Governance and Performance: Theory-Based Evidence from US Coast Guard Inspections

Maurice Moffett

Baylor College of Medicine and Department of Veteran Affairs

Alok K. Bohara

University of New Mexico

Kishore Gawande

Bush School of Government, Texas A&M University

March 2004

Bush School Working Paper # 406

Governance and Performance:
Theory-Based Evidence from US Coast Guard Inspections[1]

Maurice Moffett
Baylor College of Medicine and Department of Veteran Affairs

Alok K. Bohara
University of New Mexico

Kishore Gawande*
Bush School of Government, Texas A&M University

Version: March 2004

ABSTRACT: Given three stylized facts about the US Coast Guard (USCG), namely, soft penalties for safety violations, low incidence of penalties relative to the number of violations, and substantial resources devoted to inspections of vessels, this paper seeks (i) a theoretical lens to view USCG activities and (ii) an empirical assessment of whether those activities improve performance. Harrington's (1988) model is motivated by these stylized facts about US regulation in general, and provides a solution via targeting of good and poor performers. The model generates hypotheses about optimal regulation in the context of pollution prevention activities of the USCG. An organization-level panel data set consisting of thousands of US flag tank barges is constructed to test those hypotheses. A count model that controls for vessel heterogeneity yields mixed evidence. If USCG inspections are considered exogenous variables (as the theory presumes), they appear to prevent pollution spills. But if inspections are endogenous and respond to previous spills then correcting for endogeneity reverses the earlier result. In addition, violations are found to be good predictors of pollution occurrences, suggesting that inspections are not as effective as they could be. Targeting as in Harrington's model therefore appears to be incomplete, and the findings suggest that more complete targeting could increase performance. An interesting finding is that stronger penalties could increase performance.

[1] Funding from the NSF is acknowledged. This paper is part of a project testing predictions from agency models about regulation using US Coast Guard inspections and incidents data.

* Corresponding author. Email: kgawande@tamu.edu.

1. Introduction

The question of how law enforcement agencies organize their activities has attracted considerable attention in the economics and political science literature. Empirical studies of whether these agencies perform effectively, far too numerous to list, include examinations of police and the reduction of crime, the Environmental Protection Agency and the control of pollution and hazardous waste, OSHA and the enforcement of safety laws, and the Nuclear Regulatory Commission and compliance with safety standards at reactors and nuclear power plants.

A theory often invoked to study the effectiveness of law enforcement agencies is the principal-agent model (e.g. Shavell 1979; Holmstrom 1979). The law enforcing government agency seeks to minimize violations using appropriate incentives. The regulated firm or individual is interested in maximizing private profits, and cares less about the costs or negative externalities it imposes on society. Thus, a polluting firm fails to internalize the externalities it imposes on society if it only minimizes its private costs. In the principal-agent model the enforcement agency recognizes that the objective of maximizing social welfare runs counter to the firm's objectives, and uses incentives in the form of penalties for noncompliance and rewards for compliance in order to make the firm internalize the externalities as much as possible. Principal-agent relationships in law enforcement are usually hierarchical relationships in which the regulating agency has the force of legal authority to conduct inspections and penalize.

We consider a principal-agent model proposed by Harrington (1988) in which the regulating agency has the force of law behind it but is severely limited in its ability to use high-powered incentives, such as penalties, to solve the problem. Our context is the law enforcement effort of the US Coast Guard (USCG), the agency charged with maintaining safe seaways and waterways. One of its main responsibilities is conducting safety inspections of vessels in order to prevent pollution incidents. What distinguishes the US Coast Guard from other law enforcement agencies is that it rarely uses the courts or harsh monetary penalties to enforce US maritime laws. In part, this is because harsh penalties would restrict commerce and raise costs to consumers.

Although a system of penalties exists, for all but repeat offenders they amount to a slap on the wrist. It is therefore surprising that pollution incidents in US waters are not more frequent.

The seminal empirical study of the USCG by Epple and Visscher (1984), using data from 1970s, found that increased monitoring activity resulted in lower oil spill volume.[2] However, they also found that the frequency of spills increased with resources devoted to enforcement. Their explanation is that increased enforcement of pollution increased detection of spills that would otherwise be unreported. That is, enforcement is endogenous. In a subsequent study that emphasized optimal penalties, Cohen (1987) found that while monitoring oil transfer operations and random port patrols designed to detect spills were effective, routine inspections designed to determine if vessels were in compliance with oil spill prevention regulations had no significant effect on spill size. Anderson and Tally (1995) compared USCG enforcement efforts on US and foreign tankships and confirmed Cohen's results. Gawande and Wheeler (1999) actually found routine inspections to be effective in lowering the number of oil spills aboard US flag tankships during the late 1980s, but did not account for possible endogeneity of hours spent on enforcement. Gawande and Bohara (2003) used panel data from the 1990's and confirmed Cohen's earlier conclusion about the ineffectiveness of inspections designed to check compliance. Other studies of enforcement and pollution, comprehensively surveyed in Cohen (1998), generally indicate that enforcement lowers pollution, although there is no real consensus about whether there is over-enforcement, that is, whether enforcement efforts pass a cost-benefit test.

In this paper we investigate whether that conclusion hold for USCG inspections of tank barges. Barges are numerous and, though some sail ocean routes, mainly transport cargo across inland waterways. Typically, tank barges transfer their cargo from large ocean-sailing tankships that come into an ocean port. During ship-to-ship transfer of oil and chemicals spills are likely to occur if the personnel aboard the barges are inattentive or not well trained. Pollution incidents

[2] The existence of the comprehensive MSMS database from which more recent studies, including this one, draw is in large part due to their work and recommendations.

while sailing US waterways are also likely if a barge is not in peak operating condition, or if the barge owner/operator is negligent, or is the barge owner/operator seeks to reduce costs by using disposal techniques that are cheaper but not legal.

A study of the USCG that is based on Harrington's (1988) model, and close in spirit to ours, is Viladrich-Grau and Groves (1997). Viladrich-Grau and Groves examine the USCG's recently implemented policy of grouping vessels into a less frequently monitored low-risk group and a regularly monitored high-risk group, a policy consistent with Harrington's model. While they find that this policy of targeting vessels both reduces the cost of enforcement and achieves compliance, our results are not unambiguous. A result that stands out is our finding that violations aboard vessels are excellent predictors of pollution occurrences. But in a panel data set that represents a repeated game setting, we should not find such a result if targeting is done effectively according to theory.

The results raise questions about public management issues. Might it be that the USCG uses a combination of governance styles to achieve its regulatory objective: hierarchical governance using incentives such as penalties (as postulated by the principal-agent model) and horizontal governance that emphasizes networking and gentle suasion? Perhaps it uses penalties only as a last resort, and building networks as a primary strategy. Notably, the number of pollution incidents, especially large spills, has declined in recent years. It is appropriate at this point in time to question whether styles of governance other than the command-and-control style implicit in the principal-agent logic of law enforcement might not work better. This paper examines these questions.

The paper proceeds as follows. Section 2 provides relevant background information on USCG vessel inspections. Section 3 describes Harrington's model and derives testable predictions based on the model, presuming the model represents how the USCG organizes its activities. Section 4 describes the data and the count data model used to study tank barge inspections. Section 5 discusses the results. Section 6 discusses an agenda for future research that emphasizes public management issues. Section 7 presents our conclusions.

2. Background: US Coast Guard Inspections

The US Coast Guard is charged with creating and regulating standards for ships in order to promote marine safety and environmental protection.[3] The purpose of the standards is to prevent human casualties and pollution occurrences, and reduce the severity of harm if such events do occur. The enforcement authority of the USCG is bestowed upon it by the Oil Pollution Act of 1990 (OPA90), the Clean Water Act, the Clean Vessel Act, the Marine Plastic Pollution Research and Control Act, and the International Convention for the Prevention of Pollution from Ships at Sea (MARPOL).

The standards enforcement effort by the Coast Guard can broadly be defined as *ex ante* and *ex post* inspections. *Ex post* inspections investigate the causes and liability of a reported collision, allision, grounding, or some other accident. *Ex ante* inspections are scheduled for fixed intervals and are independent of casualties. Many *ex ante* inspections are periodic in order to certify a vessel's seaworthiness. For example, vessels are required to come to a Coast Guard facility for a general audit or a comprehensive hull inspection. Non-routine inspections are random, follow-up or re-inspections. If a ship is found to be substantially out of compliance in any given type of inspection, it may be re-inspected. The penalties for non-compliance are surprisingly small, and are discussed below in the context of the theory. In fact, this is generically the case with enforcement of US regulations, and is not anomalous. The theory discussed in the next section provides a rationale for why this may not necessarily hinder USCG enforcement efforts.

3. Theory and Hypotheses

3.1 State-independent theory (Becker, 1982): Maximal fines

The best-known solution to the principal-agent problem of optimal fines in order to achieve maximum deterrence is Becker (1968). The model is *ex post* to the violation, and

[3] 42 CFR 1 outlines the organization and authority for marine safety functions.

presumes the violation is detected only with a probability less than one. In the context of the USCG, Cohen (1987) and Epple and Visscher (1984) have derived the optimal fines as follows. Supposing the vessel purposefully or accidentally discharges x gallons of oil, the probability it will be detected is $p(x, m)$, where m is the resources expended by the USCG towards detection. For on-sea incidents $p(x, m)$, while positive, is low given the detection technology and resources devoted to inspections. For on-shore incidents during oil transfers, the detection probability is higher because monitoring resources can be and are used more efficiently. If detected, the vessel is charged a penalty $t(x)$.

Suppose the damage and clean-up costs from spillage of x gallons of oil are $D(x)$ and $C(x)$, respectively. Assuming risk-neutrality on the part of the vessel owner (agent), the optimal penalty formula, derived by Cohen (1987), is

$$t(x)=[D(x)+C(x)]/\ p(x,0). \tag{1}$$

With this penalty function, the social optimum may be achieved without expending any resources toward detection so long as $p(x,0)>0$. The optimal penalty function equates the penalty, if the polluting vessel is detected, to environmental damage plus cleanup cost scaled by the probability of detection. Where the probability of detection is low, the optimal penalty, once detected, far exceeds the actual social cost. This is precisely when deterrence is most effective. In order to induce vessel owners to take the socially optimal level of care of their vessels, penalties increase as the probability of detection decreases, an idea that was advanced in Becker (1968).

However, fines in actuality are nowhere near this level. While the penalties paid as a result of the *Exxon Valdez* spill ($1 bn. toward damage and $2 bn. toward cleanup) appear to be in line with the optimal penalty formula, this was largely the result of negligence on the part of the crew captain. OPA90 applies liability limits in the event that the accident is not due to negligent behavior. These limits are a small fraction of the penalties paid by Exxon.

Gawande and Bohara (2003) explain the considerable resources devoted to *ex ante* inspections due to the fact that *ex post* penalties are large. They extend the Becker formula to *ex ante* inspections and penalties on violations found due to such inspections. Nevertheless, theirs is also an optimal penalty solution, and does not resolve the fact that USCG penalties are small. Furthermore, their theories are static and do not consider inspections as a repeated game.

3.2 State-dependent theory (Harrington, 1988): Limited fines

A collection of papers beginning with Greenberg (1984) and Landsberger and Meilijson (1982) has considered the moral hazard problem of regulation in the more realistic repeated game setting. Relaxing some assumptions to make the model more suitable to the real world delivers predictions that sometimes are fundamentally different from the Becker/Stigler optimal penalty rule. The first paper to do this in the context of regulating environmental pollution is Harrington (1988). In Harrington's model the regulating agency (EPA, NRC, or USCG) is assumed to know the cost of compliance for each firm under its regulatory jurisdiction. It is also assumed that, upon monitoring a firm, the agency knows with certainty whether the firm is in compliance or is not in compliance. For example, inspections reveal with certainty the precise amount of hazardous waste emitted (in the case of the EPA), or safety violations in nuclear power plants (in the case of the NRC). Based on this information the agency can then determine whether the firm is in compliance with the law or not. If the firm is found to be non-compliant then the agency has a set of tools at its disposal, as described below.

Harrington's model is motivated by the need to explain three stylized facts that have been empirically documented in the literature. These facts also apply to the USCG that is the subject of this study. First, the severity of penalties sanctioned by regulating agencies is low. Second, this occurs in the face of a considerable number of violations noted by the regulating agencies. Third, despite the fact of lenient penalties, many firms are actually in compliance. Harrington constructs a state-dependent model which makes predictions consistent with these three observations. The regulating agency classifies firms into two groups (states), G1 and G2, depending on their record of compliance. G1 firms are compliant firms whereas G2 firms are not. In order to be compliant and therefore in group G1 or move to it from G2, non-compliant firms must incur costs. Compliance costs are the same for all firms. Firms decide whether to incur such a cost or to cheat and hope that they are not inspected. If a G1 firm is inspected, it reveals with certainty whether the firm is compliant or not. If it is found to be non-compliant, the firm is moved into state G2 (and may be penalized). Firms in state G2 can only return to state G1 if they are inspected and found to be in compliance. Their return, even if found to be compliant, is not certain and occurs with a probability that the agency sets. If a G2 firm is found to be non-compliant, it may be fined. Firms make their decision based on the expected present value of that decision (equal to the present cost plus the present value of expected future penalties). The decision variables for the agency are (i) the probability of inspection of a firm being in each state, (ii) the penalty that agency will apply to firms in each state, and (iii) the probability with which a compliant G2 firm is reclassified as a G1 firm.

The model predicts that, depending on their compliance costs and the agency's probability of inspection, firms will either (i) comply in both states whether they are G1 or G2 firms, (ii) cheat in both states, or (iii) cheat in state G1 and comply in state G2.[4] What is the agency's best policy in terms of its five decision variables, given a (low) ceiling on maximum allowable fine? The agency would like to achieve three objectives: minimize its resource costs (average inspection rate), maximize the average compliance rate, and give proper incentives to firms with the highest compliance cost, that is, the firms that are the least likely to comply in the absence of incentives. But these objectives are in conflict, and thus the agency must achieve one of these conditionally to a target rate of the other two. For example, if the agency seeks perfect compliance, then the inspection rates must be high, and the maximum fine must exceed the highest compliance cost. High fines make it possible, even likely, for high cost firms to not comply since the cost of complying exceeds the present value of future fines. In order to achieve

[4] The surprise is that no firms will comply in state G1 and cheat in state G2, that is, the "good guys" cheat and the "bad guys" comply in order to go back to G1 where they get a chance to cheat.

some level of compliance, then, the agency must lower the fine. Harrington finds that the agency trades lower fine for a higher rate of inspection. In fact, the optimal penalties are zero for firms in G1, and the maximum allowable (although lower than according to the Becker rule) for firms in G2. But since the fine for G1 firms is zero, there is incentive for G2 firms to always comply (in order to return to G1 and possibly cheat). As a result no fines are actually collected. In order to obtain the maximum compliance possible for the G2 firms, it is also necessary for the probability of inspection to be high for G2 firms. Harrington also shows that this state-dependent strategy produces a higher compliance rate with the same resources as a state-independent strategy in which the decision to inspect and penalize is independent of past behavior of firms (so long as perfect compliance, which is very expensive to achieve anyway, is not desired).

Thus, the ability (or desire) to levy only low penalties may not hamper regulatory enforcement. Low penalties for firms in state G1 combined with high frequency of inspection for firms in G2 (consistent with real-world observations about the general incidence of low penalties together with considerable resources devoted to inspections) can produce fairly high compliance rates (consistent with real-world findings in this regard).

A set of papers has sought to qualify or extend the results from Harrington's model, beginning with Harford and Harrington (1991). They show that if the objective is to minimize control costs for a given total pollution reduction, then a state-independent approach in which the pollution standard used to define compliance and non-compliance is different from Harrington's model works better. Raymond (1995) challenges Harrington's conclusion that a high compliance rate can co-exist with low expected fines on the grounds that firms are neither identical nor are their compliance costs known with certainty. He shows that Harrington's results are reversed in the presence of such information asymmetry and uncertainty. Intuitively, if an industry contains a high proportion of firms with low compliance costs then keeping the fine for this group to a maximum is optimal. Lowering their fine encourages even low-cost firms to become non-compliant, with the result that the average compliance rate declines and the average inspection rate goes up. Therefore, setting the G1 penalties to zero is sub-optimal.

Other papers bolster Harrington's predictions. Bose (1995) shows that when inspections by the agency lead the agency to wrongly determine that a compliant firm is out of compliance ("regulatory error") or a non-compliant firm is being compliant, then Becker's maximum fine, even if it were possible to levy, is not the optimal solution. Expending monitoring resources is more effective than levying large fines. In fact, lower penalties and lower monitoring rates can induce full compliance in the presence of regulatory errors. Bose's model works best in a hierarchical regulatory structure where the regulatory agency operates within a legal structure that has been determined by the government (for example, where laws might limit the amount of fines as in the case of the U.S Coast Guard).

An interesting extension of Harrington's model is by Livernois and McKenna (1999), who introduce self-reporting by firms into the model. In this model lowering the fine for non-compliance has two effects. The first is the conventional effect of reducing the number of firms that choose not to comply. The second and more interesting effect is that lowering the fine raises the proportion of non-compliant firms that file truthful reports about their compliance status. Thus, non-compliant firms identify themselves and save the agency from expending resources on determining non-compliance. Innes (1999) also shows that with self-reporting the government can costlessly impose stiffer non-reporter penalties that simultaneously increase compliance and reduce the agency's enforcement effort.

Heyes and Rickman (1999) provide an alternative explanation for why firms will comply despite the small fines imposed by the regulatory agency. Their argument is that the regulatory agency uses tolerance in some areas that induces compliance in other areas. Tolerance is practiced in certain areas due to the difficult regulatory environment in those areas, where it would be difficult to induce compliance without expending substantial resources anyway. For example, when performing safety inspection, USCG inspectors often train the crew by giving them valuable advice on best practices.

Despite its seemingly restrictive assumptions, Harrington's model is an attractive theory upon which to base an empirical study of the USCG for a variety of reasons. First, the low level of equilibrium penalties in the model is in line with USCG policies. Figure 1 depicts the empirical distribution of monetary penalties that USCG inspectors have levied on vessels during the period between 1986-1998. These data are from the USCG Marine Safety Management System (MSMS) database. Of the 3050 penalty cases, 32% have assessments of less than $100. These small penalties are akin to traffic tickets that can be mailed in along with evidence that the penalized violation has been corrected. About 92% of the penalties are at or below $1000, which is not an onerous fine for most vessel operators. Weber and Crew (2000) document low penalties for actual spillage. In 1996, 26 of the 46 enforcement jurisdictions assessed mean penalties of less than $3.60 per liter. Thus, small penalties appear to be the norm. Repeat violators can be taken to court by the USCG, but such legal cases are rare. Due to the costs involved, only extreme cases are penalized in this manner.[5]

Second, numerous violations are recorded by the USCG inspectors. Since Harrington's model shows that even with low penalties in the face of a considerable number of violations, an agency is still capable of achieving a target rate of compliance in a repeated game setting, consistent with USCG data, we view USCG law enforcement activities through the theoretical lens provided by the model. The model's assumption that is most vulnerable in the context of the USCG is that inspections precisely reveal whether the vessel is in compliance or not. Violations as a measure of compliance or non-compliance are necessarily inaccurate, even though they may be good predictors of oil spills.[6] This point is brought home in Gawande and Bohara (2003). In fact, the possibly large variance of the conditional distribution of oil spills (conditional on violations observed by U.S Coast Guard) discourages the use of penalties based on observed violations.[7] Research extending Harrington's model along these lines would be useful.

---

[5] The Oil Pollution Act of 1990 (OPA90), under which Exxon Corp. was sued for the 1989 *Exxon Valdez* spill in Alaska, perhaps provides the greatest deterrence. But even so, OPA90 limits liabilities for accidents in which negligence of the ship owner/operator or crew is not an issue (e.g. Gawande and Bohara, 2003).

[6] Further, if we assume imprecision about compliance, then individual heterogeneity across vessels makes it difficult to model because the predictive distribution of spills conditional upon violations varies across vessels.

[7] Bose's (1995) analysis of regulatory errors and the optimal use of low fines is consistent with USCG policy as well.

Third, circumstantial and direct evidence suggests that USCG inspections are state-dependent. Viladrich-Grau and Groves (1997) document such a policy in effect since 1985:

> "Since 1985, the Coast Guard has followed a two-tier policy; ships entering a harbor are classified either as High or Low Priority vessels. A vessel is classified as High Priority if there has been a recent history of either: (a) a safety violation, (b) an accident, and (c) if it has not been inspected during the last year or monitored during the previous six months. The transfer operations of High Priority vessels are automatically monitored, whereas those of the Low Priority vessels are only infrequently monitored. LP vessels may be randomly selected for inspection but only if all the HP vessels that enter the harbor have been monitored." (Viladrich-Grau and Groves, 1997, fn 6).

Our conversations with numerous USCG inspectors indicate this to be the case with foreign-flag vessels, and to some extent with US-flag vessels. In the case of foreign-flag vessels, an explicit USCG-wide policy that classifies vessels according to flag and other historic vessel information is in effect. In the case of US-flag vessels, such a policy is implicit. Even though many U.S Coast Guard inspections are periodic (e.g., hull inspections, annual inspections, and certificate inspections), the intensity with which a vessel is inspected during these scheduled inspections is based on the historic behavior of the vessel owner/operator. Interviews with several USCG personnel indicate that vessels with significant violations in the past or with a record of oil spills are inspected with greater intensity than vessels with cleaner records. This is consistent with Harrington's model with two states. The USCG frequently requires reinspections of vessels found by inspectors to have numerous violations in areas such as human safety, navigational equipment and maintenance. Reinspections are designed to keep firms from being out of compliance for too long. They therefore serve the purpose of allowing vessels to move from state G2 to state G1. In sum, USCG enforcement policy has many features in common with Harrington's model, which makes the model appropriate to use to theoretically analyze USCG enforcement.

3.3 Hypotheses

Harrington's model has been empirically studied by Helland (2000) using data from the EPA's Permit Compliance System database specifically for the pulp and paper industry, which is the largest single industrial polluter of the nation's waterways. Quarterly data on inspections of paper mills by the EPA and self-reporting and violations at those mills during 1990-1993 are used for this study. Helland finds that these mills are noncompliant about 16% of the time. He finds some support for Harrington's model. Consistent with the model, very low-cost and very high-cost plants do not self-report as much as do intermediate-cost firms. In Harrington's model the incentives largely apply to these firms. Harrington's model describes the plant–regulator interaction for that subset of paper mills that the EPA has decided to inspect for political reasons and at which it wishes to discourage violations actively. Thus, targeting does produce greater cooperation in the form of self-reporting, but such interest-driven targeting (as opposed to targeting based purely on past violations) does not deter violations.

The USCG is less politically driven, and its targeting of vessels based on past vessel records is in line with Harrington's model. Since greater compliance should result in a lower number of oil spills, Harrington's model would imply that (even with the lower amount of penalties) USCG resources devoted to inspections should lower the expected number of oil spill incidents. That is, the model would imply that USCG policy with regard to differential inspections and differential (and low) penalties for vessels in the two states should be effective in lowering the number of oil spills. Furthermore, since USCG budget constraints do not allow an unlimited number of inspections, oil spills should be *negatively* related to resource hours devoted to inspections in a cross-section of vessels. This is the first hypothesis we empirically examine.

An insightful view of this hypothesis is through the theoretical lens of the Harrington model. The USCG would like to achieve the twin objectives of minimizing the number of inspections (resource cost) and maximizing the rate of compliance. It is not possible to optimize both simultaneously. While it would like to achieve complete compliance, that is not possible with its available budget (and the implicit limit on penalties). Thus, the USCG maximizes the rate of compliance given its budget constraint on inspections resources. Since the constraint is binding, at the margin an additional hour of inspection resources would be effective in further lowering oil spills. We state this as our working hypothesis H1.

H1: The number of oil spills is negatively related to the resources devoted to vessel inspections.

Inspections will reveal violations and infractions aboard vessels. Based on this "state" information, vessels are targeted and placed in group G1 or group G2. With the appropriate targeting, in a repeated game, there should either be no relationship or a negative relationship between the number of infractions and violations found during inspections and pollution occurrences. This is the "enforcement leverage" hypothesis from Harrington's model. The incentives are such that vessels placed in G2 are motivated to keep a cleaner record in order to move to G1. Hence, those vessels that are likely to pollute more often (G2-vessels) should show fewer violations upon inspection. Of course, once these vessels move to group G1, they have an incentive to reduce compliance and thus spill. In sum, the two influences should either cancel out or the first one should dominate since, at any point in time, there are more high-risk vessels in G2 than in G1 and inspections are more frequent for G2 vessels. We state this as our next working hypothesis.

H2: The number of violations or deficiencies found during inspections is either negatively related to pollution occurrences, or bears no relationship to them.

Finally, the constraint on the size of penalties is real. Any relaxation of this constraint should lower the number of pollution incidents. We state this as the last working hypothesis.

H3: Stiffer penalties reduce pollution occurrences.

This hypothesis can be tested with data pertaining to the number of legal cases initiated by the USCG inspectors on vessel owners.

4. Data and Econometric Model

Data

A panel of 4,896 U.S. deep-draft (over 100 gross tons of displacement) tank barges over the period 1986-1998 was extracted from the Marine Safety Management System (MSMS) database of the USCG. The fairly comprehensive MSMS database contains hours devoted to various types of inspections, vessel characteristics, and pollution incidents aboard these vessels. Count data on pollution incidents for each vessel were created from the pollution module of the MSMS database, and aggregating spills for vessels by year. Nearly 490 types of oil were recorded as being spilled into the waterways during this period.[8]

The sample has 48,524 observations and is organized as a panel of vessels for each year. Since there is some entry of new barges and exit of old ones, the panel is unbalanced. There were a total of 7,821 pollution incidents and 474 large spills involving tank barges. The highest number of pollution cases for any single tank barge was 22. Over 80% of the tank barges were involved in at least one spill during this period, and 8.12% were involved in at least one large spill.

Table 1 indicates that the mean number of incidents was 0.161 (sd=0.425) in the sample. Conditional on the occurrence of pollution, the sample mean is 1.134 spills per tank barge. A significant portion of the variation in the number of pollution incidents may be the result of unobserved heterogeneity across vessels. The experience of the captain, the training and salary of the crew, the extent to which alcohol consumption is common, and the financial state of the

[8] In order of number of occurrences over the sample period (in parentheses), the most frequently spilled pollutants aboard tank barges were: Fuel Oil No. 6 (738), Diesel Oil (599), Automotive Gasoline (538), Crude Oil (499), Fuel Oil No. 2-D (303), Fuel Oil No. 2 (272), Misc. Oil Lubricating (216), Asphalt (111), Other Oil (105), Cracked Gas Oil (77), Jet fuel: JP-4 (70), Solvent Naphtha (70), Oil, Waste/Lubricants - possible contaminant (64), Benzene (54), Jet fuel: JP-5 (52), Diesel Oil (45), Fuel Oil No. 4 (41), Toluene (41), Motor Oil (39), Styrene (39), Kerosene (37), Fuel Oil No. 1-D (34), Misc. Oil Lubricating (33).

vessel operator are some examples of unobserved variables that result in the unobserved heterogeneity.

Table 1 shows that the average age of tank barges is 21 years. Approximately 20% of all barges primarily ply ocean routes, while the rest sail on inland waterways. About 48% are double-sided and 45% are double-bottomed. These are sturdier designs than single-bottom and single-sided vessels.

Inspection variables were based on the most recent routine inspection. Routine inspections are those that involve a certification inspection (COI) and/or a hull inspection. The average inspection lasts approximately 14 hours. Hull inspections last on average about 30 hours and a basic certification inspection lasts about 8 hours. The average hull inspection resulted in 1.5 deficiencies, while the average certification inspection only resulted in 0.5 deficiencies. The use of legal action is rare, and only 0.2% of all inspections led to a legal case. Table 1 indicates that inspection hours are scaled by the size of the vessel (in thousand gross tons). This prevents spurious scale effects since large vessels require greater resources to inspect. The variable ln(InpsectionHours) is the log of the scaled inspection hours plus 1 (so when no inspection occurs, this variables takes the value zero). Deficiencies are defined as the number of infractions and safety violations found during inspections. ln(Deficiencies) is the log of one plus Deficiencies.

Ship characteristics were based on the information from 1998. Where such information was missing, we assumed a negative answer in order to compute the data.[9] For each vessel, barge characteristics data was merged with inspections data for the year preceding the year of the pollution incident if no inspections were performed in the year of the incident (i.e. inspections data were lagged by a year). If inspections were performed in the same year as an incident, then the inspections data from the same year was used.

[9] For example, if the question was whether a vessel was double-sided and the question was left blank, we could assume with some certainty that it was left blank because the answer was "no."

Unfortunately, penalty data from before 1992 cannot be matched to vessels.[10] Rather than lose a significant part of the sample, we decided to use the full 1986-1998 sample without the penalty data. We do use available information for whether the USCG initiated a legal case against the vessel.

Econometric Model

We model the number of pollution incidents using a count data econometric model. Count data models explain the variation in the count of incidents by variation in covariates, here the inspection hours and vessel characteristics. The count of events for observation i in the panel data set (i = 1, 2,…, n) is denoted y_i>0. Letting x_i indicate the vector of covariates for each i, with an associated vector of coefficients β. The conditional probability density function $f(y_i|x_i, \beta)$ for the Poisson distribution is

$$g(y_i \mid x_i) = \frac{e^{-\lambda_i}\lambda^{y_i}}{y_i!}, \qquad y_i = 0, 1, 2, \ldots, \qquad \text{where } \lambda_i = e^{x_i'\beta}. \tag{2}$$

The exponential specification for the mean λ is popular for the ease of interpretation of the parameter vector β. For any observation (suppressing the i), $\beta_j = \frac{1}{\lambda}\frac{\partial\lambda}{\partial x_j}$, or the percent change in the mean due to a one-unit change in the exogenous variable x_j.

A concern about the Poisson distribution is that it presumes "equidispersion" (see e.g. Cameron and Trivedi 1998). Specifically, the (conditional) mean equals the (conditional) variance, $E[y_i \mid x_i] = V[y_i \mid x_i] = \exp(x_i'\beta)$. It is often the case that in the data the conditional variance is greater than the conditional mean; that is, there is generally overdispersion.

The more general Negative Binomial (NB) model corrects for overdispersion. Specifically, the conditional variance function takes the form

[10] The MSMS database was integrated with the penalty database only in 1992. Previously, it existed separately and did not identify the penalized vessel.

$$V[y_i \mid x_i] = \lambda_i + \alpha\lambda_i \tag{3}$$

where α is a dispersion parameter. The Poisson model is the special case of the NB model where $\alpha = 0$. Among NB models, the most tractable are the NB Type I and NB Type II models, so called because of the difference in their variance specifications (Type I has a linear variance structure, and Type II has a quadratic variance structure; see Gurmu and Trivedi 1996).

A second problem (Gurmu and Trivedi 1996) occurs if there are multiple observations on the same unit, which causes temporal dependence of the data because the same unit (here a vessel) is being observed. The problem of temporal dependence will appear as unobserved heterogeneity in cross-sectional data, and a source of overdispersion. In panel count data, the heterogeneity associated with error that is correlated across time can be captured using a random-effects NB model (see, e.g., Woolridge, 2002, for a discussion of random effects estimation in general). The NB likelihood function captures the heterogeneity from both the unobserved and the temporal error.[11]

Before proceeding to the model results, it is instructive to look at the data distribution. Figures 2.1 and 2.2 depict the frequency distributions of all pollution occurrences and large pollution occurrences aboard tank barges over the sample period. The mode count is 1 for all pollution occurrences and 0 for large pollution occurrences, where "large" pollution occurrences

---

[11] The likelihood function is

$$L(\beta) = \prod_{r=1}^{R} \int_{-\infty}^{+\infty} \prod_{i=1}^{N} \left\{ \frac{\Gamma(y_i + 1/\alpha_i)}{\Gamma(1/\alpha_i)\Gamma(y_i+1)} \left(\frac{1/\alpha_i}{\lambda_i + 1/\alpha_i} \right)^{1/\alpha_i} \left(\frac{\lambda_i}{\lambda_i + 1/\alpha_i} \right)^{y_i} \right\} b(u_r)du_r ,$$

where $\lambda_i = e^{x_i'\beta}$. This is the Type II NB model, where r indexes the unit of observation with errors that are temporally correlated, u_r is the error term on rth unit-specific effect, $b(u_r)$ is the density function of u_r, and Γ is the gamma distribution. Characteristics of the group or unit are unobservable in the data. The error term, u_r is normally distributed with mean zero and variance σ_u. Using this specification allows the error term to be numerically integrated out (we use the Gaussian quadrature method) and σ_u to be estimated together with other model parameters. The integration is computationally intensive, with the result that each tank barge model took about 5 hours to estimate on a 1.5 Ghz Pentium.

were defined as incidents involving spills over 500 gallons. While arbitrary, this cutoff is useful in indicating the difference in the frequency distributions of potential serious incidents and pollution incidents generally. We note that these incidents are self-reported or detected by the USCG. Many pollution occurrences probably go unreported and are not in the data, thus understating the actual number of pollution occurrences. In the econometric analysis we take the data as representing the actual amount of pollution occurrences, and do not model unreported incidents. Figure 2.2 indicates that relatively fewer vessels were involved in large pollution incidents: 398 tank barges were involved in 474 large spills. Thus, the count data for large spills and spills generally are quite different, with the sample of large spills comprising many zeros. Our choice of the Negative Binomial model is appropriate given the large number of zeros and the potential for overdispersion in the data.[12]

5. Results and Discussion

Table 2.1 presents NB random effects estimates from the tank barge sample consisting of 48,524 observations over the 12-year sample period. Estimates from six models appear in the table. The first three models are for count data on all pollution cases while the last three models are for count data on large pollution cases. Consider Model 1, a baseline model in which only vessel characteristics and the region in which they sailed are included as explanatory variables. This model indicates that older vessels have more spills (this is barely statistically significant), tank barges that ply ocean routes have more spills, tank barges with double-sided design have fewer spills, and the relatively few tank barges that sail in the west region have fewer spills than those that sail in the east or central regions.

The dispersion parameter α suggests that overdispersion in the dependent variable makes the Poisson model too restrictive. The statistical significance of α is indicative of unobserved

[12] The descriptive statistics in Table 1 actually indicate that the sample mean for pollution counts (0.161 for all incidents and 0.010 for large spills) are close to their variances in the sample. It would appear that the Poisson distribution would thus fit. We conducted tests of models and chose the NB model based on formal model comparisons of the NB versus the Poisson model.

heterogeneity due to unmeasurable explanatory variables (e.g., weather conditions, crew experience, and the general policy of owners of the vessel regarding expenditures on maintenance). The statistical significance of σ_u (see fn 11) indicates a one-year temporal dependence of pollution incidents for any vessel. This result suggests that there may be multiple risk classes for ships and that if the USCG can identify high-risk ships, based on oil spills (that is, targeting based on *outcomes* as opposed to targeting based on safety violations), then more effort on those ships could be elicited, increasing performance.

Model 2 introduces USCG interventions, measured by the logged hours of inspections on each vessel, the logged deficiency count found in the last inspection, and the number of legal actions generated during the last inspection. By presuming that inspection hours are exogenous, we are taking Harrington's model quite literally. In Harrington's model inspections occur randomly. The probability of inspections is endogenous, as is the targeting of vessels into groups G1 or G2 and the resulting penalties.[13] If Harrington's model is correct then model 2.1 indicates that inspection hours are very effective in reducing pollution incidents aboard tank barges. The coefficients of –0.112 indicate that, all else being constant, a 10% increase in inspection hours decreases the expected number of pollution incidents by 1.12%. This is a strong affirmation of Hypothesis H1, and therefore a validation of Harrington's model. With low penalties, an excessive burden is placed on inspection resources, and with budget constraints the "shadow price" of an additional inspection hour on the margin is the reduction in pollution incidents foregone.

The positive coefficient on ln(Deficiencies) is a troubling indicator that the deficiencies found aboard vessels are good predictors of pollution incidents. If targeting of vessels into the two groups is done based on deficiencies, then we should not find a positive estimate over the long run on ln(Deficiencies). We not only find this in this model, but it persists across all models

[13] Recall that the agency's decision variables are (i) the probability of inspection of a firm being in each state, (ii) the penalty that agency will apply to firms in each state, and (iii) the probability with which a compliant G2 firm is reclassified as a G1 firm. Inspection resources are not a decision variable, and are fixed exogenously.

in Table 2.1 Thus, hypothesis H2 is not validated empirically. This reveals that targeting as in Harrington's model is incompletely done and is not effective; in the presence of incomplete targeting, penalties for violations and spills are inadequate. Done effectively, targeting should lead to no particular relationship between deficiencies and pollution incidents, especially in the repeated game setting that the long panel captures. The number of legal actions brought against repeat violators is not statistically significantly different from 0 in Model 2. We will see that legal action is quite effective in deterring large spills, and probably used for that reason rather than for deterring pollution incidents generally.

Model 3 introduces two other variables. Those variables are the logged number of years since the last inspection and its square. The coefficients on these two variables indicate a U-shaped relationship of pollution counts with this variable, with the minimum occurring at 1.75 years. That is, if the last inspection occurred more than 1.75 years ago, the expected number of pollution incidents increases at an increasing rate. Since the mean for ln(LastInspection) is 1.5 years (the exponential of 0.391, the mean of ln(LastInspection) in Table 1) and a standard deviation of 1.625 years, quite a large number of vessels are inspected at long intervals. For these, the expected number of spills is higher and increases as more time passes without an inspection. Working just from the data, it is difficult to determine if the vessels that are inspected over longer intervals are Harrington's type G1 vessels. If this is so, then this result is quite consistent with Harrington's model: the incentives are present for G1 vessels to pollute.

The last three models in Table 2.1 model large pollution incidents. Strikingly, a number of results about pollution incidents remain valid for large pollution incidents. Model 5 shows that inspection hours continue to deter large pollution incidents, if, as in Harrington's model, we presume inspection hours to be exogenous. The coefficient of –0.169 indicates that a 10% increase in inspection hours lowers the expected number of pollution incidents by 1.69%. A simple cost-benefit analysis shows that if the marginal hour deters sizable spills, it is worth increasing the number of inspection hours to deter them. The sample mean for ln(InspectionHours) is 13 hours. A 10% increase (1.3 hours) lowers the expected number of pollution incidents by approximately 0.0037 spills with a 95% probability (1.69% of 0.01+2×.0.102). Since 1.3 hours cost approximately $65, if a spill costs $10 per gallon to clean up (this varies considerably depending on the type of ecology, environment and shoreline impacted), it is worth expending the marginal hour if a large spill is defined as being over 1,756 gallons.

Less easily explained is the large positive coefficient of 0.241 on ln(Deficiencies). USCG inspectors do an admirable job of discovering the number of deficiencies in "high-risk" vessels that are likely to be involved in large pollution cases. In fact, for every 10% increase in the number of deficiencies, the expected number of large spills increases by 2.4%. The number of deficiencies discovered aboard a vessel are an excellent predictor of large spills. What is surprising is that they appear to be good predictors in the panel data. If targeting as in Harrington's model is done effectively, then we should not see such a result. High-risk vessels placed in Group 2 should have the incentives to show few violations in order to move to Group 1, not more violations as the results show. Thus, targeting seems to be incomplete, or penalties (including legal cases) are so low that effective targeting is difficult to accomplish because accepting the penalties is cheaper than incurring the costs to remedy violations. In sum, this result leads to a strong rejection of hypothesis H2.

A new result in Models 5 and 6 is that legal actions deter large pollution incidents, in line with hypothesis H3. In terms of the theory, the binding constraint on monetary penalties is relaxed by introducing a new kind of penalty, and this should do precisely what the results indicate. The coefficient of –5.221 in Model 5 indicates that as legal actions increase by 10% large pollution incidents decrease by 52%. As Table 1 indicates, legal actions are rarely used, probably because they are expensive for the USCG to see through to the end. The results indicate that they are selectively used to elicit the greatest effect, as predicted in hypothesis H3. Whether the lack of stiff penalties should be made up by more legal actions requires a cost-benefit analysis for which we do not have the cost data.

Other than cost considerations, from a public management point of view the U.S Coast Guard resorts to legal actions only as a last resort. The Coast Guard governance style mixes hierarchical governance, where inspectors enforce laws using incentives such as penalties, and horizontal governance where gentle suasion and networking with vessel owners, operators, and crew are used to improve performance.

While inspection hours are exogenous in Harrington's model, it may not necessarily be true in the data. That is, USCG inspection hours may "chase" the number of pollution incidents. If inspection hours increase in response to past pollution incidents, and pollution incidents are temporarily correlated for each vessel, then inspection hours are not exogenous in the data. In Table 2.2, we thus instrument inspection hours using, in addition to all other exogenous variables in the model, these inspection-specific instruments: Certification, Hull, Trend, and WDCOI. The first two are dummy variables for whether hours were spent on a COI (certification) inspection or a hull inspection. The trend is simply the year of inspection, and WDCOI is a dummy for whether the vessel's COI was withdrawn after the inspection.

The first stage regressions in Table A1 indicate that the instruments perform admirably. Hours certainly vary according to the type of inspection; the trend takes care of the fact that there may be increases or decreases to USCG budget. WDCOI is borderline significant.

The effect of instrumenting inspection hours on the model results is dramatic. Table 2.2 indicates that in all models the signs for ln(InspectionHours) have reversed. Inspection hours are not effective in deterring either large pollution cases or pollution cases generally. Even though in Model 5′ the instrumented inspection hours are statistically insignificant, Model 6′ is preferred over this model in terms of any formal model comparison criteria. Thus hypothesis H1 is rejected by the data. Effectively, when ln(InspectionHours) is endogenous, USCG resources devoted to detecting violations does not deter large spills or spills generally. This corroborates a similar finding by Cohen (1987) using data from 15-20 years earlier. Thus, it appears that there are aspects of USCG enforcement that have remained unchanged over the years.

The first-stage estimates in Table A1 indicate two possible reasons why this is so. The first is that since the number of deficiencies is strongly positively correlated with the number of hours, and also highly positively correlated with the number of pollution incidents, the instrumented ln(InspectionHours) is positively correlated with the number of incidents. The second is that the large standardized estimates (not reported) on Hull indicate that the majority of hours (even after scaling by gross tonnage) are spent on labor-intensive hull inspections. If hull inspections do not deter large or small pollution incidents, then we will get the observed result. It would be hard to convince the USCG to lower the number of resources devoted to hull hours. In our interviews with several USCG personnel, they have indicated that hull inspections deserve greater intensity, since damage to the hull during transit will almost surely result in an extremely large spill, possibly an event of national significance. Their risk-aversion to extremely large spills makes USCG inspectors reluctant to decrease the amount of resources spent on hull inspections.

We sum up as follows. As Viladrich-Grau and Groves (1997) document, the USCG follows a two-tiered targeting strategy. But while they find that this works aboard tank ships and tank barges, we find that targeting is incomplete. Even if hours are held to be exogenous as in Harrington's model, there remains the troubling finding that deficiencies are positively correlated with spills. This should not be the case if targeting is done effectively in a repeated game setting. Thus, hypothesis H2 is overwhelmingly rejected by the data. If hours are endogenous, this violates Harrington's model assumption. Now, inspection hours are used to target vessels, rather than violations found in random inspections. Thus violations predict spills well, and so do inspection hours. This is similar to the original finding of Epple and Visscher. But hours and violations are good predictors of spills; appropriate actions should be taken to prevent those spills. We speculate that, as stated in hypothesis H3, if fines were stiffer, they would provide the required deterrence. Perhaps then we would *not* find the positive coefficients on ln(InspectionHours) and ln(Deficiencies). We actually find that legal cases can be used effectively to deter large spills, thus providing empirical support for hypothesis H3. A case for stiffer fines is made in Weber and Crew (2000) who find the small size of fines wanting. They also find that stiffer fines, without being unduly harsh, could lower spills aboard barges. According to their results, a 10-day improvement in the speed with which penalties are assessed should reduce the volume of oil spillage by 0.6%. Of course, increases in the severity of punishment can reduce spillage even further.

The difference between our results and those of Viladrich-Grau and Groves may be due to data differences as well as model differences. Our panel data captures elements of a repeated game. Our data is from the post-OPA90 period, when a regime change may have occurred, while Viladrich-Grau and Groves use data from the 1980s. Finally, we introduce the number of deficiencies in our econometric model, which is missing from Viladrich-Grau and Groves' study. Furthermore, they find that penalties do not matter on the margin, whereas our results (about legal cases) and those of Weber and Crew (2000) find that they do. The application of Viladrich-Grau and Groves' method to the panel data would certainly be revealing, and we leave that as an open research issue.

6. Public Management Issues

Lynn, Heinrich, and Hill (2001) define public sector governance broadly as "regimes of laws, rules, judicial decisions, and administrative practices that constrain, prescribe, and enable the provision of publicly supported goods and services through formal and informal relationships with agents in the public and private sectors." Governance thus involves any constitutionally legitimate means, both vertical and horizontal, for achieving direction, control, and coordination of individuals or organizations (Hill and Lynn, 2004).

This is very much a model of hierarchical (vertical) governance, in which the principal-agent relationship between the USCG as a law enforcement agency is solved using high-powered incentives (penalties). The motivation for using this model is succinctly stated by Hill and Lynn (2004):

> "the causal logic of governance is complex and difficult to study, yet that is the intellectual challenge facing the governance research community: producing the kind of 'strong causal insights' that have a plausible claim to validity in various contexts."

The hierarchical model we use, due to Harrington (1988), delivers causal insights and produces testable hypotheses that are valid in a variety of law enforcement contexts. In the real-world environment of limited penalties and budget constraints, state-dependent targeting is used in order to economize on both the use of high-powered incentives as well as resources devoted to monitoring and inspections.

However, this approach neglects other types of horizontal governance methods that the USCG may well use in combination with hierarchical methods in order to improve performance (i.e., reduce pollution occurrences). Kettl (2002) notes that transformations in governance have "made government both *horizontal* – in search of service coordination and integration with nongovernmental partners in service provision – and *vertical* – through both traditional, hierarchical bureaucracies and multi-layered federalism." Scholz (1991) advances the notion of cooperative regulatory enforcement as a way to increase performance, a message that has been echoed in the context of environmental regulation by Fiorino (1999, 2001) Potoski and Prakash (2004), and Steinzor (1998).

Indeed, the USCG may be employing a more cooperative approach in terms of the actual interactions their inspectors have with vessel owners and operators. For example, while examining safety violations, experienced inspectors may tutor and exemplify the "right" way to maintain safety. A more cooperative approach may send the signal that even though they are ultimately law enforcers and it is their job to inspect and correct violations, they are willing to forgive violations if they are not repeated with regularity. Thus, penalties are forgiven. In turn, vessel owners respond by their own signals about having done the best they can to remedy violations but only to the extent that is financially feasible for them. In this way, a horizontal system of governance co-exists with a vertical one. While in this example one does not necessarily enhance the other, a deeper examination of horizontal governance as practiced by the USCG is relevant and would be revealing. In closing, we outline a research program along these lines.

The theory for such a program should borrow from the game theory literature on the evolution of cooperation. Applications to networking in the field of industrial organization are plentiful. The methodology for such a program would require an internal survey of USCG personnel with experience in inspections of vessels at various port safety offices, so as to capture the heterogeneity of their experiences.

A survey instrument would also shed light on the major question of how public management affects governance. The effect of public management on governance subsumes the previous question about whether governance is comprised of horizontal networks as well as hierarchical relationships. In their meta analysis of governance studies, Hill and Lynn (2004) indicate three elements of public management that influence governance. These elemental sources of performance improvements or declines are Administrative Structures, Tools, and Values and Strategies (Hill and Lynn, Table 6).

The 1990s, during which, in response to the newly passed Oil Pollution Act on the heels of the *Exxon Valdez* incident, the USCG drastically changed its policies to respond to the new laws and initiatives, provides a natural experiment. This regime change can be used to assess not only the source of changes in governance, but also its differential impact on performance. It is clear that since OPA90 there have been far fewer spills than in earlier periods. It has been 15 years since a large spill like the *Valdez* incident took place is US waters. USCG's organizational change in terms of these three elements of their management should be measured, and their effectiveness sourced to them.

7. Conclusion

This paper constructs an organization-level database on monitoring and pollution incidents for the U.S Coast Guard (USCG). The database informs a theory-based investigation of the effectiveness of law enforcement when the use of high-powered incentives such as penalties is very limited. The theoretical context in which USCG enforcement is placed is Harrington's model of targeting. In this model, vessels are put into two groups for which there is differential monitoring and (limited) penalties. If USCG enforcement is in line with the theory, then data on inspections and performance can be used to test three hypotheses generated from the theory. The first hypothesis is that USCG resources spent on inspections are effective in curtailing pollution occurrences. The second is that there should be no relationship between infractions and safety violations detected during inspection and pollution occurrences. Third, if the limit on the penalties is relaxed, or complementary penalties can be imposed, these will deter pollution occurrences.

We assemble a panel data set for about 4,500 tank barges over the period 1986-1998. A Negative Binomial panel econometric model is used to explain count data on the number of pollution occurrences aboard these vessels using variables that measure USCG enforcement effort and vessel characteristics. The findings about the hypotheses are mixed. We reject the first and second hypotheses and fail to reject the third. It appears that U.S Coast Guard inspections do not target completely in accordance with Harrington's model. Thus, noncompliance by vessels is not fully deterred in the presence of limited penalties.

On the other hand, the model we have investigated is a hierarchical command-and-control model of governance. In the public administration literature there have been calls for mixing hierarchically-based governance together with an approach that emphasizes networking and two-sided cooperation, termed horizontal governance. A future line of research inquiry should conduct a theory-based investigation into whether these two modes of governance in combination are more effective than they are alone.

References:

Anderson, E. and Talley, W. (1995). The oil spill size of tanker and barge accidents: Determinants and policy implications. *Land Economics*, 71, 216–228.

Becker, G. S. (1968). Crime and punishment: An economic approach. *Journal of Political Economy*, 76, 169-217.

Bose, P. (1995). Regulatory errors, optimal fines and the level of compliance. *Journal of Public Economics*, 56, 475-484.

Cameron, A. C., & Trivedi P. K. (1998). *Regression analysis of count data.* New York, NY: Cambridge University Press.

Cohen, M. A. (1987). Optimal enforcement strategy to prevent oil spills: An application of a principal-agent model with moral hazard. *Journal of Law and Economics*, 30, 23-51.

Cohen, M. A. (1998). Monitoring and enforcement of environmental policy. Manuscript.

Earnhart, D. (2004). Panel data analysis of regulatory factors shaping environmental performance. *Review of Economics and Statistics*, 86, 391-401.

Epple, D. & Visscher, M. (1984). Environmental pollution: Modeling occurrence, detection, and deterrence. *Journal of Law and Economics*, 27, 29-60.

Fiorino, D. J. (1999). Rethinking environmental regulation. *Harvard Environmental Law Review, 23, 441-69*.

Fiorino, D. J. (2001). Environmental policy as learning. *Public Administration Review,* 61, 322-34.

Gawande, K., & Wheeler, T. A. (1999). Measures of effectiveness for governmental organizations: A study of the US Coast Guard. *Management Science*, 45, 42-58.

Gawande, K., & Bohara A. K. (2003). Inspections, penalties, and oil spills: Theory, evidence and policy. Bush School Working Paper, Texas A&M.

Greenberg, J. (1984). Avoiding tax avoidance: A (repeated) game-theoretic approach. *Journal of Economic Theory*, 32, 1-13.

Grey, W. B., and M. E. Deily. (1996). Compliance and enforcement: Air pollution regulation in the U.S. steel industry. *Journal of Environmental Economics and Management*, 31, 96-111.

Gurmu, S., & Trivedi, P. K. (1996). Excess zeros in count data models for recreational trips. *Journal of Business and Economics Statistics,* 14(4), 469-477.

Harford, J. & Harrington, W. (1991). A reconsideration of enforcement leverage when penalties are restricted. *Journal of Public Economics*, 45, 391-395.

Harrington, W. (1988). Enforcement leverage when penalties are restricted. *Journal of Public Economics*, 37, 29-53.

Heyes, A. & Rickman, N. (1999). Regulatory dealing: Revisiting the Harrington paradox. *Journal of Public Economics*, 72, 361-378

Hill, C. J. & Lynn, L. E. Jr. (2004). Is hierarchical governance in decline? Evidence from empirical research. Forthcoming in *Journal of Public Administration Research and Theory*.

Holmström, B. (1979). Moral hazard and observability. *The Bell Journal of Economics*, 10, 74-91.

Innes, R. (1999). Remediation and self-reporting in optimal law enforcement. *Journal of Public Economics*, 72, 379-393.

Kettl, D. F. (2002). *The transformation of governance: Public administration for the twenty-first century.* Baltimore, MD: Johns Hopkins University Press.

Landsberger, M. & Meilijson, I. (1982). Incentive generating state dependent penalty system. *Journal of Public Economics*, 19, 333-352.

Livernois, J. & McKenna, C.J. (1999). Truth or consequence: Enforcing pollution standards with self-reporting. *Journal of Public Economics*, 71, 415- 440.

Lynn, L. E., Jr., Heinrich, C. J., & Hill, C. J. (2001). *Improving governance: A new logic for empirical research*. Washington, D.C.: Georgetown University Press.

Magat, W.A., & W. Kip Viscusi (1990). Effectiveness of the EPA's regulatory enforcement: The case of industrial effluent standards. *Journal of Law and Economics*, 33, 331-360.

Potoski, M & Prakash, A (2004). The regulation dilemma: Cooperation and conflict in environmental governance. *Public Administration Review,* 64, 152-163.

Raymond, M. (1999). Enforcement leverage when penalties are restricted: A reconsideration under asymmetric information. *Journal of Public Economics*, 73, 289-295.

Scholz, J. T. (1991). Cooperative regulatory enforcement and the politics of administrative effectiveness. *American Political Science Review,* 85, 115-36.

Shavell, S. (1979). Risk sharing and incentives in the principal and agent relationship. *The Bell Journal of Economics,*10(1), 55-73.

Steinzor, R. I. (1998). Reinventing environmental regulation: The dangerous journey from command to self-control. *Harvard Environmental Law Review,* 22, 103.

Viladrich-Grau, M. & Groves, T. (1997). The oil spill process: The effect of Coast Guard monitoring on oil spills. *Environmental and Resource Economics*, 10, 315-339.

Weber, J. M. & Crew, R. E. (2000). Deterrence theory and marine oil spills: Do Coast Guard civil penalties deter pollution? *Journal of Environmental Management*, 58, 161–168.

Woolridge J. M. (2002) *Econometric analysis of cross-sectional and panel data*. Cambridge, MA: MIT Press.

Figure 1: Distribution of USCG-imposed harm-based Penalties
N=3050 penalties for spills between 1986-98

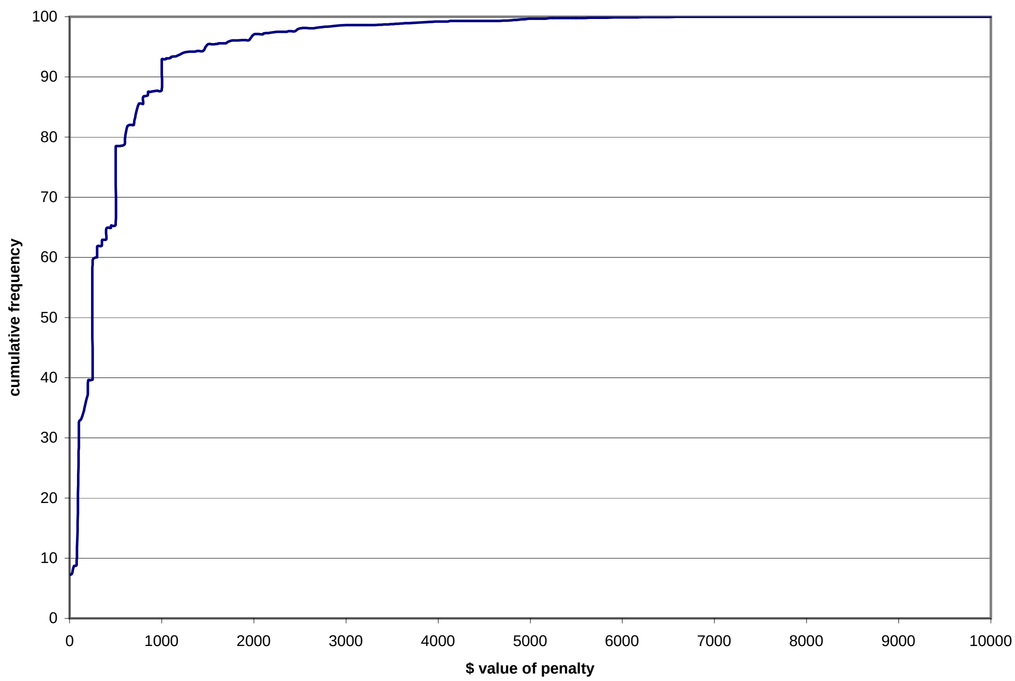

Table 1: Variable description and descriptive statistics

		Mean	sd
#Pollution	Count of pollution cases per year.	0.161	0.425
#LargePollution	Count of large pollution cases (>500 gallons/pounds) per year.	0.010	0.102
ln(InspectionHours)	Natural log of (total inspection hours from last inspection divided by (registered gross tonnage divide by 1000)).	2.245	0.850
ln(LastInspection)	Natural log of the number years since the last inspection.	0.391	0.486
ln(Deficiencies)	Natural log of the deficiency count of the last inspection	0.247	0.535
#LegalAction	Count of legal actions generated during last inspection.	0.002	0.040
Age	(Calendar year of ship minus build year) divided by 100.	0.216	0.119
OceanRoute	Dummy variable, 1 = vessel's primary route is ocean.	0.081	0.273
DoubleSided	Dummy variable, 1 = vessel is double-sided.	0.542	0.498
DoubleBottomed	Dummy variable, 1 = vessel is double-bottomed.	0.507	0.500
East	Dummy variable, 1 = last inspection occurred in eastern U.S.	0.411	0.492
West	Dummy variable, 1 = last inspection occurred in western U.S.	0.047	0.211
Central	Dummy variable, 1 = last inspection occurred in central U.S.	0.518	0.500
NonSiteSpecific	Dummy variable, 1 = last inspection by non-site specific USCG group or outside US	0.024	0.153
Tonnage	Registered gross tonnage of barge.	1355.5	1878.5
Certification	The inspection was for a certificate of inspection.	0.561	0.557
Hull	The inspection was for a hull inspection.	0.226	0.437
Trend	Observation year minus 1986 (beginning observation year)	6.839	3.332
WDCOI	USCG withdrew the vessel's Certificate of inspection.	0.001	0.029

Notes:

1. All variables are constructed from the US Coast Guard MSMS database over the 1986-1998 period.
2. Data pertain to Tank barges. Sample has 48524 observations and 4896 Tank barges.

Figure 2.1: Frequency distribution for Number of Pollution Occurrences

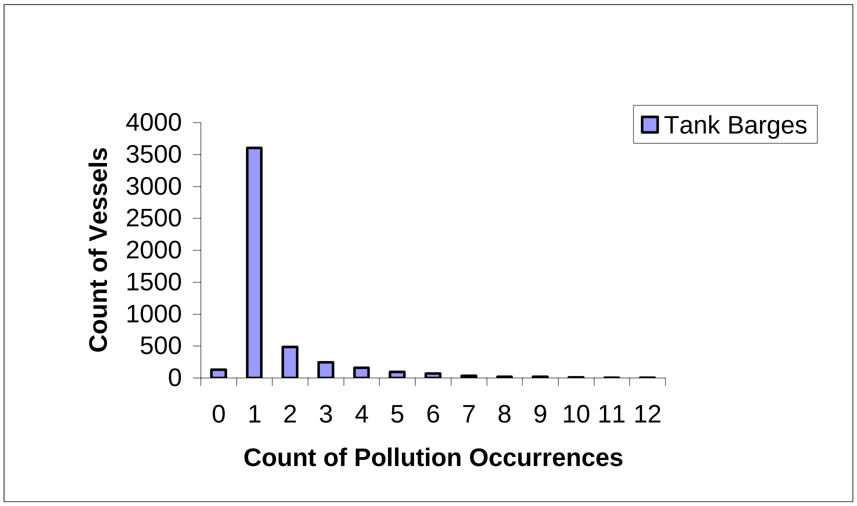

Figure 2.2: Frequency distribution of Number of <u>Large</u> Pollution Occurrences

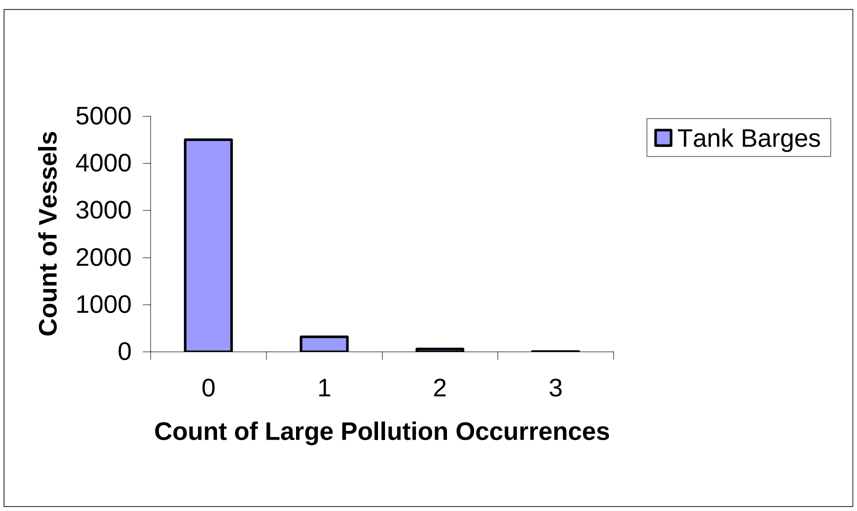

Table 2.1: Random Effects Estimates from Negative Binomial model
Harrington Model: Inspection Hours Exogenous

	All pollution cases			Large Pollution Cases		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	−1.835*** (−47.87)	−1.595*** (−31.26)	−1.542*** (−29.34)	−4.869*** (−29.91)	−4.502*** (−20.91)	−4.380*** (−20.46)
ln(InspectionHours)	–	−0.112*** (−7.497)	−0.108*** (−7.214)	–	−0.169*** (−2.950)	−0.167*** (−2.876)
ln(LastInspection)	–	–	−0.382*** (−7.603)	–	–	−0.253 (−0.623)
$[\ln(\text{LastInspection})]^2$	–	–	0.340*** (11.57)	–	–	−0.492 (−1.097)
ln(Deficiencies)	–	0.043** (1.968)	0.035 (1.599)	–	0.241*** (3.169)	0.252*** (3.331)
#LegalAction	–	0.193** (0.763)	0.216 (0.854)	–	−5.221*** (−23.75)	−4.368*** (−20.14)
Age	0.197* (1.824)	0.223* (1.929)	−0.037 (−0.302)	−0.675* (−1.650)	−0.632 (−1.510)	−0.087 (−0.204)
OceanRoute	0.492*** (9.668)	0.426*** (9.372)	0.434*** (9.292)	1.101*** (8.389)	0.913*** (6.777)	0.889*** (6.640)
DoubleSided	−0.218*** (−4.342)	−0.234*** (−4.267)	−0.231*** (−4.128)	−0.320 (−1.514)	−0.343 (−1.631)	−0.345 (−1.640)
Double-bottomed	−0.062 (−1.235)	−0.058 (−1.048)	−0.063 (−1.121)	−0.651*** (−2.999)	−0.632*** (−2.936)	−0.620*** (−2.877)
East	0.014 (0.512)	0.028 (1.092)	0.021 (0.799)	0.261** (2.456)	0.261** (2.458)	0.272*** (2.577)
West	−0.245*** (−3.936)	−0.230*** (−3.589)	−0.221*** (−3.390)	−0.498** (−2.134)	−0.484** (−2.082)	−0.463** (−2.017)
α (NB dispersion parameter)	0.312*** (7.318)	0.316*** (6.693)	0.254*** (6.126)	1.176** (1.986)	1.268** (2.082)	1.365** (2.118)
σ_u (random-effects parameter)	0.358*** (13.30)	0.343*** (19.01)	0.387*** (22.21)	1.031*** (11.41)	0.974*** (10.25)	0.920*** (9.252)
N	48,524	48,524	48,524	48,524	48,524	48,524
# parameters	9	12	14	9	12	14
Log-Likelihood	−22409.9	−22380.0	−22306.1	−2543.0	−2533.7	−2511.9

Notes:

1. Numbers in parentheses are heteroscedastic-consistent *t*-statistics
2. *, **, and *** denote significance at the 10, 5, and 1 percent levels, respectively (two-tailed test).

Table 2.2: Random Effects Estimates from Negative Binomial model
Inspection Hours Endogenous and Instrumented

	All pollution cases		Large Pollution Cases	
Variable	Model 2′	Model 3′	Model 5′	Model 6′
Intercept	−2.469*** (−18.70)	−2.496*** (−19.82)	−5.005*** (−9.217)	−5.945*** (−13.16)
ln(InspectionHours)	0.290*** (5.c138)	0.333*** (6.086)	0.039 (0.161)	0.533*** (2.740)
ln(LastInspection)	–	−0.190*** (−3.188)	–	0.047 (0.110)
$[\ln(\text{LastInspection})]^2$	–	−0.013 (−0.194)	–	−1.050** (−2.088)
ln(Deficiencies)	0.002 (0.086)	0.125*** (4.470)	0.224*** (2.778)	0.395*** (4.102)
#LegalAction	0.128 (0.533)	0.151 (0.615)	−0.755*** (−3.521)	−0.904*** (−4.260)
Age	0.088 (0.805)	−0.170 (−1.432)	−0.638 (−1.532)	−0.284 (−0.669)
OceanRoute	0.611*** (10.55)	0.637*** (11.07)	1.022*** (5.79)	1.231*** (7.85)
DoubleSided	−0.174*** (−3.441)	−0.165*** (−3.192)	−0.334 (−1.539)	−0.229 (−1.072)
Double-bottomed	−0.071 (−1.445)	−0.077 (−1.526)	−0.617*** (−2.811)	−0.655*** (−3.019)
East	−0.032 (−1.157)	−0.045 (−1.590)	0.238** (2.144)	0.168 (1.552)
West	−0.294*** (−4.700)	−0.290*** (−4.568)	−0.515** (−2.165)	−0.599** (−2.530)
α (NB dispersion parameter)	0.314*** (6.799)	0.251*** (6.128)	1.181** (2.207)	0.964* (1.821)
σ_u (random-effects parameter)	0.354*** (12.90)	0.395*** (15.60)	1.016*** (11.07)	0.977*** (10.47)
N	48,524	48,524	48,524	48,524
# parameters	12	14	12	14
Log-Likelihood	−22396.1	−22313.3	−2538.2	−2512.6

See Notes to Table 2.1

Table A1: First Stage (OLS) Estimates
Dependent Variable: ln(InspectionHours)

Variable	**Model 1**	**Model 2**
Intercept	2.055*** (145.422)	1.657*** (70.407)
ln(Deficiencies)	0.110*** (15.46)	0.104*** (14.64)
ln(LastInspection)	–	0.829*** (20.80)
$[\ln(\text{LastInspection})]^2$	–	−0.300*** (−18.02)
#LegalAction	0.091 (0.978)	0.111 (1.203)
Age	0.353*** (10.31)	0.300*** (8.641)
OceanRoute	−0.540*** (−35.84)	−0.537*** (−35.82)
DoubleSided	−0.144*** (−9.183)	−0.143*** (−9.205)
DoubleBottomed	0.030* (1.912)	0.031** (2.021)
East	0.164*** (21.32)	0.166*** (21.66)
West	0.139*** (7.304)	0.145*** (7.675)
Certification	−0.110*** (−15.56)	0.262*** (13.92)
Hull	0.468*** (51.93)	0.468*** (52.19)
Trend	0.010*** (9.089)	0.009*** (8.151)
WDCOI	0.398*** (3.094)	0.230* (1.798)
N	48524	48524
# Parameters	13	15
R^2	0.096	0.087
Adjusted R^2	0.095	0.087