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ESTIMATING THE EFFECT PENALTIES ON REGULATORY COMPLIANCE

BY

VID ADRISON

A Dissertation Submitted in Partial Fulfillment
of the Requirements for the Degree
of
Doctor of Philosophy
in the
Andrew Young School of Policy Studies
of
Georgia State University

GEORGIA STATE UNIVERSITY
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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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TABLE OF CONTENTS

Page

LIST OF TABLES

LIST OF FIGURES

Figure Page

ABSTRACT

ESTIMATING THE EFFECT OF PENALTIES ON REGULATORY COMPLIANCE

BY

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This dissertation has two main objectives. First, we investigate the effectiveness of penalties and other enforcement tools on regulatory compliance, and comprehensively address problems that exist in previous regulatory compliance studies. Second, we develop a model that explains why most empirical studies of regulatory compliance yield results that seem to be inconsistent with the theoretical predictions of Harrington's (1988) seminal article on regulatory compliance. Thus the dissertation comprises two essays.

In Essay One, we estimate facility compliance with the Clean Water Act (CWA) by comprehensively addressing the problems that exist in previous studies. The first problem is the failure to take into account undetected violations. To address this problem, we employ Detection Controlled Estimation (DCE) model, developed by Feinstein (1990). The DCE variant that we use is the two-sided expectation simultaneity version. We use this version because we assume that potential violators will react to what the regulator would do, and *vice versa*. The second problem that we address is in the measurement of regulatory penalties. Previous studies use dummy variables, but using a

continuous measure of penalty enables us to differentiate the responses of minor from substantial violators, and avoid measurement error. Finally, we use a richer set of covariates. We include variables that were found to be statistically and economically significant in different previous studies, but which have never been estimated jointly.

The results in Essay One indicate that facilities do respond to penalties, but the effect is economically insignificant. We argue that the small effect of penalties in reducing noncompliance comes from the way regulators enforce the regulations: penalties are rarely imposed on detected violators, or if imposed, the amount is usually negligible. The policy implication that arises from our findings is that if regulators want to see a substantial increase in the probability of compliance, it should consider imposing more frequent and severe penalties. The positive effects of more stringent enforcement on compliance rates come from three sources: (1) through specific deterrence effect; (2) through general deterrence effect; and (3) through an increase in the probability of self-reported violations, which allows for more efficient use of inspection budgets.

In Essay Two, we extend Harrington's (1988) theoretical model by (1) introducing an imperfect detection parameter, and (2) relaxing the movement between the groups, as in Friesen (2003). The extended model shows that when detection is imperfect, the zone for the "always-violate" strategy expands. This expansion has two implications. First, when firms are uniformly distributed in cost space, the number of firms that choose the "always-violate" strategy increases. Second, any empirical study that uses major facilities will be more likely to confirm "always-violate" strategy, but fail to confirm the other two strategies discussed in Harrington (1988). We also discuss other possibilities that can contribute to the difference between empirical results and theoretical predictions.

CHAPTER I

INTRODUCTION

For at least four decades (Becker 1968), economists have applied economic theory and empirical methods to study an individual's decision to commit an illegal act. In the theoretical literature, the majority of studies predict that higher inspection rate and severe monetary penalty improve compliance rates.[1] Some studies, however, suggest that increasing enforcement stringency does not necessarily lead to higher compliance rates. For instance, Heyes (1993) analytically shows that increasing inspection frequency may lead firms to spend more resources toward decreasing probability of detection.[2] Kambhu (1989) shows that increased enforcement stringency may have a reverse effect on environmental performance. Such unconventional conclusion comes from the possibility that firms may invest more on penalty eroding activities instead of installing pollution abatement technologies. Kadambe and Segerson (1998) also show that increased enforcement stringency does not necessarily lead to higher compliance rate.

In the empirical literature, many studies detect the positive impact of inspection on compliance decisions.[3] However, the effectiveness of penalties in promoting

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[1] For instances, see Downing and Watson (1974), Harford (1978), Story and McCabe (1980), Lansberger and Meilijson (1982), Greenberg (1984) and Harrington (1988)

[2] He uses the term "inspectability" to describe the ability of the regulator to detect a violation. The inspectability can be reduced by using less transparent technologies.

[3] Environmental compliance studies that confirm the positive effect of inspection on compliance include Magat and Viscusi (1990), Deily and Gray (1991), Gray and Deily (1996), Laplante and Rilstone (1996),

environmental compliance is less conclusive. We argue that weak empirical support for the effectiveness of penalty in promoting regulatory compliance is primarily due to two reasons. First, the number of environmental compliance studies that include penalty is still very scant. Based on our literature search, we found seven studies that include penalty in their analysis between the period of 1989 and 2006.[4] Second, each study that includes penalties in its analysis has attributes that can bias its conclusions.

First, most studies fail to take into account undetected violations. As shown by Feinstein (1989; 1990; 1991), ignoring undetected violations will lead to downward bias of parameter estimates. Among the seven studies that include penalty, only Feinstein (1989) and Scholz and Wang (2006) take into account the undetected violations.

Second, most studies fail to incorporate the general deterrence effect of penalties. Shimshack and Ward (2005) argue that ignoring regulatory "reputation" –the term they use for general deterrence--leads to an overestimate of the parameters for penalties and other sanctions.

Third, most studies fail to use a correct penalty measure. All studies of environmental compliance, with the exception of Shimshack and Ward (2005), use a discrete measure for penalty. Using a discrete penalty measure introduces measurement error in the model. Since compliance decisions are mostly estimated using nonlinear model, the effects of measurement error can be serious. As shown by Carroll et al.

Nadeau (1997), Helland (1998a;1998b), Stafford (2002), Shimshack and Ward (2005) and Scholz and Wang (2006).

[4] Those studies are Feinstein (1989), Hamilton (1996), Kleit et al. (1998), Stafford (2002), Earnhart (2004), Shimshack and Ward (2005), and Scholz and Wang (2006. Hamilton (1996) and Kleit et al. (1998), however, treated penalty as dependent instead of independent variable.

(1984), the impact of measurement error in a nonlinear model is substantial if the sample size is large and the error is severe.

In addition to the contradictory empirical results regarding the effect of penalties on compliance decisions, there is also a gap between theoretical predictions and the empirical evidence on the relationship between past and current compliance decisions. One widely cited theoretical work that explains firms' compliance behavior is Harrington (1988). He analytically shows that the strategy chosen by a firm depends on its compliance cost. To be specific, firms with low compliance cost will always comply, firms with large compliance cost will always violate, and firms with medium compliance cost will alternate compliance decisions based on their previous inspection outcome (i.e., a firm will comply in current period if it was found in violation in previous inspection, and *vice versa*). However, the majority of empirical studies only detect one strategy (the "always-violate" strategy). We reconcile the disparity between prediction and evidence by extending Harrington's model to allow imperfect detection and movement between enforcement groups.

We organize this dissertation as follows. Chapter II presents the literature review on regulatory compliance. Chapter III presents Essay One, where we investigate the effect of penalties (and other enforcement variables) on compliance decisions. Chapter IV presents Essay Two, where we attempt to explain why empirical studies only partially support Harrington theoretical predictions.

CHAPTER II

LITERATURE REVIEW

Theoretical

The literature of regulatory enforcement has been available before 1968. Yet, it is Becker's (1968) work which becomes the benchmark for many economists in conducting their research. Since his seminal paper, studies on regulatory enforcement have been enriched by various theoretical and empirical works. Becker (1968) describes two policy variables to reduce the number of offenses to socially optimal level; probability of conviction (p) and penalty (f). He contends that the magnitude impact of these variables on crime reduction depends on the risk preference of potential violators. For risk lovers, an increase in p will have a larger impact on crime reduction compare to an equal percentage increase in f. The opposite case holds for those who are risk averse. If the potential violators are risk neutral, both policies have the same effect.

Becker's article triggered more studies on regulatory enforcement in the following years. In the early years, theoretical models developed by scholars are mostly static. For instances, see Downing and Watson (1974), Harford, (1978), Storey and McCabe (1980). In a static model, potential violators and regulator can not react to each other's action. Since this is unlikely the case in the real world, scholars developed theoretical models where agents anticipate what others would react if they choose a particular action.

The new models which constructed in game theory and multi-period setting emerged in the 80s (for example, see Lansberger and Meilijson 1982; Greenberg 1984; Harrington 1988). Harrington (1988) developed his model due to inability of one-period game model to explain somewhat contradictory fact in U.S. case: i.e., enforcement is carried out by EPA at such a low level, and violations are rarely punished even if discovered, yet, most of the firms are in compliance. To explain such phenomenon, he develops a model where firms are divided into two categories and one group faces more severe enforcement than another. Movement between the groups is possible, and it depends on previous inspection result. The main results of his model are (1) firms with low compliance cost will always comply, (2) firms with high compliance cost will always violate, (3) firms with medium cost of compliance will alternate decision based on the previous inspection result. Firms found in compliance in the previous inspection will be more likely to violate in the subsequent period, while firms found in violations will comply in the next period. This interesting firms' behavior is called "Harrington Paradox" by follower authors.

Other extension derives from the fact that regulator have some constraints in conducting audit. One of the constraints is operating/inspection cost, which cause regulator to direct inspection more towards those who are a more likely to violate. By doing so, the expected social welfare would be higher given the same level of enforcement effort. This kind of targeting policy is initially developed in taxation context (Lansberger and Meilijson 1982; Greenberg 1984).

In the theoretical work, increasing inspection/enforcement effort does not necessarily lead to better outcome, as shown by Heyes (1993, 2000), Kambhu (1989) and Kadambe and Segerson (1998).

Heyes (1993, 2000) creates a theoretical model by focusing on the ability of the regulator to discover a violation once it occurs, which he refers as “inspectability.” Heyes (1993) describes two factors that determine the probability of detecting an incident of non-compliant; thoroughness (*t*) and the amount of firms’ investment to increase un-inspectability (*n*). Analytically, he shows that increasing the thoroughness of inspection induces firms to substitute towards more transparent technologies. On the other hand, increasing frequency of inspection will cause substitution the other way. One surprising result of his model is that increasing frequency of inspection may worsen firms’ environmental performance. This lead to an important policy implication: inspection should be carried out more thoroughly, but less frequent.

Besides spending resources to increase un-inspectability, firms may also invest in activities that reduce penalty if it is found in violation. Kambhu (1989) develops a model where firms have two spending options: (1) abatement activities, or (2) activities to erode penalty if they end up paying. One interesting implication of his model is if the regulator attempts to raise the standard, it may have a reverse effect on environmental performance. Such unconventional conclusion arises because most of other analyses ignore possibility of firms spending resources on penalty-eroding activities (such as hiring a good lawyer to increase the probability of winning in the court). When the regulator increases environmental standard, it will cause firms to invest more in such activities to bring down the liability they should have paid.

In 1998, Kadambe and Segerson developed a model where there is a significant interaction between firms and regulator. If the regulator increases the level of penalty, it will have direct and indirect effect. They define direct effect as the effect of an increase in the fine on the expected cost of a violation holding the probabilities of enforcement-related decisions constant, whereas indirect effect is defined as the effect of the fine on the probability of a violation through its effect on the probabilities of the enforcement actions taken by the enforcers. Using comparative static, they show that the direct effect is always positive, while the indirect effect is ambiguous. The intuitive explanation for the indirect effect is that fines also affect the probabilities of several actions that need to be considered in when making a decision whether to comply or violate. Specifically, it will affect the likelihood that the regulator will issue an order, then the likelihood that a firm would challenge if an order is issued, and finally the likelihood that the regulator would fight if the firm decides to challenge. While the effect of fines on probability of the regulator to fight a challenge is positive, the signs for the other two effects can not be determined, which makes the total effect on compliance becomes ambiguous.

Empirical Research

Inspection and Enforcement

Contrary to theoretical works, results from empirical studies show convergence. In spite of differences in the focus of attention and methodology, most of the empirical research show positive impact of monitoring and enforcement on subsequent compliance behavior. The empirical work which we will review in this section is particularly on the environmental context.

One of the early works on enforcement of environmental regulation is the research conducted by Magat and Viscusi (1990). They examine whether EPA's inspection reduce the level of water pollution as well as incentive to violate in the pulp and paper industry. Additionally, since there is a requirement for some plants to submit monthly DMR (Discharge Monitoring Report), they also perform additional investigation to test the effect of incident on DMR non-reporting.

Two regressions are estimated using the same explanatory variables. The dependent variable of the first regression is pollution level (continuous), while the second regression uses dichotomous dependent variable to represent compliance status. Pollution level is estimated using ordinary least square (OLS), whereas compliance status is estimated using maximum likelihood estimation (MLE). To investigate the incident of DMR non-reporting, they performed a simple test of difference in means. Among the groups of explanatory variables are the distributed lagged of inspections, which they employ to test whether the effect of inspection is permanent or just a transitory – i.e., whether there would be a rebound effect after an inspection is performed.

Using quarterly data (1982:1 – 1985:1) from 170 plants out of 194 with BOD (Biological Oxygen Demand) discharge, they find that inspections substantially reduce BOD level after about one quarter. The effects are permanent in reducing the firms' future pollution level. Using an interaction term made of inspection variable and compliance status, they conclude that inspections do reduce the pollution levels irrespective of compliance status. Maximum likelihood estimation also provides similar result to those of OLS. Without inspections, noncompliance rate would have been double.

While for the incident of DMR non-reporting, they found that inspection is effective in reducing the number of DMR non-reporting.

A slightly different study is performed by Nadeau (1997). Not only does he make a distinction between monitoring and formal action, but he also analyzes the effect on duration of noncompliance rather than just the compliance status *per se*. He uses two-stage estimation based on the consideration that enforcement and compliance decision are made simultaneously. In the first stage he estimated EPA enforcement and monitoring activity using Poisson estimation. The predicted values of enforcement and monitoring obtained in the first stage are used in the second stage in the survival model. Using quarterly data from 1979:3 to 1989:3, he concludes that EPA is effective in reducing the time that plants violate standards. A 10 % increase in monitoring activity leads to a 4.2 % reduction in the time that plants violate EPA regulation, while 10 % increase in enforcement will reduce length of violation by 4 – 4.7 %

Other slightly different works are the research conducted by Deily and Gray (1991) and Gray and Deily (1996). Their studies are based on the premise that EPA would also consider economic and political impact in carrying out enforcement action. Among the impact is plant closing. Theoretically, a plant will choose to close if the compliance cost is higher than the expected revenue. Although closing a heavily polluting plant is good for environmental quality, local residents may not necessarily like this idea when it causes many people loosing their jobs. It implies that if EPA really takes into account non environmental factor, any enforcement action should be at the level such that it minimizes support loss given a particular target environmental quality.

To test their hypothesis, they choose 49 plants in steel industry as sample of observation. This is based on the consideration that the industry was experiencing a declining demand. Given this condition, enforcement action directed towards a firm in the steel industry will increase the likelihood of plant-closing.

They perform two-stage estimation with instrumental variable (IV). In the first stage, two equations are estimated, namely (1) enforcement and (2) closing decision. In the next stage, the predicted sum of enforcements are used to estimate the plant closing decision, while the predicted closing decisions obtain in the first stage, are used to estimate the number of enforcement. The enforcement equation in the first stage is estimated using linear regression, while plant-closing equation is estimated using logit model.

They conclude that enforcement behavior is indeed influenced by potential adjustment cost to local community. Plants with higher probability of closing (as effect of enforcement) will face less enforcement action. And plants with sizeable amount employment in the region will also face less enforcement. They find that there is a tendency that marginal plants facing less enforcement are concentrated in counties with high unemployment. Their results also indicate that plants with more enforcement have a higher probability to close. A 12 % increase in the expected enforcement increases the probability of closing by 1 percentage point.

In their 1996 study, the relationship between enforcement and compliance is examined. Probability of closing—which they obtain from their 1991 study--is also included in the determining the amount of enforcement. They conclude that enforcement actions (in any measures) are statistically significant in affecting plant compliance decision, and greater compliance leads to less enforcement. Additionally, the plants' future viability and the cost of bringing it into compliance also influence a firm's compliance decision. One surprising result they obtain is that larger plants are less likely to comply. Larger plants are less likely to face enforcement, indicating political consideration take place in enforcement. They also discover that firms' characteristic are not statistically significant in determining compliance decision, but have significant impact on enforcement decision, although the signs are not always as expected.

Self Reporting

In addition to inspection and formal enforcement, topic that has attracted scholars' attention is self-report policy. As the regulator has a budget constrain in enforcing environmental regulation, there is a need for a policy that acts as a screening mechanism before conducting inspections. One viable option is for facilities to self-report their emission level. Some studies that include self-reporting emission are Magat and Viscusi (1990), Laplante and Rilstone (1996), and Helland (1998a), and Stafford (2002).

Laplante and Rilstone (1996) investigate the impact of inspection of self-reported emission level on compliance decision in the pulp and paper industry in Quebec. Although similar research has been done by Magat and Viscusi (1990) for U.S. case, their study differs in four aspects: (1) The data on standard of emission is available for every plant which enable them to see the impact relative to the standard, (2) They take into account the endogeneity of inspections, whereas Magat and Viscusi (1990) only use lagged of inspections to control for endogeneity, (3) They also take into account the selection bias problem created by self-reporting regime, (4) They estimate not only BOD, but also TSS (Total Suspended Solid).

In order to test their hypotheses, three types of estimates are performed: (1) Least squares regression without controlling for endogeneity and selection bias, (2) IV estimation where they control for endogeneity of inspection, (3) Two-step Heckman procedure to take into account self-selection. Using monthly data of 46 plants from 1985:1 – 1990:12, they find that selection bias does exist, where larger plants are more likely to self-report. After controlling the self-selection due to reporting and inspection endogeneity, they conclude that inspections reduce impact on emission level. One interesting result from their study is that the sign of time trend is negative and statistically significant in three cases of four. As they contend, "This may be evidence that, apart from inspection inducements, there is no effort on the part of plants to reduce their emission level."

A slightly different type of self-reporting regime has been implemented by the EPA in the beginning of 1996. Under this regime, the amount of penalty is reduced if a violating facility reports its violation during self audit. To our knowledge, Helland (1998a) is the first to investigate the impact of self-reporting policy of this kind (i.e., self report only if violation has occurred). Similar to most of previous enforcement studies, the object of research is also pulp industry. He investigates the role of targeting in producing regulatory compliance and self-reporting under the Clean Water Act. His research was mainly to empirically test Harrington's (1988) work on targeting.

Five hypotheses were tested: (1) The absence of any detected violations in previous periods should produce more violations in the contemporaneous period; (2) Plants that have detected violations in previous periods are more likely to self-report contemporaneous violations; (3) Mills with intermediate compliance cost are more likely to self-report, while higher and lower cost mills are less likely to self-report; (4) To the extent that regulators do not target mills, fewer violations will be reported; (5) Mills that have had mo detected violations in previous periods are less likely to self-report contemporaneous violations.

He uses detection controlled estimation model, developed by Feinstein (1990), where he estimates three equations: (1) violation, (2) Inspection and (3) Self-report decision. The dependent variable used for all equation is discrete variable. He chooses quarterly data for 57 mills in EPA region 4 between 1990 and 1993. This region is chosen for two reasons; (1) it has highest concentration of pulp and paper mills, and (2) data availability.

Based on his results, there is no evidence that inspections that do not detect violations increase the probability of future violations (inconsistent with Harrington paradox). However, he does notice that Harrington model only consistent with a subset of paper mills. He also concludes that detecting a violation does make plants more likely to self-report a violation. In summary, he contends that targeting produce more cooperation, in the form of self-reporting, although it does not deter violations. What targeting does is encourage firms to report violations they detect and presumably take steps to correct them.

Penalty

Although in the theoretical work penalty has been acknowledged for a long time as one policy variable to induce compliance decision, it has not been included in most studies for years. During the 90s, there were only two articles that include penalty in their analysis; Hamilton (1996), which investigates impact of informal and formal rule in enforcing RCRA regulation, and Kleit et al. (1998) who investigate the factors that determine the severity of penalty of water pollution in Louisiana.

In Kleit et al. (1998), three groups are included as independent variables; environmental performance, legal factors and political factors. The environmental performances are measured by count variables (number of previous enforcement action and number of excursion), while legal and political factors were represented by dummy variables. In order to test their hypothesis, probit and tobit estimation were conducted. In the probit estimation, the dependent variable is a discrete choice (whether a plant receives a penalty from the Office of Water Resource/OWR, or only a compliance order). Meanwhile for tobit estimation, two regressions were performed. The first tobit regression uses the initial penalty while the second regression uses the final penalty (i.e. the final amount of the penalty determined in the settlement agreement between OWR and the respondent).

Using monthly data (December 1993 – December 1994) from the Department of Environmental Quality, Louisiana, they find that penalties are positively related to severity of violations. Firms with previous violations are more likely to get higher penalties if they violate again. The largest increase in penalty happens when a facility does not have a permit or commit an illegal discharge.

Although Hamilton (1996) and Kleit et al. (1998) have brought back penalty into environmental compliance study, penalties are treated as dependent variable. Referring to Becker's (1968) seminal work, it is the probability of inspection and the severity of penalty that affect decision of committing crime. Therefore, compliance decision should be treated as endogenous.

The first article after Feinstein (1989) that discuss penalty with causality direction as suggested by Becker (1968) is Stafford (2002). She examines the impact of a change in EPA's penalty regime in 1991 on firms' compliance. Under the new regime, some penalties were increased to 10 or 20 times of the previous penalty level. She uses dummy variable to represent the change in regime.

To test her hypothesis, she runs two censored probit regressions simultaneously, assuming the error terms of violation and inspection equation are positively correlated. This is intended to handle the possibility of correlation between unmeasured facilities' characteristics and the likelihood to violate (hence more likely to be inspected). Her results are consistent with Becker's model, where an increase in penalties would lead to increase in compliance, *ceteris paribus*. The estimated increase in the number of compliance for 10-fold increase in penalty is between 10 and 20 %.

Penalty given to a firm also provides a signal to other firms regarding the regulator reputation in enforcing environmental regulation. If the regulator has a good reputation, then penalty given to detected violators will have a spillover effect on other firms. Other firms will have more incentive to comply if the enforcement threat is real.

If the regulator reputation is an important determinant in compliance decision, then as Shimshack and Ward (2005) argue, focusing only on the response of the sanctioned firm would overestimate the parameter for penalties and other sanction. Based on that premise, they conduct a research to find out the effect of three types of enforcement actions if the spillover effect is taken into account. The three enforcement actions that become the focus of attention are fines, intermediate enforcement action

(IEA), and inspection. The regulator reputation (spillover effect) is measured from the coefficient of fines and IEAs on other firms (within the same jurisdiction).

Their observations consist of major plants in the pulp and paper industry. Estimation is performed using Chamberlain's conditional random effect (CRE) probit model.[5] The first two finding are not that surprising; (1) that inspection last year have statistically significant effect in increasing compliance, and (2) intermediate enforcement actions in any measures have no detected impact on compliance decision. What quite striking from their research is the last finding; after taking into account the spillover effect, self-penalty does not have a significant impact on compliance decision. It is the spillover effects which have a statistically significant impact on compliance decision.

Laboratory Experiment

An effort to investigate the effect of punishment using laboratory experiment is conducted by Anderson and Stafford (2003), where they examine voluntary compliance model in providing public goods. Their design models a regulatory regime in which compliance is equivalent to contributing to a public good. Although the model is not applicable to all types of illegal behavior, they argue that it is still reasonable for environmental compliance. For example, installing pollution control equipment is analogous to contributing to a public good.

In their experiment, if someone is found being a free-rider, he/she will be given a penalty and the amount of penalty will depend on the degree of free-riding. The design of the experiment allows them to distinguish the effect of increased probability of audit to

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[5] As Helland (1998a) finds evidence of targeting policy, plant specific effect should be introduced. They argue that including fixed effect in a panel probit regression yields inconsistent estimates of the slope coefficients. As the solution, they use Chamberlain's conditional random effect probit model.

the increase in severity of punishment. They perform two types of experiment; (1) one-time and (2) repeated treatment.

Their findings are generally consistent with other experimental result. Public good provision is increasing as the expected cost of punishment increases. Their result indicates that the punishment severity has quantitatively larger effect on compliance behavior than the increased probability of punishment (being audited), which is contrary to most of the empirical findings. However, they note that the difference might be due to the measurement error in the empirical literature. One surprising result is that previous punishment has negative rather than positive effect on compliance behavior.[6] They note that this perhaps due to a 'lightning does not strike twice' attitude.

[6] The negative effect of previous punishment might not apply in enforcement of environmental regulation. In their experiment, audit is performed randomly, which might generate 'lightning does not strike twice' attitude. By law, EPA is not allowed to perform inspection in a random basis.

CHAPTER III
ESSAY ONE: ESTIMATING THE EFFECT OF PENALTIES ON REGULATORY COMPLIANCE

Introduction

Since the seminal work of Becker (1968) on the economics of crime, economists have explored various dimensions of regulatory enforcement. Becker's framework has been applied and extended to myriad types of regulations, including tax and environmental regulations. The environmental regulation literature has focused on the relationship between inspections and compliance decisions. For example, see Magat and Viscusi (1990), Deily and Grey (1991), Grey and Deily (1996), Laplante and Rilstone (1996), Nadeau (1997) and Helland (1998a).

Empirical analyses that jointly consider the effect of inspection and penalties on compliance are much less common. Two studies (Earnhart 2004, Shimshack and Ward 2005) include both inspection and penalties in modeling compliance decision, but fail to account for undetected violations.[7] As Feinstein (1989) noted, when violations can go undetected, parameter estimates of enforcement actions can be biased downwards. A more recent study (Scholz and Wang 2006) considers the potential for undetected violations, but uses a discrete, rather than continuous, penalty measure. Using a discrete measure prevents one from discerning responses of minor violators from those of

[7] There are three other studies that include penalty in their analysis. Hamilton (1996) and Kleit et al. (1998) treated penalties as dependent variable rather than independent variable. While it is true that the extent of noncompliance affects penalty severity, the literature on economics of crime emphasizes causality in the other direction, that the expected penalties affect compliance decision. Other study, Stafford (2002), focuses on the impact of penalty regime change, but did not include past penalties to represent specific deterrence effect.

substantial violators and introduces a form of measurement error that may bias results. Additionally, one cannot calculate the change in the probability of noncompliance resulting from a percentage change in penalty.

Our study improves on previous studies in three important ways. First, we use a statistical method that takes into account undetected violations in modeling firms' compliance behavior. Second, we use a continuous measure of penalties. Third, in order to avoid omitted variable bias, we use a richer set of covariates than has been used to date. We discuss each of these improvements in more detail in the next section.

Although it may seem obvious that penalties will induce greater compliance, recent theoretical work has pointed out that the effect of penalties on compliance can be ambiguous because firms may invest in penalty-eroding activities instead of pollution abatement technologies (Kambhu 1989; Kadambe and Segerson 1998). Moreover, assigning penalties for environmental noncompliance is legally more complicated than assigning such penalties in other policy areas, such as tax noncompliance, and thus the impact of penalties may be small. Indeed, our results imply that although the effect of penalties is statistically significant in reducing noncompliance, the effect is not economically significant. Compliance is affected more by a facility's characteristics and previous compliance status than by penalties or other enforcement actions.

Contribution to Literature

Undetected Violations

To take into account undetected violations, we use the Detection Controlled Estimation (DCE) approach, developed by Feinstein (1989, 1990). In the environmental compliance literature, three studies employ DCE analysis (Brehm and Hamilton 1996; Helland 1998a; Scholz and Wang 2006). We use a two-sided expectation simultaneity DCE approach (developed in Feinsten 1990) because we assume that potential violators will take into account what the regulator would do, and *vice versa*. No published compliance study in any field has employed the two-sided expectation approach.

Penalty Measure

Studies that model penalty as an explanatory variable usually use a dummy or count variable to represent the penalty (for instance, see Stafford 2002; Earnhart 2004; Scholz and Wang 2006). In contrast, Shimshack and Ward (2005) use a continuous penalty measure, but they fail to address undetected violations. Feinstein (1989) addresses undetected violations, but measures penalty at the facility level with a dummy variable and at the industry-level with an aggregate (national) continuous measures of industry-level penalties.[8]

A discrete measure for penalty represents a form of measurement error. Classical errors-in-variables (CEV) leads to attenuation bias and inconsistency of penalty parameter estimates (Griliches 1986; Greene 1997; Wooldridge 2002). This measurement error is transmitted to other variables in the model, but the direction of the bias is unknown. For non-linear models, such as probit and logit, Carroll et al. (1984) show that whenever the measurement errors are severe and the sample size is large, "[T]he usual estimate of the probability of the event in question can be substantially in error." Moreover, the impact of measurement errors on the estimated coefficient can be

[8] Feinstein (1989) use two deterrence variables: (1) plant sanction, measured by dummy variable, (2) aggregate sanction in industry, measured by the 3-months moving average of industry fines. Given that a facility-level fine will have a greater impact than an industry-level moving average, we believe measuring penalties as a continuous variable at the facility-level is important.

magnified by some transformations, such as when the true model includes a quadratic function of the variable measured with error (Griliches 1986)."

Covariates

We incorporate covariates that have been found to be important in previous studies, but which have yet not been assessed jointly. For example, we include regulator reputation to incorporate general deterrence effects, intermediate enforcement actions (IEA) to represent enforcement with zero penalties, facility industrial type to account for inherent differences on the propensity to violate.[9] By jointly assessing all variables that have been found to be important in previous studies, we reduce the likelihood of bias from omitted variables.

We focus on water pollution because of the high degree of consistency in data collection of this outcome by federal and state agencies. The period of analysis is 1997–2004 based on two considerations. First, it contains one penalty regime.[10] Second, we expect that using more recent data would give us more accurate estimates of the facilities' response to enforcement action.[11] The facilities included in this study are major facilities listed in the National Pollution Discharge Elimination System (NPDES). We do not restrict observations to a single industry, as some other studies have done (e.g., Shimshack and Ward 2005; Helland 1998a; Earnhart 2004; Nadeau 1997).[12]

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[9] Most of the regulatory compliance studies focus only on one industrial type.

[10] There was a regime change in 1995 which instructed the EPA to reduce the penalty if the violating facility self-reports the violation.

[11] The reliability of pre-1995 penalty data is questionable. Helland (1998b) indicates that there appear to have been no systematic effort to track penalty records in the NPDES database before 1995.

[12] Estimation of a DCE model requires sufficient variation in the detection equation, and thus including multiple industries in our sample also serves the purpose of increasing such variability.

Methodology

Empirical Model

To account for undetected violations, the empirical estimation is performed using Feinstein's (1989, 1990) Detection Controlled Estimation (DCE). There are three decisions that are estimated jointly: violations, inspection, and self report. Thus we use a modified DCE, as used in Helland (1998a) and Scholz and Wang (2006). The way we categorize observations in the modified DCE is described in figure 1. The likelihood function of the modified DCE is explained in the appendix.

Furthermore, there are possibilities that potential violators take into account what the regulator will do, *vice versa*. Thus we also estimate the model using a two-sided expectation simultaneity version of the modified DCE. We also estimate the model using probit and Chamberlain conditional random effects probit (CRE) to provide a comparison of results under different assumptions (i.e., when we ignore undetected violations).

We estimate three decisions jointly: violation and self report decisions, which are made by facilities, and inspection decisions, which are made by the regulator. Each decision is measured by dummy variable. In the violation decision, a dependent variable equal to 1 indicates that the facility is in violation, while zero indicates the facility is in compliance. The same logic applies for the inspection and self report decisions, where 1 indicates the presence of inspection or a self-reported violation. Our violation equation describes the decision to commit an effluent violation.[13]

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[13] We use both measures of effluent violation in the NPDES database; (1) monthly average, and (2) non monthly average, which reflects the maximum amount read during the reporting period. As a robustness check, we also use "significant violations," which comprise effluent violations, compliance schedule violations, compliance schedule monitoring report violations, and non receipt of Discharge Monitoring Report (DMR). The results are qualitatively similar in general.

We model facility's violation decision as a function of lagged penalty and intermediate enforcement actions (IEA), regulator's reputation, previous inspection outcome, demographic characteristic, and probability of inspection. IEAs are all enforcement actions without monetary fines. Lagged penalty and IEAs are included to capture specific deterrence effects. To capture general deterrence effects, we include regulator reputation, which is measured by the average penalty and average IEA in the state (Shimshack and Ward 2005). Demographic characteristics of the communities near the facility are also included.

Inspection is modeled as a function of the lagged number of inspections, lagged compliance status, lagged penalties, demographic characteristics of neighboring communities, state government environmental expenditures,[14] number of facilities (in the same 2-digit SIC) in the state, and a facility's probability of violation. Lagged inspection, compliance status, and penalties represent a facility's record of enforcement and compliance. Government expenditures and the number of facilities capture the regulator's enforcement resources. Demographic characteristics of neighboring communities are also included.

A facility's decision to self-report is modeled as a function of lagged compliance status, lagged penalty, lagged intermediate enforcement actions, lagged report violation and the number of facilities in the same 2-digit SIC code in the region.

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[14] For government budget, we use the state expenditure for environmental and natural resources (normalized by the total number of facility)

In each decision, we also include a facility's industrial type,[15] and seasonal dummies to account for inherent differences in the propensity to violate across firms and time. Additionally, since the estimation procedure in the CRE also includes average variables of the most direct theoretical concern (which are used to condition the error term), the estimation in DCE (and probit) should also use the same conditioning variables to be comparable. The summary of expected of sign for each variable in each decision is described in Table 1.[16] We estimate the model under five specifications, A to E. A summary of each specification is described in Table 3.

Identification

A two-sided simultaneous DCE model requires three conditions for identification:

1. We need explanatory variables that are uniquely associated with each stage. Previous inspection outcome (i.e., inspection that did not detect violations) only exists in the violation decision. We exclude it from inspection equation since we consider that the regulator is more concerned on the extent of violation, and this information can still be obtained even in the absence of inspection (through self report violation). Since self report is intended to reduce the maximum penalty, and many violators go only with warning, we may expect that previous inspection that did not detect any violation does not have any effect on self report. Thus, we exclude it from self report decision. Number of previous inspections and government expenditures exist only in the inspection equation. They do no affect

[15] The industrial types in NPDES represent facilities' SIC and ownership. There are five industrial types used in the NPDES database; (1) primary industry on effluent limitation guidelines/ELG, (2) non-primary industry but listed on ELG, (3) industry not listed on ELG, (4) municipal facilities, which is determined by SIC 4952 and public ownership, and (5) facilities without classification.

[16] The argument of each decision is available in the appendix

violation decisions because they are unrelated to compliance costs and have no direct effect on facilities. They affect facilities only through the probability of inspection. The regulator's decision to perform inspection depends on previous inspections as well as the regulator's resource availability. As in Helland (1998a), we use lagged detected violation as exclusion restriction for self report decision.

2. Given that our explanatory variables include both discrete and continuous variables, we must have at least one explanatory variable with an unbounded support. Penalty and regulator reputation are two examples of variables that have unbounded support.
3. For a two-sided expectation simultaneity model to have a solution, the sign of the endogenous right hand side variable must differ between models. As noted above, we expect a negative relationship between expected inspections and the violation decision, and a positive relationship between expected violation rates and the inspection decision. Whether or not these signs differ in practice must be determined empirically.

Data

Data come from the EPA, Census Bureau, Bureau of Labor Statistics (BLS), and Bureau of Economic Analysis (BEA). We use the NPDES data set from the EPA to obtain facility information, compliance records, and histories of inspection and enforcement performed by state and federal agencies. While inspection and enforcement histories include the exact date of action, compliance records are only available quarterly. Consequently, we can not extend the analysis beyond quarterly data. For data consistency consideration, we only include major facilities in the analysis.[17] County-level demographic characteristics come from the 1990 and 2000 Decennial Censuses. Monthly employment rates come from Local Area Unemployment Statistics (LAUS) of the BLS. We calculate quarterly unemployment rates by taking the average of the four months. All datasets are merged using Federal Information Processing Standard (FIPS) county codes.

We vary the set of industries used in the estimation to see if the results change drastically with different datasets. In the first dataset, we include all municipal and non-municipal facilities from all SICs, which has never been done in an environmental compliance study. The second dataset includes only non-municipal facilities. We perform regression using the second dataset based on two considerations. First, Scholz and Wang (2006) claim that municipal facilities have different budget constraints that may alter their responses to enforcement actions. Second, municipal facilities account for a relatively larger proportion of violations in the first dataset: (1) 74% of the penalty actions are assigned to municipal facilities, (2) 58% of total value of penalties is imposed on municipal facilities, and (3) 63% of the observations in the first dataset are municipal facilities. The third dataset includes facilities in SIC 49 (gas, utilities and sanitary services) because facilities in this SIC code are the most frequent violators.

One interesting fact about the NPDES database is that there are many records where facilities are in violation, yet no inspections or enforcements take place in the same quarter. These observations reflect the option that firms have to self-report noncompliance. The EPA requires major plants to submit a monthly Discharge

[17] Major facilities are required to submit monthly discharge monitoring report (DMR), and by law, must be inspected at least once a year. On the other hand, minor facilities are not required to submit monthly DMR, nor required to be inspected at least once a year. Thus, including minor facilities will increase the number observations with missing information.

Monitoring Report (DMR) and a 1995 regulatory change provides incentives (through penalty reductions) for self-reporting violations.

Although self-reports provide information regarding firms' compliance status, they may also be subject to strategic nonreporting. Two studies fail to reject the accuracy of self-reports and thus ignore this source of bias in studying compliance decisions (Laplante and Rilstone 1996; Shimshack and Ward 2005). In a DCE approach, however, the self-report decision is included in the joint likelihood function and thus any strategic non-reporting is directly controlled in the modeling.

Analyses and Results

Violations

The results in Tables 4, 5 and 6 indicate that facilities respond to penalties. The negative coefficient indicates that the larger the amount of penalty, the greater the likelihood that the facility will comply in the next period. The coefficient of penalty lagged one year is greater than penalty lagged two years.

Interestingly, facilities with IEAs in the previous year are more likely to remain in violation in the next period, while plants with IEAs two years ago will be more likely to comply. The positive coefficient for IEAs lagged one year indicates that facilities find it difficult to correct violations.[18] In the event that the facility is still unable to correct the violation, it will submit self report to avoid severe penalty.[19] The change in coefficient

[18] Shimshack and Ward (2005) is the only study that includes IEA into analysis. The qualitative signs for self IEA are similar with their result, but they do not find it significant.

[19] This is supported by the result in self report equation, where there is a positive correlation between lagged IEAs (1-4 quarters) and self report decisions. See Table 8 for detail.

sign from IEAs lagged one year to IEAs lagged two years is not surprising. This may reflect the regulator's enforcement cycle length,[20] and may indicate that facilities are concerned that extended periods of violation will result in higher penalties because regulators will perceive the facilities as failing to act in "good faith."

Regulator reputation, whether measured by the average penalty or the number of IEAs per facility in the state, also improves compliance. In contrast to Shimshack and Ward (2005), introducing reputation variables does not change the effectiveness of self-penalty or self IEAs. Only two variables change in magnitude or significance. The unemployment rate coefficient changes from positive to negative, and, under the DCE model, the percentage of owner occupants becomes statistically insignificant.

With regard to the coefficient on previous compliance status, we find that previous inspection that did not detect violation is associated with higher likelihood to violate in the next year. This is consistent with Harrington (1988) prediction for firms with medium compliance cost. However, note the support for Harrington prediction is not as strong as one might expect, as the coefficient for lagged 5-8 quarters is negative. Moreover, the number of previous violation is positive correlated with current violation.

The sign of demographic characteristics are mostly as expected, except for unemployment rate and share of white population. In most models and specifications, the coefficient of unemployment is negative in the violation equation. Although this seems surprising, Shimshack and Ward (2005) also estimate a negative coefficient. Their explanation for such result is that high levels of unemployment result in an increased community sensitivity to plants' polluting and social behavior.

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[20] There are some indications that the enforcement cycle is two years: (1) coefficients of reputation variables lagged two years in the violation equation are larger than those lagged one year, (2) coefficients of inspection lagged two years are larger than those lagged one year in the inspection equation.

Inspection

Table 7 presents the results from the inspection equation. Six variables have the expected signs and statistical significance across specifications: (1) lagged penalty, (2) lagged IEAs, (3) lagged inspection, (4) number of facility in the same 2-digit SIC code, (5) percentage of urban area, and (6) percentage of owner occupant. Positive signs on lagged inspection are not surprising because major facilities are required to be inspected once a year. We find that the regulator has greater likelihood to inspect plants in industries (2-digit SIC) with larger numbers of facilities. We expected this relationship because total pollution will increase and the net benefit of performing inspection towards the industry increases as the number of plant in the industry increases. The results from self report equation (see below) also confirm that plants in industry with smaller number of facilities are more likely to self report. In three specifications (A, B, and D), we find evidence that the regulator's decision to perform inspections is affected by the racial structure: inspections are more likely in communities with a higher percentage of white citizens. Scholz and Wang (2006) find a similar relationship.[21]

Self Report

Table 8 presents the results from the self-report equation. The results are mostly as expected. Interestingly, we find that probability of inspection and regulator reputation are negatively correlated with facility's decision to self report. Looking at the sign of the probability of inspection in the violation decision, it is not surprising that we have negative coefficient on the self report decision. The facility that has higher likelihood of

[21] They used different measure of race structure. They found that greater percentages of Hispanic and Black residents are associated with lower inspection probabilities.

being inspected is more likely to comply, thus there is no need to submit self report. The possible explanation for negative coefficient for regulator reputation is that the penalty reduction in the state where the regulator is strict is not large enough. Therefore, by not submitting self report violation, a facility has a chance of avoiding the penalty.

Marginal Effects

Our models are non-linear, which means that the coefficients cannot be interpreted as marginal effects. In order to discern the relative importance of each variable, we calculate the change of probability of violation when one variable is changed by given value, holding the other variables constant at their mean values. The results are presented in Tables 9 (probit model) and 10 (DCE model).

For self-penalty, we measure the change in the predicted probability of violation with a change from zero to $19,799 in the penalty (i.e., the mean of non-zero penalties lagged one year). Under the probit model, a facility that was fined by $19,799 last year is 1.00 to 1.26% less likely to violate than the facility that did not receive monetary fines. The estimates under DCE are higher, ranging from 2.75 to 3.54% (Table 10).

Imposing a penalty on one facility will also have indirect effects on other facilities through a change in the regulator's reputation. A change from $0 penalty to a $19,799 penalty on a firm implies, on average, a $139 increase in the penalty reputation variable (lagged one year).[22] Under the probit model, if the average penalty in the state increased

[22] Adding $19,799 to aggregate penalty and then divide it with number of facility in the state gives us an average of $139 increase in reputation penalty.

by \$139 last year, *each* facility is approximately 0.01% less likely to violate. Under the DCE model, the reduction in the probability of violation is between 0.02% and 0.04%.[23]

The change in predicted probability of violation caused by an increase in IEAs is based on one unit increase of IEA. Similar to penalty, we also calculate the change of predicted probability of violation due to one unit increase of regulator reputation for IEAs. Tables 9 and 10 show that an additional IEA in the last four quarters is *not* associated with a lower probability of violation. A reduction in the probability of violation due to an additional IEA can only be seen after 5-8 quarters.

The fact that penalty increases do not generate substantial reductions in the probability of violation is not surprising for two reasons. First, penalties are rarely imposed on detected violators. Second, even if a detected violator is fined, the amount is usually small (as noted above, the mean is less than \$20,000).

The rarity of severe monetary sanctions by the EPA is partially due to large litigation costs. The 1995 CWA penalty settlement formula supports this argument, where litigation costs act as penalty-reducing factor. Theoretically, imposing large penalties increases the probability that the facility will challenge the decision in judicial courts, as shown by Kambhu (1989) and Kadambe and Segerson (1998). Kambhu (1989) contends that increases in penalties may cause firms to invest more in penalty-eroding activities instead of investing in abatement technologies. One form of penalty-eroding activity is hiring a good lawyer to increase the probability of winning the case in court. Kadambe and Segerson (1998) contend that penalty increases have indirect effects, where

[23] We also calculate the impact of \$19,799 increase in penalty reputation. We find that the marginal effect of penalty reputation is 0.49%-0.67% for lagged 1 year, and 1.01%-1.34% for lagged 2 years.

by they change the violator's probability to challenge the regulator's decision, and consequently change the regulator's probability to fight the violator's challenge.

One may also argue that our failure to model a penalty equation contributes to the small estimated response from penalties.[24] We believe the potential for bias in this direction is small. First, even if we were to model the penalty decision, as long as there is no penalty expectation in the violation equation, the coefficients in the violation equation will remain the same. This is because the number of detected and undetected violation does not change *and* the explanatory variable in the violation decision remains unchanged. Consequently, the marginal effect in the violation decision would be the same. Second, if we were to model the penalty decision *and* we add a penalty expectation in the violation equation, theoretically the coefficients of the penalty expectation will be negative. If this is the case, then omitting the penalty expectation implies that other coefficients would be biased downward. In our case, self-penalty has a negative impact. Thus a downward bias means that the absolute value of our estimated coefficient of self-penalty in the compliance equation is larger than the true coefficient. Hence including penalty expectation in the violation decision would cause the coefficient of self-penalty to be closer to zero.[25]

Non-municipal Facilities

As noted previously, municipal facilities comprise a proportionally large part of our sample and thus may greatly influence our parameter estimates. Although dummy variables indicate that non-municipal facilities have lower *overall* likelihood to violate,

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[24] As a robustness check, we added a penalty equation in the DCE model, but the model failed to converge.

[25] For further discussion on the consequence of ignoring simultaneity among decisions, see Brehm and Hamilton (1996).

we are also interested in the effect of each covariate in affecting compliance decisions. Therefore, we re-estimate the model using just non-municipal facilities.

Table 11 presents the results. In general, the results are qualitatively similar with the results shown in Table 6. The most notable difference is on the statistical significance of self penalty and IEA, where we fail to reject null for lagged 5-8 quarters of self-penalty and IEA.

SIC 49

We also re-estimate the model for facilities in SIC 49 because this industry is the most frequent violator. Table 12 presents the results. We find that self-penalty and regulator reputation are effective in deterring violation in every specification.

Undetected Violations

The DCE approach also allows one to estimate the probability of undetected violations. We estimate the predicted probability of undetected violation within facilities that are not inspected or do not submit self-reports of a violation. Such information can be useful in evaluating the effectiveness of a regulatory regime and in improving the targeting of inspections.

Table 13 presents the results. During the entire period of 1997-2004, the average predicted probability of undetected effluent violations in municipal facilities is 16.5% (Specification E). In other words, 16.5% of facilities that were not inspected or did not submit self-reports of a violation are estimated to have been in violation. This is higher than the non-municipal facilities in the primary industries (11.79%). The probability of undetected violation for SIC 49 is close to that of municipal facilities (15.74%), which is not surprising because the majority of facilities in SIC 49 are owned by municipal governments.

We cannot find a comparison for our estimates in the environmental compliance studies, as previous studies do not provide such estimates. However, the estimates of undetected violations in the tax literature can be used for parallel comparison. For instance, Erard and Ho (2001) estimates the number of non filers in tax year 1988 is 7.9 millions 1988. This is equivalent to 7.18% of the total filers (7.9/110). Out of 7.9 millions non filers, 71% are estimated to have tax liability by the amount of $11 billions, which is 15% of total overall tax gap (11/73).[26] Other studies such as Feinstein (1991) and IRS (2006) focus on the extent of tax evasion but did not provide the estimated number of violating taxpayers.

Conclusion and Policy Implication

Conclusion

To ascertain the effect of financial penalties and other enforcement actions on compliance behavior, we used three estimation methods under various specifications and data restrictions. Most results imply that penalties are effective in deterring violations, have an effect on compliance less than one year after the penalty is applied, and continue to have an effect up to two years later. In contrast, intermediate enforcement actions (IEAs) do not improve compliance within one year of being applied, but do have an effect five to eight quarters later.

[26] Tax gap is the standard term used in tax compliance literature to reflects the extent to which taxpayers do not file their tax return and pay the correct tax on time.

Our results also demonstrate that the estimated effects of penalties and IEAs on facility compliance based on traditional econometric methods are biased towards zero because they fail to account for undetected violations. However, although the estimated marginal effects of penalties using the DCE model are two to three times the effects from a probit model, they remain economically small. Compliance decisions are affected more by the facility's characteristics and previous compliance status than penalties and IEAs.

With regard to the reputation of regulators in a state, measured by the average penalty and average IEA per facility in the state, such reputation does improve compliance. However, like penalties on specific firms, the reputational effects remain economically small. In contrast to Shimshack and Ward (2005), we find that the inclusion of regulators' reputations in the compliance equation does not render the effects of own penalties statistically insignificant.[27] The probability of inspection can be considered another component of regulator reputation and we find that increasing the probability of inspection by 17% (one standard deviation) has a moderate effect on compliance.

In the inspection decision, we found evidence that the regulator tends to perform inspections on those who have a previous record of violation. Holding everything else constant, facilities that were penalized or given IEAs have a higher likelihood of being inspected in the current period. Results from the inspection equation estimates also provide some evidence of environmental injustice. We found inspections were more likely in facilities whose surrounding areas had higher proportions of white citizens and owner occupants (note, however, that compliance was negatively correlated with the proportion of whites).

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[27] The sole exception is the regression (Table 11) that uses only non-municipal firms. Note that our results do hold, however, when we use facilities from SIC code 26 (pulp and paper), which is the sample used by Shimshack and Ward (2005).

Policy Implications

Our results indicate that penalties do reduce noncompliance with environmental regulations. However, marginal increases in the penalties applied under the existing regime will not generate substantial reductions in the probability of violation. The absence of a substantial response to penalties arises from the way in which regulators enforce the Clean Water Act: penalties are rarely imposed or, if imposed, are typically small.

We argue that if regulators want to see economically significant effects from penalties, they should consider a nonmarginal change in the penalty regime; specifically, they should greatly increase the frequency and severity of penalties.[28] Based on our results, we believe a large change in the penalty regime will affect facility behavior in three ways. First, it will have a specific deterrence effect. Second, it will increase the enforcement reputation of the regulator. Third, it increases the probability that facilities will self-report violations. A greater frequency of self-reported violations allows for more efficient use of inspection budgets. Inspections can be targeted to facilities that have high likelihood of violating, based on observable characteristics, but that do not self report violation. Although we cannot precisely predict the effects of a nonmarginal change in the penalty regime, Stafford (2002) found that facilities were 3% less likely to violate

[28] Under the existing regime, we need a significantly large penalty increase to generate an economically significant impact on compliance decisions. However, because our models are non-linear, marginal effects of a significantly large penalty increase would far from accurate.

after the RCRA penalty regime change in 1990, which increased some penalties 10 to 20 times their previous levels.

The regulator can also improve compliance rates by harnessing a facility's sensitivity to local community characteristics. We find that education levels in the communities surrounding a facility are negatively correlated with violations. Thus, as noted by other authors (Foulon et al. 2002; Fung and O'Rourken, 2000; and Khanna and Damon 1999), the public disclosure of facilities' environmental performances to local communities can provide additional incentives for facilities to comply with existing regulations.

Table 1. Expected Signs of Empirical Model

	Expected Sign		
	Violation	Inspection	Self Report
Probability of inspection	-		-/+
Probability of violation		+	
Probability of self report		-	
Lagged penalty (Self)	-	+	+
Lagged penalty (Reputation)	-		+
Lagged IEA (Self)	-	+	+
Lagged IEA (Reputation)	-		+
Inspected and no violation detected (Lagged)	+		
Inspected and violation was detected (Lagged)			+
Percent urban	+	+	
Percent white	-	+	
Unemployment rate	+	+	
Percent of owner occupant	-	+	
Percent of bachelor + graduate degree	-	-/+	
Average penalty	+	+	
Average IEA	+	+	
Average inspection	+		
Lagged inspection		-	
Lagged number of violation		+	+
Budget per facility		+	
Number of facility in the same 2-digit SIC		+	-
Lagged number of reporting violation			+
Primary industry	-	+	+
Not primary industry	-/+	-/+	-/+
Not on ELG	-/+	-/+	-/+
Facility with no classification	-/+	-/+	-/+

Table 2: Descriptive Statistics of Enforcement with Non-Zero Penalty

Classification	Frequency		Total Penalty		Average Penalty
	Total	%	Total	%	
Municipal	1556	74.24%	19,944,746	58.24%	12,818
Primary industry listed on ELG	408	19.47%	11,163,982	32.60%	27,363
Listed on ELG but not primary industry	69	3.29%	2,385,928	6.97%	34,579
Not listed on ELG	63	3.01%	748,769	2.19%	11,885
Total	2096	100%	34,243,421	100%	16,338

Table 3: Empirical Model Specifications

	Base	Reputation Variables	Expectation Term	Time Effects
Specification A	√			
Specification B	√	√		
Specification C	√	√	√	
Specification D	√	√		√
Specification E	√	√	√	√

Table 4: Effluent Violation Decision under Probit

	Specification				
	A	**B**	**C**	**D**	**E**
Probability of inspection			-0.0640		-0.0115
			(0.0743)		(0.0716)
Penalty (Self) 1-4 quarters ago	-0.0185 ***	-0.0179 ***	-0.0178 ***	-0.0157 ***	-0.0157 ***
	(0.0032)	(0.0032)	(0.0032)	(0.0032)	(0.0032)
Penalty (Self) 5-8 quarters ago	-0.0127 ***	-0.0115 ***	-0.0116 ***	-0.0094 ***	-0.0095 ***
	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)
Penalty (Reputation) 1-4 quarters ago		-0.0031	-0.0029	-0.0035	-0.0034
		(0.0023)	(0.0023)	(0.0024)	(0.0024)
Penalty (Reputation) 5-8 quarters ago		-0.0108 ***	-0.0105 ***	-0.0110 ***	-0.0109 ***
		(0.0024)	(0.0024)	(0.0024)	(0.0024)
IEA (Self) 1-4 quarters ago	0.0115 ***	0.0184 ***	0.0186 ***	0.0157 ***	0.0157 ***
	(0.0033)	(0.0036)	(0.0036)	(0.0036)	(0.0036)
IEA (Self) 5-8 quarters ago	-0.0267 ***	-0.0156 ***	-0.0156 ***	-0.0184 ***	-0.0185 ***
	(0.0036)	(0.0037)	(0.0037)	(0.0038)	(0.0038)
IEA (Reputation) 1-4 quarters ago		-0.0086 **	-0.0087 **	-0.0046	-0.0045
		(0.0042)	(0.0042)	(0.0042)	(0.0042)
IEA (Reputation) 5-8 quarters ago		-0.0319 ***	-0.0316 ***	-0.0346 ***	-0.0346 ***
		(0.0044)	(0.0045)	(0.0045)	(0.0045)
Inspected and no violation detected 1-4 quarters ago	0.0653 ***	0.0730 ***	0.0728 ***	0.0709 ***	0.0708 ***
	(0.0129)	(0.0129)	(0.0129)	(0.0130)	(0.0130)
Inspected and no violation detected 5-8 quarters ago	0.0140	0.0207	0.0240 *	0.0154	0.0155
	(0.0132)	(0.0132)	(0.0139)	(0.0132)	(0.0139)
Number of effluent violation 1-4 quarters ago	0.6376 ***	0.6294 ***	0.6295 ***	0.6278 ***	0.6277 ***
	(0.0060)	(0.0060)	(0.0060)	(0.0061)	(0.0061)
Number of effluent violation 5-8quarters ago	0.0733 ***	0.0649 ***	0.0657 ***	0.0778 ***	0.0780 ***
	(0.0067)	(0.0067)	(0.0068)	(0.0068)	(0.0069)
Percent urban	-0.0136	-0.0160	-0.0146	-0.0059	-0.0041
	(0.0277)	(0.0278)	(0.0279)	(0.0278)	(0.0279)
Percent white	0.4891 ***	0.3124 ***	0.3212 ***	0.2381 ***	0.2434 ***
	(0.0452)	(0.0466)	(0.0469)	(0.0473)	(0.0475)
Unemployment rate	-0.0046 *	-0.0089 ***	-0.0091 ***	-0.0031	-0.0032
	(0.0028)	(0.0028)	(0.0028)	(0.0030)	(0.0030)

	Specification									
	A		B		C		D		E	
Percent of owner occupant	-0.3662	***	-0.1670	**	-0.1634	*	0.0673		0.0722	
	(0.0832)		(0.0848)		(0.0849)		(0.0880)		(0.0882)	
Percent of bachelor + graduate degree	-0.8159	***	-0.9303	***	-0.9370	***	-0.5282	***	-0.5356	***
	(0.1243)		(0.1259)		(0.1261)		(0.1320)		(0.1326)	
Primary industry	-0.1817	***	-0.1670	***	-0.1697	***	-0.1699	***	-0.1709	***
	(0.0136)		(0.0136)		(0.0139)		(0.0137)		(0.0139)	
Not primary industry	-0.0943	***	-0.0862	***	-0.0884	***	-0.0820	***	-0.0826	***
	(0.0231)		(0.0231)		(0.0232)		(0.0231)		(0.0232)	
Not on ELG	-0.0176		-0.0174		-0.0226		-0.0150		-0.0186	
	(0.0260)		(0.0261)		(0.0263)		(0.0262)		(0.0264)	
Facility with no classification	-0.0567		-0.1097		-0.1109		-0.0933		-0.0932	
	(0.2418)		(0.2413)		(0.2413)		(0.2408)		(0.2408)	
Average penalty	0.0434	***	0.0467	***	0.0470	***	0.0449	***	0.0450	***
	(0.0026)		(0.0027)		(0.0027)		(0.0027)		(0.0027)	
Average IEA	0.2087	***	0.3190	***	0.3185	***	0.3334	***	0.3341	***
	(0.0228)		(0.0240)		(0.0241)		(0.0242)		(0.0242)	
Average inspection	-0.0167		-0.0109		0.0076		-0.0132		-0.0099	
	(0.0119)		(0.0117)		(0.0242)		(0.0118)		(0.0240)	
Constant	-2.0730	***	-1.9481	***	-1.9491	***	-1.9382	***	-1.9446	***
	(0.0757)		(0.0771)		(0.0776)		(0.0831)		(0.0833)	

Seasonal dummies and time effects are omitted for brevity
*, **, *** indicate 10%, 5%, and 1% significance respectively

Table 5: Effluent Violation Decision under Chamberlain Conditional Random Effects

	Specification					
	A		B		D	
Penalty (Self) 1-4 quarters ago	-0.0133	***	-0.0132	***	-0.0112	***
	(0.0034)		(0.0034)		(0.0034)	
Penalty (Self) 5-8 quarters ago	-0.0100	***	-0.0092	**	-0.0072	**
	(0.0036)		(0.0036)		(0.0036)	
Penalty (Reputation) 1-4 quarters ago			-0.0033		-0.0036	
			(0.0027)		(0.0027)	
Penalty (Reputation) 5-8 quarters ago			-0.0098	***	-0.0103	***
			(0.0027)		(0.0027)	
IEA (Self) 1-4 quarters ago	0.0251	***	0.0326	***	0.0295	***
	(0.0036)		(0.0038)		(0.0038)	
IEA (Self) 5-8 quarters ago	-0.0119	***	-0.0020		-0.0051	
	(0.0038)		(0.0040)		(0.0040)	
IEA (Reputation) 1-4 quarters ago			-0.0158	***	-0.0113	**
			(0.0046)		(0.0046)	
IEA (Reputation) 5-8 quarters ago			-0.0282	***	-0.0308	***
			(0.0050)		(0.0050)	
Inspected and no violation detected 1-4 quarters ago	0.0541	***	0.0591	***	0.0567	***
	(0.0145)		(0.0145)		(0.0145)	
Inspected and no violation detected 5-8 quarters ago	0.0014		0.0062		0.0015	
	(0.0149)		(0.0148)		(0.0148)	
Number of effluent violation 1-4 quarters ago	0.4981	***	0.4983	***	0.5034	***
	(0.0072)		(0.0073)		(0.0073)	
Number of effluent violation 5-8quarters ago	-0.0417	***	-0.0423	***	-0.0239	***
	(0.0077)		(0.0078)		(0.0079)	
Percent urban	-0.0129		-0.0198		-0.0034	
	(0.0463)		(0.0452)		(0.0444)	
Percent white	0.7630	***	0.5621	***	0.3947	***
	(0.0755)		(0.0754)		(0.0764)	
Unemployment rate	-0.0099	***	-0.0144	***	-0.0067	*
	(0.0037)		(0.0037)		(0.0040)	

	Specification					
	A		B		D	
Percent of owner occupant	-0.6602	***	-0.4416	***	0.0071	
	(0.1367)		(0.1348)		(0.1414)	
Percent of bachelor + graduate degree	-1.5627	***	-1.6296	***	-0.8895	***
	(0.1992)		(0.1963)		(0.2082)	
Primary industry	-0.2691	***	-0.2463	***	-0.2459	***
	(0.0232)		(0.0227)		(0.0223)	
Not primary industry	-0.1391	***	-0.1292	***	-0.1206	***
	(0.0401)		(0.0390)		(0.0384)	
Not on ELG	-0.0471		-0.0418		-0.0371	
	(0.0461)		(0.0448)		(0.0440)	
Facility with no classification	0.0081		-0.0511		-0.0256	
	(0.3990)		(0.3875)		(0.3791)	
Average penalty	0.0627	***	0.0642	***	0.0612	***
	(0.0045)		(0.0045)		(0.0044)	
Average IEA	0.2052	***	0.3405	***	0.3454	***
	(0.0329)		(0.0339)		(0.0337)	
Average inspection	-0.0034		0.0024		-0.0013	
	(0.0206)		(0.0199)		(0.0195)	
Constant	-2.1208	***	-1.9805	***	-2.1119	***
	(0.1191)		(0.1182)		(0.1242)	
Lnsig2u	-1.3489	***	-1.4448	***	-1.5080	***
	(0.0505)		(0.0534)		(0.0552)	
Sigma u	0.5094	***	0.4856	***	0.4705	***
	(0.0129)		(0.0130)		(0.0130)	
Rho	0.2061	***	0.1908	***	0.1812	***
	(0.0083)		(0.0082)		(0.0082)	

Seasonal dummies and time effects are omitted for brevity
*, **, *** indicate 10%, 5%, and 1% significance respectively

Table 6: Effluent Violation Decision under DCE

	Specification									
	A		B		C		D		E	
Probability of inspection					-1.5487	***			-1.4563	***
					(0.0880)				(0.0870)	
Penalty (Self) 1-4 quarters ago	-0.0199	***	-0.0187	***	-0.0174	***	-0.0165	***	-0.0153	***
	(0.0043)		(0.0043)		(0.0043)		(0.0043)		(0.0044)	
Penalty (Self) 5-8 quarters ago	-0.0102	**	-0.0084	*	-0.0102	**	-0.0076	*	-0.0083	*
	(0.0044)		(0.0045)		(0.0045)		(0.0045)		(0.0045)	
Penalty (Reputation) 1-4 quarters ago			-0.0064	**	-0.0034		-0.0056	*	-0.0035	
			(0.0029)		(0.0029)		(0.0030)		(0.0030)	
Penalty (Reputation) 5-8 quarters ago			-0.0172	***	-0.0112	***	-0.0169	***	-0.0120	***
			(0.0030)		(0.0030)		(0.0031)		(0.0031)	
IEA (Self) 1-4 quarters ago	0.0110	***	0.0214	***	0.0266	***	0.0205	***	0.0227	***
	(0.0041)		(0.0048)		(0.0048)		(0.0049)		(0.0049)	
IEA (Self) 5-8 quarters ago	-0.0316	***	-0.0140	***	-0.0093	*	-0.0146	***	-0.0130	**
	(0.0045)		(0.0050)		(0.0050)		(0.0051)		(0.0051)	
IEA (Reputation) 1-4 quarters ago			-0.0129	**	-0.0160	***	-0.0079		-0.0104	*
			(0.0053)		(0.0053)		(0.0055)		(0.0055)	
IEA (Reputation) 5-8 quarters ago			-0.0436	***	-0.0347	***	-0.0474	***	-0.0388	***
			(0.0053)		(0.0053)		(0.0055)		(0.0056)	
Inspected and no violation detected 1-4 quarters ago	0.0825	***	0.0952	***	0.0932	***	0.0990	***	0.0895	***
	(0.0177)		(0.0177)		(0.0168)		(0.0177)		(0.0169)	
Inspected and no violation detected 5-8 quarters ago	-0.1247	***	-0.1137	***	-0.0159		-0.1208	***	-0.0279	
	(0.0183)		(0.0182)		(0.0184)		(0.0184)		(0.0185)	
Number of effluent violation 1-4 quarters ago	0.6941	***	0.6808	***	0.6870	***	0.6802	***	0.6834	***
	(0.0087)		(0.0087)		(0.0087)		(0.0088)		(0.0088)	
Number of effluent violation 5-8quarters ago	0.0639	***	0.0511	***	0.0708	***	0.0662	***	0.0840	***
	(0.0097)		(0.0097)		(0.0097)		(0.0098)		(0.0098)	
Percent urban	0.0213		0.0207		0.0064		0.0270		0.0177	
	(0.0349)		(0.0351)		(0.0353)		(0.0353)		(0.0355)	
Percent white	0.5409	***	0.2829	***	0.3808	***	0.2279	***	0.3029	***
	(0.0572)		(0.0590)		(0.0585)		(0.0599)		(0.0593)	

	Specification									
	A		B		C		D		E	
Unemployment rate	0.0030		-0.0032		-0.0067	*	-0.0027		-0.0005	
	(0.0035)		(0.0035)		(0.0035)		(0.0038)		(0.0038)	
Percent of owner occupant	-0.4657	***	-0.1471		-0.1681		0.0014		0.0735	
	(0.0968)		(0.1003)		(0.1023)		(0.1046)		(0.1069)	
Percent of bachelor + graduate degree	-0.9042	***	-1.0930	***	-1.0239	***	-0.8919	***	-0.6337	***
	(0.1550)		(0.1589)		(0.1594)		(0.1669)		(0.1680)	
Primary industry	-0.1567	***	-0.1321	***	-0.1834	***	-0.1326	***	-0.1836	***
	(0.0174)		(0.0175)		(0.0176)		(0.0176)		(0.0177)	
Not primary industry	-0.0466		-0.0343		-0.0813	***	-0.0339		-0.0781	**
	(0.0296)		(0.0297)		(0.0299)		(0.0299)		(0.0301)	
Not on ELG	0.0432		0.0469		-0.0080		0.0486		-0.0020	
	(0.0346)		(0.0348)		(0.0348)		(0.0348)		(0.0348)	
Facility with no classification	0.1067		0.0178		-0.0196		0.0881		0.0446	
	(0.3538)		(0.3545)		(0.3576)		(0.3524)		(0.3555)	
Average penalty	0.0405	***	0.0460	***	0.0507	***	0.0441	***	0.0487	***
	(0.0034)		(0.0035)		(0.0035)		(0.0035)		(0.0035)	
Average IEA	0.2049	***	0.3739	***	0.3390	***	0.3710	***	0.3595	***
	(0.0273)		(0.0298)		(0.0299)		(0.0306)		(0.0307)	
Average inspection	-0.4092	***	-0.3995	***	0.0642	**	-0.3972	***	0.0453	
	(0.0307)		(0.0295)		(0.0273)		(0.0295)		(0.0280)	
Constant	-1.2797	***	-1.1069	***	-0.9642	***	-0.9780	***	-0.9681	***
	(0.0899)		(0.0922)		(0.0934)		(0.1006)		(0.1014)	

Seasonal dummies and time effects are omitted for brevity
*, **, *** indicate 10%, 5%, and 1% significance respectively

Table 7: Inspection Decision under DCE

	Specification									
	A		**B**		**C**		**D**		**E**	
Probability of violation					12.5781	***			12.4828	***
					(0.3531)				(0.3463)	
Probability of self report					-16.3901	***			-16.2070	***
					(0.4243)				(0.4158)	
Penalty (Self) 1-4 quarters ago	0.0039	*	0.0039	*	0.0066	***	0.0041	*	0.0066	***
	(0.0022)		(0.0022)		(0.0024)		(0.0022)		(0.0024)	
Penalty (Self) 5-8 quarters ago	-0.0027		-0.0027		-0.0053	**	-0.0008		-0.0037	
	(0.0022)		(0.0022)		(0.0023)		(0.0022)		(0.0024)	
Number of IEA 1-4 quarters ago	0.0081	***	0.0081	***	0.0039		0.0031		-0.0004	
	(0.0023)		(0.0023)		(0.0025)		(0.0023)		(0.0025)	
Number of IEA 5-8 quarters ago	0.0105	***	0.0105	***	0.0134	***	0.0053	**	0.0099	***
	(0.0023)		(0.0023)		(0.0025)		(0.0023)		(0.0025)	
Inspected 1-4 quarters ago	0.1421	***	0.1421	***	0.1021	***	0.1268	***	0.0932	***
	(0.0077)		(0.0077)		(0.0077)		(0.0077)		(0.0078)	
Inspected 5-8 quarters ago	0.3908	***	0.3908	***	0.2968	***	0.3936	***	0.3033	***
	(0.0080)		(0.0080)		(0.0083)		(0.0081)		(0.0083)	
Number of effluent violation 1-4 quarters ago	0.0012		0.0012		-0.2783	***	-0.0015		-0.2858	***
	(0.0049)		(0.0049)		(0.0200)		(0.0049)		(0.0196)	
Number of effluent violation 5-8quarters ago	-0.0021		-0.0021		-0.0009		-0.0034		-0.0086	
	(0.0050)		(0.0050)		(0.0058)		(0.0051)		(0.0059)	
Number of reporting violation 1-4 quarters ago	-0.0610	***	-0.0610	***	-0.0563	***	-0.0670	***	-0.0605	***
	(0.0069)		(0.0069)		(0.0069)		(0.0069)		(0.0070)	
Number of reporting violation 5-8 quarters ago	-0.0445	***	-0.0445	***	-0.0327	***	-0.0471	***	-0.0386	***
	(0.0071)		(0.0071)		(0.0071)		(0.0072)		(0.0072)	
Budget per Facility	-0.0646	***	-0.0646	***	-0.0323	***	-0.0697	***	-0.0403	***
	(0.0054)		(0.0054)		(0.0055)		(0.0055)		(0.0056)	
Number of facility in the same 2-digit SIC	0.0001	***	0.0001	***	0.0001	**	0.0001	***	0.0000	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)	

	Specification									
	A		**B**		**C**		**D**		**E**	
Percent urban	0.1093	***	0.1093	***	0.0793	***	0.1243	***	0.0907	***
	(0.0161)		(0.0161)		(0.0161)		(0.0161)		(0.0162)	
Percent white	0.2101	***	0.2101	***	0.0321		0.1834	***	0.0392	
	(0.0255)		(0.0255)		(0.0262)		(0.0260)		(0.0266)	
Unemployment rate	-0.0109	***	-0.0109	***	-0.0054	***	0.0011		0.0037	**
	(0.0017)		(0.0017)		(0.0017)		(0.0018)		(0.0018)	
Percent of owner occupant	0.3367	***	0.3367	***	0.4113	***	0.5207	***	0.4921	***
	(0.0468)		(0.0468)		(0.0468)		(0.0487)		(0.0487)	
Percent of bachelor + graduate degree	0.0170		0.0170		0.2411	***	0.4137	***	0.4659	***
	(0.0689)		(0.0689)		(0.0700)		(0.0726)		(0.0733)	
Primary industry	-0.2056	***	-0.2056	***	-0.1580	***	-0.2166	***	-0.1668	***
	(0.0080)		(0.0080)		(0.0082)		(0.0080)		(0.0083)	
Not primary industry	-0.1604	***	-0.1604	***	-0.1103	***	-0.1655	***	-0.1152	***
	(0.0141)		(0.0141)		(0.0142)		(0.0142)		(0.0143)	
Not on ELG	-0.2177	***	-0.2177	***	-0.1915	***	-0.2194	***	-0.1941	***
	(0.0162)		(0.0162)		(0.0163)		(0.0163)		(0.0164)	
Facility with no classification	-0.2503		-0.2503		-0.5506	***	-0.2492		-0.5522	***
	(0.1529)		(0.1529)		(0.1547)		(0.1523)		(0.1554)	
Average penalty	0.0200	***	0.0200	***	-0.0026		0.0199	***	-0.0022	
	(0.0018)		(0.0018)		(0.0020)		(0.0018)		(0.0020)	
Average IEA	0.0661	***	0.0661	***	0.0234		0.1097	***	0.0592	***
	(0.0152)		(0.0152)		(0.0167)		(0.0155)		(0.0170)	
Constant	-0.8313	***	-0.8313	***	-0.9353	***	-1.0467	***	-1.1199	***
	(0.0584)		(0.0584)		(0.0589)		(0.0614)		(0.0620)	

Seasonal dummies and time effects are omitted for brevity
*, **, *** indicate 10%, 5%, and 1% significance respectively

Table 8: Self Report Decision under DCE

	Specification									
	A		B		C		D		E	
Probability of inspection					-0.1413	**			-0.1488	***
					(0.0560)				(0.0555)	
Number of reporting violation 1-4 quarters ago	0.0237	*	0.0177		0.0157		0.0097		0.0074	
	(0.0123)		(0.0124)		(0.0124)		(0.0124)		(0.0124)	
Number of reporting violation 5-8 quarters ago	0.0155		0.0091		0.0072		0.0213	*	0.0194	
	(0.0123)		(0.0124)		(0.0125)		(0.0125)		(0.0125)	
Inspected and violation detected 1-4 quarters ago	1.2321	***	1.2076	***	1.2125	***	1.2063	***	1.2110	***
	(0.0172)		(0.0173)		(0.0174)		(0.0174)		(0.0175)	
Inspected and violation detected 5-8 quarters ago	0.5487	***	0.5216	***	0.5287	***	0.5421	***	0.5496	***
	(0.0204)		(0.0207)		(0.0209)		(0.0208)		(0.0211)	
Penalty (Self) 1-4 quarters ago	0.0086	**	0.0126	***	0.0131	***	0.0143	***	0.0148	***
	(0.0038)		(0.0039)		(0.0039)		(0.0039)		(0.0039)	
Penalty (Self) 5-8 quarters ago	-0.0069	*	-0.0015		-0.0012		0.0006		0.0010	
	(0.0041)		(0.0042)		(0.0043)		(0.0042)		(0.0043)	
Penalty (Reputation) 1-4 quarters ago			-0.0053	**	-0.0050	**	-0.0074	***	-0.0071	***
			(0.0025)		(0.0025)		(0.0026)		(0.0026)	
Penalty (Reputation) 5-8 quarters ago			-0.0145	***	-0.0139	***	-0.0142	***	-0.0137	***
			(0.0026)		(0.0026)		(0.0026)		(0.0026)	
Number of IEA 1-4 quarters ago	0.0605	***	0.0868	***	0.0869	***	0.0846	***	0.0846	***
	(0.0037)		(0.0044)		(0.0044)		(0.0044)		(0.0044)	
Number of IEA 5-8 quarters ago	-0.0121	***	0.0112	**	0.0112	**	0.0094	**	0.0092	**
	(0.0040)		(0.0045)		(0.0045)		(0.0045)		(0.0045)	
IEA (Reputation) 1-4 quarters ago			-0.0270	***	-0.0269	***	-0.0250	***	-0.0248	***
			(0.0069)		(0.0069)		(0.0069)		(0.0069)	
IEA (Reputation) 5-8 quarters ago			-0.0306	***	-0.0299	***	-0.0297	***	-0.0289	***
			(0.0064)		(0.0064)		(0.0064)		(0.0064)	
Number of facility in the same 2-digit SIC	-0.0004	***	-0.0004	***	-0.0004	***	-0.0003	***	-0.0004	***
	(0.0001)		(0.0001)		(0.0001)		(0.0001)		(0.0001)	

	Specification									
	A		B		C		D		E	
Primary industry	-0.2588	***	-0.2349	***	-0.2454	***	-0.2351	***	-0.2461	***
	(0.0157)		(0.0158)		(0.0164)		(0.0158)		(0.0164)	
Not primary industry	-0.1339	***	-0.1208	***	-0.1305	***	-0.1170	***	-0.1271	***
	(0.0267)		(0.0269)		(0.0272)		(0.0270)		(0.0273)	
Not on ELG	-0.1207	***	-0.1170	***	-0.1268	***	-0.1106	***	-0.1205	***
	(0.0289)		(0.0292)		(0.0296)		(0.0293)		(0.0296)	
Facility with no classification	-0.7975	*	-0.8966	*	-0.9085	**	-0.9147	**	-0.9278	**
	(0.4614)		(0.4604)		(0.4612)		(0.4565)		(0.4575)	
Constant	-1.7767	***	-1.6494	***	-1.6104	***	-1.5283	***	-1.4865	***
	(0.0166)		(0.0184)		(0.0241)		(0.0368)		(0.0400)	

Seasonal dummies and time effects are omitted for brevity
*, **, *** indicate 10%, 5%, and 1% significance respectively

Table 9: Change of Predicted Probability of Violation under Probit

	Specification									
	A		B		C		D		E	
Probability of inspection (1)					-0.08%				-0.02%	
Penalty (Self) 1-4 quarters ago (2)	-1.26%	***	-1.14%	***	-1.14%	***	-1.00%	***	-1.00%	***
Penalty (Self) 5-8 quarters ago (2)	-0.91%	***	-0.78%	***	-0.79%	***	-0.64%	***	-0.64%	***
Penalty (Reputation) 1-4 quarters ago (3)			0.00%		0.00%		0.00%		0.00%	
Penalty (Reputation) 5-8 quarters ago (3)			-0.01%	***	-0.01%	***	-0.01%	***	-0.01%	***
IEA (Self) 1-4 quarters ago (4)	0.09%	***	0.14%	***	0.14%	***	0.12%	***	0.12%	***
IEA (Self) 5-8 quarters ago (4)	-0.21%	***	-0.12%	***	-0.12%	***	-0.13%	***	-0.14%	***
IEA (Reputation) 1-4 quarters ago (4)			0.00%	**	0.00%	**	0.00%		0.00%	
IEA (Reputation) 5-8 quarters ago (4)			0.00%	***	0.00%	***	0.00%	***	0.00%	***
Inspected and no violation detected 1-4 quarters ago (5)	0.51%	***	0.54%	***	0.54%	***	0.51%	***	0.51%	***
Inspected and no violation detected 5-8 quarters ago (5)	0.11%		0.16%		0.18%	*	0.11%		0.12%	
Number of effluent violation 1-4 quarters ago (1)	5.36%	***	4.97%	***	4.98%	***	5.84%	***	4.88%	***
Number of effluent violation 5-8quarters ago (1)	0.42%	***	0.35%	***	0.35%	***	0.54%	***	0.41%	***
Percent urban (1)	-0.03%		-0.03%		-0.03%		-0.01%		-0.01%	
Percent white (1)	0.65%	***	0.38%	***	0.39%	***	0.28%	***	0.29%	***
Unemployment rate (1)	-0.08%	*	-0.14%	***	-0.15%	***	-0.05%		-0.05%	
Percent of owner occupant (1)	-0.25%	***	-0.11%	**	-0.10%	*	0.04%		0.05%	
Percent of bachelor + graduate degree (1)	-0.36%	***	-0.38%	***	-0.38%	***	-0.22%	***	-0.22%	***
Primary industry (5)	-1.37%	***	-1.18%	***	-1.20%	***	-1.18%	***	-1.19%	***
Not primary industry (5)	-0.71%	***	-0.61%	***	-0.63%	***	-0.57%	***	-0.58%	***
Not on ELG (5)	-0.14%		-0.13%		-0.17%		-0.11%		-0.14%	

*, **, *** indicate 10%, 5%, and 1% significance respectively

(1) The change of predicted probability is based on one standard deviation increase
(2) The change of predicted probability is based on changing penalty from $0 to $19,799 (mean of non-zero penalty 1-4 quarters)
(3) The change of predicted probability is based increased of reputation penalty by $139
(4) The change of predicted probability is based on one additional IEA
(5) The change of predicted probability is based on a change of dummy variable from zero to one

Table 10: Change of Predicted Probability of Violation under DCE

	Specification				
	A	B	C	D	E
Probability of inspection (1)			-4.50% ***		-4.36% ***
Penalty (Self) 1-4 quarters ago (2)	-3.54% ***	-3.11% ***	-3.02% ***	-2.86% ***	-2.75% ***
Penalty (Self) 5-8 quarters ago (2)	-1.93% **	-1.49% *	-1.86% **	-1.40% *	-1.56% *
Penalty (Reputation) 1-4 quarters ago (3)		-0.01% **	-0.01%	-0.01% *	-0.01%
Penalty (Reputation) 5-8 quarters ago (3)		-0.04% ***	-0.02% ***	-0.04% ***	-0.03% ***
IEA (Self) 1-4 quarters ago (4)	0.23% ***	0.41% ***	0.53% ***	0.40% ***	0.46% ***
IEA (Self) 5-8 quarters ago (4)	-0.63% ***	-0.26% ***	-0.18% *	-0.28% ***	-0.26% **
IEA (Reputation) 1-4 quarters ago (4)		0.00% **	0.00% ***	0.00%	0.00% *
IEA (Reputation) 5-8 quarters ago (4)		0.00% ***	0.00% ***	-0.01% ***	0.00% ***
Inspected and no violation detected 1-4 quarters ago (5)	1.63% ***	1.75% ***	1.77% ***	1.86% ***	1.74% ***
Inspected and no violation detected 5-8 quarters ago (5)	-2.62% ***	-2.23% ***	-0.31%	-2.43% ***	-0.56%
Number of effluent violation 1-4 quarters ago (1)	15.76% ***	14.54% ***	15.12% ***	14.82% ***	15.26% ***
Number of effluent violation 5-8quarters ago (1)	1.19% ***	0.88% ***	1.27% ***	1.17% ***	1.54% ***
Percent urban (1)	0.11%	0.10%	0.03%	0.14%	0.09%
Percent white (1)	1.76% ***	0.84% ***	1.18% ***	0.69% ***	0.95% ***
Unemployment rate (1)	0.13%	-0.13%	-0.28% *	-0.11%	-0.02%
Percent of owner occupant (1)	-0.78% ***	-0.23%	-0.28%	0.00%	0.12%
Percent of bachelor + graduate degree (1)	-1.01% ***	-1.12% ***	-1.09% ***	-0.95% ***	-0.70% ***
Primary industry (5)	-3.04% ***	-2.40% ***	-3.40% ***	-2.47% ***	-3.47% ***
Not primary industry (5)	-0.92%	-0.64%	-1.52% ***	-0.65%	-1.49% **
Not on ELG (5)	0.90%	0.91%	-0.16%	0.97%	-0.04%

*, **, *** indicate 10%, 5%, and 1% significance respectively

(1). The change of predicted probability is based on one standard deviation increase

(2). The change of predicted probability is based on changing penalty from $0 to $19,799 (mean of non-zero penalty 1-4 quarters)

(3). The change of predicted probability is based increased of reputation penalty by $139

(4). The change of predicted probability is based on one additional IEA

(5). The change of predicted probability is based on a change of dummy variable from zero to one

Table 11: Effluent Violation Decision under DCE (Non-municipal Facilities)

	Specification									
	A		B		C		D		E	
Probability of inspection					-1.4535	***			-1.3592	***
					(0.2333)				(0.2333)	
Penalty (Self) 1-4 quarters ago	-0.0191	**	-0.0177	**	-0.0159	*	-0.0159	*	-0.0143	*
	(0.0085)		(0.0085)		(0.0086)		(0.0086)		(0.0086)	
Penalty (Self) 5-8 quarters ago	-0.0118		-0.0079		-0.0076		-0.0066		-0.0063	
	(0.0085)		(0.0086)		(0.0086)		(0.0086)		(0.0086)	
Penalty (Reputation) 1-4 quarters ago			-0.0072		-0.0046		-0.0083		-0.0064	
			(0.0056)		(0.0056)		(0.0058)		(0.0058)	
Penalty (Reputation) 5-8 quarters ago			-0.0171	***	-0.0119	**	-0.0167	***	-0.0122	**
			(0.0057)		(0.0057)		(0.0059)		(0.0059)	
IEA (Self) 1-4 quarters ago	0.0180	**	0.0276	***	0.0308	***	0.0280	***	0.0282	***
	(0.0081)		(0.0093)		(0.0093)		(0.0094)		(0.0094)	
IEA (Self) 5-8 quarters ago	-0.0136		0.0058		0.0051		0.0067		0.0034	
	(0.0093)		(0.0103)		(0.0104)		(0.0104)		(0.0105)	
IEA (Reputation) 1-4 quarters ago			-0.0182	*	-0.0167	*	-0.0135		-0.0117	
			(0.0093)		(0.0094)		(0.0097)		(0.0098)	
IEA (Reputation) 5-8 quarters ago			-0.0383	***	-0.0363	***	-0.0412	***	-0.0388	***
			(0.0091)		(0.0092)		(0.0099)		(0.0100)	
Inspected and no violation detected 1-4 quarters ago	0.1231	***	0.1386	***	0.0906	***	0.1414	***	0.0896	***
	(0.0316)		(0.0315)		(0.0308)		(0.0316)		(0.0314)	
Inspected and no violation detected 5-8 quarters ago	-0.0908	***	-0.0738	**	-0.0275		-0.0771	**	-0.0359	
	(0.0320)		(0.0319)		(0.0320)		(0.0322)		(0.0320)	
Number of effluent violation 1-4 quarters ago	0.7503	***	0.7355	***	0.7426	***	0.7346	***	0.7387	***
	(0.0183)		(0.0184)		(0.0185)		(0.0185)		(0.0186)	
Number of effluent violation 5-8quarters ago	0.0722	***	0.0587	***	0.0751	***	0.0730	***	0.0882	***
	(0.0208)		(0.0208)		(0.0212)		(0.0211)		(0.0214)	
Percent urban	0.1859	***	0.1977	***	0.1496	**	0.2103	***	0.1713	**
	(0.0657)		(0.0667)		(0.0674)		(0.0673)		(0.0678)	
Percent white	1.0194	***	0.7106	***	0.7393	***	0.6821	***	0.6924	***

	Specification									
	A		B		C		D		E	
	(0.1077)		(0.1103)		(0.1099)		(0.1120)		(0.1111)	
Unemployment rate	0.0207	***	0.0147	**	0.0068		0.0159	**	0.0130	*
	(0.0066)		(0.0067)		(0.0068)		(0.0070)		(0.0070)	
Percent of owner occupant	-0.4376	**	-0.0733		-0.1854		0.0712		0.0528	
	(0.1878)		(0.1963)		(0.1991)		(0.2063)		(0.2081)	
Percent of bachelor + graduate degree	-0.4105		-0.7275	**	-0.8428	**	-0.5029		-0.4276	
	(0.3260)		(0.3376)		(0.3377)		(0.3551)		(0.3559)	
Primary industry	-0.2847		-0.1837		-0.1704		-0.2624		-0.2464	
	(0.3618)		(0.3620)		(0.3672)		(0.3596)		(0.3650)	
Not primary industry	-0.1654		-0.0737		-0.0620		-0.1523		-0.1354	
	(0.3625)		(0.3628)		(0.3679)		(0.3603)		(0.3657)	
Not on ELG	-0.0940		-0.0113		-0.0040		-0.0868		-0.0730	
	(0.3632)		(0.3635)		(0.3686)		(0.3610)		(0.3664)	
Average penalty	0.0440	***	0.0474	***	0.0467	***	0.0463	***	0.0458	***
	(0.0065)		(0.0067)		(0.0066)		(0.0067)		(0.0066)	
Average IEA	0.1966	***	0.4013	***	0.4119	***	0.3833	***	0.4099	***
	(0.0585)		(0.0625)		(0.0624)		(0.0645)		(0.0647)	
Average inspection	-0.5979	***	-0.5931	***	0.0167		-0.5988	***	-0.0167	
	(0.0797)		(0.0764)		(0.0940)		(0.0764)		(0.0984)	
Constant	-1.8306	***	-1.7226	***	-1.4523	***	-1.6452	***	-1.4996	***
	(0.4017)		(0.4019)		(0.4095)		(0.4058)		(0.4118)	

Seasonal dummies and time effects are omitted for brevity
*, **, *** indicate 10%, 5%, and 1% significance respectively

Table 12: Effluent Violation Decision under DCE (SIC 49)

	Specification									
	A		B		C		D		E	
Probability of inspection					-1.5580	***			-1.4690	***
					(0.0947)				(0.0933)	
Penalty (Self) 1-4 quarters ago	-0.0213	***	-0.0204	***	-0.0198	***	-0.0183	***	-0.0177	***
	(0.0049)		(0.0049)		(0.0050)		(0.0050)		(0.0050)	
Penalty (Self) 5-8 quarters ago	-0.0116	**	-0.0107	**	-0.0138	***	-0.0100	*	-0.0115	**
	(0.0051)		(0.0052)		(0.0052)		(0.0053)		(0.0053)	
Penalty (Reputation) 1-4 quarters ago			-0.0050		-0.0026		-0.0041		-0.0024	
			(0.0033)		(0.0033)		(0.0034)		(0.0034)	
Penalty (Reputation) 5-8 quarters ago			-0.0174	***	-0.0107	***	-0.0169	***	-0.0115	***
			(0.0034)		(0.0034)		(0.0035)		(0.0035)	
IEA (Self) 1-4 quarters ago	0.0089	*	0.0199	***	0.0254	***	0.0187	***	0.0213	***
	(0.0046)		(0.0054)		(0.0055)		(0.0056)		(0.0056)	
IEA (Self) 5-8 quarters ago	-0.0366	***	-0.0186	***	-0.0129	**	-0.0198	***	-0.0171	***
	(0.0050)		(0.0056)		(0.0057)		(0.0058)		(0.0058)	
IEA (Reputation) 1-4 quarters ago			-0.0117	*	-0.0174	***	-0.0066		-0.0114	*
			(0.0063)		(0.0063)		(0.0065)		(0.0065)	
IEA (Reputation) 5-8 quarters ago			-0.0473	***	-0.0347	***	-0.0511	***	-0.0393	***
			(0.0062)		(0.0063)		(0.0065)		(0.0066)	
Inspected and no violation detected 1-4 quarters ago	0.0796	***	0.0910	***	0.1015	***	0.0949	***	0.0974	***
	(0.0205)		(0.0203)		(0.0194)		(0.0204)		(0.0195)	
Inspected and no violation detected 5-8 quarters ago	-0.1356	***	-0.1271	***	-0.0140		-0.1348	***	-0.0264	
	(0.0212)		(0.0211)		(0.0215)		(0.0212)		(0.0216)	
Number of effluent violation 1-4 quarters ago	0.6876	***	0.6743	***	0.6803	***	0.6742	***	0.6775	***
	(0.0097)		(0.0097)		(0.0097)		(0.0098)		(0.0097)	
Number of effluent violation 5-8quarters ago	0.0643	***	0.0513	***	0.0716	***	0.0668	***	0.0848	***
	(0.0107)		(0.0107)		(0.0107)		(0.0109)		(0.0108)	
Percent urban	-0.0504		-0.0552		-0.0557		-0.0503		-0.0480	
	(0.0397)		(0.0398)		(0.0400)		(0.0400)		(0.0402)	
Percent white	0.3649	***	0.1271	*	0.2399	***	0.0621		0.1528	**

	Specification									
	A		B		C		D		E	
	(0.0653)		(0.0675)		(0.0668)		(0.0685)		(0.0679)	
Unemployment rate	0.0015		-0.0050		-0.0062		-0.0049		-0.0003	
	(0.0040)		(0.0040)		(0.0040)		(0.0043)		(0.0043)	
Percent of owner occupant	-0.3914	***	-0.0904		-0.1119		0.0668		0.1336	
	(0.1074)		(0.1112)		(0.1137)		(0.1162)		(0.1191)	
Percent of bachelor + graduate degree	-0.9400	***	-1.0938	***	-0.9887	***	-0.8988	***	-0.6133	***
	(0.1705)		(0.1744)		(0.1751)		(0.1829)		(0.1843)	
Primary industry	-0.3110	***	-0.2806	***	-0.3328	***	-0.2786	***	-0.3303	***
	(0.0301)		(0.0302)		(0.0306)		(0.0305)		(0.0309)	
Not on ELG	0.1727	***	0.1776	***	0.1122	**	0.1669	***	0.1042	**
	(0.0516)		(0.0517)		(0.0517)		(0.0518)		(0.0518)	
Average penalty	0.0380	***	0.0440	***	0.0514	***	0.0418	***	0.0492	***
	(0.0040)		(0.0040)		(0.0041)		(0.0040)		(0.0041)	
Average IEA	0.2036	***	0.3711	***	0.3199	***	0.3705	***	0.3444	***
	(0.0301)		(0.0331)		(0.0332)		(0.0339)		(0.0340)	
Average inspection	-0.3831	***	-0.3714	***	0.0745	***	-0.3681	***	0.0581	**
	(0.0317)		(0.0304)		(0.0282)		(0.0303)		(0.0288)	
Constant	-1.1266	***	-0.9600	***	-0.8676	***	-0.8142	***	-1.4629	***
	(0.0997)		(0.1021)		(0.1031)		(0.1117)		(0.0453)	

Seasonal dummies and time effects are omitted for brevity
*, **, *** indicate 10%, 5%, and 1% significance respectively

Table 13: Descriptive Statistics of Undetected Violation Estimates

	Effluent Violation		
	Observation	**Mean**	**Std Deviation**
Specification C			
All facilities	131,140	13.74%	12.59%
Municipal facilities	78,815	15.06%	13.63%
Primary industries on ELG	37,835	10.70%	9.55%
SIC 49	93,906	14.35%	13.10%
Specification E			
All facilities	131,140	15.04%	14.86%
Municipal facilities	78,815	16.50%	15.98%
Primary industries on ELG	37,835	11.79%	11.79%
SIC 49	93,906	15.74%	15.44%

CHAPTER IV
ESSAY TWO: TARGETING ENFORCEMENT UNDER IMPERFECT DETECTION

Introduction

In the regulatory enforcement literature, Harrington's (1988) work has been frequently cited in empirical and theoretical studies to explain firms' compliance decisions in a regime where the probability of inspection is low and penalties are restricted. While experimental studies confirm Harrington's predictions, many nonexperimental (econometric) studies only partially support Harrington's predictions. Through an extension of the Harrington model, we identify a possible explanation for the discrepancy between Harrington's theoretical predictions and the nonexperimental empirical evidence.

Harrington (1988) proposed a dynamic repeated game model to reconcile the low expected penalties for noncompliance with pollution regulation laws and the high observed compliance rates among regulated firms. In his model, the regulator alters the expected penalty and the inspection probability based on the firm's past performance. The regulator places the firm in one of two groups, the target group or the non-target group, based on the firm's past performance.

We extend the Harrington model in two ways. First, given that a violation happens, the probability of detecting a violation during an inspection can be less than one. In other words, undetected violations are possible. Harrington's model assumes that whenever a violator is inspected, the regulator detects the violation with probability equal to one. Second, similar to Friesen (2003), movement between groups can arise from three outcomes: (1) no inspection, (2) inspection that detects no violation,[29] and (3) inspection that discovers a violation.

We find that imperfect detection changes the threshold points where firms change their strategy. Assuming that the firms are uniformly distributed, imperfect detection in the non target group reduces the number of firms that always comply, increases the number of firms that adopt an alternating strategy (i.e., comply in non target group, but violate when in the target group), and surprisingly, reduces the number of firms that always violate. On the other hand, imperfect detection in the target group increases the number of firm that always violate. The increase in the number of firm that always violate (due to imperfect detection in the target group) is greater than the decrease caused by imperfect detection in the non target group. Thus, given the same detection rate in both groups, the number of firms that always violate will increase. Furthermore, these results have implications for the way in which Harrington's model is tested empirically and suggests an explanation for the discrepancy in results among experimental and nonexperimental tests of the Harrington model.

The model

The model consists of two separate decisions made by two agents. The regulator makes an inspection decision, while the firm makes a compliance decision. On the regulator side, limited enforcement resources cause the regulator to adopt targeting strategy. The regulator classifies firms into two groups: the non target group (G_1) and

[29] Friesen (2003) assumes complete detection (implicitly). This assumption implies that whenever no violation was found during an inspection, the facility was truly in compliance. Assuming imperfect detection implies that no violation may be uncovered even if the firm were to be out of compliance.

the target group (G_2). The target group faces more stringent enforcement than the non target group. The probability of any firm in G_1 and G_2 being inspected are p_1 and p_2 respectively. Firms in G_2 has a greater probability of being inspected $(p_2 > p_1)$. If the regulator detects a violation during an inspection, a penalty of F_1 will be given if the violator is in G_1, and by the amount of F_2 if the violator is in G_2. By construction, penalty in the target group is larger than the non target group $(F_2 > F_1)$.

On the firm side, we assume that the firm has already installed the capital equipment to meet the environmental regulation (in other words, firm is already in "initial compliance").[30] However, to keep the firm in "continuing compliance", it must spend a cost of \$*c* per period. This cost can be avoided if the firm decides to violate, but at the expense of an increase in the expected cost of non compliance. The objective of a firm is to find a policy – i.e., a compliance choice in each group – that minimizes its expected cost.

There are two innovations that we add to the Harrington model. First, we introduce two additional parameters—d_1 and d_2 --which reflect the probability of detecting a violation in G_1 and G_2 conditional that a violation exists *and* inspection is performed. This is to accommodate the possibilities that not every violation is detected even if inspection is performed.[31] Second, we relax Harrington's assumption on the movement between groups. Movement between groups is possible even without the

[30] "Initial compliance" is the term used by Livernois and McKenna (1999), and later adapted by Friesen (2003) to refer that firm has already installed the pollution abatement device.

[31] To avoid the compliant firm being fined, we exclude the possibility of wrongful conviction

presence of inspection or detection of violation.[32] The regulator can condition the transition probabilities between groups. The transition parameters are given in Table 14. The advantage of using this framework is that it allows us to make different assumptions about the movement between groups, yet it remains general enough to cover Harrington's original framework (by setting $a_1 = 0,\ b_1 = 0,\ u_1 = 1,\ a_2 = 0,\ u_2 = 0$).

Table 14: Transition parameters

Initial Group	Observation	Probability of being moved to	
		G_1	G_2
G_1	No inspection	$1-a_1$	a_1
	No violation was detected	$1-b_1$	b_1
	Violation was detected	$1-u_1$	u_1
G_2	No inspection	a_2	$1-a_2$
	No violation was detected	b_2	$1-b_2$
	Violation was detected	u_2	$1-u_2$

Our extension to Harrington model changes the probabilities of movement between groups. The transition probabilities are depicted in Table 15. Let t_{ij}^V denotes the transition probability of movement from group *i* to group *j* when firm decides to violate, and t_{ij}^C denotes the transition probability of movement from group *i* to group *j* when firm decides to comply. Having defined t_{ij}^V and t_{ij}^C, Table 15 is simplified into Table 16, which will be useful to summarize the calculation of expected cost.

[32] Friesen (2003) shows that random movement to the target group leads to a reduced inspection cost

Table 15: Transition Probabilities

	Comply		Violate			
			Undetected		Detected	
Initial group	G_1	G_2	G_1	G_2	G_1	G_2
G_1	$(1-p_1)(1-a_1)$ $+ p_1(1-b_1)$	$(1-p_1)a_1$ $+ p_1 b_1$	$(1-p_1)(1-a_1)+$ $p_1(1-d_1)(1-b_1)$	$(1-p_1)a_1 +$ $p_1(1-d_1)b_1$	$p_1 d_1(1-u_1)$	$p_1 d_1 u_1$
G_2	$(1-p_2)a_2$ $+ p_2 b_2$	$(1-p_2)(1-a_2)$ $+ p_2(1-b_2)$	$(1-p_2)a_2 + p_2(1-d_2)b_2$	$(1-p_2)(1-a_2)+$ $p_2(1-d_2)(1-b_2)$	$p_2 d_2 u_2$	$p_2 d_2(1-u_2)$

Table 16: Simplified Transition Probabilities

	Comply		Violate	
Initial group	G_1	G_2	G_1	G_2
G_1	$t_{11}^C = (1-p_1)(1-a_1)$ $+ p_1(1-b_1)$	$t_{12}^C = (1-p_1)a_1 + p_1 b_1$	$t_{11}^V = (1-p_1)(1-a_1)+$ $p_1(1-d_1)(1-b_1)+ p_1 d_1(1-u_1)$	$t_{12}^V = (1-p_1)a_1 +$ $p_1(1-d_1)b_1 + p_1 d_1 u_1$
G_2	$t_{21}^C = (1-p_2)a_2 + p_2 b_2$	$t_{22}^C = (1-p_2)(1-a_2)$ $+ p_2(1-b_2)$	$t_{21}^V = (1-p_2)a_2 +$ $p_2(1-d_2)b_2 + p_2 d_2 u_2$	$t_{22}^V = (1-p_2)(1-a_2)+$ $p_2(1-d_2)(1-b_2)+ p_2 d_2(1-u_2)$

To calculate the expected cost of each strategy, we also need the payoff matrix for each decision. A firm's payoff matrix for every alternative decision is presented in Table 17. When a firm decides to comply, the compliance cost would be c regardless the presence of inspection. Monetary penalty of F_1 (or F_2) is only imposed if a violation was detected.

Table 17: Payoff Matrix

		G_1		G_2	
		Comply	Violate	Comply	Violate
No Inspection		C	0	C	0
Inspection	No Detection	C	0	C	0
	Detection		F_1		F_2

Having the information on the transition probabilities and payoff matrix, we can now calculate the expected cost of each decision in each group. The expected cost of decision *i* is simply the weighted average of the present value of expected costs in G_1 and G_2. Let E_1 and E_2 denote the expected cost in G_1 and G_2 respectively, and β denotes the discount factor. The expected costs of each decision in each group are described in equation (1) to (4).

Expected Cost of Complying:

When initially at group 1: $E_1 = c + \beta\left(t_{11}^{C} E_1 + t_{12}^{C} E_2\right)$ (1)

When initially in group 2: $E_2 = c + \beta\left(t_{21}^{C} E_2 + t_{22}^{C} E_2\right)$ (2)

Expected Cost of Violating:

When initially in group 1: $E_1 = p_1 d_1 F_1 + \beta\left(t_{11}^{V} E_1 + t_{12}^{V} E_2\right)$ (3)

When initially in group 2: $E_2 = p_2 d_2 F_2 + \beta\left(t_{21}^{V} E_1 + t_{22}^{V} E_2\right)$ (4)

Take equation (3) for instance. The expected cost of violating when a firm is initially in G_2 is equal to the expected fine $(p_1 d_1 F_1)$ plus the present value of the expected cost of being moved to G_1 $(\beta t_{21}^V E_1)$ and the present value of the expected cost of staying in G_2, $(\beta t_{22}^V E_2)$.

Equations (1) to (4) are put in Table 18 to generate simultaneous equations for a particular strategy. Let f^{ij} denotes the strategy that a firm choose decision *i* if in G_1 and choose decision *j* if in G_2. Strategy f^{00} reflects that a firm decides to comply in G_1 and G_2, while strategy f^{10} reflects that a firm decides to violate in G_1, but comply whenever in G_2. As in Harrington (1988), the expected cost of strategy f^{ij} is found by solving the simultaneous equations of decision i in the first column and decision j in the second column. For instance, the expected cost of strategy f^{00} is the solution for simultaneous equations (1) and (2).

Table 18: Matrix of expected cost

	G_1	G_2
Comply (0)	$E_1 = c + \beta\left(t_{11}^C E_1 + t_{12}^C E_2\right)$	$E_2 = c + \beta\left(t_{21}^C E_1 + t_{22}^C E_2\right)$
Violate (1)	$E_1 = p_1 d_1 F_1 + \beta\left(t_{11}^V E_1 + t_{12}^V E_2\right)$	$E_2 = p_2 d_2 F_2 + \beta\left(t_{21}^V E_1 + t_{22}^V E_2\right)$

Solving for E_1 and E_2 from four possible simultaneous equations provide us with the expected cost of every strategy as presented in Table 19. The value in column E_1^{ij} reflects the expected cost of each strategy when a firm is initially in group 1. If a firm is initially in group 2, the expected costs are as described in column E_2^{ij}.

Table 19: Expected Costs of Alternative Strategies

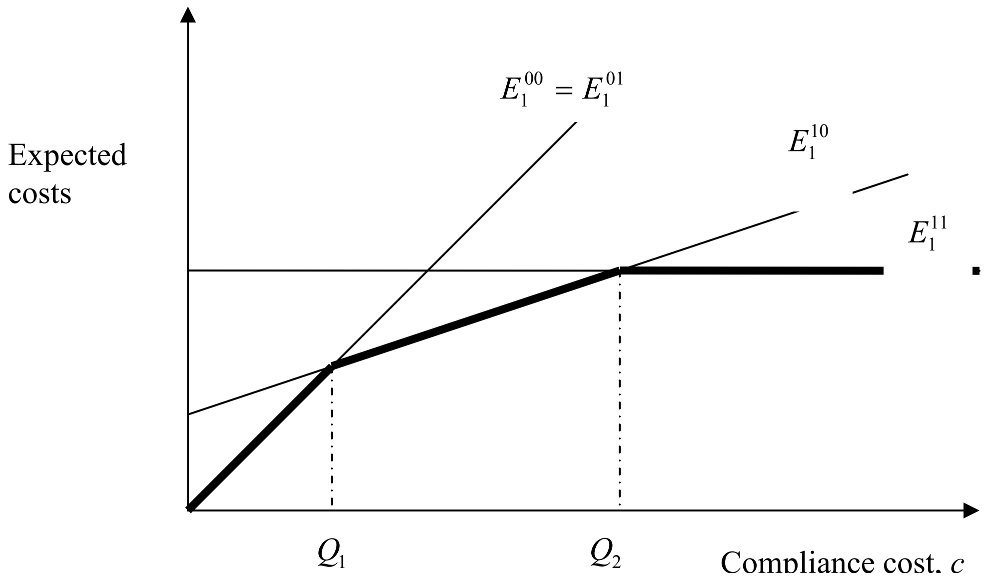
	E_1^{ij}	E_2^{ij}
f^{00}	$\dfrac{c}{(1-\beta)}$	$\dfrac{c}{(1-\beta)}$
f^{01}	$\dfrac{\left(c+\beta\left(p_2 d_2 F_2 t_{12}^C - c t_{22}^V\right)\right)}{\left(1-\beta\left(t_{22}^V + \beta t_{12}^C t_{21}^V + t_{11}^C\left(1-\beta t_{22}^V\right)\right)\right)}$	$\dfrac{\left(p_2 d_2 F_2 + \beta\left(c t_{21}^V - p_2 d_2 F_2 t_{11}^C\right)\right)}{\left(1-\beta\left(t_{22}^V + \beta t_{12}^C t_{21}^V + t_{11}^C\left(1-\beta t_{22}^V\right)\right)\right)}$
f^{10}	$\dfrac{\left(p_1 d_1 F_1 + \beta\left(c t_{12}^V - p_1 d_1 F_1 t_{22}^C\right)\right)}{\left(1-\beta\left(t_{11}^V + \beta t_{21}^C t_{12}^V + t_{22}^C\left(1-\beta t_{11}^V\right)\right)\right)}$	$\dfrac{\left(c+\beta\left(p_1 d_1 F_1 t_{21}^C - c t_{11}^V\right)\right)}{\left(1-\beta\left(t_{11}^V + \beta t_{21}^C t_{12}^V + t_{22}^C\left(1-\beta t_{11}^V\right)\right)\right)}$
f^{11}	$\dfrac{\left(p_1 d_1 F_1 + \beta\left(p_2 d_2 F_2 t_{12}^V - p_1 d_1 F_1 t_{22}^V\right)\right)}{\left(1-\beta\left(t_{22}^V + \beta t_{12}^V t_{21}^V + t_{11}^V\left(1-\beta t_{22}^V\right)\right)\right)}$	$\dfrac{\left(p_2 d_2 F_2 + \beta\left(p_1 d_1 F_1 t_{21}^V - p_2 d_2 F_2 t_{11}^V\right)\right)}{\left(1-\beta\left(t_{22}^V + \beta t_{12}^V t_{21}^V + t_{11}^V\left(1-\beta t_{22}^V\right)\right)\right)}$

The optimal strategy chosen by a firm is the one that minimizes the expected cost in group m

$$g_m = \min_{i,j} E_m^{ij}$$

The optimal strategy when firm is initially in G_1 is shown by the bold line in figure 1. As can be seen, the optimal strategy depends on the compliance cost c. Firms with very low compliance cost will choose f^{00} (always comply), firms with very large compliance cost will choose f^{11} (always violate), and firms with medium compliance choose f^{10} (violate whenever in non target group, but comply whenever in the target group).

Figure 1: Optimal strategy when firm initially in G_1



Setting expected cost of E_1^{00} equals to E_1^{10} provides us with the threshold point Q_1, where a firm is indifferent between f^{00} and f^{10}. The other threshold point Q_2, where a firm is indifferent between f^{10} and f^{11}, is found by setting E_1^{10} equals to E_1^{11}. The strategy that a firm chooses depends on its compliance cost, a relationship which is described in the following proposition.

Proposition 1: *Firms with compliance cost $c \le Q_1$ will choose strategy f^{00}, firms with $Q_1 \le c \le Q_2$ will choose strategy f^{10}, and firms with compliance cost $c \ge Q_2$ will choose strategy f^{11}; where $Q_1 = p_1 d_1 F_1$ and*

$$Q_2 = \frac{\left(p_2 d_2 F_2 \left(1 - \beta\left(t_{11}^V + \beta t_{21}^C t_{12}^V\right) - \beta t_{22}^C \left(1 - \beta t_{11}^V\right)\right) + \beta p_1 d_1 F_1 \left(t_{21}^V - \beta t_{22}^C t_{21}^V - t_{21}^C \left(1 - \beta t_{22}^V\right)\right)\right)}{\left(1 - \beta\left(t_{22}^V + \beta t_{21}^V t_{12}^V\right) - \beta t_{11}^V \left(1 - \beta t_{22}^V\right)\right)}$$

With the inclusion of a detection parameter, the Harrington/Friesen results hold. First, targeting is only feasible if the agency's goal is partial compliance. Full compliance can never be achieved as firms with compliance cost greater than Q_2 will always be in violation. Second, a firm in the target group G_2 can be induced to comply even if its compliance cost exceed the expected fine, $p_2 d_2 F_2$.

When we assume that detection is imperfect, the available strategies remain the same. However, the threshold points Q_1 and Q_2 will move. The effect of imperfect detection on Q_1 and Q_2 in the target group differs the effect on the non target group, as described in the following propositions.

Proposition 2a: *Given* $p_1, p_2, F_1, F_2 > 0$ *and a uniform firm distribution, imperfect detection in group 1 lowers the threshold point* Q_1 *and raises* Q_2*, thus increasing the number of firms that adopt the* f^{10} *strategy.*

Proposition 2b: *Given* $p_1, p_2, F_1, F_2 > 0$ *and a uniform firm distribution, imperfect detection in 2 lowers the threshold point* Q_2*, thus reducing the number of firms that adopt the* f^{10} *strategy.*

Proof for proposition 2.a and 2.b can be obtained by calculating the first derivative of the threshold points, with respect to the detection parameter.

$$\frac{dQ_1}{dd_1} > 0 \qquad \frac{dQ_2}{dd_1} < 0$$

$$\frac{dQ_2}{dd_2} = 0 \qquad \frac{dQ_2}{dd_2} > 0$$

As the first derivative of Q_1 with respect to the detection parameter in G_1 is positive, lower detection is associated with lower Q_1. This means that some f^{00} firms will change their strategy into f^{10} because the expected cost of violating is lower due to the possibility of escaping detection. The sign of the first derivative of Q_2 with respect to detection parameter in G_1 has interesting consequence. Imperfect detection in group 1 will cause Q_2 to increase. This means that some firms that choose f^{11} under perfect detection will adopt f^{10} under imperfect detection. In other words, some (former) f^{11} firms will comply in G_2. The benefit of complying in G_2 for such a firm comes from two sources; (1) a reduction in the expected cost while in G_2 because the firm can avoid a penalty with certainty, and (2) the expected benefit of being in G_1, which rises because of the possibility of escaping detection. As long as this expected benefit exceeds the compliance cost, firms will change their strategy from f^{11} to f^{10}.

The first derivative of Q_1 and Q_2 with respect to d_2 indicates that imperfect detection in G_2 lowers the threshold Q_2, while Q_1 remains the same. Smaller Q_2 means that some firms that adopt the f^{10} strategy under perfect detection will choose f^{11} under imperfect detection. Imperfect detection in G_2 reduces the expected cost of violating in G_2, and thus the incentive to violate increases.

Since the effect of imperfect detection on Q_2 differs between the target group and the non target group, the net impact would depend on size of the marginal effect of imperfect detection in each group. A further examination reveals that the marginal effect of imperfect detection in the target group is greater than the (absolute) marginal effect of imperfect detection in the non target group $\left(dQ_2 / dd_2 > \left|dQ_2 / dd_1\right|\right)$. This means that given the same level of detection rate, Q_2 will be at a lower point. Consequently, the number of firms that adopt the f^{11} strategy will increase.

Implication for Testing the Harrington Model

We have shown that adding imperfect detection does not change Harrington's prediction regarding firms' available strategies. However, the zone for the f^{00} strategy is reduced, while the zone for the f^{11} strategy is expanded as the result of imperfect detection.

Studies that were designed to test Harrington's prediction have been use experimental and nonexperimental (observational) methods. Strong support for Harrington's prediction comes from laboratory experiments conducted by Cason and Gangadharan (2004). They found that when the probability that an inspected compliant moves back to the non target group is high (0.9), most of the subjects behave as predicted by the Harrington model. The consistency rate – defined as the proportion of correct prediction for each strategy – for the f^{00} , f^{10} and f^{11} strategies are 89%, 94%, and 67% respectively.

On the other hand, nonexperimental studies only partially support Harrington's prediction. Helland (1998a) empirically tests the existence of the f^{10} strategy. His results show that inspections that did not detect any violation are not associated with a higher likelihood of firms violating in the next period. Thus he claims that there is no evidence for the f^{10} strategy. However, he found that previous violations are positively correlated with the current violation, which can be interpreted as the f^{11} strategy. This positive correlation between previous violation and current violation can also be found in Helland (1998b), Stafford (2002, 2005), and Scholz and Wang (2006).

Our extension to Harington's model can be used to explain the difference between the experimental and nonexperimental empirical evidence. As we have shown, the zone for f^{11} firms expands as a result of imperfect detection. If the firms are uniformly distributed, this implies that we will observe more f^{11} firms. Since Helland (1998a, 1998b), Stafford (2002, 2005) and Scholz and Wang (2006) use major facilities who likely have a high cost of complying with regulations, there is a great chance that the majority of their observations fall in the f^{11} zone.

Three additional reasons may also account for the difference between the conclusions drawn by experimental and nonexperimental studies. *First*, the theoretical model, and the experimental implementations, assumes that each facility knows with certainty the group to which it belongs. In reality, facilities do not have such information. Having no information on the group to which it belongs, the firm may miscalculate the expected cost of each decision, thus generating results that are inconsistent with the theoretical prediction. *Second*, the nonexperimental studies fail to categorize firms based on their compliance costs. In Harrington's model, firms can be easily categorized into low, medium or high compliance cost categories simply by comparing their compliance costs with the threshold points. The nonexperimental studies have used different proxies for compliance costs, but they do not estimate the thresholds Q_1 and Q_2, which makes it difficult to categorize each firm by their compliance costs. Without proper categorization of each firm, the results are biased toward the group with the most observations. In the nonexperimental studies, all observations are major facilities. Thus, it is not surprising if they confirm only the existence of the f^{11} strategy. *Third*, there is a possibility that it takes time to correct a violation, which is not permitted in Harrington's model or the experimental design of Cason and Gangadaran. If violations are indeed difficult to correct, the result would be biased toward observing the f^{11} strategy. Thus for a variety of reasons, one should not be surprised that Cason and Gangadaran's experimental study confirms Harrington's predictions, whereas the nonexperimental studies fail to do so. The contexts of the nonexperimental studies are unlikely to satisfy the assumptions of Harrington's model. Moreover, these studies are not well suited to testing Harrington's model because of the samples they use and the modeling strategies they adopt.

APPENDIX A

LOG LIKELIHOOD FUNCTION OF MODIFIED DCE

Figure A.1 describes how we categorize each observation in the modified DCE model, which is similar to Helland (1998a) and Scholz and Wang (2006). It is shown that there are three separate decisions; two are made by facility (violation and self report), and one is made by the regulator (inspection). Since the dependent variable of each decision is binary variable, we use latent variable approach of binary-choice model to model the probability of each decision.

Violation Equation

Let $Y^*_{V,i,t}$ denotes the violation decision made by facility *i* at time *t*., which is modeled as a function of vector of exogenous variables X_V, and a random error term $\varepsilon_{V,i,t}$.

$$Y^*_{V,i,t} = X_{V,i,t}\beta_V + \varepsilon_{V,i,t} \tag{A.1}$$

Exogenous variable X_V consists of some control variables, and lagged values of penalty (which is our variable of interest). As in the standard latent variable model, we can not directly observe $Y^*_{V,i,t}$. We can only observe $Y_{V,i,t}$, where:

$$Y_{V,i,t} = 1 \text{ (violate) } \textit{if} \quad Y^*_{V,i,t} > 0$$

$$Y_{V,i,t} = 0 \text{ (comply) } \textit{if} \quad Y^*_{V,i,t} \leq 0$$

Under the distributional assumption on the error term $\varepsilon_{V,i,t}$, the probability of violation is equal to $P(Y_{V,i,t} = 1) = P(X_{V,i,t}\beta_V + \varepsilon_{V,i,t} > 0) = V(X_{V,i,t}\beta_V)$, where $V(\bullet)$ is the cumulative distribution function for the violation equation.[33] Consequently, the predicted probability of facility i is not in violation at time t is $1 - V\left(X_{V,i,t}\beta_V\right)$

Inspection Decision

Similarly to violation decision, the regulator's decision to perform inspection $Y^*_{I,i,t}$ can be modeled as a function of vector of exogenous variables X_I, and a random error term $\varepsilon_{I,i,t}$, such that:

$$Y^*_{I,i,t} = x_{I,i,t}\beta_I + \varepsilon_{I,i,t} \qquad \text{(A.2)}$$

$$Y_{I,i,t} = 1 \quad \text{(inspect)} \ \ if \ \ Y^*_{I,i,t} > 0$$

$$Y_{I,i,t} = 0 \quad \text{(no inspection)} \ if \ \ Y^*_{I,i,t} \leq 0$$

As in the case for violation decision, we can only observe $Y_{I,i,t}$ instead of $Y^*_{I,i,t}$. Assuming that the error term follows normal distribution function, the probability of inspection $I\left(X_{I,i,t}\beta_I\right)$ is the cumulative normal distribution function for the inspection equation.

Self Report Equation

The self report equation represents the facility's decision to submit a self-report its violation, which is modeled as a function of a vector of exogenous variables X_S, and a random error term $\varepsilon_{S,i,t}$.

$$Y^*_{S,i,t} = x_{S,i,t}\beta_S + \varepsilon_{S,i,t} \qquad \text{(A.3)}$$

$$Y_{S,i,t} = 1 \quad \text{(self report)} \ \ if \ \ Y^*_{S,i,t} > 0$$

$$Y_{S,i,t} = 0 \quad \text{(no self report)} \ if \ \ Y^*_{S,i,t} \leq 0$$

---

[33] The distribution of the error term can be normal or logistic. In this study, since we also provide the result under probit and Chamberlain conditional random effects probit, we decided to use normal link function.

As in violation and inspection decision, we assume that the error term follow normal distribution. This gives us the probability of self report $S(X_{S,i,t}\beta_S)$, where $S(\bullet)$ is the cumulative normal distribution function for the self report equation.

The estimation of DCE is performed by maximizing the likelihood of different events shown in figure A.1. The three-equation model leads to five outcomes; (1) inspected violators, (2) inspected compliers, (3) self report violators, (4) compliers that are not inspected, and (5) violators with no inspection *and* no self report.

The likelihood functions of each outcome are as follow;

The log likelihood function of inspected violators

$$L_{IV} = \sum_{Y_V=1, Y_I=1, Y_S=0} \log V(X_{Vi}\beta_V)I(X_{Ii}\beta_I) \tag{A.4}$$

The log likelihood function of inspected compliers

$$L_{IC} = \sum_{Y_V=0, Y_I=1, Y_S=0} \log[1 - V(X_{Vi}\beta_V)]I(X_{Ii}\beta_I) \tag{A.5}$$

The log likelihood function of self-report violators

$$L_{SR} = \sum_{Y_V=1, Y_I=0, Y_S=1} \log V(X_{Vi}\beta_V)[1 - I(X_{Ii}\beta_I)]S(X_{Si}\beta_S) \tag{A.6}$$

The log likelihood function of not inspecting a compliant

$$L_{NIC} = \sum_{Y_V=0, Y_I=0, Y_S=0} \log[1 - V(X_{Vi}\beta_V)][1 - I(X_{Ii}\beta_I)] \tag{A.7}$$

The log likelihood function of not inspecting violator that do not self report

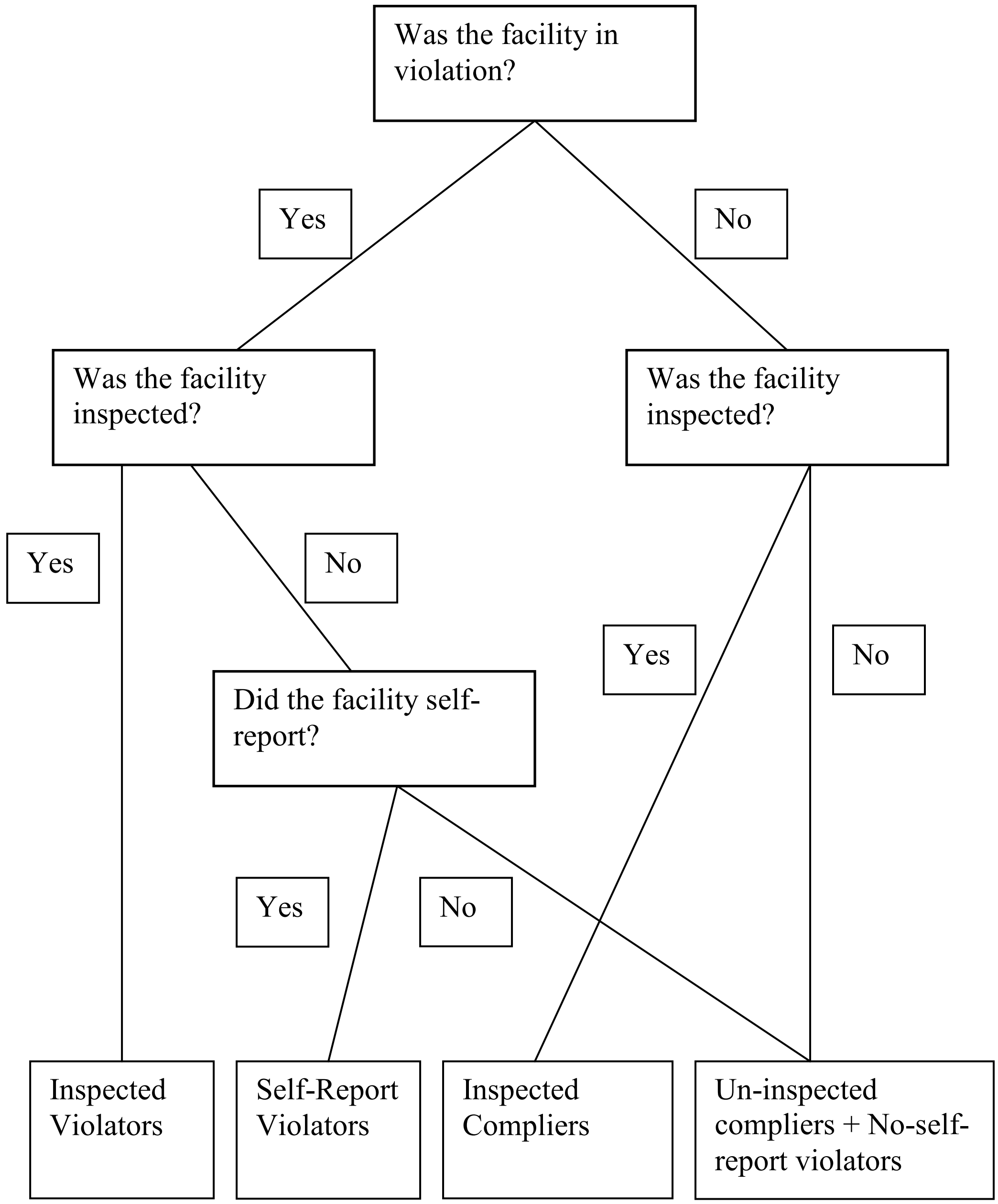
$$L_{NSR} = \sum_{Y_V=1, Y_I=0, Y_S=0} \log V(X_{Vi}\beta_V)[1 - I(X_{Ii}\beta_I)][1 - S(X_{Si}\beta_S)] \tag{A.8}$$

Since compliers that are not inspected are observationally equivalent with violators that are not inspected *and* do not submit self report, the likelihood function of the last two group are combined. Thus, the likelihood function of modified DCE is as follows;

$$
\begin{aligned}
L_{DCE}(\beta_V,\beta_I,\beta_S) = & \sum_{i\in IV}\log V(X_{Vi}\beta_V)I(X_{Ii}\beta_I) \\
& +\sum_{i\in IC}\log[1-V(X_{Vi}\beta_V)]I(X_{Ii}\beta_I) \\
& +\sum_{i\in SR}\log[1-V(X_{Vi}\beta_V)][1-I(X_{Ii}\beta_I)]S(X_{Si}\beta_S) \\
& +\sum_{i\in(NIC\cup NSR)}\log\{V(X_{Vi}\beta_V)[1-I(X_{Ii}\beta_I)][1-S(X_{Si}\beta_S)] \\
& +[1-I(X_{Ii}\beta_I)][1-S(X_{Si}\beta_S)]\}
\end{aligned}
$$

For DCE model with two sided expectation simultaneity, we use the same approach in categorizing each observation. The only difference is that we have expectation variable in equation A.1 and A.2, in addition to the original list of covariates. The detail of the derivation for two-sided expectation simultaneity DCE model is available in Feinstein (1990).

Figure A.1. Modified DCE Model



APPENDIX B
ARGUMENTS FOR COVARIATES IN THE EMPIRICAL MODEL

Violation Decision

In NPDES database, there are six categories of non compliance; (1) compliance schedule, (2) effluent violation (monthly average), (3) non monthly average effluent violation, (4) compliance schedule monitoring report, (5) non receipt of Discharge Monitoring Report (DMR), and (6) reportable non compliance. The first five violations are considered as significant violation, while the last one is considered as non significant violation. In this study, we use two measures of violations: (1) Effluent violation which consists of monthly and non monthly average effluent violation, and (2) significant violation, which consists of the first five of the above categories.

We model plants' violation decision as a function of lagged penalty, lagged compliance status, regulator's reputation, demographic characteristic, and probability of inspection. The arguments for inclusion as well as the expected sign of each variable are discussed in the following.

Probability of Inspection: Several empirical regulatory compliance studies—such as Gray and Deily (1996), Nadeau (1997), and Earnhart (2004)--confirm theoretical prediction that compliance decision is also affected by the probability of inspection. While Feinstein (1990) has laid out the methodology for DCE model that incorporates expectation term, no previous DCE studies has included expected inspection in the compliance decision. If plants do indeed take into account the probability of inspection in making compliance decision, then leaving this variable out would generate omitted variable bias. On the other hand, if in fact plants do not take into account probability of inspection, including this variable will only affect the efficiency of the estimates. We expect negative relationship between probability of inspection and violation decision. In other words, the higher is the probability of being inspected, the less likely the plant will violate. For comparison purpose, we also provide the result without expectation term.

Lagged penalty: We assume that regulator never mistakenly punish a complying firm. Therefore, only caught violators will be given penalties. Once a violation is detected, the regulator will calculate the amount of penalty such that it increases the firm's incentive to comply.[34] Hence, we expect that the larger the amount of penalty, the lower the likelihood of firm to violate in the subsequent period. In the very few literature that include penalty in the compliance decision, three studies found that penalty is an effective deterrence variable (Feinstein 1989; Stafford 2002; Scholz and Wang 2006). Shimshack and Ward (2005), however, fail to detect the effectiveness of penalty to reduce violation. As previous theoretical and previous studies suggest, we expect negative relationship between lagged penalty and violation decision.

Lagged Intermediate Enforcement Actions (IEAs): It is a common practice in regulatory enforcement that the regulator allows the violating facilities to go only with warning rather than just giving them penalty in every detected violation. In fact, enforcements with zero-penalty contribute the largest share in the CWA enforcement. Between 1990 and 2004, only 14 thousand cases (out of 167 thousand enforcements) are with penalties. Since most of enforcements are without penalties, it is of interest to see

[34] Interim CWA Settlement Penalty Policy (1995) designs penalty such that (1) it is large enough to deter non compliance, and (2) ensure a level of playing field by ensuring that violators do not obtain an economic advantage over their competitors.

how facilities react to warnings. In this study, we combine all enforcements with zero-penalty into one category called intermediate enforcement actions.[35] We expect that facilities will be more likely to comply after being issued a warning, as continue violating is considered as lacking of "good faith" by the regulator, and lead them to increased penalty.[36]

Regulator reputation: The compliance decision made by facilities can also be affected by the regulator stringency in conducting inspection and imposing penalties. The effect of a penalty might go beyond merely the penalized plant if other plants view the imposed fine as the indicator of regulator's stringency. If regulator reputation does affect compliance decision, then leaving this variable out will lead to underestimate the efficacy of fines and other sanctions (Shimshack and Ward 2005). There are two measures of reputation that we use; (1) the amount of penalty given by the regulator in the same jurisdiction (state), and (2) number of IEAs in the same jurisdiction. We normalize the reputation variables with the number of major facility in the state. We expect negative relationship between these two measures of reputation with violation decision.

Lagged compliance status: Harrington (1988) argues that firm's compliance decision depends on its compliance cost. Firms with low compliance cost will always comply, while those with high compliance cost will always violate. Firms with medium cost of compliance will make a decision based on previous inspection result. Firms found in the state of violation in the previous period will likely to comply in the next period. An empirical test performed by Helland (1998a) fails to confirm Harrington's prediction, and

[35] The detailed list of formal and informal actions in CWA is available at http://www.epa.gov/echo/dfr_data_dictionary.html, accessed November, 2007.

[36] USEPA (1995b)

is consistent with the view that “[V]iolations are difficult to correct and hence are not the best means for firms to signal their desire to cooperate with a regulator once a violation is detected.”

In order to be consistent with theoretical model, lagged compliance status is measured based on the outcome of previous inspections. For inspected compliant the value equals to one if the facility was inspected *and* no violation was detected. Meanwhile for previous violation, we include violations from two sources; inspection and self report.

Demographic characteristics: Recent regulatory compliance studies, such as Earnhart (2004), Stafford (2005), and Scholz and Wang (2006), found that social demographic characteristics have statistically significant impact on firms’ compliance decision. We will use several measures of demographic variables; unemployment, percent of urban area, race composition, percent of owner occupant, and educational attainment.

Unemployment: There are three studies that include unemployment in the violation equation. Brehm and Hamilton (1996) and Shimshack and Ward (2005) found that unemployment have negative relationship with violation, while Earnhart (2004) found it positively related. As the empirical evidence is mixed, the coefficient of this variable is not signed.

Share of urban area: Whether a violation by a facility is easily visible to the public can also be affected by the initial environmental quality in the facility’s site. A violation by a facility located in the urban area is relatively less visible compare to similar violation in the rural area because the urban area is more likely to have lower environmental quality due to higher activities. Therefore, we expect that facilities located in urban area are more likely to violate. Unfortunately, the data does not distinguish whether the plant is located in urban or rural area. As solution, we use the percentage of urban area in the county as a proxy variable. We are confident that the share of urban area is a good proxy variable for location, as greater urban area means more activities and is usually associated with lower environmental quality, hence will produce the same qualitative result.

Race composition: We use the percentage of white population in the county to represent race composition. As the majority race in the U.S., we consider the higher the share of white population, the higher is the pressure for the firm to comply with the regulation. Two previous studies have included racial composition in firms' violation decision. Scholz and Wang (2006) found that the percentage of Hispanic and Black population have positive correlation with violation, while Shimshack and Ward (2005) did not detect the significant impact of racial structure

Share of owner occupant: We argue that property owner has direct interest to put pressure on facility to maintain environmental quality, since any violations that lead to increased pollution will result in a decrease in property value. Moreover, as taxpayers, property owners can also affect local authority decision in allowing or rejecting a facility to operate in their area. We expect that the higher the share of owner occupant, the bigger is the pressure for the firm to comply.

Educational attainment: We use the percentage of population with bachelor or higher degree to represent educational attainment. We argue people with high educational attainment are more likely to have better understanding about the hazardous impact of environmental violation. We also expect that well-educated people have better ability to put social pressure on facility or convincing the regulator to enforce regulation towards violating facilities. Therefore, we expect negative relationship between educational attainment and violation decision.

Proxies for Unobserved Heterogeneity

The common practice in the estimating model with panel data format is by taking into account unobserved heterogeneity, either with fixed effect or random effect specification. Unfortunately, the likelihood function for DCE that takes into account unobserved heterogeneity has not been developed yet.[37]

We are fully aware that ignoring unobserved heterogeneity will affect the estimation result. Our attempt to capture (time invariant) plant's specific tendency to comply is by choosing variables of most direct theoretical concern, then take the average value over the period, and include as additional covariates. Introducing average variables $\bar{x}_i$ - in addition to their own original values x_{it} - means we are estimating the effect of those variables holding the time average fixed (Wooldridge 2002). A random effect probit model that allows some dependence between individual specific effect and covariates also use similar average variables (Chamberlain 1980). Consequently, we can compare the DCE model with Chamberlain's approach since we are using the exact same list of covariates.

[37] In cross section format, DCE model calculates the probability that plant i is inspected conditional on the plant is in violation. Under panel data format, we observe V detected violations in I number of inspection in T period. However, the actual number of violation (V^*) is $V \leq V^* \leq T$. In model with complete detection process like fixed effect logit, the likelihood function is conditioned based on detected violation (which is assumed equals to actual violation). In panel DCE, since detection is an incomplete process, the actual violation is *at least* equal to the number of detected violation. The challenge lies in how to derive the likelihood function for fixed effect DCE is to find V^* that will be used as condition in maximizing the likelihood function.

There are three variables that we think have the most direct impact on compliance decision; inspection, intermediate enforcement action, and penalty.[38] Regulator will conduct inspection more frequently towards facilities with larger (perceived) propensity to violate. Once a violation is detected, the regulator has two choices: issue intermediate enforcement actions (warning / compliance order) or penalize the plant. Large average value of these variables indicates greater facility's inherent factors to violate. Therefore, we expect positive relationship of the average values of these variables with compliance decision.[39]

Other Control Variables

Industrial classification: The NPDES database records four types of industrial classification.[40] However, existing environmental compliance studies only focus on one type of industry.[41] Including industrial classification dummy would help us to see if there are differences in compliance behavior among different industries, as claimed by Scholz and Wang (2006).

Seasonal dummies: There are two reasons for including seasonal dummy in the violation equation. First, the emission level is closely related to the production level, and production level may vary by season due to demand. Second, from the auditor point of

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[38] These variables are also used in Shimshack and Ward (2005)

[39] We also estimate the model *without* average variables. Excluding these three variables cause the sign for self penalty to be positive which is inconsistent with theory.

[40] The industries are; (1) primary industry listed on Effluent Limitations Guidelines (ELG), (2) municipal facility, which is determined by from SIC code (SIC 4952) and ownership type, (3) facility listed on ELG but not considered as primary industry, and (4) industry that has not been categorized by ELG.

[41] Scholz and Wang (2006) exclude municipal facilities as public ownership creates different budget constraints that alter their responses to enforcement. Meanwhile, Eanrhart (2004) focuses only on municipal waste water treatment. He argues that since wastewater treatment plant must be located in every community, it avoids potential endogeneity problem between location and community characteristics. Other studies do not explicitly indicate the industrial category used in their studies

view, inspections are sometimes constrained by weather condition. For instance, a really cold winter may prevent auditors from performing inspection.

Inspection Decision

Although there are various types of inspection, we will not distinguish inspection either by types or by inspectors. In our formulation, inspection is modeled as a function of lagged number of inspection, lagged compliance status, lagged penalty, demographic characteristic, number of facility (in the same 2-digit SIC) in the region, number of previous enforcement in the region, demographic characteristic, and expected violation rate. Inspection decision is measured by dummy variable, where 1 indicates inspection is performed, zero otherwise.

Probability of violation: Unless the number of facilities is extremely small, regulator will not be able to inspect all facilities in its jurisdiction due to resource constraint. Theoretical models suggest that regulator will direct the inspection towards those who are more likely to violate. Therefore, we expect positive relationship between inspection and probability of violation.

Probability of self report: With limited budget constraint, self report can be used as screening mechanism for the regulator to perform inspection. Although firms have a choice to misreport, there is no evidence of strategic non-reporting or false reporting by firms.[42] After all, misreporting is punishable by law. Therefore, it is better for the regulator to direct inspection towards those who are less likely to submit self report.

Lagged inspection: Whether a facility is inspected in a given period depends on the strategy used by the regulator. Laplante and Rilstone (1996) suggest that plants with large number of cumulative inspections will be less likely to be inspected if the regulator

[42] See Laplante and Rilstone (1996) and Shimshack and Wards (2005).

adopt sampling-without-replacement strategy (i.e., to visit as many plants as possible), like the one which is practiced by Quebec Ministry of Environment. In U.S. case, regulator is required to inspect major facility at least once a year (Shimshack and Ward 2005). However, we found many cases in the dataset where inspections have been absent for more than a year.[43] This discrepancy between law and practice requires us to expand the length of lagged inspection beyond just one year. As the law requires major facility to be inspected once a year, we expect positive relationship between lagged inspections and current inspection decision.

Lagged number of violation: A facility that has been found in violation in the previous period will be given more attention by the regulator. This premise is supported both from theoretical and empirical point of view. In the theoretical side, a model by Harrington (1988) suggests that a detected violator will have greater probability of being inspected.[44] Meanwhile, the support from empirical work comes from the studies by Helland (1998a) and Nadeau (1997).

Unlike in violation decision, we use the cumulative number of violation instead of previous inspection outcome. Using number of violations implies that we include violations from two sources, inspection and self report. And we consider that this is a good measure since the regulator is more concerned about the extent of non compliance regardless how it gets the information about non compliance. With regard to the expected sign, we expect positive relationship between lagged of number of non compliance and

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[43] Rechtschaffen (2004) quotes studies that indicate that states authority fail to carry out inspection, which is consistent with what we found in the dataset

[44] To be specific, a detected violator in group 1 (group of plants with low probability of inspection and low penalty) will have a certain probability to move to group 2 (group of plants that face higher enforcement scrutiny, i.e., higher probability of inspection and higher penalty). A detected violator in group 2 will remain in group 2.

inspection decision. However, the effect of non compliance will diminish overtime, in the sense that non compliance in period t will have a larger in $t+1$ than $t+2$ and so on.

Lagged penalty: The amount of penalty indicates the extent of violations. The more severe the violation, the higher is the penalty. While this argument is supported theoretically by Harrington (1988), unfortunately—among the very scant literature of environmental compliance that include penalty--there is no single empirical study that incorporate penalty into inspection decision. As the magnitude of penalty indicates the severity of violation, we expect that the larger the magnitude of penalty, the greater the probability of being inspected in the next period.

Lagged IEAs: The effect of IEAs on the probability of inspection is the same as the effect of lagged penalty, as this is another indicator of the degree of violation. Therefore, as in the lagged penalty, we expect positive relationship between the number of lagged IEA with inspection decision.

Lagged report violation: Under CWA, major facilities are required to submit monthly DMR. Failure to submit this report is considered as non compliance. We expect that facilities that fail to submit the required reports are more likely to be inspected.

Demographic characteristics: Similar to compliance decision, demographic characteristic also found to be an important consideration for the regulator in conducting inspection. We use the same list of demographic characteristics as in the violation equation. The only difference is on the expected signs for some variables.

Unemployment: The support of including unemployment as covariate in inspection decision is based on the environmental federalism-regulatory literature model prediction that the costs and benefits of environmental protection determine the stringency of enforcement.[45] While the benefit of stringent environmental enforcement is pollution reduction, the general cost includes profit loss and potential plant closing. In empirical studies, unemployment has been included as it reflects the opportunity cost of the lost jobs if the plant does close as the result of stringent enforcement. The evidence from empirical studies, however, is mixed.[46] Therefore the coefficient for this variable is not signed.

Share of urban area: We use similar argument as in the violation equation, that violations in the rural area are relatively more visible compare to those in urban. Since facilities in urban are more likely to violate due to less visibility, it is better for the regulator to direct inspection toward facilities in the urban area. For the same reason used in violation equation, we use percentage of urban area as proxy. We expect positive relationship between percent of urban area and inspection decision.

Race composition: Scholz and Wang (2006) use the percent of Black and Hispanic residents to test whether there is an environmental injustice from the regulator in performing inspection. While they failed to reject null with regard to the correlation between inspection and percent of Black residents, they found that proportion of Hispanic residents is negatively related with inspection decision. In this study, we use the share of white population to test if there is environmental injustice. If the environmental injustice indeed exists, we expect positive correlation between percentage of white population and inspection decision.

[45] See for instance Peltzman (1976) and Oates (1988)

[46] Helland (1998b) found similar result with theoretical prediction, while Deily and Gray (1991) and Gray and Deily (1996) found it positive and significant

Share of owner occupant: A strict environmental enforcement is usually desirable by property owners, since environmental degradation will affect property values negatively. And as tax payer, property owners can put the pressure on the local government to supply an adequate amount of public good (in this case, good environmental quality). As the share of property owner live in the area is higher, local authority will face a greater pressure to enforce the regulation. Therefore, we expect positive relationship between the share of owner occupant and the inspection decision.

Educational attainment: As has been explained in the violation decision, people with high educational attainment are more likely to have better understanding about the hazardous impact of environmental violation, and also expected to have better ability to put social pressure on facility or convincing the regulator to enforce regulation towards violating facilities. The effect of educational attainment on inspection decision depends on the effectiveness of social pressure being put on facility. The more effective the social pressure, the lesser is the need to perform inspection. In other words, if we found educational attainment is negatively related with violation decision, then we would expect negative relationship between educational attainment with inspection decision.

*Government budget***:** Helland (1998a, 1998b) found that government budget is statistically significant in determining inspection decision. We use government expenditure on natural resource protection (obtained from census bureau) as proxy for government budget, and normalize it with number of plants in the state. Similar to Helland's findings, we expect positive relationship between budget per plant with inspection decision.

*Number of facility in the same 2-digit SIC***:** Another constraint to perform inspection comes from the number of facilities in the jurisdiction. Helland (1998a) finds that number of (total) manufacturing facilities is negatively related with inspection decision, which is not surprising. In this study, since we already use the number of total plants to normalize the government budget, we will use different measure for number of plants. We will use the number of plants in the same industry (2-digit SIC). As the number of plant in the industry increases, total pollution will increase and the net benefit of performing inspection towards the industry increases. Therefore, we expect positive correlation between inspection and number of plant in the same 2-digit SIC.

Other control variables: Similar to violation decision, we also additional control variables such as seasonal dummies and industrial classification dummies. We use similar approach as in violation decision for proxies of unobserved heterogeneity. The only difference is that we exclude the average number of inspection.

Self Report Decision

Since plants that submit self report are those who are in violation, we argue that plants decisions to self report are closely related the compliance decision. Therefore, we model plants' decision to self-report as a function of lagged compliance status, lagged penalty, lagged intermediate enforcement actions, lagged report violation and number of facilities in the same 2-digit SIC. We exclude demographic variables appeared in the violation equation since self report is a matter between facility and regulator, and irrelevant with the local community characteristics.

Probability of Inspection: As in violation decision, we also consider that the probability of inspection affects self report decision. However, the expected sign depends on the effectiveness of probability of inspection in the violation decision. If it is negative and statistically significant in the violation decision, then we would expect the probability of inspection has a negative sign in the self report decision. As the probability of inspection reduces the probability of violation, consequently it will reduce the probability of self report.

Lagged compliance status: The compliance status that we use is based on previous inspection outcome. That is, we create a dummy variable equal to one if a violation was detection during previous inspection. Because it takes time to correct a violation—as found by Helland (1998a)--a detected violator will have higher likelihood to submit self-report violation in the subsequent period in order to avoid severe penalty for its inability to comply. Therefore, we expect positive relationship between lagged violations with self report decision.

Lagged report violation: Under CWA, major facilities are required to submit monthly DMR. Failure to submit this report is considered as non compliance. Another form of report violation is failure to submit compliance schedule report. We expect that facilities that fail to submit the required reports have higher probability of self reporting, as failure to do so will be considered by the regulator as lacking of ‘good faith’, hence will face more stringent enforcement.

Lagged penalty: The data PCS dataset indicates that enforcement with non-zero penalty account only less than ten percent of total CWA enforcement. It means that only serious and/or repeated violators receive monetary penalty. The sign of lagged penalty in self report equation depends on the effectiveness of penalty in deterring violation. If the penalty is effective in deterring non compliance, it means that the penalized violator will comply in the next period, hence there is no need to submit self report. Thus, we expect negative relationship between lagged penalty and self-report. However

Lagged IEAs: As we have mentioned in violation and inspection decision, intermediate enforcement actions reflect the severity of violation. We expect that the sign of IEAs on self report equation will be similar to its sign in the violation decision. If Harrington prediction is correct, then we expect negative relationship between lagged IEAs and self report. On the other hand, if our findings in the compliance decision are similar as in Helland (1998a)—which confirm the view that violations are difficult to correct--then we expect the positive relationship between lagged IEAs and self report decision. After all, it is better for the facilities to submit self report as they have higher probability of being inspected.

Number of facility in the same 2-digit SIC: Under the new penalty regime, the regulator will reduce or waive the penalty if the violating facility submit a self report. The benefit of submitting self report is greater in an industry with smaller number of plants because the violation is more visible. Therefore, we expect that the smaller the number of plant in an industry, the more likely the violating plant to self report.

Other Control Variables: As in the violation decision and inspection decision, we also use industrial and seasonal dummies to control for differences due to industrial type and seasonal fluctuation.

APPENDIX C

ROBUSTNESS CHECK

To ensure that the results presented in chapter III are the robust results, we also estimate the model under different dataset and specification. The summary regression results in chapter III and additional robustness tests are presented in Table 20.

Regression Result using Significant Noncompliance Measure

The results that we present in chapter III are based on effluent violation. As robustness check, we also estimate the model under alternative measure of noncompliance. By NPDES definition, a facility is considered in significant noncompliance if it has at least one of the following criteria; (1) commit effluent violation, (2) fail to meet compliance schedule, (3) fail to submit compliance schedule monitoring report, or (4) fail to submit monthly Discharge Monitoring Report (DMR).

Since significant noncompliance definition covers three more types of violation, we have more non complying firms in the dataset (compare to using effluent violation measure). With the same explanatory variable, this means that we expect smaller coefficients and more insignificant variables from the new regression. Tables 21-22 present the estimation results using significant noncompliance measure for non-municipal facilities and SIC 49.

The qualitative result presented in Table 21 is not much different from Table 11 of chapter III. Using significant noncompliance measures indeed lower the magnitude of parameter for some variables (like reputation penalty lagged 1-4 quarters and unemployment rate). Other coefficients remain in the similar magnitude.

When we use SIC 49, the qualitative results of both measures are similar. The notable difference is self-penalty lagged 1-4 quarters becomes statistically insignificant using significant noncompliance measure in all specifications.

Table 20: Summary of Robustness Test

	Used in		Notes
	Chapter III	**Robustness Check**	
Period	1997-2004	1990-2004 1990-1996	We do not find self-penalty statistically significant using 1990-2004 dataset Regression using 1990-1996 data generate positive coefficients on self penalty
Violation measures	Effluent violations	Significant violations All types of violations	All measures provide similar qualitative results, except using SIC 26 dataset. Under significant violation measure, we fail to reject null for self-penalty using SIC 26 dataset.
Penalty measures	Continuous	Dummy	The notable change exists when we use non-municipal facilities. When measured by dummy variable, self-penalty is significant in non-municipal group. However, once reputation variables are included, the effects become insignificant.

	Used in		Notes
	Chapter III	**Robustness Check**	
Reputation variables measures	Normalized by number of facility	Un-normalized	Two measures provide the same qualitative results
Lagged compliance status measures	Previous inspection outcome	Number of noncompliance Distributed noncompliance dummy	All three measures provide consistent qualitative results.
Average enforcement variables	Average enforcement variables (penalty, IEA, and inspection) are included	Average enforcement variables are excluded	Excluding average enforcement variables causes the coefficient of self-penalty to be positive in each methodology

Table 21: Significant Violation Decision under DCE (Non Municipal Facilities)

	Specification				
	A	B	C	D	E
Probability of inspection			-1.7204 ***		-1.6171 ***
			(0.4455)		(0.4187)
Penalty (Self) 1-4 quarters ago	-0.0134 *	-0.0121	-0.0092	-0.0112	-0.0084
	(0.0073)	(0.0074)	(0.0074)	(0.0075)	(0.0075)
Penalty (Self) 5-8 quarters ago	-0.0156 **	-0.0119	-0.0111	-0.0132 *	-0.0123
	(0.0075)	(0.0076)	(0.0076)	(0.0076)	(0.0076)
Penalty (Reputation) 1-4 quarters ago		-0.0013	0.0014	-0.0022	-0.0003
		(0.0046)	(0.0046)	(0.0047)	(0.0047)
Penalty (Reputation) 5-8 quarters ago		-0.0214 ***	-0.0159 ***	-0.0209 ***	-0.0162 ***
		(0.0046)	(0.0048)	(0.0048)	(0.0049)
IEA (Self) 1-4 quarters ago	0.0087	0.0215 ***	0.0263 ***	0.0239 ***	0.0252 ***
	(0.0075)	(0.0081)	(0.0082)	(0.0083)	(0.0083)
IEA (Self) 5-8 quarters ago	-0.0089	0.0045	0.0045	0.0060	0.0027
	(0.0081)	(0.0085)	(0.0085)	(0.0087)	(0.0088)
IEA (Reputation) 1-4 quarters ago		-0.0289 ***	-0.0275 ***	-0.0245 ***	-0.0228 ***
		(0.0072)	(0.0073)	(0.0074)	(0.0075)
IEA (Reputation) 5-8 quarters ago		-0.0142 **	-0.0123 *	-0.0192 ***	-0.0168 **
		(0.0070)	(0.0071)	(0.0070)	(0.0071)
Inspected and no violation detected 1-4 quarters ago	0.1221 ***	0.1370 ***	0.0642 **	0.1486 ***	0.0731 **
	(0.0263)	(0.0262)	(0.0321)	(0.0266)	(0.0330)
Inspected and no violation detected 5-8 quarters ago	-0.1102 ***	-0.0970 ***	-0.0489 *	-0.0961 ***	-0.0526 *
	(0.0264)	(0.0263)	(0.0271)	(0.0267)	(0.0268)
Number of significant violation 1-4 quarters ago	0.6591 ***	0.6488 ***	0.6412 ***	0.6532 ***	0.6428 ***
	(0.0131)	(0.0131)	(0.0132)	(0.0132)	(0.0135)
Number of significant violation 5-8quarters ago	0.0527 ***	0.0434 ***	0.0534 ***	0.0541 ***	0.0630 ***

	Specification									
	A		B		C		D		E	
	(0.0140)		(0.0140)		(0.0143)		(0.0143)		(0.0145)	
Percent urban	0.1152	**	0.1260	**	0.0727		0.1376	**	0.0942	*
	(0.0524)		(0.0529)		(0.0547)		(0.0539)		(0.0551)	
Percent white	0.6485	***	0.3976	***	0.4218	***	0.4626	***	0.4672	***
	(0.0833)		(0.0863)		(0.0855)		(0.0894)		(0.0882)	
Unemployment rate	0.0093	*	0.0041		-0.0050		0.0031		0.0000	
	(0.0054)		(0.0055)		(0.0060)		(0.0059)		(0.0059)	
Percent of owner occupant	-0.1995		0.0850		-0.0429		0.0231		0.0042	
	(0.1568)		(0.1627)		(0.1674)		(0.1738)		(0.1751)	
Percent of bachelor + graduate degree	-0.6750	**	-0.9649	***	-1.1272	***	-1.2026	***	-1.1398	***
	(0.2650)		(0.2720)		(0.2762)		(0.2926)		(0.2931)	
Primary industry	-0.1654		-0.0673		-0.0604		-0.1007		-0.0901	
	(0.2953)		(0.2965)		(0.2976)		(0.3008)		(0.3027)	
Not primary industry	-0.1049		-0.0118		-0.0069		-0.0477		-0.0357	
	(0.2959)		(0.2971)		(0.2983)		(0.3015)		(0.3034)	
Not on ELG	-0.0215		0.0685		0.0722		0.0467		0.0588	
	(0.2965)		(0.2977)		(0.2989)		(0.3020)		(0.3040)	
Average penalty	0.0227	***	0.0251	***	0.0253	***	0.0267	***	0.0271	***
	(0.0058)		(0.0059)		(0.0058)		(0.0059)		(0.0059)	
Average IEA	0.0884	*	0.2371	***	0.2463	***	0.2218	***	0.2512	***
	(0.0525)		(0.0558)		(0.0555)		(0.0589)		(0.0593)	
Average inspection	-0.8725	***	-0.8726	***	-0.1114		-0.8628	***	-0.1365	
	(0.0846)		(0.0826)		(0.2137)		(0.0831)		(0.2070)	
Constant	-1.1759	***	-1.0746	***	-0.7319	**	-0.9168	***	-0.7225	**
	(0.3266)		(0.3277)		(0.3416)		(0.3383)		(0.3443)	

*, **, *** indicate 10%, 5%, and 1% significance respectively

Table 22: Significant Violation Decision under DCE (SIC 49)

	Specification									
	A		B		C		D		E	
Probability of inspection					-1.8016	***			-1.7131	***
					(0.0882)				(0.0872)	
Penalty (Self) 1-4 quarters ago	-0.0204	***	-0.0204	***	-0.0192	***	-0.0181	***	-0.0169	***
	(0.0044)		(0.0045)		(0.0045)		(0.0045)		(0.0046)	
Penalty (Self) 5-8 quarters ago	-0.0021		-0.0012		-0.0049		-0.0015		-0.0034	
	(0.0045)		(0.0045)		(0.0045)		(0.0046)		(0.0046)	
Penalty (Reputation) 1-4 quarters ago			0.0018		0.0044		0.0041		0.0060	**
			(0.0029)		(0.0029)		(0.0030)		(0.0029)	
Penalty (Reputation) 5-8 quarters ago			-0.0195	***	-0.0124	***	-0.0210	***	-0.0152	***
			(0.0030)		(0.0030)		(0.0031)		(0.0030)	
IEA (Self) 1-4 quarters ago	0.0035		0.0114	**	0.0187	***	0.0106	**	0.0146	***
	(0.0041)		(0.0047)		(0.0048)		(0.0048)		(0.0048)	
IEA (Self) 5-8 quarters ago	-0.0300	***	-0.0159	***	-0.0088	*	-0.0159	***	-0.0121	**
	(0.0043)		(0.0048)		(0.0048)		(0.0049)		(0.0049)	
IEA (Reputation) 1-4 quarters ago			-0.0081		-0.0152	***	-0.0041		-0.0101	**
			(0.0049)		(0.0050)		(0.0051)		(0.0051)	
IEA (Reputation) 5-8 quarters ago			-0.0363	***	-0.0224	***	-0.0400	***	-0.0273	***
			(0.0053)		(0.0054)		(0.0052)		(0.0053)	
Inspected and no violation detected 1-4 quarters ago	0.0490	***	0.0547	***	0.0552	***	0.0639	***	0.0561	***
	(0.0177)		(0.0176)		(0.0165)		(0.0177)		(0.0166)	
Inspected and no violation detected 5-8 quarters ago	-0.1932	***	-0.1901	***	-0.0678	***	-0.1954	***	-0.0774	***
	(0.0181)		(0.0180)		(0.0182)		(0.0181)		(0.0182)	
Number of significant violation 1-4 quarters ago	0.6240	***	0.6167	***	0.6143	***	0.6179	***	0.6125	***
	(0.0075)		(0.0075)		(0.0075)		(0.0076)		(0.0076)	
Number of significant violation 5-8quarters ago	0.0347	***	0.0267	***	0.0463	***	0.0376	***	0.0542	***
	(0.0080)		(0.0080)		(0.0080)		(0.0081)		(0.0081)	
Percent urban	-0.0001		0.0047		-0.0006		-0.0030		-0.0056	
	(0.0342)		(0.0342)		(0.0344)		(0.0344)		(0.0346)	
Percent white	0.2190	***	0.0342		0.1534	***	0.0232		0.1184	**

	Specification									
	A		B		C		D		E	
	(0.0555)		(0.0578)		(0.0567)		(0.0591)		(0.0581)	
Unemployment rate	-0.0116	***	-0.0163	***	-0.0182	***	-0.0145	***	-0.0096	**
	(0.0035)		(0.0035)		(0.0035)		(0.0038)		(0.0038)	
Percent of owner occupant	-0.3913	***	-0.1631	*	-0.1915	*	-0.1282		-0.0526	
	(0.0939)		(0.0963)		(0.0984)		(0.1006)		(0.1030)	
Percent of bachelor + graduate degree	-1.2098	***	-1.3590	***	-1.2662	***	-1.2586	***	-0.9568	***
	(0.1470)		(0.1489)		(0.1500)		(0.1573)		(0.1590)	
Primary industry	-0.1022	***	-0.0780	***	-0.1385	***	-0.0827	***	-0.1422	***
	(0.0231)		(0.0233)		(0.0236)		(0.0235)		(0.0237)	
Not on ELG	0.1336	***	0.1377	***	0.0698		0.1299	***	0.0648	
	(0.0467)		(0.0468)		(0.0468)		(0.0472)		(0.0472)	
Average penalty	0.0232	***	0.0275	***	0.0369	***	0.0261	***	0.0356	***
	(0.0036)		(0.0037)		(0.0037)		(0.0037)		(0.0037)	
Average IEA	0.1949	***	0.3282	***	0.2665	***	0.3275	***	0.2940	***
	(0.0276)		(0.0300)		(0.0302)		(0.0307)		(0.0309)	
Average inspection	-0.4948	***	-0.4858	***	0.0600	**	-0.4831	***	0.0436	
	(0.0321)		(0.0312)		(0.0278)		(0.0313)		(0.0286)	
Constant	-0.5332	***	-0.3932	***	-0.2583	***	-0.2011	**	-0.2152	**
	(0.0867)		(0.0888)		(0.0893)		(0.0974)		(0.0976)	

Seasonal dummies and time effects are omitted for brevity
*, **, *** indicate 10%, 5%, and 1% significance respectively

REFERENCES

Anderson, Lisa R. and Sarah L. Stafford. 2003. Punishment in a regulatory setting: Experimental evidence from the VCM. *Journal of Regulatory Economics* 24, no. 1: 91-110.

Becker, Gary S. 1968. Crime and punishment: An economic approach. *The Journal of Political Economy* 76, no. 2: 169-217.

Brehm, John and James T Hamilton. 1996. Noncompliance in environmental reporting: Are violators ignorant, or evasive, of the law? *American Journal of Political Science* 40, no. 2: 444-447.

Carroll, Raymond J, Clifford H. Spiegelman, K. K. Gordon Lan, Kent T. Bailey, and Robert D. Abbott. 1984. On errors-in-variables for binary regression models. *Biometrika* 71, no. 1: 19-25.

Cason, Timothy N. and Lata Gangadharan. 2006. An experimental study of compliance and leverage in auditing and regulatory enforcement. *Economic Inquiry* 44, no. 2: 352-366.

Chamberlain, Gary. 1980. Analysis of covariance with qualitative data. *The Review of Economic Studies* 47, no. 1: 225-238.

Deily, Mary E. and Wayne B. Gray. 1991. Enforcement of pollution regulations in a declining industry. *Journal of Environmental Economics and Management* 21, no. 3: 260-274.

Downing, Paul B. and Watson, William D., Jr. 1974. The economics of enforcing air pollution controls. *Journal of Environmental Economics and Management* 1, no. 3: 219-236.

Earnhart, Dietrich. 2004. The effects of community characteristics on polluter compliance levels. *Land Economics* 80, no. 3: 410-432.

Feinstein, Jonathan S. 1989. The safety regulation of U.S. nuclear power plants: Violations, inspections, and abnormal occurrences. *The Journal of Political Economy* 97, no. 1: 115-154.

________. 1990. Detection controlled estimation. *Journal of Law and Economics* 33: 233-277.

Foulon, Jerome, Paul Lanoie, and Benoit Laplante. 2002. Incentives for pollution control: Regulation or information? *Journal of Environmental Economics and Management* 44, no. 1: 169-187.

Friesen, Lana. 2003. Targeting enforcement to improve compliance with environmental regulations. *Journal of Environmental Economics and Management* 46, no. 1: 72-85.

Fung, Archon and Dara O'rourke. 2000. Reinventing environmental regulation from the grassroots up: Explaining and expanding the success of the toxics release inventory. *Environmental Management* 25, no. 2: 115-127.

Gray, Wayne B. and Mary E. Deily. 1996. Compliance and enforcement: Air pollution regulation in the U.S. steel industry. *Journal of Environmental Economics and Management* 31, no. 1: 96-111.

Greene, William H. 1997. *Econometrics analysis*. Upper Saddle River, New Jersey: Prentice-Hall.

Griliches, Zvi. 1984. Economic data issues. In *Handbook of econometrics*, ed. Zvi Griliches and Michael D Intriligator, III. Amsterdam: Elsevier Science Publishers B V.

Harford, Jon D. 1978. Firm behavior under imperfectly enforceable pollution standards and taxes. *Journal of Environmental Economics and Management* 5, no. 1: 26-43.

Harrington, Winston. 1988. Enforcement leverage when penalties are restricted. *Journal of Public Economics* 37, no. 1: 29-53.

Helland, Eric. 1998a. The enforcement of pollution control laws: Inspections, violations, and self-reporting. *Review of Economics & Statistics* 80, no. 1: 141-153.

________. 1998b. The revealed preferences of state EPAs: Stringency, enforcement, and substitution. *Journal of Environmental Economics and Management* 35, no. 3: 242-261.

Heyes, Anthony G. 1993. Environmental enforcement when inspectability is endogenous. *Environmental and Resource Economics* 4, no. 5: 479-494.

________. 2000. Implementing environmental regulation: Enforcement and compliance. *Journal of Regulatory Economics* 17, no. 2: 107-129.

Kadambe, Surabhi and Kathleen Segerson. 1998. On the role of fines as an environmental enforcement tool. *Journal of Environmental Planning and Management* 41, no. 2: 217-226.

Khanna, Madhu and Lisa A. Damon. 1999. EPA's voluntary 33/50 program: Impact on toxic releases and economic performance of firms. *Journal of Environmental Economics and Management* 37, no. 1: 1-25.

Kleit, Andrew N., Meredith A. Pierce, and R. Carter Hill. 1998. Environmental protection, agency motivations, and rent extraction: The regulation of water pollution in Louisiana. *Journal of Regulatory Economics* 13, no. 2: 121-137.

Landsberger, Michael and Isaac Meilijson. 1982. Incentive generating state dependent penalty system : The case of income tax evasion. *Journal of Public Economics* 19, no. 3: 333-352.

Laplante, Benoit and Paul Rilstone. 1996. Environmental inspections and emissions of the pulp and paper industry in Quebec. *Journal of Environmental Economics and Management* 31, no. 1: 19-36.

Livernois, John and C. J. McKenna. 1999. Truth or consequences: Enforcing pollution standards with self-reporting. *Journal of Public Economics* 71, no. 3: 415-440.

Magat, Wesley A. and W. Kip Viscusi. 1990. Effectiveness of the EPA's regulatory enforcement: The case of industrial effluent standards. *Journal of Law and Economics* XXXIII, no. October: 331 - 360.

Nadeau, Louis W. 1997. EPA effectiveness at reducing the duration of plant-level noncompliance. *Journal of Environmental Economics and Management* 34, no. 1: 54-78.

Oates, Wallace E. and Robert M. Schwab. 1988. Economic competition among jurisdictions: Efficiency enhancing or distortion inducing? *Journal of Public Economics* 35, no. 3: 333-354.

Peltzman, Sam. 1976. Toward a more general theory of regulation. *Journal of Law and Economics* 19, no. 2: 211-240.

Rechtschaffen, Clifford. 2004. Enforcing the clean water act in the twenty-first century: Harnessing the power of the public spotlight. *Center for Progressive Regulation White Paper* 404: 1-32.

Scholz, John T. and Chen-Lung Wang. 2006. Cooptation or transformation? Local policy network and federal regulatory enforcement. *American Journal of Political Science* 50, no. 1: 81-97.

Segerson, Kathleen. 1988. Uncertainty and incentives for nonpoint pollution control. *Journal of Environmental Economics and Management* 15, no. 1: 87-98.

Shimshack, Jay P. and Michael B. Ward. 2005. Regulator reputation, enforcement, and environmental compliance. *Journal of Environmental Economics and Management* 50, no. 3: 519-540.

Stafford, Sarah L. 2002. The effect of punishment on firm compliance with hazardous waste regulations. *Journal of Environmental Economics and Management* 44, no. 2: 290-308.

Stafford, Sarah L. 2005. Does self-policing help the environment? EPA's audit policy and hazardous waste compliance. *Vermont Journal of Environmental Law* 6.

Storey, D. J.and P. J. McCabe. 1980. The criminal waste discharger. *Scottish Journal of Political Economy* 27, no. 1.

USEPA. 1995a. Incentives for self-policing: Discovery, disclosure, correction and prevention of violations. *Federal Register* 60, no. 246: 66705-66712.

________. 1995b. Interim clean water act penalty settlement policy.

Wooldridge, Jeffrey M. 2002. *Econometrics analysis of cross section and panel data*. Cambridge, Massachusetts: The MIT Press.

VITA

Vid Adrison was born in Padang, West Sumatera, Indonesia, on November 29th, 1974. He received a Bachelors degree of Economics from the University of Indonesia in 1999. In 1998, he was chosen to represent Indonesia in Asia Europe Foundation (ASEF) summer school in Reutlingen, Germany. After returning from the summer school, he was recruited to join the Institute for Economics and Social Research, Faculty of Economics, University of Indonesia (LPEM-FEUI). While working as a senior research assistant at LPEM-FEUI, he was also assigned as teaching assistant for several undergraduate courses during 1998-2001. The courses included intermediate macroeconomics, intermediate and advanced microeconomics, basic statistics and econometrics. During 1998-2001, he was involved in various research projects in LPEM-FEUI such as energy policy reform, a free trade zone comprehensive study, a natural resource revenue sharing study, and Indonesian economic, industry and finance analysis. He was also involved in various trainings held by LPEM-FEUI.

In 2001, he began his graduate study in economics at Georgia State University as a part of the USAID-GSU Indonesian masters program. After completing his Master's degree in Economics in 2002, he joined the Ph.D. program. The first three years of his doctoral study was co-funded by USAID and Georgia State. He worked as a graduate research assistant in the International Studies Program (ISP) from 2002. His research assignments in the ISP were mostly in the public finance area. Besides public finance, his research interests include environmental economics.

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