(0.6202)
Repvot		0.2625**	0.2582**	-	0.1412**	0.1305**
		(0.1113)	(0.1104)		(0.0630)	(0.0621)
Strict		0.0415*	0.0401*	-	-0.0113	0.0111
		(0.0234)	(0.0234)		(0.0111)	(0.0111)
Facility		-0.0052**	-0.0052**	-	-0.0022**	-0.0022**
		(0.0019)	(0.0019)		(0.0006)	(0.0006)
Privilege	P-ac	-0.1088**			-0.0831**	
		(0.0283)	-0.0940**	-0.0847**	(0.0139)	-0.0733**
	P-aco	-0.0825**	(0.0227)	(0.0200)	-0.0648**	(0.0105)
		(0.0283)			(0.0128)	
Immunity	I-ac	0.0819**			0.0539**	
		(0.0289)	0.0691**	0.0695**	(0.0152)	0.0406**
	I-aco	0.0616*	(0.0240)	(0.0214)	0.0280*	(0.0113)
		(0.0315)			(0.0154)	
Selfpolice	Sp-ab	-0.0034			-0.0022	
		(0.0165)	-0.0140	-0.0269*	(0.0094)	-0.0104
	Sp-sb	-0.1103**	(0.0158)	(0.0158)	-0.0996**	(0.0086)
		(0.0523)			(0.0359)	
R^2		0.1075	0.1073	0.0999	0.1025	0.1024
F Stat. for $\delta=0$		70.44	77.12	121.46	52.50	57.52
Obs		22408	22408	22408	17857	17857

Note: Robust standard errors in parenthesis. ** (*) Statistically significant at the 5% (10%) level (two-tail).

Table 6. Inspections Equation

Variables		6 Policies Poisson RE	Neg Bin RE	Neg Bin FE	3 Policies Poisson RE	Neg Bin RE	Neg Bin FE
Constant		1.3031**	2.7046**	1.4041**	1.3770**	2.7388**	1.4943**
		(0.2000)	(0.2191)	(0.3177)	(0.1986)	(0.2174)	(0.3142)
$Inspection_{-1}$		0.4560**	0.4625**	0.2948**	0.4574**	0.4634**	0.2935**
		(0.0088)	(0.0115)	(0.0109)	(0.0088)	(0.0116)	(0.0110)
Age		-0.0563	-0.0353	-0.0351	-0.0578	-0.0355	-0.0345
		(0.0514)	(0.0617)	(0.0656)	(0.0514)	(0.0618)	(0.0658)
Herf		0.0036	0.0060	0.0095**	0.0036	0.0060	0.0096**
		(0.0034)	(0.0040)	(0.0044)	(0.0034)	(0.0040)	(0.0045)
Sales		-6.1135	0.3043	0.3826	-5.2259	1.2279	1.4598
		(5.4849)	(6.5812)	(7.0694)	(5.4634)	(6.5544)	(7.0314)
RD		-0.0110**	-0.0087	-0.0062	-0.0115**	-0.0090	-0.0067
		(0.0049)	(0.0056)	(0.0065)	(0.0049)	(0.0056)	(0.0065)
Growth		0.0008	0.0002	0.0004	0.0009	0.0003	0.0004
		(0.0017)	(0.0021)	(0.0022)	(0.0017)	(0.0021)	(0.0022)
Empl		11.9784**	10.9444**	12.0451**	12.1353**	11.0374**	12.1533**
		(1.9161)	(2.2391)	(2.3802)	(1.9099)	(2.2316)	(2.3697)
Sierra		-6.5076**	-4.2058**	-5.2795**	-7.2108**	-4.7258**	-5.7796**
		(1.6015)	(1.8395)	(1.9279)	(1.5960)	(1.8331)	(1.9137)
Pop		0.0130*	-0.0332**	-0.0278**	0.0153**	-0.0323**	-0.0252**
		(0.0072)	(0.0081)	(0.0100)	(0.0072)	(0.0081)	(0.0100)
Income		-29.0935**	-26.8081**	-27.7178**	-29.1354**	-26.4492**	-28.3725**
		(6.6198)	(6.8161)	(10.0455)	(6.5738)	(6.7734)	(9.9365)
Nrexp		-0.0070	0.2261**	-0.2051**	-0.0014	0.2353**	-0.1980**
		(0.0656)	(0.0754)	(0.0927)	(0.0654)	(0.0751)	(0.0923)
Gspmm		-0.0733	5.7367**	10.8341**	-0.3086	5.6226**	10.5118**
		(1.0064)	(1.1742)	(1.3389)	(0.9959)	(1.1616)	(1.3256)
Repvot		-0.8319**	-0.9280**	-0.9865**	-0.9976**	-1.0480**	-1.1577**
		(0.1578)	(0.1814)	(0.2001)	(0.1543)	(0.1772)	(0.1948)
Strict		-0.0041	-0.0337	-0.0150	0.0056	-0.0300	-0.0126
		(0.0218)	(0.0243)	(0.0276)	(0.0216)	(0.0243)	(0.0275)
Facility		0.0316**	0.0251**	0.0261**	0.0315**	0.0250**	0.0260**
		(0.0007)	(0.0008)	(0.0008)	(0.0007)	(0.0008)	(0.0008)
Privilege	P-ac	-0.1571**	-0.1955**	-0.2400**			
		(0.0287)	(0.0341)	(0.0364)	-0.0571**	-0.1186**	-0.1622**
	P-aco	-0.0136	-0.0809**	-0.1223**	(0.0178)	(0.0218)	(0.0231)
		(0.0201)	(0.0248)	(0.0263)			
Immunity	I-ac	0.2177**	0.2233**	0.2851**			
		(0.0328)	(0.0390)	(0.0416)	0.0713**	0.1120**	0.1597**
	I-aco	-0.0316	0.0338	0.0621*	(0.0216)	(0.0259)	(0.0274)
		(0.0273)	(0.0328)	(0.0347)			
Selfpolice	Sp-ab	-0.0146	-0.0122	-0.0252			
		(0.0192)	(0.0226)	(0.0239)	-0.0642**	-0.0495**	-0.0620**
	Sp-sb	-0.2653**	-0.2013*	-0.0466	(0.0168)	(0.0201)	(0.0212)
		(0.1048)	(0.1170)	(0.1290)			
Wald χ^2 (df 31/34)		14197.87	10273.33	8354.73	14183.22	10205.06	8289.33
z-statistic		1.4182	1.5057	1.4976	1.4192	1.5081	1.5000
Obs		17857	17857	13473	17857	17857	13473

Note: Standard errors in parenthesis. **Statistically significant at the 5% level. *Statistically significant at the 10% level. Time dummies included. Cameron and Trivedi's (1998) z-statistic (asymptotically distributed standard normal) tests for serial correlation. RE denotes random effects, FE denotes fixed effects, and Neg Bin denotes Negative Binomial.

Table 7. Inspection Equation: Reduced Model

	Random Effects		Fixed Effects
Variable	Poisson	Neg Bin	Neg Bin
Facility	0.0446**	0.0346**	0.0325**
	(0.0005)	(0.0007)	(0.0047)
Privilege	-0.0682**	-0.1658**	-0.1949**
	(0.0166)	(0.0232)	(0.0437)
Immunity	0.1022**	0.1565**	0.1829**
	(0.0198)	(0.0265)	(0.0366)
Selfpolice	-0.0606**	-0.0338*	-0.0359
	(0.0148)	(0.0195)	(0.0228)
Constant	0.8334**	2.0894**	-
	(0.0325)	(0.0350)	
Wald $\chi^2(18)$	13656.42	7782.36	7009.43
z-statistic	1.5017	1.6201	1.6511*
Log likelihood	-39464.658	-38227.301	-28622.429
Obs	22408	22408	16918

Note: Standard Errors in parenthesis. **Statistically significant at the 5% level. *Statistically significant at the 10% level. Time Dummies included. Standard errors for the Fixed Effects NB model are obtained by bootstrapping (with 500 samples).