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Essays on Environmental Policies Under Incomplete Enforcement

Lirong Liu
University of Tennessee - Knoxville

To the Graduate Council:

I am submitting herewith a dissertation written by Lirong Liu entitled "Essays on Environmental Policies Under Incomplete Enforcement." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Economics.

William S. Neilson, Major Professor

We have read this dissertation and recommend its acceptance:

Mary Evans, Scott Gilpatric, Russell Zaretzki, Matthew N. Murray, Robert A. Bohm

Accepted for the Council:
Dixie L. Thompson

Vice Provost and Dean of the Graduate School

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Essays on Environmental Policies under Incomplete Enforcement

A Thesis Presented for

the Doctor of Philosophy Degree

The University of Tennessee, Knoxville

Lirong Liu

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Dedication

To my parents, Xuesi Liu and Zhenjie Sun, for their love, support and encouragement.

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This dissertation could not have been completed without a number of professors, among others that I worked with during my study at the University of Tennessee. I would like to take this opportunity to express my gratitude to them. Dr. William Neilson, who served as my advisor, led me through my dissertation writing with tremendous insights and knowledge. His influence went far beyond this dissertation and will be reflected in my future academic career. I sincerely thank him for his valued input. Dr. Mary Evans has been an excellent mentor that guided through my PhD study. Her encouragement, support and patience with me was instrumental to my work at the University of Tennessee. Dr. Scott Gilpatric inspired my original interests in theoretical research. I thank him for willingly spending time and talking with me, which produced numerous ideas for my research.

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ABSTRACT

Essay 1
In this paper I model the optimal monitoring and enforcement strategy when inspection capacity is fixed by budget or manpower constraints. I adopt a leverage enforcement structure that classifies firms into two groups with different enforcement intensities. Optimal monitoring and enforcement requires effective allocation of the fixed number of inspections to the two groups. In each period, a fixed number of firms are selected from each group for inspection, and those with the highest emissions are placed in the targeted group in which the inspection probability is higher. This transition structure induces rank-order tournaments among inspected firms. Once selected for inspection, the emissions of each firm are subject to a standard above which the firm pays a fixed penalty. I find that a regulator facing inspection capacity constraints should leverage the limited inspections by allocating more inspections to the targeted group. In addition, I show that targeting enforcement is generally superior to static enforcement. This is in accordance with findings in the literature. These results are consistent over different ranges of regulatory parameters.

Essay 2
We model the optimal design of programs requiring firms to disclose harmful emissions when disclosure yields both direct and indirect benefits. The indirect benefit arises from the internalization of social costs and resulting reduction in emissions. The direct benefit results from the disclosure of previously private information which is valuable to potentially harmed parties. Previous theoretical and empirical analyses of such programs restrict attention to the former benefit while the stated motivation for such programs highlights the latter benefit. When disclosure yields both direct and indirect benefits, policymakers face a tradeoff between inducing truthful self-reporting and deterring emissions. Internalizing the social costs of emissions, such as through a Pigovian tax, will deter emissions, but may also reduce incentives for firms to truthfully report their emissions.

Essay 3
This paper investigates the compliance behavior of firms simultaneously regulated under multiple environmental programs. Three possible relationships among regulatory programs are considered: complementarity, substitution and independence. I develop a theoretical model of firm decision making that shows the potential for interrelationships among regulations. I propose an indirect test of the theoretical results and implement the empirical model using data on compliance with Resource Conservation and Recovery Act (RCRA) for facilities in Michigan that are regulated under both RCRA and Clean Air Act (CAA). Results show evidence of positive cross program effects such that an increase in measures of CAA enforcement intensity lead to increased firm compliance with RCRA; the empirical results are consistent with a complementary relationship between the two programs. Thus coordination is required for optimal monitoring and enforcement strategies.

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CHAPTER I GENERAL INTRODUCTION

Facing constrained budgets, a regulator is not able to monitor every firm and enforce compliance continuously. Incomplete enforcement means it is necessary to optimally allocate the limited resources for monitoring and enforcement. Information disclosure programs or other enforcement strategies such as targeting may help reduce enforcement costs. The first two chapters of my dissertation address the above regulation issues under incomplete enforcement. In addition, the enforcement of various environmental programs may also interact for the same regulated firms such that the enforcement of one program have positive, negative or zero spillover effects on firm compliance with other programs. The third chapter endeavors to uncover and determine the nature of the spillover effects by inspecting facilities regulated under multiple programs.

The first essay addresses optimal environmental regulation with fixed inspection capacity. I adopt the leverage enforcement structure that classifies firms into two groups with different inspection probabilities. Previous literature on leverage enforcement assumes that the inspection probability of one firm is independent of that of another firm. This assumption can no longer hold if the number of inspections in each period is fixed. My goal is to model a regulator's policy choice as optimally allocating the fixed number of inspections in the two groups. It is shown that allocating more inspections in the targeted group is generally optimal. This result is consistent across different ranges of enforcement parameters, such as the number of inspections, the penalty for violation, the fixed inspection costs, and the standard. In addition, I show that targeting enforcement is generally superior to the static enforcement where inspections are randomly allocated across all firms. This conclusion is in accordance with previous literature.

The second essay is a joint work with Drs. Mary Evans and Scott Gilpatric. We analyze the benefits of information disclosure programs when there are competing regulatory objectives: deterring emissions and inducing truthful reporting. While the deterrent effects of such programs have been explored extensively, the direct benefits of information disclosure remain unexplored. Emissions revealed through self-reporting requirements are less damaging to the society than those undisclosed because impacted parties can take precautionary and mitigating actions. Our goal is to justify and model these direct benefits of self-reporting in social welfare analysis and investigate the optimal regulatory parameters. In this paper, we model the optimal design of regulatory policies that requires firms to self-report emissions when disclosure yields both direct and indirect benefits. The regulator chooses the environmental tax and the probability that a firm will be audited to minimize the social cost of emissions. In this context policymakers face a tradeoff between inducing truthful reports and deterring emissions. Levying a heavy environmental tax helps deter excess emissions but also create incentives for the firm to reduce reporting to evade taxes.

In the third essay, I investigate firm compliance when it is regulated under multiple environmental programs. The externalities that one program imposes on other programs can be positive, negative or zero. Based on a theoretical model developed in the paper, I indirectly test the existence and nature of the spillover effects for facilities in Michigan that are regulated under both the Resource Conservation and Recovery Act (RCRA) and Clean Air Act (CAA). Empirical results show evidence of positive cross-program effects such that an increase in measures of CAA enforcement intensity lead to increased firm compliance with RCRA; the empirical results are consistent with a complementary relationship between the two programs. In addition, it is confirmed that enforcement actions exert positive effects on compliance within the same program.

CHAPTER II ESSAY 1: CONTROLLING POLLUTION WITH FIXED INSPECTION CAPACITY

1.1 Introduction

The Environmental Protection Agency (EPA) is responsible for implementing environmental regulations in the United States. It has ten regional offices, each of which, cooperating with the states, performs inspections to enforce compliance with environmental laws and regulations within its responsible areas. However, constrained fiscal budgets and limited workforce make it impossible for the EPA and the states to inspect all polluting firms every year. In this paper, I consider a dynamic model of monitoring and enforcement in which a regulator faces fixed inspection capacity. The regulator's objective is to determine the enforcement strategy that achieves the optimal abatement effort levels of firms. I adopt the leverage enforcement structure, also known as state-dependent enforcement or targeting enforcement, that classifies firms into two groups with different enforcement intensities. It has been shown that leverage enforcement is superior to static enforcement in terms of firm compliance or emission levels under certain conditions (see Harrington, 1988; and Harford, 1991).[1] In my model, optimal enforcement requires effectively allocating these inspections to the two groups.

According to Enforcement and Compliance History Online (ECHO) data,[2] only about 40% of the firms registered with hazardous waste management programs in EPA Region 4[3] were inspected at least once from September 2006 to August 2007. The ECHO data also reveal that during the same period, about half and 3/4 of firms in EPA Region 4 registered with air programs and water programs, respectively, were inspected at least

[1] These conditions include: (a) there is no asymmetric information; (b) the desired compliance rate is not extremely high; (c) firms are homogeneous in their abatement cost.
[2] The data can be found at http://www.epa-echo.gov/echo/.
[3] EPA Region 4 includes Alabama, Florida, Georgia, Kentucky, Mississippi, North Carolina, South Carolina, and Tennessee.

once. The inspection capacity constraints give rise to incomplete enforcement. In such circumstances, it is crucial that the limited monitoring and enforcement resources are optimally allocated. The 2004 Strategy Plan of Region 4 states, "the vast number of regulated facilities in the region dictates that Region 4 prioritize where we devote our limited resources…the region has far more areas of critical concern than resources" (chapter 2, goal 5, p. 1). Therefore, I propose that a targeting enforcement strategy should be considered as a means of allocating the fixed number of inspections.

The targeting model of income tax enforcement was first introduced into the environmental regulation literature by Harrington (1988). In his model, firms are placed into two groups according to their compliance status. The inspection probabilities and sanctions are higher in the targeted group than those in the other group. Firms in the non-targeted group will be placed in the targeted group if they are found in violation, and cannot move back until they are found in compliance. Harrington shows that the leverage between groups leads to partial compliance from firms that would have no incentive to comply otherwise. Russell (1990) considers a similar model in the presence of measurement errors. He concludes that a three-group model provides savings on enforcement costs even with imperfect monitoring. Using a more general social objective function, Harford (1991) shows that the addition of differentiated pollution standards yields lower social costs. More recently, Friesen (2003) suggests that moving firms randomly into the targeted group may further reduce monitoring costs. Other issues that are addressed within the framework of targeting enforcement include asymmetric information (Raymond, 1999), limitations on the superiority of state-dependent monitoring (Harford and Harrington, 1991), and self-reporting (Hentschel and Randall, 2000).

The targeting models mentioned above share one common feature—the regulator's enforcement strategy simplifies to the regulation of one representative firm with the consequence that the inspection probability of one firm is independent of that of another firm. This simplification cannot hold for a regulator facing fiscal or manpower constraints. For example, when the majority of firms end up in the targeted group, it is impossible for the regulator to target all these firms. When few firms are in the targeted group, having enforcement resources idle is neither efficient nor desirable from the regulator's viewpoint. The fluctuations in the regulator's enforcement costs stem from the assumption that the sizes of the groups vary while the inspection probabilities in the two groups are fixed. Thus the actual total number of inspections needed differs from one period to the next. I depart from the previous literature and assume that the number of inspections is fixed in any given period. By appropriately allocating the fixed number of inspections, the regulator targets firms in one of the groups with a higher inspection probability. Under such a targeting enforcement scheme, I investigate the optimal leverage of the fixed number of inspections.

To ensure fixed group sizes, the number of firms inspected in each group in the current period should be equal to the number of firms placed in that group in the next period. Making a firm's transition probability from one group to the other dependent upon its compliance status no longer satisfies that requirement. Thus I assume the inspected firms compete with each other for the chance of being placed in the non-targeted group. Of all inspected firms, if m of them are selected from the targeted group, then the m firms with the highest emissions in the current period are placed in the targeted group in the next period.

The structure of this transition process induces rank-order tournaments among inspected firms. Tournament models have been widely used in the study of labor economics and other related fields since the pioneering work by Lazear and Rosen (1981).[4] The tournaments induce competition among firms for the chance of being placed in the non-targeted group, and this competition may give firms an extra incentive to reduce emissions beyond those induced by enforcing the emission standard alone. This feature differs from other leverage enforcement models where firms do not interact with each other. In other models, the transition probability of a firm is determined solely by its own compliance status. In my model, whether a firm switches from one group to the other depends on the environmental performance of all the inspected firms. Even though a firm is in compliance, it may still be put in the targeted group if its emissions are above enough other firms' emissions.

This paper is organized as follows. In Section 1.2, I develop a theoretical model of firm behavior and a regulator's targeting enforcement strategies. I derive the optimal choices of abatement effort for individual firms in each group and discuss the regulator's enforcement objective—determining the optimal allocation of inspections to each group. Since the choice variables for the regulator can only be integers, the traditional first order conditions cannot be used to generalize the optimal enforcement strategy. Theoretically comparing the results from all possible inspection allocations and group sizes can be used

[4] The applications of tournament models in environmental economics are quite limited. See Govindasamy, Herriges, and Shogren (1994), and Franckx, D'Amato and Brose (2004) for examples.

to determine the optimal enforcement strategy. However, the complexity of the model makes it impossible to find a general solution for the purpose of comparison. Therefore, I use simulations to establish the patterns of the optimal enforcement strategy in Section 1.3. Concluding comments are given in Section 1.4.

The main result of the model is that a regulator facing constrained monitoring budgets or manpower should leverage the limited inspections and allocate more inspections to the targeted group than to the non-targeted group. However, maximum leverage by allocating all but one inspection to the targeted group does not necessary lead to optimal abatement effort. According to the simulations, the optimal number of inspections in the targeted group usually lies between half and three quarters of the total number of inspections.

1.2 The Model

1.2.1 Firm behavior under dynamic enforcement

Consider a total of n homogenous firms with identical abatement functions and abatement cost functions. Every firm faces a standard, s, above which excess emissions are penalized with a fixed fine, γ. Denote a firm's abatement function as $g(e) = T - e$, where T is the firm's total emissions, and e is the firm's abatement effort. Let the firm's intended emissions be $z = T - e + \varepsilon$, where ε is a random error term that is independently and identically distributed across all firms with mean zero, density function $f(\varepsilon)$ and distribution function $F(\varepsilon)$. The random errors may represent measurement errors or other factors affecting a firm's emissions that are beyond the firm's control. Thus the probability that a firm with abatement effort e is found out of compliance is

$$Q(e) = \Pr(z > s) = \Pr(g(e) + \varepsilon > s) = 1 - F[s - g(e)]. \quad (1.1)$$

When a firm is inspected, it also incurs a fixed cost, denoted α. The fixed cost represents the pecuniary and nonpecuniary costs borne by the firm other than the abatement costs, such as those associated with paperwork preparations for inspection.

The firm's total cost in a single period can be written as

$$\mu = c(e) + \rho[\gamma Q(e) + \alpha], \quad (1.2)$$

where $c(e)$ is the abatement cost function, and ρ is the probability that the firm is inspected.

In a targeting enforcement regime, the n firms are classified into two groups, 1 and 2, where group 2 is the targeted group with tougher enforcement. To keep the model simple, I assume that the only difference in the treatment of the two groups is the probability of inspection, which is higher in group 2 than in group 1. The penalty for violation, the fixed inspection cost and the standard are the same for all firms regardless of their group status.

Let n_1 and n_2 denote group sizes, where $n_1 + n_2 = n$. In each period, a total of m ($3 \le m < n$)[5] firms are inspected, with m_1 of them randomly selected from group 1 and m_2 from group 2. The number of inspections m is exogenously fixed by the inspection capacity. Note that $\rho_1 = m_1 / n_1$ and $\rho_2 = m_2 / n_2$ are effectively the inspection

[5] Here m is restricted to be greater or equal to 3 because otherwise leverage between groups is impossible.

probabilities in each group. So $\rho_1 < \rho_2$ must hold for group 2 to be the targeted group. Of the $m_1 + m_2$ inspected firms, the m_1 firms with the lowest emissions in period t are placed in group 1 for period $t+1$, and the m_2 firms with the highest emissions are placed in group 2. If a firm is not inspected in a specific period, it stays in the same group.

The structure of this transition process induces rank-order tournaments among inspected firms. In a tournament, the probability that a firm wins is a function of its own effort level, as well as the effort levels of other inspected firms. Even if a firm is found to be in compliance with the standard, it may nevertheless end up in group 2 in the next period if its emissions are among the m_2 highest. Similarly, a non-compliant firm may be placed in group 1 if the emission levels of other firms turn out to be higher. In equilibrium, firms in the same group should exert the same optimal effort. So the probability that an inspected firm from group i, $i = 1,2$, ends up in group 2 in the next period can be denoted as $p_i(e_i, e_{-i}, e_j)$, where e_i and e_{-i} are the effort levels of this specific firm and other firms in the same group, respectively, and e_j is the effort level of firms in the other group. As higher effort raises the probability that a firm wins in the tournament, it follows that $\partial p_i(e_i, e_{-i}, e_j)/\partial e_i < 0$.

For any firm in this regulation scheme, its decision is choosing the level of abatement effort to minimize the expected present value (EPV) of the total cost in all periods. The firm's decision actually follows a Markov chain process. The transition matrix that describes the probabilities of firms moving from one group to the other is shown in Table 1.1 in appendices (the arguments in p_i's are omitted).

Let V_{it} denote the EPV of the total cost for a firm starting from group i in period t. It follows that,

$$V_{1t} = \mu_{1t} + \delta(1 - \rho_{1t} p_{1t})V_{1(t+1)} + \delta\rho_{1t} p_{1t} V_{2(t+1)}, \tag{1.3}$$

$$V_{2t} = \mu_{2t} + \delta\rho_{2t}(1 - p_{2t})V_{1(t+1)} + \delta[1 - \rho_{2t}(1 - p_{2t})]V_{2(t+2)}, \tag{1.4}$$

where δ is the discount factor. Basically, these equations state that the EPV of the total cost for a firm is the sum of its current period cost and the discounted EPV of the total cost starting from the next period. The firm then chooses the optimal effort levels to minimize V_{it}. Assuming interior solutions, the first order condition for this optimization problem is,

$$\frac{\partial \mu_i}{\partial e_i} = -\delta(V_2 - V_1)\rho_i \frac{\partial p_i}{\partial e_i}. \tag{1.5}$$

According to the ergodic theorem of Markov chains, the optimal strategy for a firm is stationary (Harrington, 1988; Kohlas, 1982). Therefore, the notation for time, t, is dropped from the first order condition above.

Notice that $V_2 - V_1$ is actually the cost differential between firms starting from group 1 versus group 2, and it can be solved from equations (1.3) and (1.4) to be,

$$V_2 - V_1 = \frac{\mu_2 - \mu_1}{1 - \delta\,[1 - \rho_2(1 - p_2) - \rho_1 p_1]} > 0.$$

In equation (1.5), the only negative term on the right hand side is $\partial p_i / \partial e_i$. It follows that $\partial \mu_i / \partial e_i^* > 0$. For a convex cost function μ_i, this implies that e_i^* is higher than the optimal effort level under static enforcement $\tilde{e}_i$, which satisfies $\partial \mu_i / \partial \tilde{e}_i = 0$. In fact, this condition reveals one of the advantages of targeting enforcement: firms in both groups have an extra incentive to increase abatement effort levels. By differentiating the EPV of the total cost in the two groups, targeting enforcement creates so-called leverage effects on a firm's emissions and abatement decisions. Firms in both groups, anticipating the threat of being in group 2 and facing the higher inspection probability in the next period, exert more effort in response.

Based on the set-up of the model, it is easy to show that $e_2^* > e_1^*$ must hold. In fact, this is an expected result of targeting enforcement. When a firm is in group 2, it is at a disadvantage as the EPV of its total cost is higher than the EPV of the total cost for firms in group 1. Therefore, this firm should exert more effort to secure a higher probability of winning in the tournament. On the other hand, firms in group 1 face a lower inspection frequency and exert less effort.

Equation (1.5) characterizes the optimal effort level of the firms in each group, $e_i(m_i, n_i, \gamma, \alpha, s)$. The left-hand side of the equation is the marginal change in the current period cost. The right -hand side represents the marginal decrease in the EPV of the total cost as a higher e_i reduces the probability of being in group 2 in the next period. Even though it means incurring higher cost in the current period, a firm is nevertheless willing to exert more effort now in exchange for the expected savings as a result of decreased probability of facing tougher enforcement in the future. The optimal effort level for any firm should be the one that equates the marginal change in one-period cost to the discounted savings on the expected future cost.

1.2.2 Regulator's monitoring and enforcement strategies

Now consider a regulator who is responsible for monitoring the n firms and enforcing the standard. The potential policy instruments at its disposal include the inspection frequency, which is determined by the allocation of inspections, the standard and the penalty for violation.[6] However, to emphasize the structure of enforcement with fixed inspection capacity, I only consider the case in which the inspection frequency is the only choice variable for the regulator.

Recall that the inspection probabilities are defined as $\rho_1 = m_1 / n_1$ and $\rho_2 = m_2 / n_2$. The regulator's objective is to optimally allocate the inspections to each group and determine the sizes of the two groups to minimize the total emissions of all firms, with the assumption that this minimum total emission level is not below the social optimal level.[7] Given that the abatement function $g(e)$, is a decreasing, linear function common to all firms, minimizing total emissions is equivalent to maximizing total effort. Formally, the regulator's problem is to,

$$\underset{m_i, n_i}{Max} \quad n_1 e_1^* + n_2 e_2^*$$

As mentioned previously, the traditional optimization tools—the first order conditions with respect to the choice variables—do not apply here. Since the choice variables can take integer values only, the derivatives of the objective function with respect to these variables do not exist. Comparing the total effort from all possible

[6] Although the regulator may also have some influence on the fixed cost borne by the inspected firms and the variance of the error term, it is more likely that these parameters are beyond the control of the regulator.
[7] Theoretically the social optimal emission level is determined by the social benefits and social costs of emissions, which, in turn, determine the standard. Viscusi and Zeckhause (1979) and Jones (1989) address the issue of standard setting under incomplete enforcement. However, the discussion of environmental standard is beyond the scope of this paper. So I simply assume that the minimum total emissions from the optimal inspection strategy do not exceed the social optimal emission level so that the optimal leverage is desirable.

allocations to determine the optimal enforcement strategy is not feasible due to the complexity of the firm's problem. Therefore, I briefly discuss some intuitive inferences here. In the next section I use simulations to explore the characteristics of the optimal allocation.

To simplify the exposition, I restrict attention to the case in which the number of firms in group 2 is equal to the number of inspections in that group. In other words, firms in group 2 face an inspection probability of one. This makes $n_2 = m_2$, $n_1 = n - m_2$, and $m_1 = m - m_2$. So it reduces a problem with two choice variables to a problem with one choice variable, m_2. The simplifying assumption is also consistent with the concept of optimal leverage to some extent. According to the comparative statics results derived in Harford (1991), increasing the inspection probability and the penalty for violation in the targeted group leads to lower emission levels from firms in both groups. As the only difference between staying in the two groups in this model is the frequency of inspection, a higher ρ_2 is desirable. With this restriction, the regulator chooses m_2 to maximize the total abatement effort.

Now consider a regulator allocating 10 inspections among 100 firms. To describe the trends of firm effort under different policy choices, I start with an extreme case where there is only one inspection in group 2; that is, $m_2 = n_2 = 1$, $m_1 = 9$ and $n_1 = 99$. In the tournament, nine group 1 firms and one group 2 firm are competing in period t for the chance of being placed in group 1 in period $t+1$. Basically, group 2 firms can be regarded as strong competitors as their abatement effort is high; group 1 firms are relatively weak competitors with lower abatement effort. If the regulator increases m_2 to

2, the firms in group 2 will increase their effort due to two forces. The first lies in the leverage effect. Allocating all inspections but one to group 1 results in the highest possible inspection probability in group 1 under leverage enforcement, with $\rho_1 = 0.09$. When $m_2 = 2$, the inspection probability in group 1 decreases to $\rho_1 = 0.08$, which makes the cost differential between the two groups become larger. So it is optimal for group 2 firms to abate more in order to raise their chance of winning in the tournament. The second force is a result of the competition effect. Competing with nine other group 1 firms, the only group 2 firm has a high chance of winning in the tournament. After the change in allocation, a group 2 firm has to compete with the other group 2 firm and eight group 1 firms. As a result, intensive competition drives up the effort of group 2 firms. The two forces also impose similar effects on the effort of firms in group 1. Yet the overall change in the abatement effort of group 1 firms may not necessarily increase. The reduced inspection probability in group 1 leads to a lower expected penalty for violation, which dissipates the incentive for group 1 firms to reduce emissions. Therefore, the overall change in the effort of group 1 firms is generally ambiguous.

Another extreme case is to allocate all but one inspection to group 2. This means $m_2 = n_2 = 9$, $m_1 = 1$ and $n_1 = 91$. Now the competition for being placed in group 1 in the next period is among one group 1 firm and nine group 2 firms, and only the firm with the lowest emission level wins in the tournament. If the regulator reduces m_2 to 8, two changes in the regulatory scheme affect the effort levels: (1) the inspection probability in group 1 increases from 0.01 to 0.02 and the cost differential decreases with it; (2) firms in the tournament compete with one more group 1 firm and one fewer group 2 firm, and the two firms with the lowest emission levels win, so the competition becomes less intensive. For group 1 firms the smaller cost differential and less competition means reducing abatement effort is optimal, but the higher inspection probability induces group 1 firms to increase effort. Overall, the change in the effort of group 1 firms is ambiguous. On the other hand, group 2 firms lower abatement effort with the smaller cost differential and the reduced competition. But as a result of the interaction among firms, group 2 firms may still exert more effort in response if group 1 firms increase their effort.

In summary, assigning only one inspection in group 2 may not be optimal because reallocating one inspection from group 1 to group 2 generates more effort from firms in group 2. Although the effort of group 1 firms may decrease, placing one more firm in group 2 may still be optimal if increased in the effort from group 2 firms offsets tat decrement. On the other hand, increasing inspections in group 2 to the maximum may not always induce the most effort from all firms. The optimal enforcement strategy depends on the marginal changes in firm effort when the allocation changes.

1.2.3 The benchmark: static enforcement

To set a benchmark for comparison, I briefly outline a static model of enforcement. In a static model, where m of the n firms are randomly selected for inspection in each period, a representative firm chooses the optimal abatement effort to minimize its one-period cost. Specifically, a firm's problem is to,

$$\underset{e}{Min} \qquad \mu = c(e) + \frac{m}{n}\left[\gamma \; Q(e) + \alpha\right],$$

where γ, α, $c(e)$ and $Q(e)$ are defined as before. The optimal choice of effort, $\tilde{e}^*$, is determined implicitly by,

$$c'(\tilde{e}^*) = -\frac{m}{n}\gamma\, Q'(\tilde{e}^*) \tag{1.7}$$

Equation 1.7 suggests that under static enforcement, a firm should choose the abatement level such that the marginal abatement cost is equal to the marginal expected benefit, that is, the marginal decrease in the expected penalty

1.3 Simulations

To characterize the optimal enforcement strategy, I use numerical techniques to show the allocations of inspections that result in the maximum total effort of all firms. First, the cost of abatement effort function is specified as $c(e) = we^2$. Second, for the distribution assumptions of the error term, I consider both the normal distribution and the uniform distribution. A desirable feature of a normal distribution with mean zero is that the peak of its density function occurs at the point where the revealed emissions through inspection are equal to the firm's intended emissions. To test the robustness of the model, I also analyze simulations under the assumption of uniformly distributed error terms.

For the parameters in the model, I assign the following specific numbers in the baseline examples (Table 1.2).

According to empirical statistics, the abatement costs that firms incur are fairly high compared with penalties and other sanctions.[8] Therefore, the coefficient in the abatement cost function, w, is set higher than other parameters.

1.3.1. Normally distributed errors

Assuming that the random errors follow a normal distribution with mean zero and variance σ^2, I conduct four sets of simulations in this sub-section. First, I establish a baseline numerical example with a single set of parameters. By comparing the total effort of firms from all possible inspection allocations, I determine the optimal allocation for this specific set of parameters. Then I use the baseline parameters as a starting point and change the four key parameters, s, γ, α, and σ^2. This analysis serves two purposes: (1) it is used to check if the results of optimal allocation from the first example continue to hold when parameters change; (2) it shows the effects of changing parameters on the optimal effort of individual firms and the total effort of all firms. In the third set of simulations, I increase the total number of inspections and the total number of firms being regulated. Last but not least, I fix the total number of firms and increase the number of inspections, one at a time. The last two sets of examples are used to check the robustness of the results for different inspection capacities and to characterize the pattern of the optimal inspection allocations.

[8] For example, Pollution Abatement Costs and Expenditures Survey (1999) reveals that the total abatement cost across all industries amounts to $5.8 billion. The total payment to the government, including permits/fees and charges, fines/penalties and other, is $1.0 billion according to the same survey.

In the first set of examples, I assume that the enforcement capacity for the regulator allows 4 inspections out of 10 firms. The standard deviation of the error term is set at 0.45. The equilibrium effort of firms in each group and the total effort of all firms are shown in Table 1.3.

Several patterns can be observed in Table 1.3. First, the random inspection strategy without leverage (corresponding to $m_2 = 0$) induces the least total effort. Therefore targeting is superior to static enforcement. Second, if an inspection is moved from group 1 to group 2, the effort of each group 2 firm increases while the effort of group 1 firms may increase or decrease. When m_2 increases, it creates more competition among firms in both groups, because a group 1 firm is replaced by a group 2 firm in the tournament. In this example, the effort of a group 2 firm increases steadily when m_2 increases from 1 to 3. However, group 1 firms may exert less effort because the increase in m_2 lowers the inspection probability in group 1 (shown in the last column in Table 1.3). Thus the overall change in the effort of group 1 firms depends on the relative magnitude of two effects: increased competition and decreased inspection probability. For example, the effort of each group 1 firm increases when m_2 increases from 1 to 2 because the effect of the increased competition outweighs that of the decreased inspection probability. When m_2 increases from 2 to 3, group 1 firms lower their effort, since the effect of the decreased inspection probability dominates. Although firms in group 1 decrease their effort when m_2 increases from 2 to 3, setting $m_2 = 3$ yields the highest total effort because the increased effort by group 2 firms ($n_2 e_2$) outweighs the decreased effort by group 1 firms ($n_1 e_1$).

The key result from this example is that the regulator minimizes total emissions when it leverages its limited inspections by allocating most of them to the targeted group. Next, I change the four key parameters in the model, including s, γ, α, and σ^2, to test the robustness of this result.

Figures 1.1-1.4 (in appendices) show the results of all possible inspection allocations when s, γ, α, or σ^2 changes. Each figure consists of three graphs, showing the total effort of all firms, the effort level of individual firms in group 1 and group 2, respectively. A straight line representing the difference between T and s is added to the last two graphs in each figure. In expectation, a firm is in compliance if its effort is sufficient to eliminate the excess emissions above the standard (in the absence of random errors), which is $T-s$. Thus, effort levels above this line suggest that firms are over-complying in expectation. That is, without the random errors, a firm's intended emissions are below the standard. Similarly, effort levels below this line imply under-compliance in expectation.

Several results can be concluded from Figures 1.1-1.4. First of all, over the ranges of the four parameters, inspecting three firms in group 2 and one firm in group 1 ($m_2 = 3$) always results in the highest total effort in these examples. Therefore allocating most of the resources to monitoring firms in group 2 is an optimal enforcement strategy for the case of 4 inspections. Second, firms in group 1 exert much less effort than firms in group 2. It is an expected result of leverage since firms in group 2 face tougher enforcement. Third, the trend of the total effort is dominated by the changes in the effort of group 2 firms. This is a consequence of the previous result since the effort level of any single firm in group 2 is much higher than the effort level of every group 1 firm. Last, the total effort from the static enforcement ($m_2 = 0$) is always lower than the total effort level from targeting enforcement. Even a small leverage ($m_2 = 1$) adds incentives for firms to increase effort.

As mentioned earlier, firms are over-complying with the standard in expectation if their effort levels are above the straight line. According to the graphs in Figures 1.1-1.4, firms in group 1 almost never over-comply. Instead, they under-comply in expectation substantially. An exception is: group 1 firms over-comply when the standard is equal to a firm's actual emissions. The expected compliance status of firms in group 2 depends on the magnitude of the parameters. Specifically, firms in group 2 tend to over-comply in expectation when the penalty for violation and the fixed inspection cost are high, as a higher penalty or inspection cost induces more effort. The firms in group 2 also over-comply when the standard is high. Notice that when the standard is equal to a firm's actual emissions, firms in both groups over-comply despite that the expected penalty is zero. These over-complying behaviors of firms are driven by their intention to avoid or reduce the expected inspection costs.

The numeric examples shown in Figures 1.1-1.4 also describe the trends in the effort of individual firms when the parameters changes. Overall, the effort of firms in group 2 is more responsive to the changes in parameters according to the shapes of the curves. The four key parameters, s, γ, α, and σ^2, are related to the inspection probability: the higher the probability, the more likely that a firm incurs sanctions or inspection costs and the more likely that a firm is involved in the tournament. Since firms in group 2 are inspected in every period, changes in these parameters have more effect on their choices of effort.

In Figure 1.1, the effort of group 1 firms increases with s, and the effort of group 2 firms originally increases with s and then decreases when s approaches a firm's total emissions, T. Although one would expect that relaxing the standard leads to a lower effort level in general, in this model the changes in a firm's effort actually depend on the distribution of the error term, the firm's expected compliance status, and the effect of the standard on $V_2 - V_1$. Under the assumption of a normally distributed error term with mean zero, the derivative of the marginal probability of violation, $Q''(e_i^*) = f'[s - g(e_i^*)]$, is positive if $s - g(e_i^*)$ is below zero. This implies when the firm's expected emissions, $g(e_i^*)$, exceed the standard, relaxing the standard makes the probability of violation decrease at an increasing rate with more effort. So firms are willing to exert more effort to take the advantage of the decreased expected penalty. If a firm's expected emissions are below the standard, increasing the allowed emissions only results in lower effort, because exerting more effort only reduces the probability of a violation at a decreasing rate.

Figures 1.2-1.4 show that γ and α are positively related to the effort level while σ^2 exhibits a negative relationship with the effort level. First, γ represents sanctions on a firm's violation of the standard, no matter to which group the firm belongs. As γ increases, the expected penalty for any given level of effort is higher. With an unchanged cost of effort function, the firm should increase effort to eliminate the increase in the expected penalty caused by the higher γ. Meanwhile, changing γ also affects $V_2 - V_1$. If the cost differential also increases when γ increases, firms in both groups increase effort. Next, whether a firm incurs the fixed inspection cost depends on the probability that the firm is inspected. Increasing α effectively magnifies the leverage of targeting, because with unchanged inspection probabilities the cost differential between the two groups becomes larger. Thus the benefits of staying in group 1 are more significant and firms in both groups increase their optimal abatement effort. Third, although the variance of the error term is not explicitly involved in the equations, the intuition is straightforward. According to the tournament literature, when the randomness associated with the measurement of players' performance is small, the players tend to exert more effort. Similarly, a smaller variance means that a firm's intended emissions, $g(e_i^*)$, are more accurately measured. As a result, the firm increases its effort.

Those previous sets of simulations show that allocating more inspections to the targeted group is optimal. For an inspection capacity with $m = 4$, the optimal allocation is $m_2 = 3$. The three inspections allocated to group 2 can be interpreted as $1 + m/2$, $3m/4$, or $m - 1$. The simple example of allocating 4 inspections are not sufficient to draw a conclusion whether the optimal number of inspections in group 2 should be around $m/2$, $3m/4$ or $m-1$ for higher values of m. In the next set of simulations, I address this issue and check the consistency of other relevant results in the previous analysis as well. It is assumed that 10 out of 100 firms are inspected in each period. The standard deviation of the error term is set at 0.8 to ensure the existence of solutions.[9]

[9] The existence of solutions requires that the variance is sufficiently large. See Lazear and Rosen (1981), footnote 2, p. 845.

Under these assumptions, I first set the baseline for the example of 10 inspections and then change the four enforcement parameters, s, γ, α, and σ^2.

The optimal effort of individual firms and the total effort in the baseline example are shown in Table 1.4. As m_2 increases, e_1^* increases gradually until $m_2 = 5$, after which e_1^* begins to fall. Similarly, e_2^* and the total effort both increase with m_2 until m_2 reaches 7, then e_2^* and the total effort decrease. The intuition behind these patterns is similar to that in the example with 4 inspections. Focusing on the total effort, it is clear that allocating $m-1=9$ inspections to group 2 is not optimal. The optimal allocation is $m_2 = 7$, which is between $m/2$ and $3m/4$. Also, consistent with the previous results, the random inspection strategy without leverage results in the lowest total effort.

To present the patterns of firm effort with the changes in allocation, the same baseline results are shown in Figure 1.5. In comparison, the effort levels of group 1 firms are extremely low and firms in group 2 exert much higher effort, especially when 6 or 7 inspections are allocated to that group. Consequently, the changes in the total effort are closely related to the changes in the effort of group 2 firms.

Next, I change the enforcement parameters in the example of 10 inspections to examine the consistency of the optimal allocations and the effects on the effort of individual firms. Figure 1.6 shows the total effort associated with the optimal inspection allocations when s, γ, α, or σ^2 change. The effort levels of individual firms in each group are shown in Appendix 1.A.

When the enforcement parameters change, the optimal enforcement strategy generally occurs when the regulator allocates 6 or 7 inspections to group 2. Specifically, inspecting 7 firms in group 2 is optimal for higher γ and α, or lower s and σ^2 (the numbers in the graphs indicate the optimal number of inspections in group 2); otherwise, allocating 6 inspections to group 2 is optimal. The shifts in the effort of group 1 firms in the graphs of s, γ, α and σ^2 (Appendix 1.A) reflect this change in the optimal inspection allocation.

The relationships between the total effort and the four parameters s, γ, α, and σ^2 presented in Figure 1.7 largely confirm the results from the first set of examples. While increasing s and σ^2 reduces total effort, higher γ and α induce more total effort. Other similar results include: (1) the optimal effort of firms in group 1 is substantially lower than that of firms in group 2; (2) the shape of the total effort curve is closely related to the shape of the effort curve of the group 2 firms.

According to the numerical analyses of 4 inspections and 10 inspections, the optimal number of inspections in group 2 seems to lie between $m/2$ and $3m/4$. To further confirm this property, it is worthwhile examining the optimal inspection allocations when the number of total inspections takes other integers between 4 and 10, while holding the total number of firms constant. The next set of examples fulfills this purpose.

In the last set of examples, the total number of firms is fixed at 25, 50, and 100, respectively, and the number of inspections is increased from 4 to 10. The standard deviation of the random error term is still 0.8. Detailed results are shown in Tables 5-7. The comparison among the bold numbers within each table reveals that increasing the number of inspections induces more total effort from the optimal enforcement when the total number of firms is held constant. So the extra inspection capacity is desirable for the regulator. Meanwhile, allocating more inspections to group 2 remains to be optimal. When the total number of inspections is small, inspecting only one firm in group 1 and putting all other inspections in group 2 results in the maximum total effort. Yet, when extra budget allows one more inspection, it is not always optimal to allocate this extra inspection to group 2. Whether the regulator should put the extra inspection in group 1 or 2 depends on the marginal change in the effort of firms in each group ($n_i e_i^*$). For example, with 7 inspections out of 25 firms, the optimal allocation is $m_2 = 6$, and the effort levels of firms in group 1 and 2 are 0.0014 and 0.0854, respectively. When the number of inspections increases to 8 and the allocation changes to $m_2 = 7$, the effort levels of firms in group 1 decrease by 0.0002 and firms in group 2 by 0.02. However, for the allocation $m_2 = 6$ with 8 total number of inspections, the effort levels of firms in group 1 and 2 increase to 0.0042 and 0.1712, respectively. Thus inspecting 2 firms in group 1 and 6 firms in group 2 is optimal for a total of 8 inspections. Overall, this set of examples confirm that the optimal number of inspections in group 2 should be above $m/2$ and below $3m/4$.

1.3.2 Firms' Best Responses

In the theoretical model developed in this paper, the inspected firms compete with each other in tournaments. The interactions among firms can be summarized using best response curves, which describe one firm's best response to the changes in the effort of another firm. In this section, I discuss the best response curves for the optimal allocation, $m_2 = 3$, when there are 4 inspections.

Figure 1.7 shows: (1) the best response between the only group 1 firm and one of the group 2 firms while holding the other two group 2 firms' effort at their equilibrium levels; (2) the best response between two group 2 firms while holding the group 1 firm and the third group 2 firm at their respective equilibrium levels.

In Figure 1.7 (a), the best response curve of the group 1 firm is fairly flat with a slightly decreasing trend, indicating that the changes in the effort of one group 2 firm have little impact on the group 1 firm. The best response curve of the group 2 firm exhibits an apparent decreasing trend, except at the beginning where the curve is almost flat. Since the effort of the other two group 2 firms is fixed at their equilibrium levels, the intersection of the two curves represents the equilibrium effort levels of the group 1 firm and the group 2 firm in this numerical example. Around the equilibrium point, the effort of the group 1 firm decreases with that of the group 2 firm, and vice versa. The best response curves of the two group 2 firms, shown in Figure 1.7 (b), are symmetric with the same pattern: increasing at the beginning and then decreasing. The intersection of the two curves is the equilibrium effort level of the group 2 firms, around which the effort of one group 2 firm decreases with that of the other group 2 firm.

1.3.3 Uniformly distributed errors

In this section, I test the robustness of the results in Section 1.3.1 with uniformly distributed errors on the support [-0.5, 0.5]. Following the first set of examples in Section 1.3.1, it is assumed that the inspection capacity allows 4 inspections out of 10 firms. The effort levels in the baseline treatment are listed in Table 1.8. The basic results from the normal distribution assumption are confirmed: among all possible allocations, $m_2 = 3$ is the optimal enforcement strategy; the static enforcement induces the least total effort; the trends in the effort of individual firms when m_2 increases from 1 to 3 can be explained by the same intuition discussed in the previous sub-section.

Figure 1.8 shows the total effort from all possible allocations when the enforcement parameters change. The results under the assumption of normally distributed errors are largely confirmed by the examples with uniformly distributed errors. Over the ranges of the parameters considered in the analysis, assigning three inspections to group 2 is generally optimal and static enforcement leads to the least total effort. Results regarding effort of individual firms (shown in Appendix 1.B) also agree with the corresponding results from the examples with normally distributed errors. The effort of group 1 firms is always much lower than that of group 2 firms. Firms in group 1 almost never over-comply in expectation while firms in group 2 over-comply in expectation with higher s, γ or α.

1.4 Conclusion

In environmental regulations, optimally allocating limited enforcement resources is crucial for effective pollution controls. In this paper, I develop a model of monitoring and enforcement with an environmental standard when a regulator faces fixed inspection capacity.

Based on the theoretical analysis, I characterize the optimal allocation of a fixed number of inspections with the aid of simulations. The major conclusion is that a regulator facing fixed inspection capacity should leverage the limited inspections by allocating more inspections to the targeted group. The optimal number of inspections in the targeted group usually lies between $m/2$ and $3m/4$, where m is the fixed number of inspections. The numerical examples also confirm the superiority of leveraged enforcement such that static enforcement induces the least total effort from all firms. These results are robust to the distribution assumptions of the error term, and to different ranges of enforcement parameters, such as the number of inspections, the penalty for violations, the fixed inspection cost, and the standard.

The model presented in this paper is based on the assumption that a regulator faces fixed inspection capacity in every period. How restrictive the inspection capacity is depends on the time horizon one considers. From a short-run perspective, the enforcement budget and the inspection personnel for a regulator are unlikely to change. The effectiveness of the enforcement is confined by the limited number of inspections. In the long-run, the regulator may be able to adjust the budget or inspection staff according to actual firm behaviors.

This model can be extended in several directions in future work. For simplification purposes, I have assumed that the penalty for violation and the standard are constant across firms. One possible modification to the model is to set such parameters at different levels for the two groups. Harford (1991) points out that differentiating the standard, in addition to the inspection probabilities across groups, may be optimal. Another assumption that could be relaxed is the probability of inspection in the targeted group. It is assumed in the model that all firms in the targeted group are inspected in every period. Although a high inspection frequency in the targeted group increases the leverage, it may also facilitate firms in that group with more opportunities of moving to the non-targeted group. Thus it is interesting to investigate firm behavior and the optimal policy if the inspection probability in the targeted group is less than one. Furthermore, it is assumed that firms are homogeneous in this model. In the real world, a regulator may face the task of monitoring firms with different abatement costs. Raymond (1999) points out that with asymmetric information or firm heterogeneity, the optimal regulatory policy depends on the distribution of costs among firms. Adding firm heterogeneity will complicate the model, but it may provide further insights.

Like other targeting enforcement models, the model developed in this paper is subject to critiques. For instance, a direct result of the targeting regulation is the different abatement effort and emission levels from homogenous firms. Hence, the marginal abatement costs are not equal across firms, which violates the condition for minimizing the social costs of emission controls (Harford and Harrrington, 1991).

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ESSAY 1 APPENDICES

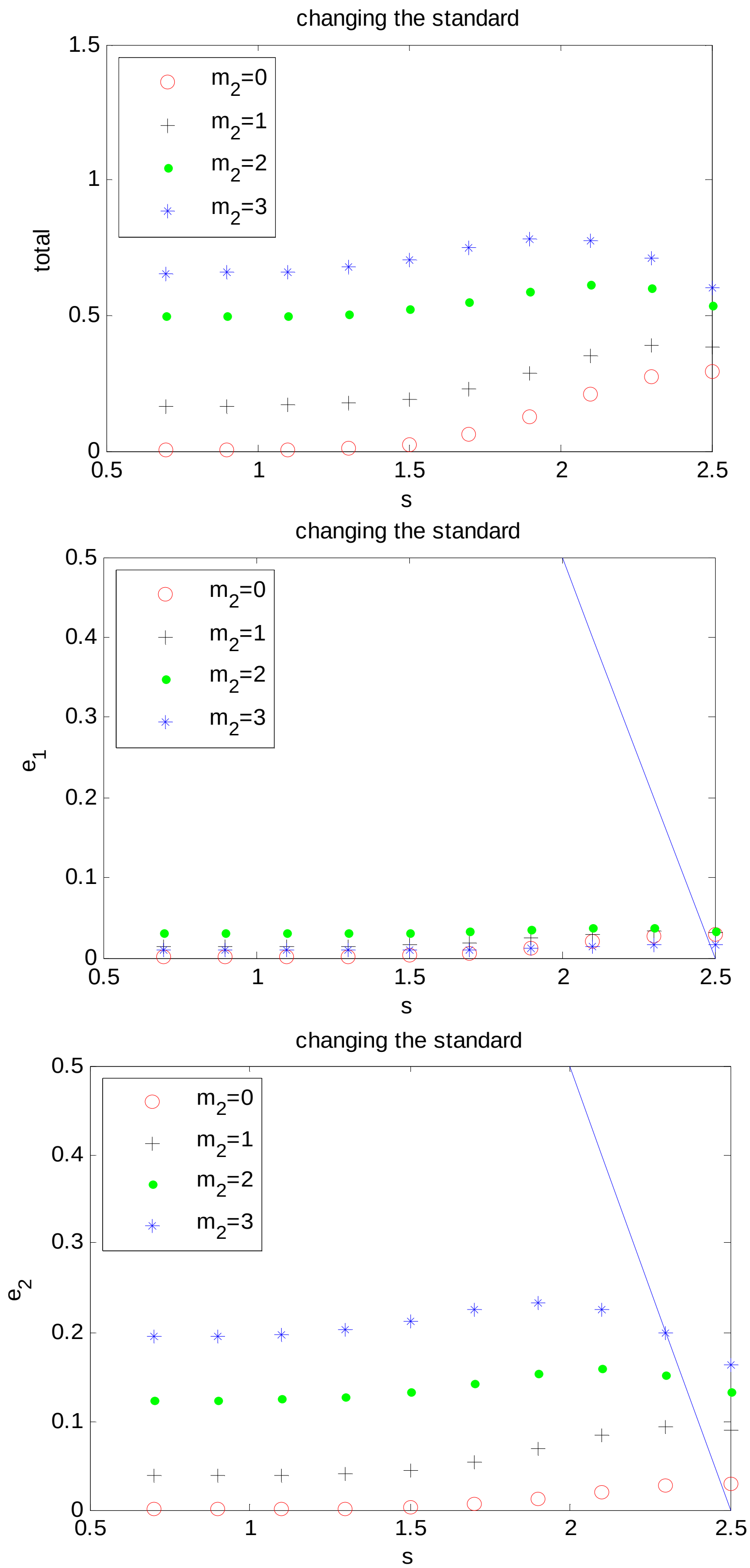


Figure 1.1 Changing the standard, $m = 4$

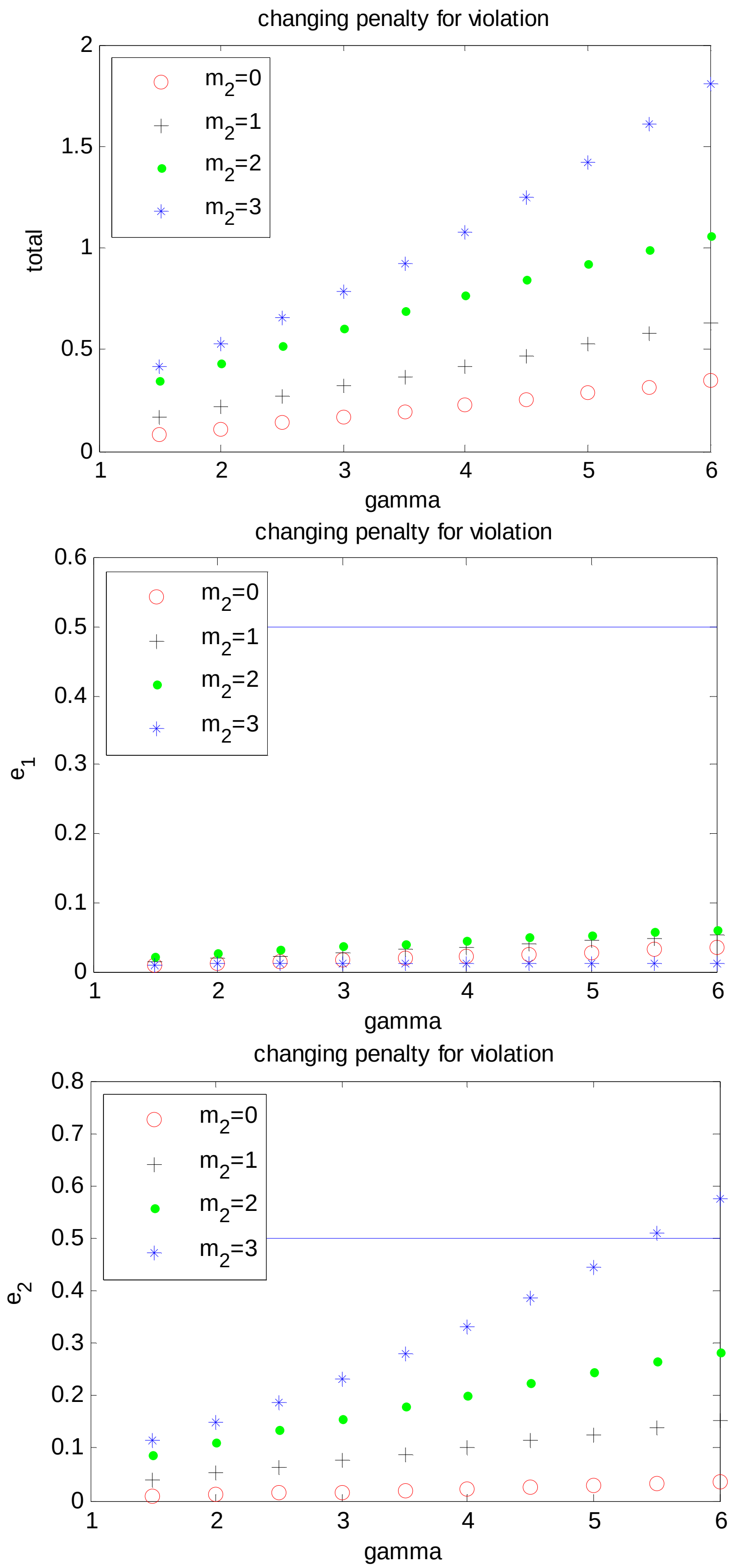


Figure 1.2 Changing penalty for violation, $m = 4$

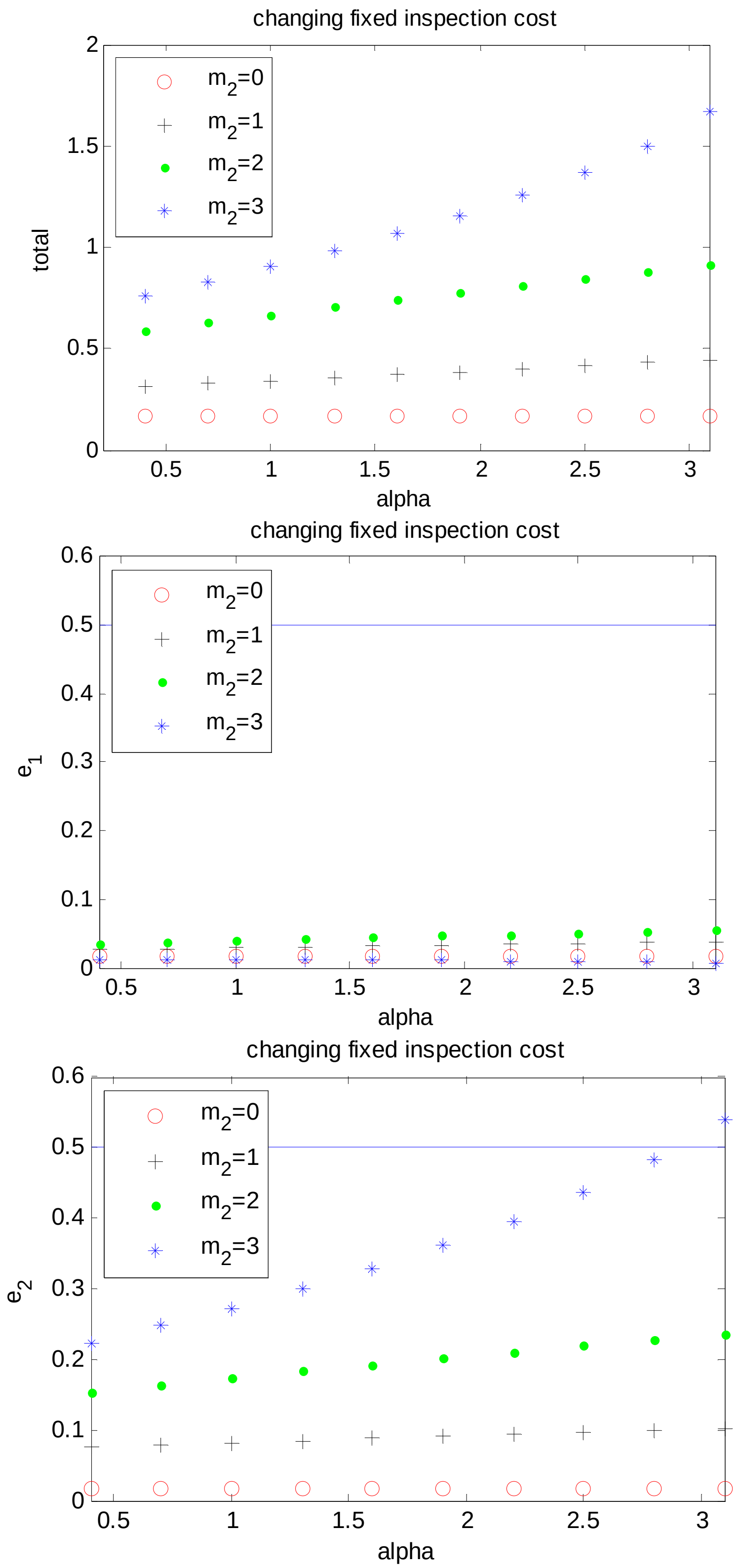


Figure 1.3 Changing fixed inspection cost, $m = 4$

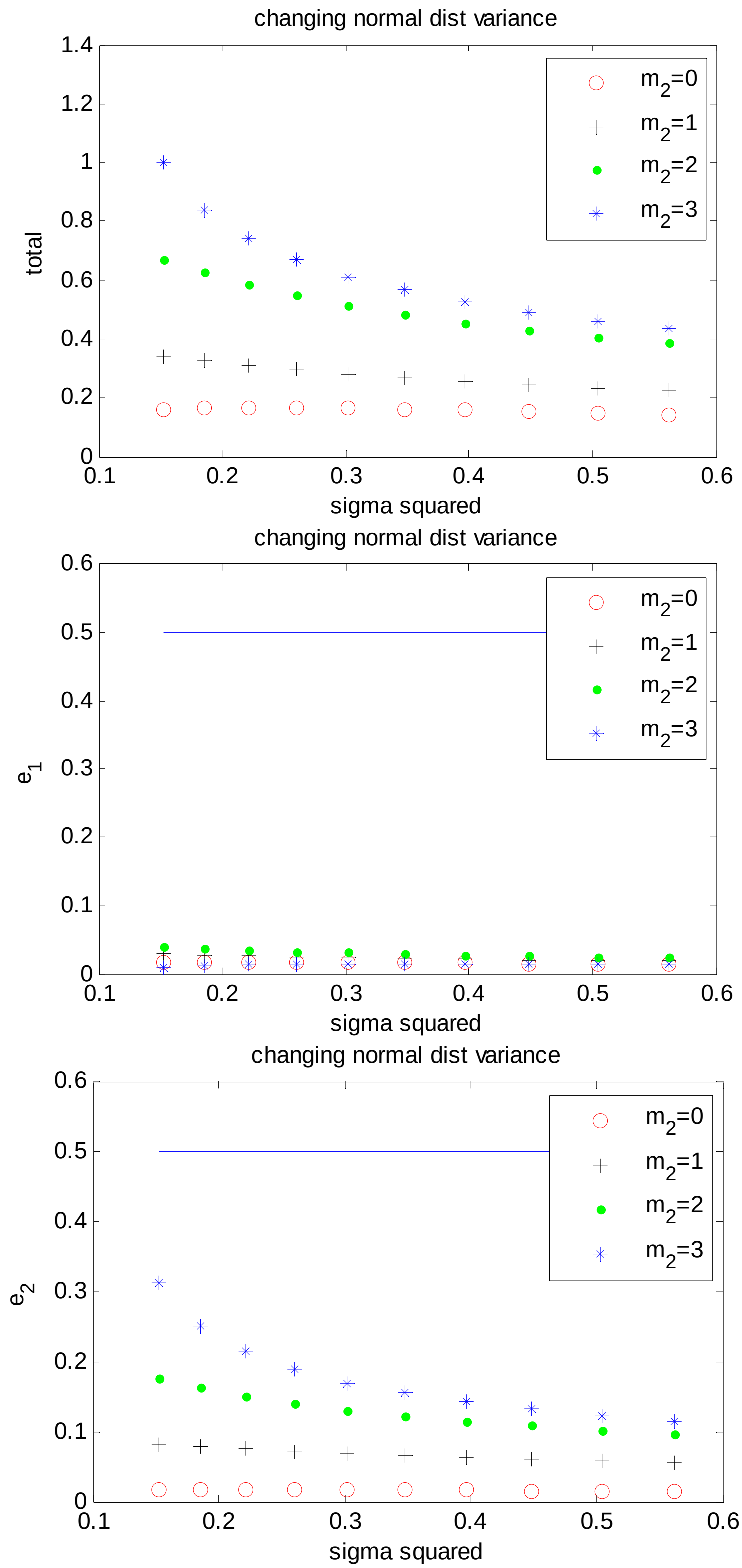


Figure 1.4 Changing variance of error, $m = 4$

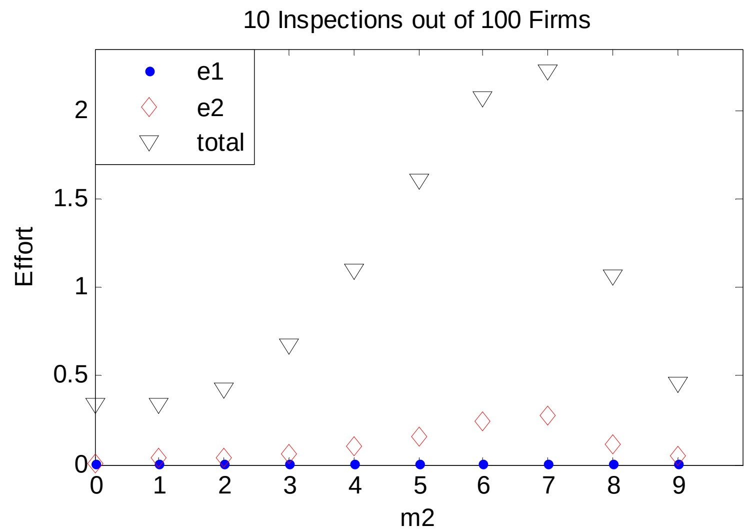


Figure 1.5 Effort levels, $m = 10$

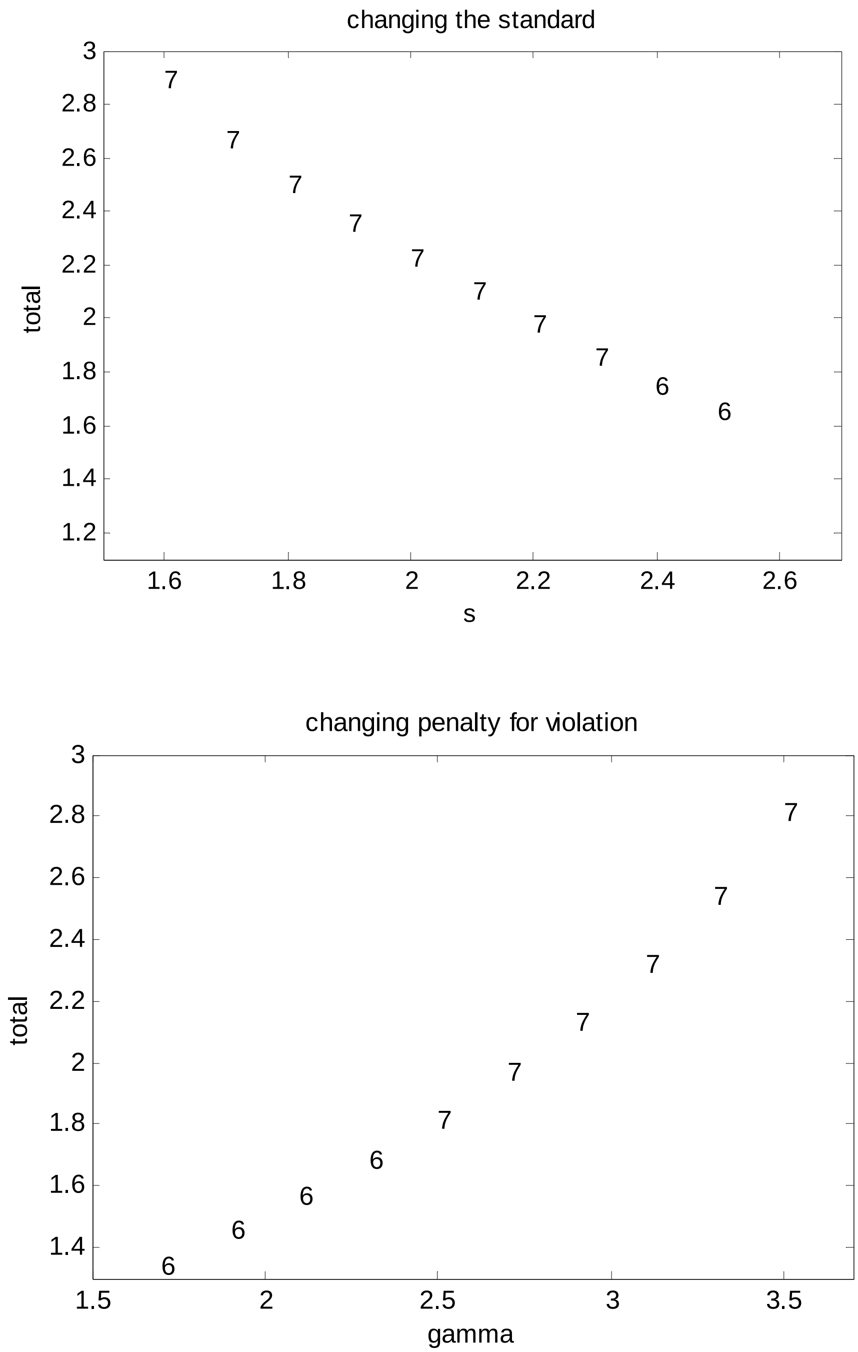
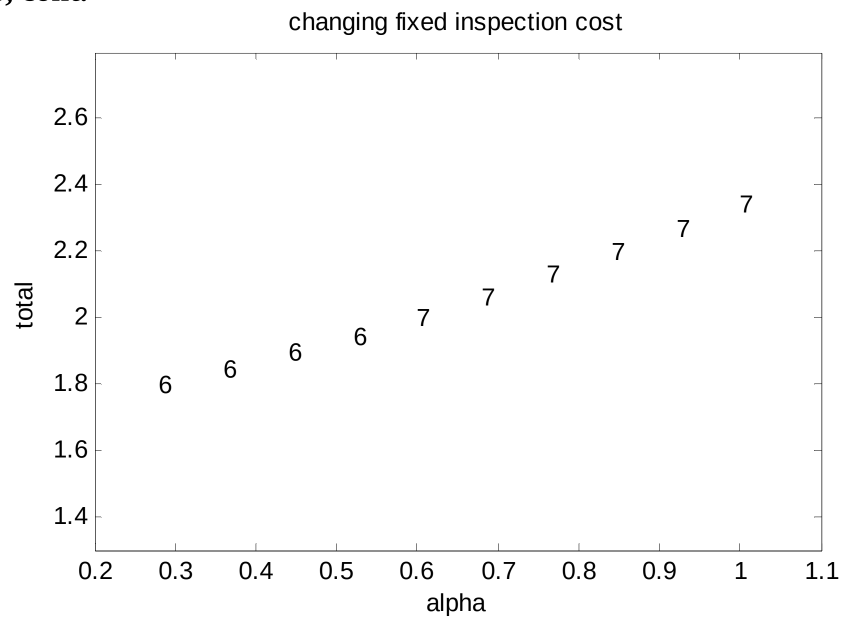
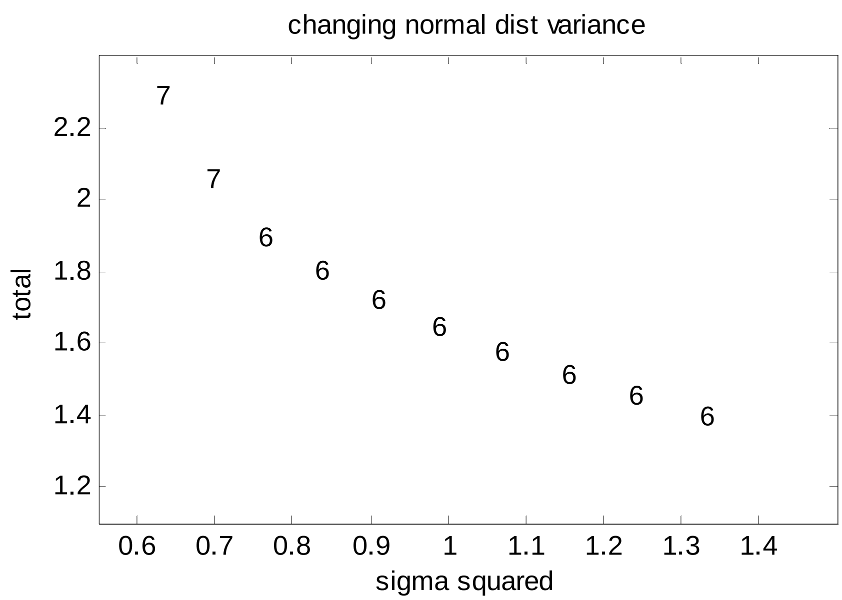


Figure 1.6 Changing parameters, $m = 10$

Figure 1.6, cont.





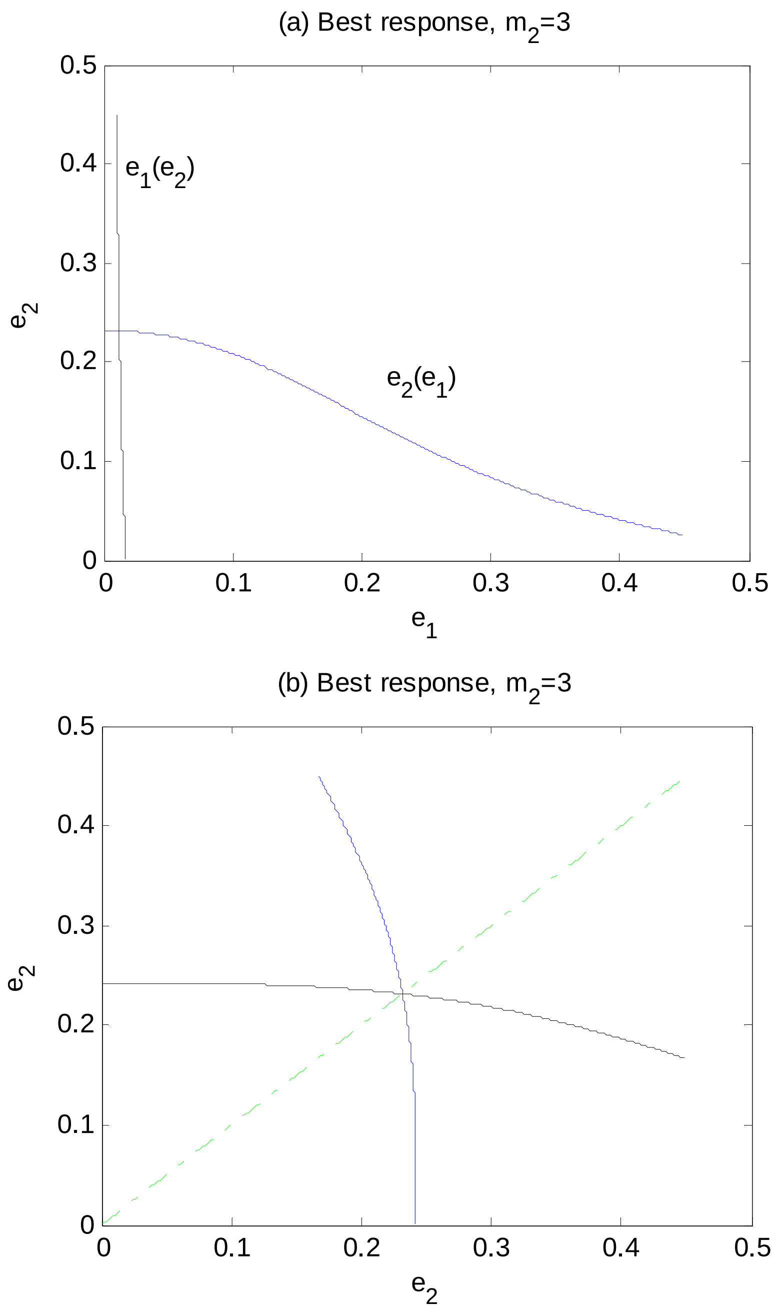


Figure 1.7 Best responses, $m = 4$

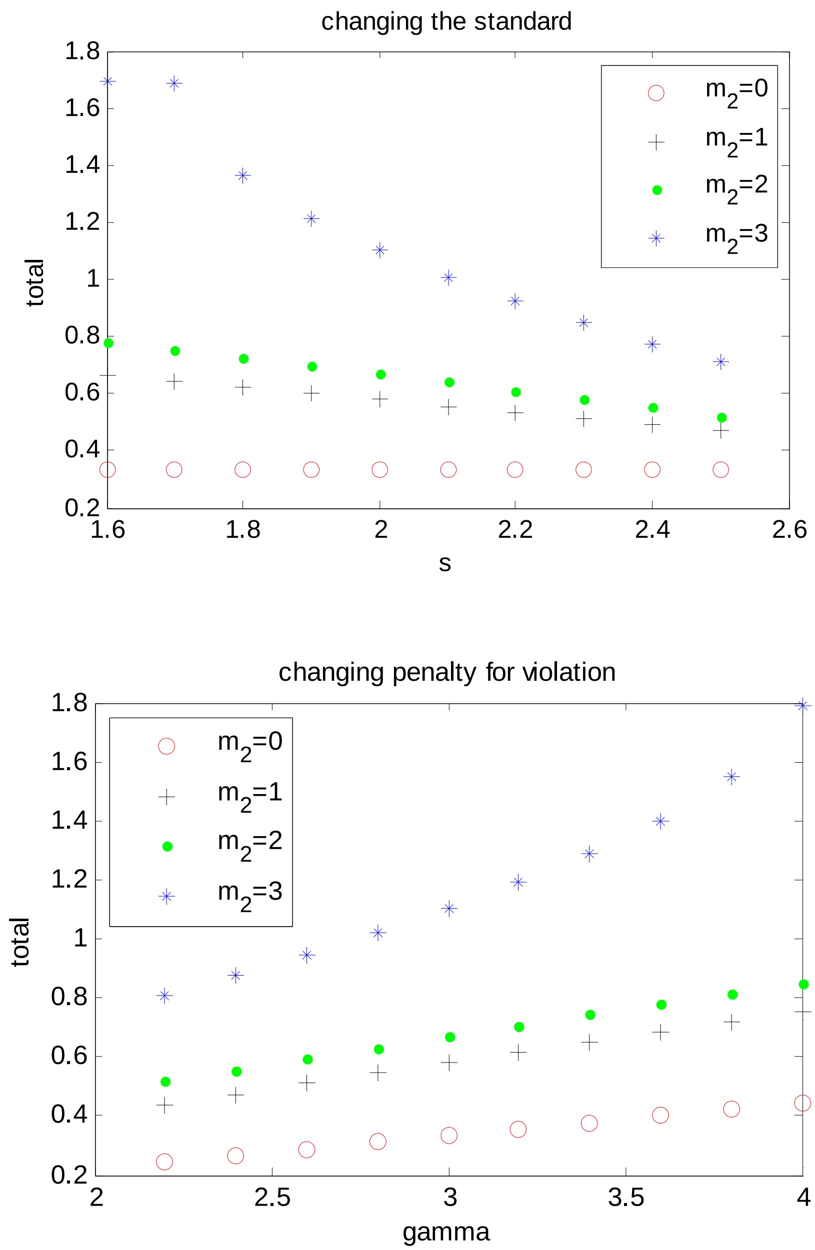
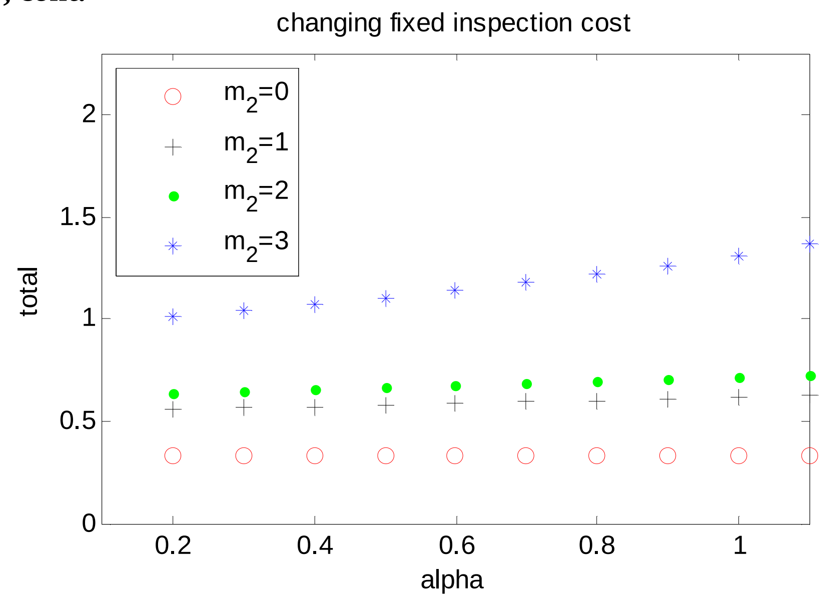


Figure 1.8 Changing parameters, uniform distribution

Figure 1.8, cont.



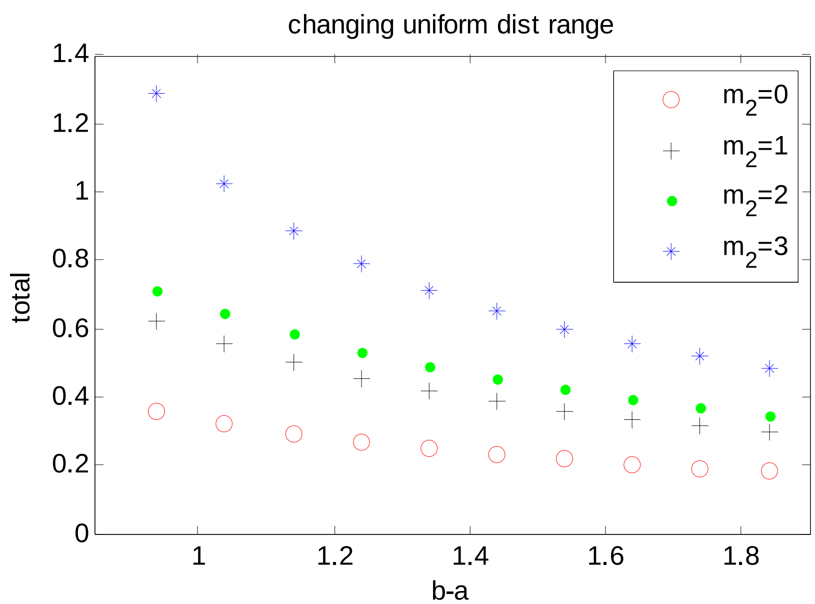


Table 1.1 Markov transition matrix

	To Group	
From Group	1	2
1	$1-\rho_1 p_1$	$\rho_1 p_1$
2	$\rho_2(1-p_2)$	$1-\rho_2(1-p_2)$

Table 1.2 Parameters

Total emissions, T	The standard, s	Coefficient of the abatement cost function, w	Penalty for violation, γ	Fixed inspection cost, α	Discount rate, δ
2.5	2	18	3	0.5	0.9

Table 1.3 Baseline example: $m = 4$

m_2	e_1^*	e_2^*	$n_1 e_1^*$	$n_2 e_2^*$	$n_1 e_1^* + n_2 e_2^*$	ρ_1
3	0.0129	0.2317	0.0900	0.6950	0.7850	1/7
2	0.0363	0.1571	0.2906	0.3142	0.6048	1/4
1	0.0267	0.0769	0.2407	0.0769	0.3177	1/3
0	0.0166	--	0.1660	--	0.1660	4/10

Note: inconsistencies of calculation are due to rounding errors.

Table 1.4 Baseline example: $m = 10$

m_2	e_1^*	e_2^*	$n_1 e_1^*$	$n_2 e_2^*$	$n_1 e_1^* + n_2 e_2^*$
9	0.0005	0.0462	0.0413	0.4158	0.4572
8	0.0015	0.1160	0.1390	0.9280	1.0668
7	0.0030	**0.2774**	0.2790	**1.9418**	**2.2207**
6	0.0063	0.2465	0.5906	1.4790	2.0696
5	**0.0084**	0.1623	**0.7933**	0.8115	1.6046
4	0.0072	0.1021	0.6951	0.4084	1.1034
3	0.0050	0.0627	0.4851	0.1881	0.6732
2	0.0035	0.0423	0.3477	0.0846	0.4324
1	0.0031	0.0359	0.3106	0.0359	0.3465
0	0.0034	--	0.3428	--	0.3428

Notes: 1. inconsistencies of calculation are due to rounding errors;
2. bold numbers indicate the maximum within each column.

Table 1.5 $n = 25$

	Number of inspections in group 2								
Total number of inspections	1	2	3	4	5	6	7	8	9
4	0.2345	0.4383	**0.5356**						
5	0.2454	0.4542	**0.6727**	0.5970					
6	0.2606	0.4450	0.7191	**0.8735**	0.5696				
7	0.2653	0.4273	0.7288	0.8588	**0.9772**	0.5117			
8	0.2972	0.4123	0.7338	0.4206	**1.1813**	0.9468	0.4613		
9	0.3237	0.4055	0.6269	0.9602	1.2481	**1.2753**	1.2408	0.4314	
10	0.3480	0.4087	0.584	0.8986	1.2428	**1.4297**	1.2408	0.7361	0.4218

Table 1.6 $n = 50$

	Number of inspections in group 2								
Total number of inspections	1	2	3	4	5	6	7	8	9
4	0.2420	0.4627	**0.5832**						
5	0.2528	0.4822	**0.7339**	0.6694					
6	0.2656	0.4743	0.7874	**1.0062**	0.6455				
7	0.2686	0.4555	0.8039	1.0597	**1.2021**	0.5764			
8	0.3006	0.4373	0.8254	0.4377	**1.4409**	1.2122	0.5105		
9	0.3256	0.4263	0.6949	1.1030	1.4976	1.6951	**1.7722**	0.4663	
10	0.3470	0.4248	0.6450	1.0394	1.4907	**1.8439**	1.7722	0.9389	0.4454

Table 1.7 $n = 100$

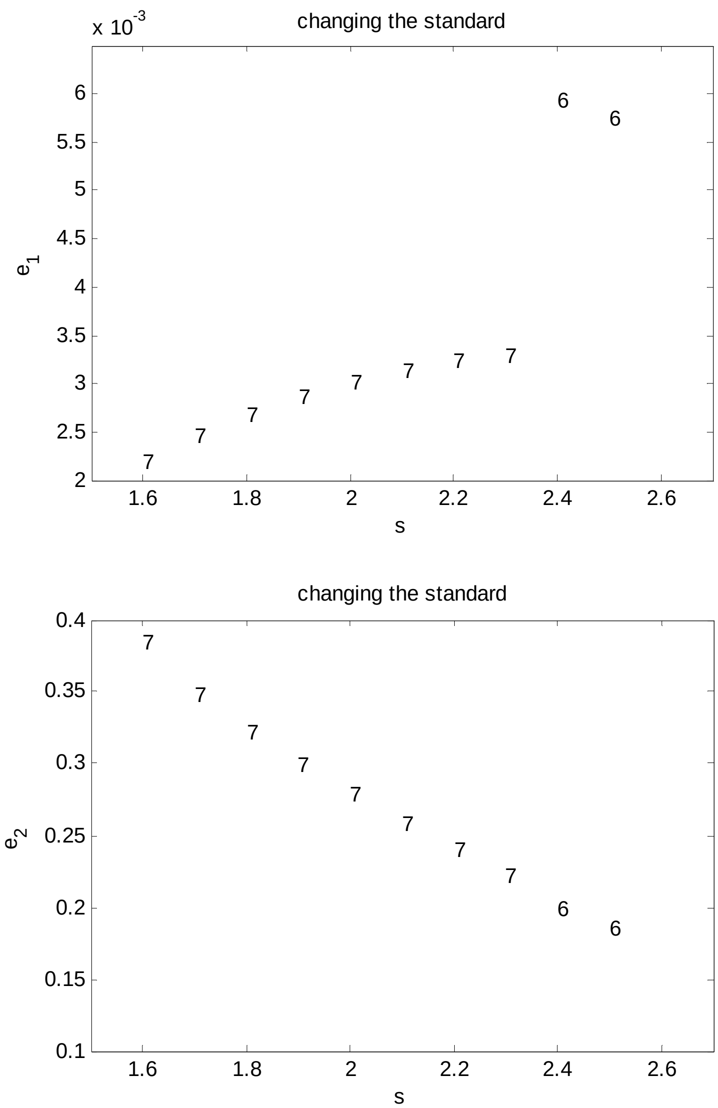
	Number of inspections in group 2								
Total number of inspections	1	2	3	4	5	6	7	8	9
4	0.2457	0.4747	**0.6082**						
5	0.2564	0.4957	**0.7645**	0.7087					
6	0.2681	0.4883	0.8203	**1.0782**	0.6866				
7	0.2701	0.4689	0.8394	1.1593	**1.3413**	0.6110			
8	0.3023	0.4492	0.8695	0.4451	**1.5842**	1.3862	0.5363		
9	0.3266	0.4361	0.7264	1.1688	1.6193	1.9827	**2.2207**	0.4842	
10	0.3465	0.4324	0.6732	1.1034	1.6046	2.0696	**2.2207**	1.0668	0.4572

Table 1.8 Baseline example: $m = 4$

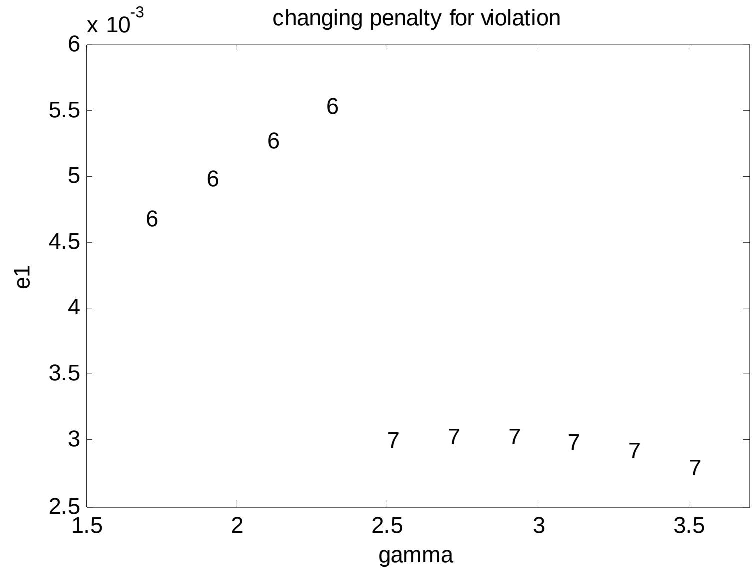
m_2	e_1	e_2	n_1e_1	n_2e_2	$n_1e_1 + n_2e_2$
3	0.0216	0.3173	0.1511	0.9518	1.1029
2	0.0418	0.1674	0.3348	0.3348	0.6696
1	0.0498	0.1308	0.4481	0.1308	0.5788
0	0.0333	--	0.3333	--	0.3333

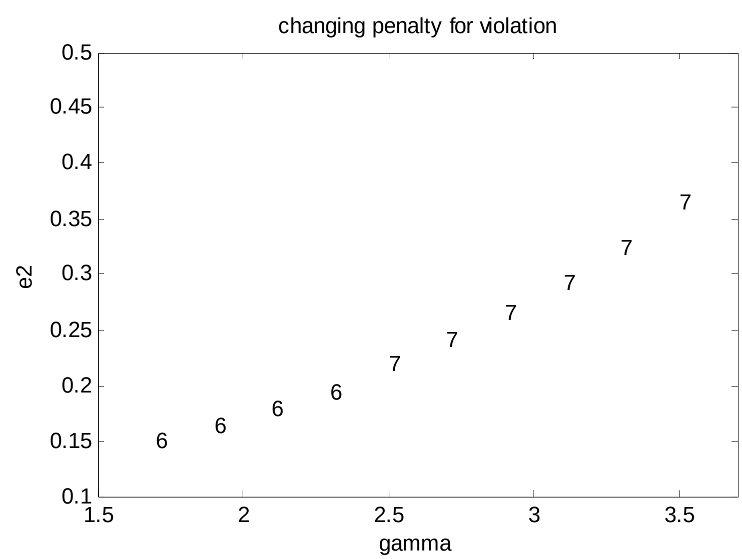
Note: inconsistencies of calculation are due to rounding errors.

Appendix 1.A Effort of individual firms in group 1 and 2 when there are 10 inspections out of 50 firms. (The numbers in the graphs indicate the optimal number of inspections in group 2)

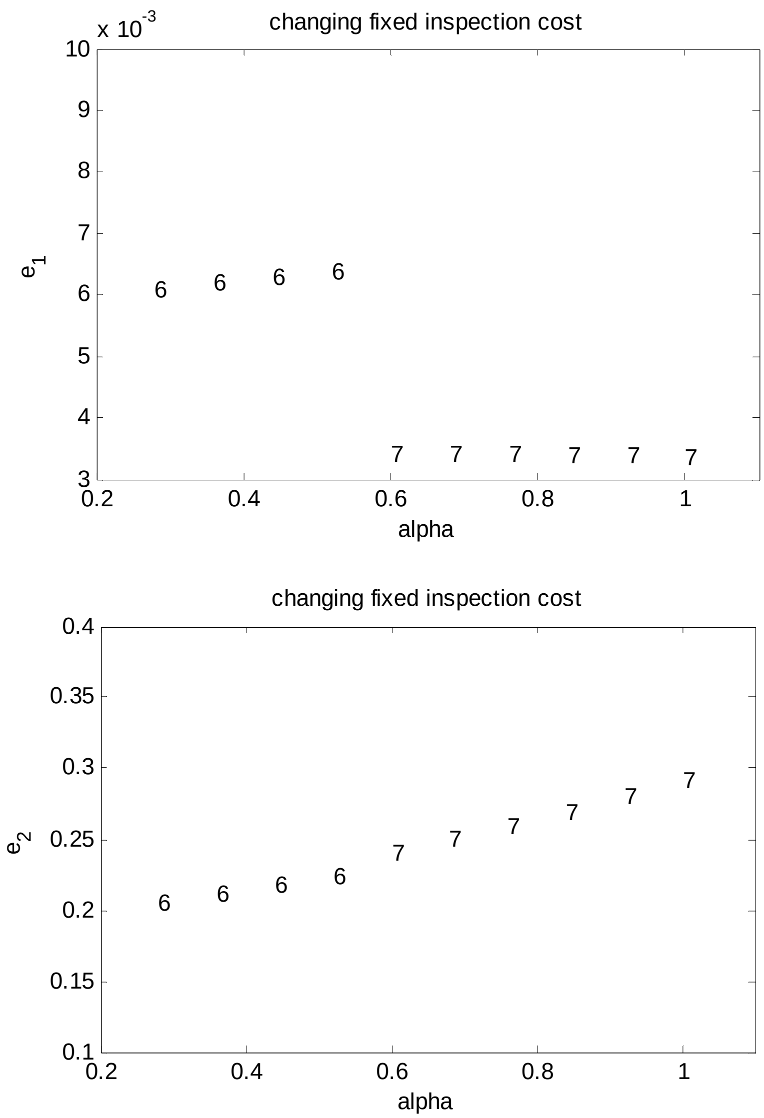


Appendix Figure 1.A1 Changing the standard, $m = 10$

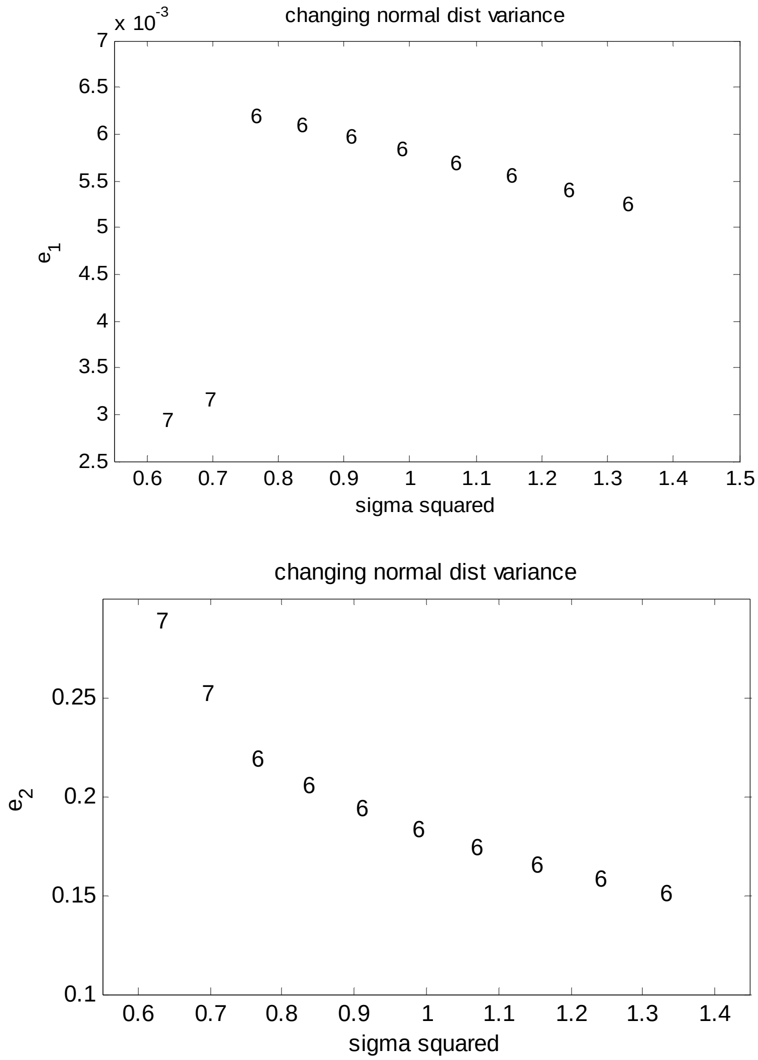




Appendix Figure 9A2 Changing penalty for violation, $m = 10$



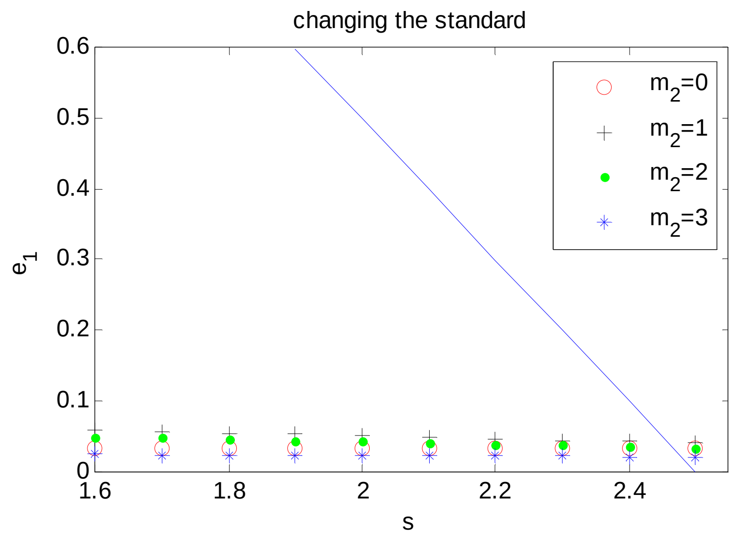
Appendix Figure 10A3 Changing fixed inspection cost, $m = 10$

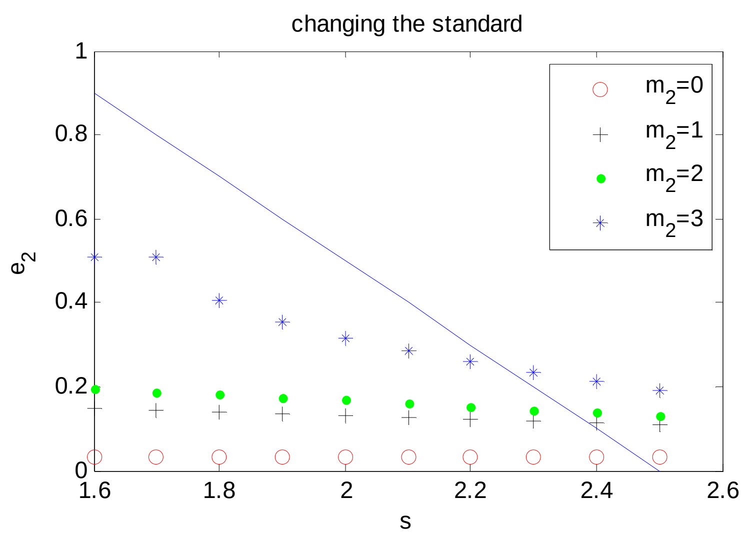


Appendix Figure 11A4 Changing variance of error, $m = 10$

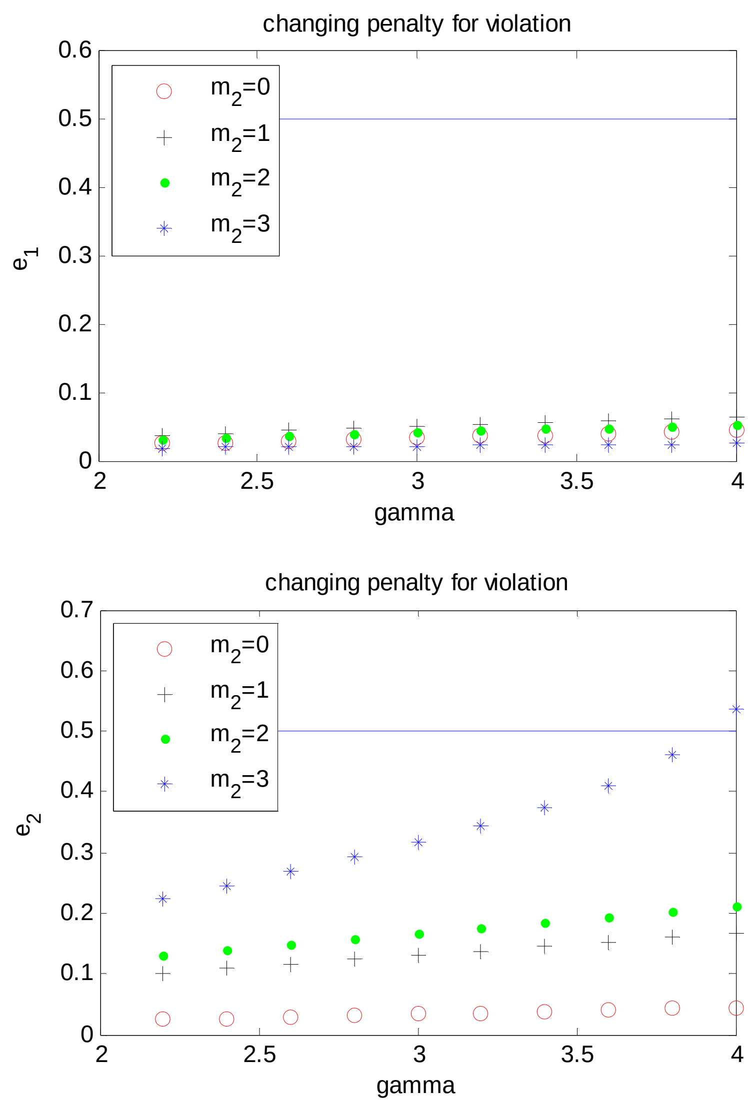
Note that when $\gamma \geq 2.5$ or $\alpha \geq 0.6$, the effort level of group 1 firms slightly decreases with these two parameters. In a static enforcement regime, increasing the penalty for violation or the fixed inspection cost should result in firms increasing their abatement effort. However, in this dynamic model where firms interact with each other, the changes in the effort of one firm also reflect its best response to that of other firms. Here the decrease in the effort of group 1 firms may suggest that those firms responds to the increased effort of group 2 firms by exerting less effort, and this reduction outweighs the increase in the effort of the group 1 firms due to the direct effect of higher sanctions. Similar intuition can be used to explain the result that group 1 firms exert more effort with higher variance when $\sigma^2 \leq 0.7$.

Appendix 1.B. Effort of firms in group 1 and 2 under uniformly distributed error terms

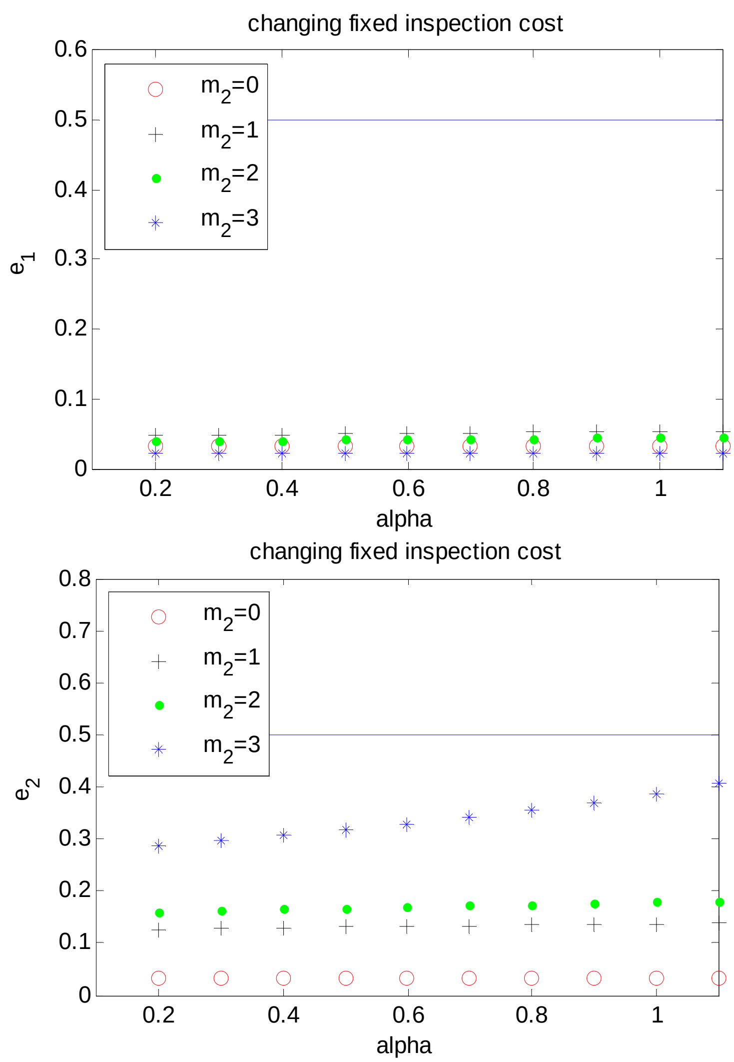




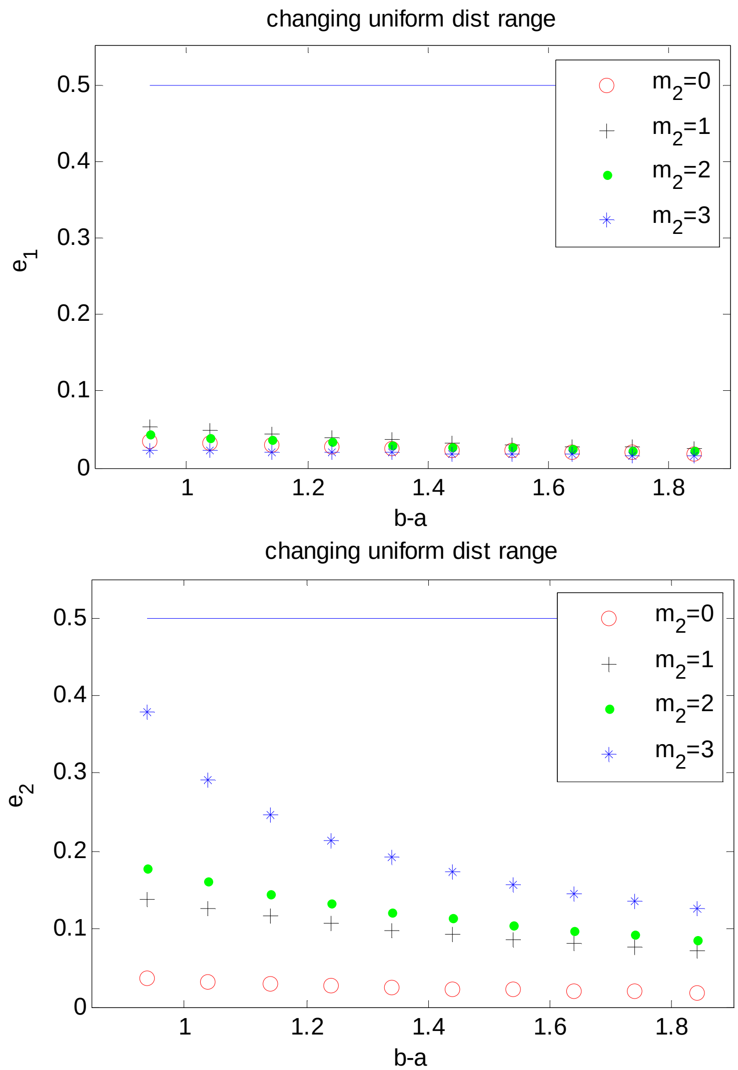
Appendix Figure 12B1 Changing the standard, uniform distribution



Appendix Figure 13B2 Changing penalty for violation, uniform distribution



Appendix Figure 14B3 changing fixed inspection cost, uniform distribution



Appendix Figure 15B4 changing distribution range, uniform distribution

CHAPTER III ESSAY 2: REGULATION WITH COMPETING OBJECTIVES, SELF-REPORTING, AND IMPERFECT MONITORING

This is a joint work with Dr. Mary Evans and Scott Gilpatric. A slightly different version of this chapter is to be published in the Journal of Environmental and Economic Management.

2.1 Introduction

Regulatory agencies, including the Environmental Protection Agency (EPA), commonly cite two categories of benefits associated with information disclosure programs. The first, an indirect benefit, arises from the internalization of the social costs of emissions (and consequent reductions in emissions) due to market responses to disclosures or regulatory instruments such as Pigovian taxes on disclosed emissions. The second, a direct benefit, results from the disclosure of previously private information. Referring to information disclosure programs in a recent report that describes the U.S. experience with various environmental policies, the EPA states "The environmental information embodied in these approaches has economic value...even in the absence of any changes in emissions by firms" (EPA, 2001, p. 153).[1] Timely information about emissions may enable potential damages to be avoided or mitigated both by affected parties and public agencies. For example, disclosure may reduce consumption of contaminated water by alerting individuals of the need for avoidance or proper treatment. Disclosure may also decrease the environmental impacts of a toxic release by accelerating clean-up efforts.

Theoretical analyses have tended to represent the social cost of emissions as a function only of emissions levels, independent of whether the presence and magnitude of emissions are publicly disclosed. The empirical work has followed a similar convention by measuring program success in terms of reductions in emissions. Neither strand of the

[1] In fact, the report refers to the benefits of disclosure from changes in consumer or producer behavior, such as reduced emissions, as "ancillary" (p. 153).

literature has yet to explicitly account for the possibility that disclosure of harmful emissions may be directly beneficial, outside of any indirect impacts of disclosure requirements on emissions. We develop a theoretical model that attempts to reconcile this apparent inconsistency between the stated motivation for information disclosure programs and previous analyses of such programs.

In our model, disclosure of emissions is directly beneficial but actual emissions are imperfectly observable so policymakers face a tradeoff between inducing truthful self-reporting and deterring emissions.[2] Internalizing the social costs of emissions, such as through a Pigovian tax, will deter emissions, but it may also reduce incentives for firms to truthfully disclose their emissions.

When monitoring firm behavior (such as through an audit process) is costly, a policymaker must account for three factors when designing regulatory policy: (1) the benefit of reduced emissions arising from internalizing social costs, (2) the direct social benefit of disclosure of emissions that do occur, and (3) enforcement costs. Previous analyses of environmental compliance have addressed factors (1) and (3) by considering a regulator whose objective is to minimize emissions (Garvie and Keeler, 1994; Macho-Stadler and Perez-Castrillo, 2005) or to minimize enforcement costs for a given level of compliance (Livernois and McKenna, 1999). We model the regulator's objective in a way that accounts for the reduction in social costs arising both from disclosure of emissions

[2] This trade-off is present in other regulatory settings such as consumer product and food safety. Firms are required to disclose product failures and hazards, but the more costly such disclosure (either due to fines or liability exposure) the greater the incentive firms have to conceal such information. Reducing fines or limiting liability costs encourages disclosure but may dull incentives to reduce product defects. However, this tradeoff is not present in some other regulatory settings where information disclosure programs have traditionally been applied, such as income taxation.

and a reduction in the quantity of emissions. This framework is both more general and more representative. In this paper our principal objective is to model the optimal policy choice in this context when the instruments at the regulator's discretion are a tax on (disclosed) emissions and the frequency (or probability) of auditing a firm's disclosure report.

In order to better understand the characteristics of the regulator's trade-off between inducing compliance with disclosure requirements and reducing emissions, we develop a model of firm behavior in the context of an imperfect audit. An imperfect audit reveals some percentage of the firm's actual emissions according to a known probability distribution. Given the imperfect nature of the audit, firms then optimize their choice of how much of their true emissions to disclose in order to minimize their expected costs. Firms also choose how much to emit conditional on their expected emissions costs. The regulator in turn optimally chooses the policy parameters based on his expectations about how firms facing a particular regulatory environment will behave.

The model we develop adds to the literature on the role of self reporting in environmental regulation. Malik (1993), Swierzbinski (1994) and others have shown that incentive-compatible mechanisms for self reporting (in which firms are induced to truthfully report their emissions) can achieve enforcement cost savings and increase social welfare. The benefit of self reporting in these models arises due to the regulator having incomplete information regarding the social costs or private benefits (i.e., abatement costs) of emissions by a particular firm. Unlike these previous models, we assume the regulator has full information in these respects.[3] The social benefit from self reporting in our model arises very differently (and more directly) from the fact that reported emissions cause less social damage than undisclosed emissions. In our model disclosure of emissions by firms is a desirable end in itself, rather than a mechanism to achieve desirable emissions reductions in a more cost effective manner.[4]

This paper is organized as follows. Section 2.2 develops our main model. We first consider the decision facing a representative firm, among many homogeneous firms, required to disclose emissions subject to a tax enforced through imperfect audits. We then analyze the optimal policy choice of the regulator, who we assume has complete information. Section 2.3 relaxes the homogeneous firms and perfect information assumptions and confirms that our main results continue to hold. Section 2.4 concludes with discussion of the implications of our model and possible extensions.

2.2 The Model

2.2.1 The Firm's Problem

We first analyze the decision facing a firm subject to a mandatory information disclosure policy requiring the firm to report a level of emissions to the regulator. The compliance decision for a firm is defined by three factors: 1) the disclosure costs the firm incurs as a function of its revealed emissions, 2) the penalty costs the firm incurs as a

[3] Section 2.3 of the paper presents a variant of our model in which firms have private information.

[4] Of course regulations requiring self reporting may serve a dual purpose, both to capture direct benefits of disclosure and to achieve enforcement cost savings from information revelation. We focus on the direct benefits of disclosure to keep our model fairly straightforward and make the implications of this regulatory motive most transparent.

function of any emissions that are revealed in excess of the level it discloses, and 3) the nature of the auditing program.[5]

Firms may face costs associated with emissions (whether disclosed or undisclosed) arising from a variety of sources.[6] Most directly, a firm may be subject to a Pigovian tax on disclosed emissions, and a subsequent penalty on unreported emissions that are later revealed. A firm may also face current or future liability costs associated with emissions, both of which may be reflected immediately in the market valuation of the firm upon the revelation of its emissions.[7] Finally, the firm may face costs associated with the revelation that it failed to disclose emissions when required. The revelation of under-reporting by a firm may be either a direct consequence of regulatory enforcement, or through other mechanisms such as internal whistleblowers, disclosures by the media or environmental watchdog groups, or simply due to random events that bring information into the public domain.

Most previous analyses of environmental compliance assume an error-free audit process (see for example Kaplow and Shavell (1994)and Innes (1999)), an assumption

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[5] Becker's (1968) "optimal penalty" model provides the theoretical basis for the literature on environmental compliance. The main insight from his model is that potential offenders respond to the probability of detection as well as the severity of the punishment. See Polinsky and Shavell (2000) (and the citations within) for a general review of the enforcement literature. Cohen (1999) and Heyes (2000) provide reviews of the environmental compliance and enforcement literature.

[6] Firms may fail to perfectly comply in some cases simply because it is costly to collect the necessary information (e.g., a firm may bear some cost of simply measuring its own emissions). We ignore the possibility here and simply assume the firm has perfect knowledge of its emissions.

[7] See Hamilton (1995), Khanna et al. (1998), and Konar and Cohen (2001) for empirical evidence on market reactions to releases of the Toxics Release Inventory (TRI).

consistent with the tax compliance literature.[8] We define an audit to be error-free if it reveals, perhaps with some probability less than one, the exact degree of misreporting. Recently, Macho-Stadler and Perez-Castrillo (2005) depart from the more common assumption in the literature of an audit that always reveals the exact degree of misreporting by allowing the probability of perfect revelation to be less than one. Notice however that the effect of this assumption is merely to decrease the probability of detection (the firm now faces a compound probability). Heyes (1993) considers a similar audit structure where the probability that an audit (perfectly) detects non-compliance is endogenous. In each of these models, provided an audit occurs, it reveals either no misreporting or the exact degree of misreporting and therefore is consistent with our definition of an error-free audit. The assumption of error-free audits seems best suited to situations where firms make dichotomous choices to comply with a regulation or not. However, in the case of environmental information disclosure requirements, where penalties are likely to vary with the degree of noncompliance, the firm's decision may be more accurately modeled as choosing the optimal degree of compliance. Therefore, we model compliance as a continuous choice and assume the firm faces an imperfect audit, one that reveals a *percentage* of the firm's actual emissions.

We assume firms are homogeneous and consider the problem facing a representative firm. Let e represent the firm's emissions and denote the firm's benefit of emitting as $B(e)$ where $B'(e) > 0$ and $B''(e) < 0$. Let z denote the share of actual

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[8] Malik (1993) is an exception. He models a binary compliance decision allowing for errors in auditing the firm's compliance status. In contrast, we model compliance with the information disclosure requirement as a continuous choice, which allows us to focus on behavioral changes at the intensive, rather than extensive, margin.

emissions reported by the firm, so the reported quantity of emissions is ze. For clarity and tractability, we assume that for each unit of reported emissions, the firm incurs a constant per unit cost, denoted α, which we characterize as the "tax" on emissions. Similarly, if the audit reveals a level of emissions that exceeds reported emissions, the firm incurs a constant per unit cost, denoted β, on the revealed but unreported emissions. We refer to β as the "penalty."[9]

The firm is audited with probability p. If an audit occurs it reveals a quantity of emissions, denoted x. We assume $x = eu$ where u is a random variable with cumulative distribution function $F(u)$ and probability density function $f(u)$, which is strictly positive on the interval $[0,b]$ with $b \geq 1$.[10] We assume $f(u)$ has a single mode at one. The model thus allows for the possibility that an audit reveals less or perhaps more than was actually emitted. We do not require that audits be unbiased (i.e., that $E[u]=1$) or that $f(x)$ be symmetrically distributed around one, but the model encompasses these possibilities. We assume that the audit distribution F is independent of the firm's actual emissions. That is, the scale of the firm or its emissions level does not impact the

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[9] Both disclosure and penalty costs could of course be non-linear. For example, the penalty cost function might increase at an increasing rate with the magnitude of the violation if regulators take the view that large infractions should be punished severely while minor infractions receive a much milder treatment. The linearity assumption renders the model much more tractable and avoids issues associated with the optimal size of a firm as a function of the regulatory environment, which is beyond the scope of our analysis.

[10] Because the audit process as has two-sided errors yielding the possibility that emissions are "revealed" in excess of the actual level (as in Harford (1991)), it is possible that a firm would find it optimal to over comply, reporting emissions in excess of its actual level. As we discuss below, in our model the regulator will never find it optimal to induce overcompliance from a representative firm. Arora and Gangopadhyay (1995), Shimshack and Ward (2006), among others explicitly focus on overcompliance with environmental regulations.

effectiveness of audits, so the audit is equally likely to reveal any given percentage of actual emissions regardless of the firm's true emissions level.

The firm's problem is to choose e and z to maximize the expected net benefit of emitting. Given our assumptions and the values of α , p, and β , the firm faces a constant per unit cost of emitting, denoted μ , with

$$\mu(\alpha,\beta,p) = \alpha z + p\beta\int_{z}^{b}(t-z)f(t)dt\,. \tag{2.1}$$

Therefore the firm's expected net benefit is given by:

$$B(e) - C(e,z) = B(e) - e\cdot\mu(z,\alpha,\beta,p) = B(e) - e\cdot\left[\alpha z + p\beta\int_{z}^{b}(t-z)f(t)dt\right]. \tag{2.2}$$

It is clear from equation (2.2) that with a constant tax and penalty and independence between the audit effectiveness and actual emissions levels, the firm's optimal choice of z is independent of e. Thus, our assumptions allow us to decouple the choices of e and z. We begin by analyzing the firm's optimal choice of z. The first order condition for an interior solution on z is given by:

$$\alpha = p\beta\int_{z^*}^{b}dF(x) = p\beta\left[1 - F(z^*)\right] \tag{2.3}$$

where z^* denotes the optimal reported share of emissions. The first order condition indicates that the firm's optimal report, z^*, equates the marginal cost of reported emissions, □, and the expected marginal benefit of reported emissions. The expected marginal benefit reflects the expected avoided per unit penalty on revealed but unreported emissions. Using equation (2.3), we can solve for z^* as a function of the policy parameters:

$$z^* = F^{-1}\left(1 - \frac{\alpha}{p\beta}\right)$$

With this we state the following proposition characterizing the firm's optimal choice of *z*. All proofs are given in the appendix.

Proposition 2.1. Given α, β, and *p*, the firm's optimal choice of *z* will be such that

(*i*) $z^* = 0$ if $\alpha \geq p\beta$

(*ii*) For $p\beta > \alpha$ an interior solution exists with z^* defined by expression (3) above.

(*iii*) For an interior solution, the firm's optimal report, z^*, is decreasing in the tax on reported emissions, α; increasing in the probability of audit, *p*; and increasing in the penalty on revealed but unreported emissions, β.

Note that $p\beta > \alpha$ is required for an interior solution on z^*. That is, in order to elicit reporting in our model, the tax on reported emissions must be below the expected penalty on revealed but unreported emissions.[11] We assume this condition is satisfied and focus attention on an interior solution for z^*.

We now consider the firm's optimal choice of emissions. Given z^*, the firm will choose e^* to maximize $B(e) - C(e, z^*) = B(e) - e \cdot \mu^*$ where

[11] Heyes (1996), Innes (1999) and Kambhu (1989), among others, present models in which fines set below their maximal levels are optimal. For example, in Kambhu (1989) higher penalties lead to lower compliance because they induce regulated firms to take actions that obstruct the enforcement process.

$\mu^* = \alpha z^* + p\beta\int_{z^*}^{b}(t - z^*)f(t)dt$. The first order condition with respect to the choice of *e* is given by:

$$\alpha z^* + p\beta\int_{z^*}^{1}(x - z^*)f(x)dx = B'(e^*) \text{ or } \mu^* = B'(e^*) \tag{2.4}$$

which simply states that the optimal level of emissions occurs where the marginal cost and marginal benefit of emitting are equal. Equation (2.4) implicitly defines the firm's demand for emissions, as a function of the marginal cost of emitting (given z^*), which we denote $e(\mu^*) = B'^{-1}(\mu^*)$, where $e'(\mu^*) < 0, e''(\mu^*) \geq 0$. Proposition 2.2 states the comparative static results for the optimal level of emissions, e^*.

Proposition 2.2 The firm's optimal level of emissions, e^*, decreases with the tax on reported emissions, α ; the penalty on revealed but unreported emissions, β ; and the probability of audit, *p*.

Proposition 2.2 confirms the intuitive result that emissions decrease with increases in those factors that raise μ^*, namely the tax, the penalty, and the frequency of audits. The next section considers the policymaker's problem conditional on the firm responding to changes in policy parameters according to Proposition 2.2.

In the model of optimal regulatory policy developed below we will employ the fact that the firm's optimized *net* benefit of emitting is $B(e^*) - C(e^*, z^*) = \int_{\mu^*}^{\mu_c^*} e(\rho)d\rho$ where μ_c^* represents the choke price for emissions. This expression simply states that the firm's net benefit of emitting is the area under the firm's demand curve for emissions above μ^*. This is denoted area *A* in Figure 2.1.

2.2.2 The Regulator's Problem

The regulator's objective function must account for (1) the welfare loss from emissions in excess of the socially optimal quantity, (2) the direct benefit of information disclosure, and (3) the costs associated with auditing firms.

Let *m* denote the per unit social cost of undisclosed emissions. Let *s* represent the difference between the unit cost of undisclosed emissions and the unit cost of disclosed emissions. We assume $s < m$, allowing for disclosure to increase the range of available private and public mitigation strategies and therefore decrease the social cost of emissions. For a particular level of disclosure, *z*, the per unit social cost of emissions is then given by $m - sz$.

When we assume, as we do in this section, that the regulator has complete information about the effectiveness of the audit process and the firm's demand for emissions, he can infer the firm's true emissions. However, this inference is no longer possible in a model with heterogeneity in the distribution of audit outcomes among firms, and incomplete information on the part of the regulator. Section 2.3 confirms that our main results continue to hold under these conditions. We maintain the complete information, homogeneous firms assumptions in this section for ease of exposition and because they allow us to develop a model which is somewhat more general in other respects.[12]

We model the situation facing the regulator as a minimization problem and assume his objective function, denoted *V*, is comprised of three terms: (1) the total damages from emissions net of expected taxes and fines paid by the firm; (2) enforcement costs; (3) the firm's net benefit from emitting. Based on our assumptions, the total social cost of emissions is equal to $e(\mu *)\cdot(m - sz *)$. The firm pays expected taxes and fines equal to $e(\mu *)\cdot \mu *$. Therefore, the total damages from emissions net of payments by the firm, the first component of *W*, is $e(\mu *)[m - sz * - \mu *]$. We denote the cost of an audit to be *w*, so enforcement costs, the second component, are simply *pw*. As described earlier, the firm's optimized *net* benefit from emissions is represented by $\int_{\mu *}^{\mu_c} e(\rho) d\rho$. This is the final component of *V*.

Give the three components, the regulator's objective function is:

$$V = e(\mu *)[m - sz * - \mu *] + pw - \int_{\mu *}^{\mu_c *} e(\rho) d\rho \tag{2.5}$$

We assume the regulator minimizes *V* with respect to his choice of α , the tax on reported emissions, and *p*, the audit probability.[13] Therefore, we assume β , the marginal penalty

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[12] In particular, the model with heterogeneous firms developed later relies on assuming linear demand for emissions among firms to obtain comparable results.

[13] In modeling the policy choices available to the regulator we have not allowed the regulator to choose a deposit-refund instrument in lieu of a tax. Swierzbinski (1994) finds a deposit-refund system to be optimal in a model of regulation with self reporting. However, as discussed earlier, the role of self reporting in Swierzbinski's model is quite different than in ours because it arises as a result of the regulator's uncertainty about a firm's pollution abatement costs (absent any direct benefits of disclosure). A deposit-

on revealed but unreported emissions, is exogenous. In the context of our model the regulator would always do best to set this penalty as high as possible because doing so achieves the highest compliance given any tax with the least enforcement costs. This fairly standard result leads us to simply assume that the regulator faces some constraint on the magnitude of the penalty that can be imposed.[14]

The first order conditions for an interior solution to the regulator's problem are given by:

$$\frac{\partial V}{\partial \alpha} = 0 \Leftrightarrow e'(\mu^*)\frac{\partial \mu^*}{\partial \alpha}(m - sz^* - \mu^*) = e(\mu^*)s\frac{\partial z^*}{\partial \alpha}. \qquad (2.6)$$

$$\frac{\partial V}{\partial p} = 0 \Leftrightarrow e(\mu^*)s\frac{\partial z^*}{\partial p} - e'(\mu^*)\frac{\partial \mu^*}{\partial p}(m - sz^* - \mu) = w. \qquad (2.7)$$

Equation (2.6) indicates that the regulator chooses α^* to equate the marginal benefit of a higher tax (lower emissions) with the marginal cost of a higher tax (less truthful reporting). Similarly equation (2.7) illustrates that p^* equates the marginal benefit of increase audit frequency (greater disclosure and reduced emissions) and the marginal cost (additional audit resources, w).

Both a higher tax and higher audit probability achieve greater internalization of social costs (and thus a reduction in emissions), but each is costly in a different way. A

refund scheme would not be optimal in general in our context because it raises the enforcement cost of internalizing social damages. Although a deposit-refund scheme could be optimal in our context under certain conditions, we've chosen to constrain the regulator to using a Pigovian tax both for simplicity and because deposit-refund mechanisms are not broadly utilized in environmental regulation (particularly in the U.S., see EPA (2001))

[14] See, for example, Becker (1968) and Harrington (1988). This assumption can also be grounded in the argument that the marginal penalty may include factors which are outside the regulator's control such as the market's reaction to news that a firm underreported its actual emissions or explicit fines and increased liability resulting from an independent judiciary process (Garvie and Keeler (1994)).

higher tax reduces disclosure, which is costly when disclosure has direct benefits. A higher audit probability is directly costly as more resources are devoted to enforcement. To understand the interplay between these choices, consider the two extreme cases regarding the value of disclosure. First, suppose disclosure has no direct benefit so $s = 0$. In this case there is no interior solution on □; it is optimal to set $\alpha^* \geq p\beta$ (in which case the firm discloses nothing). This achieves the greatest internalization of social costs (arising entirely through fines rather than taxes) with the least expenditure on enforcement. The optimal audit probability, p^*, will reflect the marginal benefit of reduced emissions resulting from internalization relative to the marginal cost of auditing, and an interior solution will exist for w sufficiently large. At the other extreme, suppose that once emissions are disclosed, they are no longer socially harmful so $s = m$. In such a case the optimal policy involves zero tax on reported emissions. Full compliance with the disclosure requirement can then be achieved with a negligible audit probability. Although this extreme case may seem unrealistic, it conveys important intuition: as s approaches m the optimal policy may be minimal taxation and infrequent auditing. Auditing is costly for the regulator and high compliance rates can still be achieved with a low probability of audit when the tax on reported emissions is also low.

An interior solution in both dimensions of the regulator's choice will exist if s is sufficiently large but strictly less than m (i.e., the costs of emissions are sufficiently reduced but not completely eliminated by disclosure) and if the cost of auditing, w, is sufficiently large. We henceforth assume this is the case and focus our analysis on the comparative statics at an interior solution.

Proposition 2.3. The regulator's optimal tax, α^*, is increasing in *m*, the per unit social cost of undisclosed emissions and decreasing in *s*, the difference between the per unit social costs of undisclosed and disclosed emissions. The optimal audit probability p^* is decreasing in the cost of auditing, *w*.

The comparative static results regarding the optimal tax are broadly intuitive. The regulator trades-off internalizing social costs with a higher tax against the consequent reduction in disclosure; the more valuable is disclosure (due to higher *s*), the lower the optimal tax. Conversely, the more socially costly all emissions are (as represented by *m*), the higher the optimal tax in order to achieve greater internalization of these costs and lower resulting emissions. The effect of the cost of auditing, *w*, on α^* is ambiguous. A higher cost of auditing, *w*, does not directly affect the optimal tax but will of course reduce the optimal audit probability, p^*. Whether the optimal tax increases or decreases with an increase in *w* depends on how the decrease in the audit probability affects the marginal benefit and cost of the tax. The expression for $\frac{\partial \alpha^*}{\partial w}$ is provided in the appendix.

Unlike the comparative statics for the optimal tax, the directions of the effects of *m* and *s* on the optimal audit frequency are in general ambiguous. Consider first the effect of *m*. As the social cost of emissions rises (holding constant the reduction that occurs due to disclosure, *s*) the marginal benefit of reducing emissions by internalizing their cost to the firm rises. For this reason it seems intuitive that that the optimal audit probability would rise as well, since raising *p* increases the internalized cost of emitting. However, an increase in *m* increases the optimal tax α^* as stated in Proposition 2.3. This in turn increases $\mu*$ and reduces emissions *ceteris paribus.* A reduction in emissions reduces the marginal benefit of achieving a higher percentage of emissions disclosure. This reduces the value of auditing with regards to achieving higher rates of disclosure. If the firm's elasticity of demand for emissions is very high, then the optimal response to an increase in *m* may be to raise the tax to reduce emissions but reduce the audit probability. The comparative static result shows that we cannot exclude the possibility that $\frac{\partial p*}{\partial m} < 0$.

However, were the regulator restricted to choosing only *p*, with α fixed, then we find unambiguously $\frac{\partial p*}{\partial m} > 0$.

The ambiguity of the effect of an increase in *s* on the optimal audit probability is more easily understood. An increase in *s* has opposing effects on the value of auditing. A higher *s* increases the value of disclosure, which increases the marginal benefit of auditing. However, the higher *s* decreases the value of forcing the firm to internalize the social costs of its emissions because the higher *s* reduces the social cost of emissions and increases the socially optimal quantity of emissions. This decreases the marginal benefit of auditing. Either effect may dominate. The expression which determines the sign of $\frac{\partial p*}{\partial s}$ is stated in the appendix.

2.3 Heterogeneous Firms and Incomplete Information

Our model in the previous section assumes a single firm representative of a homogeneous industry, and complete information on the part of the regulator. While these assumptions greatly simplify the analytics of our model, they also imply that the regulator can infer the firm's actual emissions.[15] In this section, we discuss the issues arising from inference of emissions levels, and relax our assumptions to allow for firm heterogeneity and incomplete information.

Any model that captures the trade-off faced by a regulator between reducing emissions and eliciting truthful disclosure of emissions must entail the regulator's forming some inference regarding firms' behavior. That is, the regulator must infer actual emissions and the extent to which firms' disclosures are untruthful in order to evaluate the marginal benefits and costs of policy changes that affect actual emissions and disclosure. This leads to something of a paradox: why does the regulator value disclosure if he can infer how much a firm will emit?

Most fundamentally, we argue that the reduction of social costs arising from a firm's disclosure of emissions is different from what can be achieved from inferring their presence. While we model disclosed emissions simply as a quantity, in practice emissions disclosure is likely to involve additional, directly beneficial but difficult to infer information involving the nature of emissions, the time and location of releases, etc.[16]

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[15] Optimal regulatory policy in the context of the tradeoff between deterring emissions and eliciting truthful disclosure is, of course, determined at the margin. Assuming, as we do in section 2.2, that the regulator has complete information about the firm's demand for emissions and about the firm's incentives to truthfully disclose (arising from the effectiveness and probability of audits) implies that the regulator also knows exactly what level of actual emissions is optimal for the firm, in addition to knowing what percentage of emissions the firm will optimally disclose. However, the model can be thought of as simply a framework for understanding how a regulator would evaluate policy choices at the margin. In applying the model what is required is that the regulator form beliefs regarding how the truthfulness of disclosure and cost of emitting are affected at the margin by the policy parameters, and how the level of emissions is affected by the cost of emitting (i.e., the elasticity of demand for emissions). A regulator may well be able to estimate these marginal responses without actually having complete information. For example, the regulator may be able to estimate the elasticity of demand for emissions without knowing the entirety of the demand curve.

[16] This suggests several possible extensions that are beyond the scope of the current analysis. For example, one could permit firms to report more detailed information about the characteristics of their emissions and

The ability to mitigate the harm caused by emissions is likely to be very sensitive to these specific details, perhaps most importantly the immediate knowledge of a release (or even prior knowledge in the case of planned releases). A regulator's belief (or even certainty) that a firm is emitting more than it discloses may very well be insufficient to enable mitigation. Furthermore, the regulator presumably could not act to penalize the firm based on inferred emissions since penalties could not be legally enforced on inferred emissions that have not actually been revealed by the audit.

The representative firm model employed in section 2.2 implies that the regulator's inference is applicable to a specific firm. We develop a more general model here which entails firm heterogeneity. In this framework the regulator forms inference regarding aggregate industry emissions and average disclosure behavior, but cannot infer any specific firm's emissions level. This allows meaningful analysis of policy tradeoffs but enhances the distinction between disclosed and inferred emissions. In such a context it is clear that the disclosure of emissions by individual firms would enable mitigation of social costs that could not be achieved by inference regarding aggregate industry emissions. We show that in an industry with heterogeneous firms, in which the regulator is able to infer only average industry emissions, the main results of our model continue to hold.

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allow the social cost of disclosed emissions to vary with the nature of the information. As noted by an anonymous reviewer, one could also consider a model in which undiscovered and un-inferred emissions are most costly, followed by undiscovered but inferred emissions, and finally disclosed emissions. Both extensions would add additional complexity (and choice variables for the firm and regulator). However, the general insights from the model would remain largely unchanged.

Assume that each firm has private information, represented by the parameter *k*, regarding the distribution of audit outcomes if it is audited.[17] That is, if an audit occurs it reveals a quantity of emissions equal to $e \cdot (u+k)$ where *u* is a random variable with probability density function $f(u)$ and cumulative distribution function $F(u)$ on the interval $[1-d, 1+d]$. We assume $f(u)$ is unimodal and symmetric around 1. The value of *k* varies across firms and the regulator knows only the distribution of *k*, denoted $G(k)$ with support $[-\varepsilon, \varepsilon]$. The expected value of *k* is assumed to be zero so that on average across firms audits are unbiased. An additional assumption, that $d + \varepsilon < 1$, is required to obtain an interior solution on *z*.

An individual firm's objective remains unchanged—choose the report, *z*, and emissions, *e*, to maximize the expected net benefits of emitting:

$$\underset{e,z}{Max}\left\{B(e) - e\left[\alpha z + p\beta \int_{z-k}^{d} (u + k - z) f(u) du\right]\right\}.$$

Assuming an interior solution, we can solve the first order condition on *z* to obtain an expression for z^*:

$$z^* = F^{-1}\left(1 - \frac{\alpha}{p\beta}\right) + k\,. \tag{2.8}$$

Given z^*, the first order condition on *e* can be stated as follows:

$$\alpha z^* + p\beta \int_{z^*-k}^{d} (u + k - z^*) f(u) du = B'(e^*) \text{ or } \mu^* = B'(e^*)$$

[17] There are several other ways in which we might add firm heterogeneity. For example, we could assume that firms differ in their perceived penalties for non-reporting or in their probabilities of being found noncompliant as in Innes (2000). We thank an anonymous referee for suggesting these possibilities to us.

where $\mu^* = \alpha z^* + p\beta \int_{z^*-k}^{d} (u + k - z^*) f(u) du$ denotes the marginal cost of emitting given the optimal report. The form of firm heterogeneity we have introduced enters the model fairly simply; the firm-specific audit parameter simply shifts the optimal report, z^*. The unit-cost of emissions, μ^*, for a particular firm depends both directly on k and on the resulting z^* (with μ^* of course increasing in k). Note however that taking expectations across the industry $E[z^*] = F^{-1}\left(1 - \frac{\alpha}{p\beta}\right)$ and $E[\mu^*] = \alpha E[z^*] + p\beta \int_{E[z^*]}^{d} (u - E[z^*]) f(u) du$.

The fact that the expected values of these key firm choice variable parallel the expressions for z^* and μ^* in the representative firm model of section 2.2 will enable us to model the optimal policy of the regulator very similarly. The effects of policy parameters on $E[z^*]$ and $E[\mu^*]$ (and therefore expected or average total emissions) precisely parallel the results for the representative firm model on z^* and μ^* described in Propositions 2.1 and 2.2.

Before turning our attention to the problem facing the regulator, note that the regulator is unable to infer a particular firm's true emissions, e^*, in this context. To see this, let x^* represent the <u>level</u> of emissions the firm (optimally) reports to the regulator where

$$x^* = z^* e^* = \left[F^{-1}\left(1 - \frac{\alpha}{p\beta}\right) + k\right] \cdot e(\mu^*) \tag{2.9}$$

with $\mu^* = \alpha z^* + p\beta \int_{z^*-k}^{d} (u + k - z^*) f(u) du$. The presence of *k* in the above expression breaks the inference—each x^* value is associated with more than one value of *k*.[18] To understand the intuition, consider two firms, one with a high value of *k* (audits are biased against it) and one with a low value of *k* (audits are biased in its favor). The firm with the high value of *k* will report a higher percentage of its emissions, z^*, but will emit less because its cost of emitting□*, will be higher. The firm with the low value of *k* will report a smaller share of actual emissions but will emit more. Because the level of emissions reported to the regulator is given by the product of z^* and e^*, both firms could report the same x^* thus breaking the inference.[19] While the regulator is unable to infer a particular firm's emissions based on its report, he can still infer average emissions since he knows the expected value of *k*.

When firms are heterogeneous and the regulator has incomplete information, the regulator is assumed to choose the optimal tax and audit probability based on his knowledge of expected (or average) firm behavior. This is, the regulator minimizes expected value of the social welfare function described in Section 2.2:

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[18] Consider the case where the demand for emissions is linear: $e = a - c\mu$. With a linear demand for emissions, $x^* = \left[F^{-1}\left(1 - \frac{\alpha}{p\beta}\right) + k\right][a - c\mu^*]$. The following two values of *k* yield the same value of x^*:

$$k = -F^{-1}\left(1 - \frac{\alpha}{p\beta}\right) - \frac{(a - c\gamma) + \sqrt{(a - c\gamma)^2 - 4c\alpha x^*}}{-2x^*}, -F^{-1}\left(1 - \frac{\alpha}{p\beta}\right) + \frac{(a - c\gamma) + \sqrt{(a - c\gamma)^2 - 4c\alpha x^*}}{-2x^*}$$

where $\gamma \equiv p\beta \int_{F^{-1}\left(1-\frac{\alpha}{p\beta}\right)}^{b} \left(u - F^{-1}\left(1 - \frac{\alpha}{p\beta}\right)\right) f(u) du$.

[19] More generally, a firm's reported level of emissions will not be a monotonic function of its *k* parameter.

$$E(W) = E\left[e(\mu^*)[m - sz^* - \mu^*] + pw - \int_{\mu^*}^{\mu_c^*} e(\rho)d\rho \right].$$

This problem is made far more tractable by assuming each firm faces linear demand for emissions:

$$e(\mu^*) = a - c\mu^*.$$

Given this assumption, the regulator's objective function becomes:

$$E(W) = E\left\{ (a - c\mu^*)(m - sz^* - \mu^*) + pw - \frac{1}{2}(a - c\mu^*)\left(\frac{a}{c} - \frac{1}{c}\mu^*\right) \right\}$$

The regulator minimizes $E(W)$ with respect to his choices of the tax, α, and audit probability, *p*. The fact that the respective forms of $E[z^*]$ and $E[\mu^*]$ resemble those of z^* and m^* in the homogeneous firm model, together with linearity of demand, makes the solution to the regulator's problem in this context closely parallel that discussed in section 2.2. In particular, the comparative static results obtained for an interior solution to the regulators' problem hold with heterogeneous firm of the type modeled here. These results are formalized in the appendix.

2.4 Conclusion

When information disclosure has direct social benefits but is costly for a firm and enforcement is costly and imperfect a regulator must confront the competing objectives of inducing disclosure and internalizing social costs. This tension is clearly present in many environmental regulatory contexts where the harm from emissions can be mitigated if potentially impacted parties have better information about the nature and quantity of emissions. It also exists in other regulatory settings such as product safety regulation.

Disclosure of product defects and hazards has direct social benefits, but it is desirable that firms face a cost (either liability or fines) when their products cause harm in order to induce care.

There are certainly many avenues for future work in this area. One could imagine two policymakers, one of whom chooses a tax and the other the audit probability (e.g., legislature and executive or regulatory agency) but who have different objective functions and interact strategically. A regulator may have other policy instruments at his discretion, including choosing the audit probability for a firm in a dynamic setting based on past behavior. One also might consider an endogenous audit process in which the probability of audit is a decreasing function of disclosed emissions. We have not modeled the choice between putting enforcement resources into more frequent audits or more effective audits. Clearly a regulator must achieve an optimal balance, and the model we've developed could provide a framework for exploring this issue. We have assumed that disclosure costs (tax) and penalties are constant per unit, and that audit effectiveness is independent of firm size or total emissions. Relaxing these assumptions significantly complicates the analysis, but could inform important issues regarding how regulation affects industry structure.

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ESSAY 2 APPENDICES

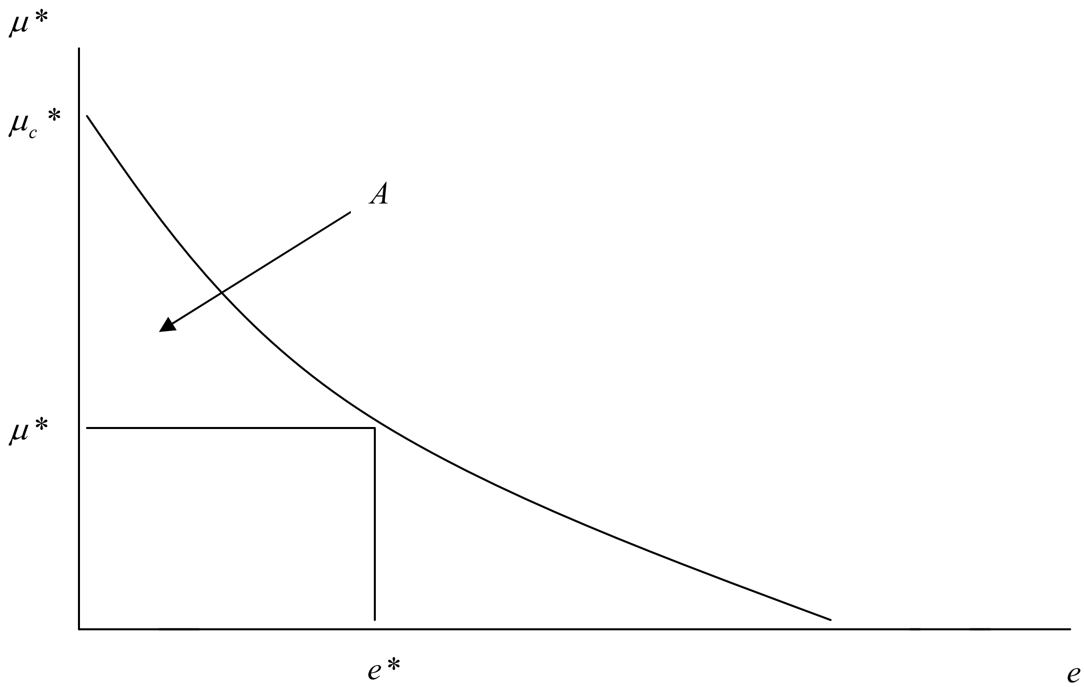

Figure 16 Firm's inverse demand for emissions

A. Proofs for Section 2.2

Proof of Proposition 2.1:

Define $\upsilon \equiv 1 - \frac{\alpha}{p\beta}$. The comparative static results for

$z^* = F^{-1}\left(1 - \frac{\alpha}{p\beta}\right) = F^{-1}(\upsilon)$ where $F(\cdot)$ is monotonically increasing in its augment and

$\alpha < p\beta$ for an interior solution are given by:

$$\frac{\partial z^*}{\partial \alpha} = -\frac{1}{p\beta}\left(\frac{1}{f(z^*)}\right) < 0 \tag{2.A1}$$

$$\frac{\partial z^*}{\partial p} == \frac{\alpha}{p^2\beta}\left(\frac{1}{f(z^*)}\right) > 0 \tag{2.A2}$$

$$\frac{\partial z^*}{\partial \beta} = \frac{\alpha}{p\beta^2}\left(\frac{1}{f(z^*)}\right) > 0 \tag{2.A3}$$

Proof of Proposition 2.2:

The second order condition for minimization is satisfied: $-B''(e^*) > 0$. The comparative static results for *e* are derived implicitly.

$$\frac{\partial e^*}{\partial \alpha} = \frac{z^*}{B''(e^*)} < 0 \tag{2.A4}$$

$$\frac{\partial e^*}{\partial p} = \frac{\beta}{B''(e^*)}\int_{z^*}^{b}(t - z^*)f(t)dt < 0 \tag{2.A5}$$

$$\frac{\partial e^*}{\partial \beta} = \frac{p}{B''(e^*)}\int_{z^*}^{b}(t - z^*)f(t)dt < 0 \tag{2.A6}$$

Proof of Proposition 2.3:

The elements of the Hessian for the policymaker's problem are:

$$\frac{\partial^2 V}{\partial \alpha^2} \equiv f_{11} = e'(\mu^*)\left[(m - sz^* - \mu^*)\frac{\partial z^*}{\partial \alpha} - (z^*)^2\right] - se(\mu^*)\frac{\partial^2 z^*}{\partial \alpha^2} + e''(\mu^*)(m - sz^* - \mu^*)(z^*)^2 > 0 \tag{2.A7}$$

$$\frac{\partial^2 V}{\partial p^2} \equiv f_{22} = e'(\mu^*)\left[(m - sz^* - \mu^*)\frac{\partial^2 \mu^*}{\partial p^2} - 2s\frac{\partial z^*}{\partial p}\frac{\partial \mu^*}{\partial p} - \left(\frac{\partial \mu^*}{\partial p}\right)^2\right] - se(\mu^*)\frac{\partial^2 z^*}{\partial p^2} + e''(\mu^*)(m - sz^* - \mu^*)\left(\frac{\partial \mu^*}{\partial p}\right)^2 > 0 \tag{2.A8}$$

$$\frac{\partial^2 V}{\partial \alpha \partial p} \equiv f_{12} = e'(\mu^*)\left[(m - sz^* - \mu^*)\frac{\partial z^*}{\partial p} - s\frac{\partial z^*}{\partial \alpha}\frac{\partial \mu^*}{\partial p} - sz^*\frac{\partial z^*}{\partial p} - z^*\frac{\partial \mu^*}{\partial p}\right] - se(\mu^*)\frac{\partial^2 z^*}{\partial \alpha \partial p} + e''(\mu^*)(m - sz^* - \mu^*)z\frac{\partial \mu^*}{\partial p} \tag{2.A9}$$

The following second order effects are necessary to compute the comparative static results of interest:

$$\frac{\partial^2 V}{\partial \alpha \partial m} \equiv f_{1m} = e'(\mu^*)z^* < 0 \tag{2.A10}$$

$$\frac{\partial^2 V}{\partial p \partial m} \equiv f_{2m} = e'(\mu^*)\frac{\partial \mu^*}{\partial p} < 0 \tag{2.A11}$$

$$\frac{\partial^2 V}{\partial \alpha \partial s} \equiv f_{1s} = -e(\mu^*)\frac{\partial z^*}{\partial \alpha} - e'(\mu^*)(z^*)^2 > 0 \tag{2.A12}$$

$$\frac{\partial^2 V}{\partial p \partial s} \equiv f_{2s} = -e(\mu^*)\frac{\partial z^*}{\partial p} - e'(\mu^*)z^*\frac{\partial \mu^*}{\partial p} \tag{2.A13}$$

$$\frac{\partial^2 V}{\partial\alpha\partial w} \equiv f_{1w} = 0 \tag{2.A14}$$

$$\frac{\partial^2 V}{\partial p\partial w} \equiv f_{2w} = 1 \tag{2.A15}$$

We begin with the comparative static results for the optimal tax on reported emissions, denoted $\alpha *$.

$$\frac{\partial\alpha *}{\partial m} = \frac{1}{SOC}\begin{vmatrix} -f_{1m} & f_{12} \\ -f_{2m} & f_{22} \end{vmatrix} = \frac{1}{SOC}\left[-f_{1m}f_{22} + f_{2m}f_{12}\right] > 0 \text{ given } SOC > 0$$

since

$$\begin{aligned} &-f_{1m}f_{22} + f_{2m}f_{12} \\ &= se(\mu *)e'(\mu *)\left[\frac{\partial\mu *}{\partial\alpha}\frac{\partial^2 z *}{\partial\alpha^2} - \frac{\partial\mu *}{\partial p}\frac{\partial^2 z *}{\partial\alpha\partial p}\right] \\ &+ \left[e(\mu *)\right]^2\left[(m - sz * - \mu *)\left(\frac{\partial\mu *}{\partial p}\frac{\partial z *}{\partial p} - z *\frac{\partial^2\mu *}{\partial\alpha^2}\right) + s\frac{\partial\mu *}{\partial p}\left(\frac{\partial z *}{\partial p} - \frac{\partial z *}{\partial\alpha}\right)\right] > 0 \end{aligned} \tag{2.A16}$$

$$\frac{\partial\alpha *}{\partial s} = \frac{1}{SOC}\begin{vmatrix} -f_{1s} & f_{12} \\ -f_{2s} & f_{22} \end{vmatrix} = \frac{1}{SOC}\left[-f_{1s}f_{22} + f_{2s}f_{12}\right] < 0 \text{ given } SOC > 0$$

since

$$
\begin{aligned}
&- f_{1s}f_{22} + f_{2s}f_{12} \\
&= s[e(\mu *)]^2\left(\frac{\alpha *}{p *}\psi\frac{\partial z *}{\partial \alpha}\right) \\
&+ sz * e(\mu *)e'(\mu *)\left(\frac{\partial \mu *}{\partial p}\frac{\partial^2 z *}{\partial \alpha \partial p} - z * \frac{\partial^2 z *}{\partial p^2}\right) \\
&+ e(\mu *)e''(\mu *)(m - sz * - \mu *)\frac{\partial \mu *}{\partial p}\left[\frac{\partial z *}{\partial \alpha}\frac{\partial \mu *}{\partial p} - z * \frac{\partial z *}{\partial p}\right] \\
&+ [e'(\mu *)]^2 z * (m - sz * - \mu *)\left(z * \frac{\partial^2 \mu *}{\partial p^2} - \frac{\partial z *}{\partial p}\frac{\partial \mu *}{\partial p}\right) \\
&+ sz * [e'(\mu *)]^2 \frac{\partial \mu *}{\partial p}\left[\frac{\partial z *}{\partial \alpha}\frac{\partial \mu *}{\partial p} - z * \frac{\partial z *}{\partial p}\right] \\
&+ e(\mu *)e'(\mu *)\left(s\frac{\partial z *}{\partial p} + \frac{\partial \mu *}{\partial p}\right)\left(z * \frac{\partial z *}{\partial p} - \frac{\partial z *}{\partial \alpha}\frac{\partial \mu *}{\partial p}\right) < 0
\end{aligned}
\tag{2.A17}
$$

where $\psi \equiv \left[\frac{\partial F(\upsilon)}{\partial \upsilon}\right]^{-1}\frac{1}{(p *)^2 \beta} > 0$ with $\upsilon \equiv 1 - \frac{\alpha *}{p * \beta}$.

The comparative static result for w on $\alpha *$ is generally ambiguous:

$$\frac{\partial \alpha *}{\partial w} = \frac{1}{SOC}\begin{vmatrix} -f_{1w} & f_{12} \\ -f_{2w} & f_{22}\end{vmatrix} = \frac{1}{SOC}\left[-f_{1w}f_{22} + f_{2w}f_{12}\right] = \frac{1}{SOC}\left[f_{12}\right]$$

Given $SOC > 0$, the sign of $\frac{\partial \alpha *}{\partial w}$ equals the sign of f_{12}, which is given as equation (2.A9) above.

We now derive the comparative static results for the optimal audit probability, $p *$. The comparative static result for w on $p *$ is given by:

$$\frac{\partial p *}{\partial w} = \frac{1}{SOC}\begin{vmatrix} -f_{11} & f_{1w} \\ -f_{12} & f_{2w}\end{vmatrix} = \frac{1}{SOC}\left[-f_{11}f_{2w} + f_{12}f_{1w}\right] = \frac{1}{SOC}\left[-f_{11}\right] < 0 \text{ since } f_{11} > 0.$$

The signs of $\frac{\partial p *}{\partial m}$ and $\frac{\partial p *}{\partial s}$ are generally ambiguous. The respective expressions follow:

$$\frac{\partial p^*}{\partial m}=\frac{1}{SOC}\begin{vmatrix}-f_{11} & f_{1m}\\ -f_{12} & f_{2m}\end{vmatrix}=\frac{1}{SOC}\left[-f_{11}f_{2m}+f_{12}f_{1m}\right]$$

$$=\frac{1}{SOC}\left\{se(\mu^*)e'(\mu^*)\left[\frac{\partial\mu^*}{\partial p}\frac{\partial^2 z^*}{\partial\alpha^2}-z^*\frac{\partial^2 z^*}{\partial\alpha\partial p}\right]+\left[e(\mu^*)\right]^2(m-2sz^*-\mu^*)\left(z^*\frac{\partial z^*}{\partial p}-\frac{\partial z^*}{\partial\alpha}\frac{\partial\mu^*}{\partial p}\right)\right\}$$

$$\frac{\partial p^*}{\partial s}=\frac{1}{SOC}\begin{vmatrix}-f_{11} & f_{1s}\\ -f_{12} & f_{2s}\end{vmatrix}=\frac{1}{SOC}\left[-f_{11}f_{2s}+f_{12}f_{1s}\right]$$

$$=\frac{1}{SOC}\left\{s\left[e(\mu^*)\right]^2\left(\psi\frac{\partial z^*}{\partial\alpha}\right)+sz^*e(\mu^*)e'(\mu^*)\left(\frac{\partial\mu^*}{\partial\alpha}\frac{\partial^2 z^*}{\partial\alpha\partial p}-\frac{\partial\mu^*}{\partial p}\frac{\partial^2 z^*}{\partial\alpha^2}\right)\right.$$

$$+e(\mu^*)e''(\mu^*)(m-sz^*-\mu^*)z^*\left[z^*\frac{\partial z^*}{\partial p}-\frac{\partial z^*}{\partial\alpha}\frac{\partial\mu^*}{\partial p}\right]$$

$$+\left[e'(\mu^*)\right]^2z^*(m-sz^*-\mu^*)\left(\frac{\partial z^*}{\partial\alpha}\frac{\partial\mu^*}{\partial p}-\frac{\partial z^*}{\partial p}\frac{\partial\mu^*}{\partial\alpha}\right)$$

$$+s(z^*)^2\left[e'(\mu^*)\right]^2\frac{\partial\mu^*}{\partial p}\left[z^*\frac{\partial z^*}{\partial p}-\frac{\partial z^*}{\partial\alpha}\frac{\partial\mu^*}{\partial p}\right]$$

$$\left.+e(\mu^*)e'(\mu^*)\left(s\frac{\partial z^*}{\partial\alpha}+z^*\right)\left(\frac{\partial z^*}{\partial\alpha}\frac{\partial\mu^*}{\partial p}-z^*\frac{\partial z^*}{\partial p}\right)\right\}$$

B. Proofs for Section 2.3

Below, we reexamine the model presented in Section 2.2 relaxing the homogeneous firms and perfect information assumptions. Consider first the problem facing a representative firm, among many heterogeneous firms. The firm's reported emissions are denoted by ez. The emissions revealed by audit are $x=e\cdot(u+k)$, where k represents the firm's individual characteristic that is unknown to the regulator. k is defined on the support $[-\varepsilon,\varepsilon]$ with mean zero. u is a random variable with probability density function $f(u)$ on the interval $[1-d,1+d]$. $f(u)$ is unimodal and symmetric around 1. The firm is found underreporting if $x>ez$. The expected level of underreporting for a representative firm is

$$\int_{z-k}^{d}[e(u+k)-ez]f(u)du = e\int_{z-k}^{d}(u+k-z)f(u)du$$

The firm's objective function is then

$$\underset{e,z}{Min}\ \ e\cdot\left[\alpha z + p\beta\int_{z-k}^{d}(u+k-z)f(u)du\right]-B(e)$$

The first order conditions for an interior solution on *e* and *z* are given respectively by:

$$\alpha z + p\beta\int_{z-k}^{d}(u+k-z)f(u)du - B'(e^*)=0 \tag{2.B1}$$

$$e\left[\alpha - p\beta\int_{z^*-k}^{d}f(u)du\right]=0 \tag{2.B2}$$

Solving (2.B1) for z^* yields

$$z^* = F^{-1}\left(1-\frac{\alpha}{p\beta}\right)+k\ .$$

Because *k* is a constant, the comparative static results on z^* are the same as in the homogenous firm model (see equations (2.A1) through (2.A3) above).

The comparative static results on e^* are given as follows:

$$\frac{\partial e^*}{\partial \alpha}=\frac{z^*}{B''(e^*)}<0 \tag{2.B3}$$

$$\frac{\partial e^*}{\partial p}=\frac{\beta}{B''(e^*)}\int_{z^*-k}^{d}(u+k-z^*)f(u)du<0 \tag{2.B4}$$

$$\frac{\partial e^*}{\partial \beta}=\frac{p}{B''(e^*)}\int_{z^*-k}^{d}(u+k-z^*)f(u)du<0 \tag{2.B5}$$

Now consider the regulator's problem when firms' demands for emissions are linear and given by $e(\mu) = a - c\mu$. Given incomplete information on *k*, the regulator now minimizes, $E(W)$, with respect to his choices of α and *p* where

$$E(W) = E\left\{e(\mu^*)(m - sz^* - \mu^*) - \frac{1}{2}e(\mu^*)\left(\frac{a}{c} - \frac{1}{c}\mu^*\right) + pw\right\}$$

$$= pw + am - \frac{1}{2}\frac{a^2}{c} - asE(z^*) - cmE(\mu^*) + csE(\mu^* \cdot z^*) + \frac{1}{2}cE\left((\mu^*)^2\right)$$

with $\mu^* = \alpha z^* + p\beta \int_{z^*-k}^{d}(u + k - z^*)f(u)du$ denoting the marginal cost of emitting given the optimal report, z^*.

Define $\phi \equiv F^{-1}\left(1 - \frac{\alpha}{p\beta}\right)$ and $\gamma \equiv p\beta\int_{\phi}^{d}(u - \phi)f(u)du$. Given our notation,

$$E(z^*) = F^{-1}\left(1 - \frac{\alpha}{p\beta}\right) = \phi$$

$$E(\mu^*) = \alpha F^{-1}\left(1 - \frac{\alpha}{p\beta}\right) + p\beta\int_{\phi}^{d}(u - \phi)f(u)du = \alpha\phi + \gamma$$

$$E(z^* \cdot \mu^*) = E[(\phi + k)\cdot(\alpha(\phi + k) + \gamma)] = \alpha\phi^2 + \gamma\phi + \alpha Var(k)$$

$$E\left[(\mu^*)^2\right] = E\left[(\alpha(\phi + k) + \gamma)^2\right] = \gamma^2 + \alpha^2\phi^2 + \alpha^2 Var(k) + 2\alpha\gamma\phi$$

where $Var(k)$ denotes the variance of the random variable *k*.

After substituting the above expressions into $E(W)$, we can write the first order conditions for an interior solution as:

$$\frac{\partial E(W)}{\partial \alpha} \equiv g_1 = -s\frac{\partial \phi}{\partial \alpha}[a - c(\alpha\phi + \gamma)] - c\phi[m - s\phi - (\alpha\phi + \gamma)] + (cs + c\alpha)Var(k) = 0$$

$$\frac{\partial E(W)}{\partial p} \equiv g_2 = w - s\frac{\partial \phi}{\partial p}\left[a - c(\alpha\phi + \gamma)\right] - c\frac{\gamma}{p}\left[m - s\phi - (\alpha\phi + \gamma)\right] = 0$$

The second order effects follow. Each expression includes a comparison between the second order effect in the heterogeneous firm model (denoted by g's), and the associated second order effect that would obtain in the homogeneous firm model assuming linear demand for emissions (denoted by $\bar{f}$'s). The latter model is a special case of the more general model in Section 2.2 of the paper (see equations (2.A10) through (2.A15) for the second order effects with a more general demand function).

$$\begin{aligned}\frac{\partial^2 W}{\partial \alpha^2} \equiv g_{11} &= -s\frac{\partial^2 \phi}{\partial \alpha^2}\left[a - c(\alpha\phi + \gamma)\right] \\ &\quad + c\left[\phi^2 + 2s\phi\frac{\partial \phi}{\partial \alpha} - (m - s\phi - (\alpha\phi + \gamma))\frac{\partial \phi}{\partial \alpha}\right] + cVar(k) \\ &= \bar{f}_{11} + cVar(k) > 0\end{aligned} \qquad (2.B6)$$

$$\begin{aligned}\frac{\partial^2 W}{\partial p^2} \equiv g_{22} &= -s\frac{\partial^2 \phi}{\partial p^2}\left[a - c(\alpha\phi + \gamma)\right] \\ &\quad + c\left[\left(\frac{\gamma}{p}\right)^2 + 2s\gamma\frac{\partial \phi}{\partial p} - (m - s\phi - (\alpha\phi + \gamma))\frac{\alpha}{p}\frac{\partial \phi}{\partial \alpha}\right] = \bar{f}_{22} > 0\end{aligned} \qquad (2.B7)$$

$$\begin{aligned}\frac{\partial^2 W}{\partial \alpha \partial p} \equiv g_{12} &= -s\frac{\partial^2 \phi}{\partial \alpha \partial p}\left[a - c(\alpha\phi + \gamma)\right] \\ &\quad + c\left[\phi\frac{\gamma}{p} + s\frac{\gamma}{p}\frac{\partial \phi}{\partial \alpha} + s\phi\frac{\partial \phi}{\partial p} - (m - s\phi - (\alpha\phi + \gamma))\frac{\partial \phi}{\partial p}\right] = \bar{f}_{12}\end{aligned} \qquad (2.B8)$$

$$\frac{\partial^2 W}{\partial \alpha \partial m} \equiv g_{1m} = -c\phi = \bar{f}_{1m} < 0 \qquad (2.B9)$$

$$\frac{\partial^2 W}{\partial p \partial m} \equiv g_{2m} = -c\frac{\gamma}{p} = \bar{f}_{2m} < 0 \qquad (2.B10)$$

$$\frac{\partial^2 W}{\partial \alpha \partial s} \equiv g_{1s} = -\frac{\partial \phi}{\partial \alpha}\left[a - c(\alpha\phi + \gamma)\right] + c\phi^2 + cVar(k) = \bar{f}_{1s} + cVar(k) \tag{2.B11}$$

$$\frac{\partial^2 W}{\partial p \partial s} \equiv g_{2s} = -\frac{\partial \phi}{\partial p}\left[a - c(\alpha\phi + \gamma)\right] + c\frac{\gamma}{p}\phi = \bar{f}_{2s} \tag{2.B12}$$

$$\frac{\partial^2 W}{\partial \alpha \partial w} \equiv g_{1w} = 0 = \bar{f}_{1w} \tag{2.B13}$$

$$\frac{\partial^2 W}{\partial p \partial w} \equiv g_{2w} = 1 = \bar{f}_{2w} \tag{2.B14}$$

We now state the comparative static results for the regulator's choice variables in the heterogeneous firms, incomplete information model.

$$\frac{\partial \alpha^*}{\partial m} = \frac{1}{SOC}\begin{vmatrix} -g_{1m} & g_{12} \\ -g_{2m} & g_{22} \end{vmatrix} = \frac{1}{SOC}\left[-g_{1m}g_{22} + g_{2m}g_{12}\right] = \frac{1}{SOC}\left[-\bar{f}_{1m}\bar{f}_{22} + \bar{f}_{2m}\bar{f}_{12}\right] > 0$$

by equation (2.A16).

$$\frac{\partial \alpha^*}{\partial s} = \frac{1}{SOC}\begin{vmatrix} -g_{1s} & g_{12} \\ -g_{2s} & g_{22} \end{vmatrix} = \frac{1}{SOC}\left[-g_{1s}g_{22} + g_{2s}g_{12}\right] = \frac{1}{SOC}\left[-\bar{f}_{1s}\bar{f}_{22} + \bar{f}_{2s}\bar{f}_{12}\right] - \frac{1}{SOC}c\delta g_{22} < 0$$

since the term in brackets is negative by (2.A17) and $g_{22} > 0$.

$$\frac{\partial p^*}{\partial w} = \frac{1}{SOC}\begin{vmatrix} -g_{11} & g_{1w} \\ -g_{12} & g_{2w} \end{vmatrix} = \frac{1}{SOC}\left[-g_{11}g_{2w} + g_{12}g_{1w}\right] = \frac{1}{SOC}\left[-g_{11}\right] = \frac{1}{SOC}\left[-\left(\bar{f}_{11} + cVar(k)\right)\right] < 0$$

The signs of $\frac{\partial \alpha^*}{\partial w}$, $\frac{\partial p^*}{\partial m}$, and $\frac{\partial p^*}{\partial s}$ are generally ambiguous. The respective expressions follow:

$$\frac{\partial \alpha^*}{\partial w} = \frac{1}{SOC}\begin{vmatrix} -g_{1w} & g_{12} \\ -g_{2w} & g_{22} \end{vmatrix} = \frac{1}{SOC}\left[-g_{1w}g_{22} + g_{2w}g_{12}\right] = \frac{1}{SOC}\left[-\bar{f}_{1w}\bar{f}_{22} + \bar{f}_{2w}\bar{f}_{12}\right] = \frac{1}{SOC}\left[\bar{f}_{12}\right]$$

$$\frac{\partial p^*}{\partial m} = \frac{1}{SOC}\begin{vmatrix} -g_{11} & g_{1m} \\ -g_{12} & g_{2m} \end{vmatrix} = \frac{1}{SOC}\left[-g_{11}g_{2m} + g_{12}g_{1m}\right] = \frac{1}{SOC}\left[-\bar{f}_{11}\bar{f}_{2m} + \bar{f}_{12}\bar{f}_{1m}\right] - c\delta g_{2m}$$

$$\frac{\partial p^*}{\partial s} = \frac{1}{SOC}\begin{vmatrix} -g_{11} & g_{1s} \\ -g_{12} & g_{2s} \end{vmatrix} = \frac{1}{SOC}\left[-\bar{f}_{11}\bar{f}_{2s} + \bar{f}_{12}\bar{f}_{1s}\right] + \frac{1}{SOC}c\delta\left(\bar{f}_{12} - \bar{f}_{2s}\right)$$

CHAPTER IV ESSAY 3: SPILLOVER EFFECTS ACROSS ENVIRONMENTAL PROGRAMS

3.1 Introduction

Firm compliance with environmental regulations has been the focus of numerous empirical studies in environmental policy analysis. Current literature examines environmental enforcement and compliance from various perspectives. To date, the majority of the empirical literature has focused on a single media program, such as Clean Air Act (CAA), Clean Water Act (CWA), Resource Conservation and Recovery Act (RCRA), etc.[1] However, in practice many firms are regulated under more than one environmental program. For example, in the state of Michigan, among a total of 51,381 facilities registered under EPA's Facility Registration System (FRS), 1796 facilities are regulated under both CAA and RCRA and 517 are regulated under both CWA and RCRA. For firms regulated under multiple programs, an important question is: do stricter regulations under one program increase, decrease or have no effect on firm compliance with another program?

This paper endeavors to answer the above question by examining firm compliance behavior under multiple programs. When a firm is regulated under multiple programs, the relationships among these environmental regulations can be substituting, complementary or independent. Complementary (substituting) regulations arise when increasing the enforcement intensity under one program causes the firm to increase (decrease) its abatement under other programs and hence results in higher (lower) compliance under other programs. When regulations are not independent, optimal monitoring and enforcement strategies require coordination between the two programs. Consider the

[1] Cohen (1998) and Cohen (2000) provide literature reviews of empirical works on environmental monitoring and enforcement.

situation where an increase in a firm's abatement level under one program reduces its marginal abatement cost under the other program. Then changes in the enforcement intensity that result in higher abatement level under one program reduce the marginal abatement cost under the other program. As a result, the firm's optimal abatement level and hence its compliance under the other program increases, although the enforcement parameters under that program remain unchanged. If policymakers ignore the complementarity among regulations and choose monitoring and enforcement strategies independently, the resulting abatement levels may be in excess of the socially optimal levels. Following the same reasoning, substituting regulations also call for coordination among programs that regulate the same firm; otherwise, there will be insufficient abatement compared to the social optimum.

The purpose of this paper is to uncover both the existence and nature of spillover effects that one regulatory program places on another regulatory program. Previous studies are suggestive. Firms may substitute away from one type of emissions to another due to technological change or optimization strategies during production. For example, Botre et al. (2007) show that technological innovation in automotive catalytic converters results in lower nitrogen oxides but increased ozone. Sigman (1996) and Gamper-Rabindran (2006) find that a single regulation can lead firms to transfer pollutants from a regulated medium such as air to a different medium such as landfill or water.[2] These studies suggest substitution-inducing regulations (or negative externalities), but do not

[2] Alberini (2001) also addresses substitution, but from a different perspective. She examines the relationship between underground and aboveground storage tanks for petroleum products and hazardous substances due to extensive regulations on underground storage. She finds that following the regulations, the relationship becomes substituting.

explicitly consider simultaneous regulatory programs. In contrast, this paper tests for potential substitution in compliance across programs.

Empirically, complementary regulations are also possible. For example, installing new abatement equipment or expanding current environmental pollution controls to accommodate the requirements of one program may also help the firm control other emissions. It could be that new personnel provide expertise in pollution control in general that benefits abatement of emissions under other programs. Enforcement of one program may also induce firms to adopt cleaner inputs for production or upgrade manufacturing processes in ways that reduce emissions in general. Thus, actions taken to reduce emissions under one program may have spillover effects such that they also reduce emissions regulated under other programs. The result is higher penalties or inspection frequencies under one regulatory program induce firms to reduce emissions under the other programs. The existing literature provides evidence of complementarities across firms induced by a single environmental program (see Shimshack and Ward, 2005, 2008, and Decker and Pope, 2005), but it does not address across-program spillovers for individual firms.

The theoretical model developed in this paper considers a representative firm regulated under two programs, i.e., two pollutants, and allows for abatement of one pollutant to have positive, negative or zero impacts on the marginal abatement cost for the other pollutant. Comparative statics results show that firms respond to more stringent regulations in one program by increasing abatement and thus the compliance rate within the same program. However, across programs, the effects of changes in the regulatory parameters of one program on the compliance of the other program are ambiguous. If changes in one abatement level lead to lower (higher) marginal abatement cost under the other program, then regulations are said to be complements (substitutes); otherwise, regulations are independent.

The empirical work focuses on facilities in Michigan that are regulated under both RCRA and CAA. A probit model with censoring is used to estimate the impacts on RCRA compliance of penalties and inspections under both RCRA and CAA. The results confirm that increasing RCRA penalties or inspection probability increases the compliance rate within the same program. Cross-program effects turn out to be positive. That is, increasing CAA penalties and enforcement rates also leads to a higher compliance rate under RCRA. This provides evidence of a complementary relationship between the two programs.

The rest of the paper is organized as follows. Section 2 develops the theoretical model of firm compliance decisions under multiple regulations. Section 3 discusses the data and Section 4 presents the empirical model. Results and interpretations are given in Section 5. Section 6 concludes.

3.2 Theoretical Model

A polluting firm is regulated under two environmental programs, denoted m and n. The regulations take the form of standards, denoted s_m and s_n respectively, on the firm's total emissions of the regulated pollutant. Emissions exceeding the standards are penalized with per unit fine, f_m and f_n, respectively. The firm faces inspection probabilities q_m and q_n, respectively. The firm chooses the levels of abatement for the two pollutants. Let a_i denote the abatement level, $\bar{e}_i$ the level of emissions in the absence of regulation, and e_i the intended emissions after abatement, where $i = m, n$. It is assumed that there is measurement errors associated with the inspection process, denoted v_i, so that the firms realized emissions are $e_i = \bar{e}_i - a_i + v_i$. Then $a_i = \bar{e}_i - e_i + v_i$. The abatement cost for the firm is $c(a_m, a_n)$, with $c_i \equiv \frac{\partial c}{\partial a_i}$, $c_{ii} \equiv \frac{\partial^2 c}{\partial a_i^2}$ and all being positive. As I show below, complementary or substitution relationships between the two regulatory programs arise when abatement of one pollutant affects the marginal abatement cost of another pollutant or when $c_{mn} \equiv \frac{\partial^2 c}{\partial a_m \partial a_n} \neq 0$.

(1) When $c_{mn} < 0$, increasing abatement of one pollutant reduces the marginal abatement cost of the other, and

(2) when $c_{mn} > 0$, increasing abatement of one pollutant increases the marginal abatement cost of the other.

Given the standard, s_i, the probability that the firm is out of compliance with regulation *i* is denoted $P_i(a_i)$, where, $P_i^{'} < 0$, $P_i^{''} < 0$, $P_i(0) = 1$ and $\lim_{a_j \to \infty} P_i(a_i) = 0$.[3] Define the firm's expected total cost, $g(a_m, a_n)$, to be the sum of abatement costs and expected penalties. It follows that

$$g(a_m, a_n) = c(a_m, a_n) + f_m q_m P_m(a_m)(\bar{e}_m - a_m + v_m - s_m) + f_n q_n P_n(a_n)(\bar{e}_n - a_n + v_n - s_n) \quad (3.1)$$

[3] To ensure the probability $P_i(a_i)$ is differentiable, it is assumed that the firm cannot completely eliminate the potential of violation due to measurement errors associated with inspection process.

The firm chooses abatement levels a_m and a_n to minimize $g(a_m, a_n)$. Assuming an interior solution, the associated first order conditions can be rearranged to yield:

$$c_m = f_m q_m P_m(a_m^*) - f_m q_m(\bar{e}_m - a_m^* - s_m)P_m^{'}(a_m^*) \tag{3.2}$$

$$c_n = f_n q_n P_n(a_n^*, s_n) - f_n q_n(\bar{e}_n - a_n^* - s_n)P_n^{'}(a_n^*)\,. \tag{3.3}$$

where * denotes the optimal abatement levels. The left- and right-hand sides of expressions (2) and (3) represent the marginal costs and expected marginal benefits of abatement effort respectively.

The relationship between the two regulatory programs m and n are derived from the comparative static results for penalties (*f*) and inspections (*q*). The main results are stated as Proposition 3.1 and the proof is given in Appendix 3.A.

Proposition 3.1 Assuming an interior solution for the firm's optimization problem, the comparative statics with respect to penalties f_i and inspections q_i are:

(i) $\dfrac{da_i}{df_i} > 0$ and $\dfrac{da_i}{dq_i} > 0$ for $i = m, n$;

(ii) Sign ($\dfrac{da_i}{df_j}$)=-sign(c_{mn}) and sign ($\dfrac{da_i}{dq_j}$)=-sign(c_{mn}), where $i, j \in \{m, n\}$ with $i \neq j$.

Proposition 3.1 describes the effects of changes in penalties and inspections on abatement levels under the two programs. I refer to the impacts of enforcement parameters on abatement (and hence compliance) under the same program as within program effects and the impacts of enforcement parameters in one program on abatement (and hence compliance) under the other program as cross-program effects. Statement (i) in Proposition 3.1 indicates that, as expected, within program effects are positive. An increase in enforcement intensity under regulation *i*, from either an increased fine or increased inspection probability, increases abatement of pollutant *i*. Statement (ii) refers to cross-program effects. When c_{mn} is negative (positive), so that regulations are complements (substitutes), then an increase in the enforcement parameters for program i increases (decreases) abatement for program j for $i \neq j$. More importantly, the result suggests that the sign of c_{mn} can be inferred from the cross-program effects. That is, $\frac{da_i}{df_j} > 0 \Rightarrow c_{mn} < 0$ and $\frac{da_i}{df_j} < 0 \Rightarrow c_{mn} > 0$. In addition, if $\frac{da_i}{df_j} = 0$ and therefore $c_{mn} = 0$, then enforcement parameters in one program have no effect on the abatement level in the other program.

Given theory does not offer guidance as to the expected direction for cross-program effects, I propose an empirical model that provides an indirect test of the implications of Proposition 3.1 in section 4. The theory implies the following testable hypothesis:

Null Hypothesis 1: The within program effects are positive.

Null Hypothesis 2: The cross-program effects are zero.

Hypothesis 2 tests the changes in abatement under one program in response to changes in enforcement parameters under the other program. Under the null hypothesis, changes in penalty and enforcement under one program have no effect on firm's abatement and compliance under the other program. If the null hypothesis is rejected, then it indicates that the two programs are correlated. Specifically, positive cross-program effects imply $c_{mn} < 0$ and hence the programs are complementary. On the other hand, if the cross-program effects are negative, then $c_{mn} > 0$ and regulations are substitutes.

3.3 Data

This study focuses on facilities in the state of Michigan that are jointly subject to hazardous waste (RCRA) and air (CAA) regulations. The major data source is EPA's Enforcement and Compliance History Online (ECHO). The ECHO data track compliance histories of EPA-regulated facilities as well as inspection and enforcement actions taken against the facilities under air, water and hazardous waste programs. Compliance and enforcement data for facilities in ECHO is recorded each quarter and is available for the most recent three years. Therefore, this study covers the time period from the third quarter of 2006 to the first quarter of 2008.

While determining facilities that are regulated under both CAA and RCRA, I find that some facilities cannot be identified uniquely by CAA ID number or RCRA ID number. For example, a single ID under CAA can be matched to multiple IDs under RCRA according to EPA's facility registration system. Since there is no other identification method to aggregate the multiple RCRA IDs, I treat each RCRA ID as a unique facility although they share the same CAA information. Similarly, there are cases where a unique ID under RCRA are assigned multiple IDs under CAA. I also treat the multiple CAA IDs as unique facilities. Therefore each facility in the analysis is jointly identified by CAA and RCRA ID. Since government facilities are essentially different from private facilities in terms of their operation and objective function, they are excluded from the analysis. The analysis include a total of 1148 facilities with enforcement and compliance history over 12 quarters.

The ECHO database is also linked to several other databases available through EPA, including the Facility Registration System (FRS) database, the Aerometric Information Retrieval System (AIRS) Facility Subsystem database and the RCRAInfo database. These databases provide information about the other environmental programs under which the facility is regulated and facility characteristics that are related to these two programs.

In addition, community characteristics are included in the analysis to control for the potential influence of community pressures on firm behavior. Specifically, I include the percentage of urban population, percentage of white population, per capita income and median housing values at the county level all obtained from the 2000 United States Census.

3.4 Econometric model

The empirical analysis focuses on the within program effects under RCRA and the cross-program effects of CAA enforcement parameters on compliance with RCRA. Under RCRA, facilities are inspected on a regular basis, although violations causing damage to human health or the environment may be self-reported or reported by third parties. Thus, compliance status is available only when a facility is inspected under RCRA and the empirical analysis must control for this censoring.

Let Y_k^* denote the latent variable representing a facility's net benefit from complying with RCRA, where k denotes the facility. Define Y_k to be the corresponding compliance dummy variable such that $Y_k = 1$ (facility complies) when $Y_k^* > 0$ and $Y_k = 0$ (facility does not comply) otherwise. Denote the net benefit to the regulator of inspecting facility k by I_k^* and the corresponding dummy variable under RCRA by I_k such that $I_k = 1$ (facility is inspected) if $I_k^* > 0$ and $I_k = 0$ (facility is not inspected) otherwise. Y_k is observed only when $I_k = 1$. Thus the empirical model is a Heckman-type probit model that includes the following two equations:

$$Y_k^* = z_k^{'}\beta + \varepsilon_k \tag{3.4}$$

$$I_k^* = x_k^{'}\alpha + u_k, \tag{3.5}$$

with the corresponding dummy variables,

$$Y_k^* = \begin{cases} 1 & if \quad Y_k^* > 0 \\ 0 & otherwise \end{cases} \text{ and is observed only when } I_k = 1$$

$$I_k^* = \begin{cases} 1 & if \quad I_k^* > 0 \\ 0 & otherwise \end{cases}.$$

The error terms in the model are assumed to follow bivariate normal distribution such that

$$\begin{bmatrix} \varepsilon_k \\ u_k \end{bmatrix} \sim N(0, \Sigma),$$

where $\Sigma = \begin{bmatrix} 1 & \sigma_{12} \\ \sigma_{12} & 1 \end{bmatrix}$.

In equation (3.4), the compliance equation, $z_k^{'}$ represents facility-specific variables that impact its decisions to comply with RCRA, and β is the corresponding parameter vector to be estimated. In equation (3.5), the inspection equation, $x_k^{'}$ includes factors that affect the inspection probability for a facility while α is the corresponding parameter vector to be estimated.

Variables representing penalties and inspections under the two regulations, RCRA and CAA, are included as explanatory variables in the compliance equation. The coefficients of the RCRA enforcement parameters represent within program effects. According to the theoretical model developed in section 2, these effects are expected to be positive. The cross-program effects are represented by the coefficients of CAA enforcement parameters in the compliance equation. If these cross-program effects are positive, then a higher penalty or inspection probability under CAA leads to more compliance under RCRA. This implies a complementary relationship between the programs. A similar rationale follows for negative cross-program effects, which implies a substitution relationship. Zero cross-program effects are consistent with evidence of independence between the programs.

Although the data are collected as panel data, they are treated as pooled cross-sectional data. For pooled cross-sectional data, observations for the same facility over different periods are correlated and thus the option CLUSTER in Stata is used to control for within groups (facilities) correlation. In addition, standard errors are calculated using robust White's (1982) covariance estimator[4].

Table 3.1 provides variable descriptions and summary statistics. The first two variables are the dependent variables in the binary probit model. The compliance rate for inspection facilities under RCRA is around 0.46. [5] The mean inspection rate under RCRA is as low as 0.02. In anticipating the lagged effects of monitoring and enforcement, the amount of penalties and number of inspections lagged one year and two years are included. They are the set of variables from *RCRA inspection 1* to *CAA penalty 2*. The average number of inspections lagged two years is higher under RCRA with a difference of 0.08, but the average number of inspections in the past 4 quarters is slightly higher under CAA. On the other hand, the average penalty under CAA is higher than that under RCRA.

The dummy variables, *MACT, PSD, NSPS, TRI* and *NEI*, identify other environmental programs to which the facility is subject. Industry differences are captured broadly using the variable *Manufacturing*. Facilities with 2 digit SIC codes between 20 and 39 are classified as manufacturing and 73% of facilities in the sample are classified as manufacturing. The set of variables from *CEG* to *Managed 2005* controls for other RCRA-related characteristics of the facility. Facility size is represented by number of employees. The remaining variables in Table 3.1 are selected to control for community characteristics.

[4] See Rogers (1993) and Williams (2000) for details.

[5] With 1148 facilities over a period of 12 quarters, a total of 236 inspections were carried out by the EPA and the state regulators.

3.5 Results

The primary estimation results of the probit model are shown in Table 3.2. Important parameters of interests are those related to past penalties and inspections. In RCRA compliance equation, five out of the eight enforcement parameters are positive and significant, including *RCRA penalty 2*, *RCRA inspection 2*, *CAA penalty 2*, *CAA penalty 1*, and *CAA inspection 1*. These variables are sufficient to test the two hypotheses stated in Section 3. First, given the positive and significant effects of RCRA enforcement parameters (penalty and inspection) on RCRA compliance, the within program effects are positive and thus Hypothesis 1 cannot be rejected. Second, three of the CAA enforcement parameters are positive and significant but none are significantly negative, suggesting that higher penalties and more enforcement actions under CAA in the past two years lead to higher compliance rate with RCRA. This provides evidence to reject Hypothesis 2 and thus compliance decisions under the two programs are correlated. In addition, the positive cross-program effects also imply a complementary relationship between the two programs for the same facilities. These within program and cross-program effects suggest that a facility's compliance is affected by not only enforcement parameters within the same program but also those from the other program.

The finding of a complementary relationship between the two programs bears important policy implications. Complementary regulations imply that for a regulator, the benefit of increasing monitoring and enforcement of one program is not confined to the reduced emissions or increased compliance under the same program. The benefit of increased compliance under other programs should also be considered when evaluating the effectiveness of monitoring and enforcement.

To better interpret the within program and cross-program effects, marginal effects for significant variables are calculated and reported in Table 3.3 in the attached appendix. The marginal effects considered here are the changes in the univariate unconditional probability of compliance with RCRA when one of the enforcement parameters increases, holding everything else constant.

The marginal effect of *RCRA penalty 2* is 0.023, meaning that increasing RCRA penalties in the past 5-8 quarters by one dollar increases the probability of compliance by 0.023. For RCRA inspections in the past 5-8 quarters, one more inspection results in an increase in the probability of compliance by 0.066. The magnitude of the marginal effects for CAA parameters also vary. Increasing CAA penalty by one unit in the past 4 quarters increases the RCRC compliance probability by 0.004, and the increment reduces to 0.001 for one more unit of penalty in the past 5-8 quarters. At the margin, a unit increase in *CAA inspection 1* can raise the RCRA compliance probability by 0.177.

Other control variables included in the compliance equations seems to provide limited effects. The only significant variable is *TRIS,* which indicates whether a facility is subject to TRI. Facilities regulated under TRI are required to report their usage, manufacturing, transportation or releases of certain toxic chemicals to state and local governments. Previous empirical analyses of information disclosure programs can be used to explain this positive effect of *TRIS*. For example, Konar and Cohen (1997) show that firms with stock prices declining due to the release of the TRI information subsequently reduce their emissions by a larger amount than other firms in the same industry. Thus, facilities reporting to TRI have more incentive to reduce emissions, resulting in better compliance with RCRA. Although several other variables show the expected sign, they are not significant at the 0.10 level. For example, the variables *generated 2005*, *managed 2005* and *manufacturing* are all expected to be negatively related with compliance. While these variables show the correct signs in the regression, they are not significant at the 0.10 level.

Variables related to community characteristics generally do not have significant impacts on facility compliance under CAA. This finding is similar to the result in Shimshack and Ward (2005), who find community characteristics insignificant in their analysis of firm compliance. As explained in their paper, this insignificance is because community characteristics impact firm compliance through their influence on enforcement, which has been included in the model.

3.6 Conclusion

In this paper, I investigate firm compliance behavior under multiple environmental regulations. Three possible relationships among compliance decisions are considered and tested: 1) complementarity, where regulatory measures under one program positively affect firm compliance with other programs; 2) substitution, where firms reduce compliance with one program in response to more stringent regulations under other programs; 3) independence, where facilities make compliance decisions independently.

Using data on facilities that are regulated under both CAA and RCRA in Michigan, I estimate a probit model with censoring, which yields evidence supporting the complementarity of regulations. As expected, RCRA penalties and inspections have significantly positive impacts on facility compliance under RCRA. The cross-program effects are positive, such that increases in CAA penalties and inspections also induce facilities to comply more often with RCRA. Therefore, the CAA regulatory program has positive spillovers on the RCRA program.

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ESSAY 3 APPENDICES

A. The second order effects that are used in deriving the comparative statics include:

$$g_{11} = c_{mm} + q_m f_m P_m^{''}(\bar{e}_m - a_m - s_m) - 2q_m f_m P_m^{'}$$

$$g_{22} = c_{nn} + q_n f_n P_n^{''}(\bar{e}_n - a_n - s_n) - 2q_n f_n P_n^{'}$$

When second order is satisfied, $g_{11} > 0$ and $g_{22} > 0$.

The following are second-order partial derivatives:

$$g_{12} = c_{mn}$$

$$g_{1f_m} = q_m P_m^{'}(\bar{e}_m - a_m^* - s_m) - 2q_m P_m\left(a_m^*, s_m\right) < 0$$

$$g_{2f_n} = q_n P_n^{'}(\bar{e}_n - a_n^* - s_n) - 2q_n P_n\left(a_n^*, s_n\right) < 0$$

$$g_{1q_m} = f_m P_m^{'}(\bar{e}_m - a_m^* - s_m) - 2f_m P_m\left(a_m^*, s_m\right) < 0$$

$$g_{2q_n} = f_n P_n^{'}(\bar{e}_n - a_n^* - s_n) - 2f_n P_n\left(a_n^*, s_n\right) < 0$$

$$g_{2f_m} = g_{1f_n} = g_{2q_m} = g_{1f_n} = 0$$

The within program effects and their signs are given below, where $SOC = g_{11}g_{22} > 0$

$$\frac{da_m^*}{df_m} = \frac{1}{SOC}\begin{vmatrix} -g_{1f_m} & g_{12} \\ -g_{2f_m} & g_{22} \end{vmatrix} = -\frac{g_{1f_m}g_{22}}{SOC} > 0$$

$$\frac{da_m^*}{dq_m} = \frac{1}{SOC}\begin{vmatrix} -g_{1q_m} & g_{12} \\ -g_{2q_m} & g_{22} \end{vmatrix} = -\frac{g_{1q_m}g_{22}}{SOC} > 0$$

The same reasoning holds for $\dfrac{da_n^*}{df_n}$ and $\dfrac{da_n^*}{dq_n}$.

The cross-program effects include:

$$\frac{da_m^*}{df_n} = \frac{1}{SOC}\begin{vmatrix} -g_{1f_n} & g_{12} \\ -g_{2f_n} & g_{22} \end{vmatrix} = \frac{g_{2f_n}g_{12}}{SOC} = \frac{c_{mn}g_{2f_n}}{SOC}$$

$$\frac{da_n^*}{df_m} = \frac{1}{SOC}\begin{vmatrix} -g_{1f_m} & g_{12} \\ -g_{2f_m} & g_{22} \end{vmatrix} = \frac{g_{2f_m}g_{12}}{SOC} = \frac{c_{mn}g_{2f_m}}{SOC}$$

$$\frac{da_m^*}{dq_n} = \frac{1}{SOC}\begin{vmatrix} -g_{1q_n} & g_{12} \\ -g_{2q_n} & g_{22} \end{vmatrix} = \frac{g_{2q_n}g_{12}}{SOC} = \frac{c_{mn}g_{2q_n}}{SOC}$$

$$\frac{da_n^*}{dq_m} = \frac{1}{SOC}\begin{vmatrix} -g_{1q_m} & g_{12} \\ -g_{2q_m} & g_{22} \end{vmatrix} = \frac{g_{2q_m}g_{12}}{SOC} = \frac{c_{mn}g_{2q_m}}{SOC}$$

The signs of the cross-program effects depend on the sign of c_{mn}. If $c_{mn} > 0$, then the cross-program effects are negative since the second order cross-partials are negative and the Hessian matrix is positive, given that second order condition is satisfied. If $c_{mn} < 0$, then the cross-program effects are positive given that second order condition is satisfied.

B.

Table 3.1 Variable Description and Summary of Statistics

Variable	Description	Mean (Standard deviation)
RCRA compliance	=1 if facility is in compliance with RCRA	0.46 (0.50)
RCRA inspection	=1 if facility is inspected in current period under RCRA	0.02 (0.14)
RCRA inspection 1	Number of inspections under RCRA, lagged one year	0.15 (0.74)
RCRA inspection 2	Number of inspections under RCRA, lagged two years	0.23 (0.91)
RCRA penalty 1	Amount of penalties under RCRA, lagged one year, in hundred dollars	2.23 (57.36)
RCRA penalty 2	Amount of penalties under RCRA, lagged two years, in hundred dollars	2.06 (56.09)
CAA inspection 1	Number of inspections under CAA, lagged one year	0.16 (0.43)
CAA inspection 2	Number of inspections under CAA, lagged two years	0.15 (0.42)
CAA penalty 1	Amount of penalties under CAA, lagged one year, in hundred dollars	9.42 (231.91)
CAA penalty 2	Amount of penalties under CAA, lagged two years, in hundred dollars	12.33 (294.44)
MACT	=1 if facility is subject to MACT (maximum achievable control technology)	0.09 (0.28)
PSD	=1 if facility is subject to PSD (prevention of significant deterioration)	0.16 (0.37)
NSPS	=1 if facility is subject to NSPS (new source performance standards)	0.69 (0.46)
TRI	=1 if facility is subject to TRI (Toxic Release Inventory) reporting	0.32 (0.47)
NEI	=1 if facility is in the National Emissions Inventory for criteria air pollutants	0.01 (0.07)
NSR	=1 if facility is subject to NSR (new source review)	0.01 (0.12)
CERCLIS	=1 if facility is tracked in CERCLIS	0.03 (0.17)
ICIS	=1 if facility is tracked in ICIS	0.23 (0.42)

Table 3.1 continued.

Variable	Description	Mean (Standard deviation)
Manufacturing	=1 if facility is classified as manufacturing (SIC codes 20-39)	0.73 (0.44)
CEG	=1 if facility is a RCRA conditionally exempt generator	0.22 (0.42)
LQG	=1 if faciliyt is a RCRA large quantity generator	0.30 (0.46)
SQG	=1 if facility is a RCRA small quantity generator	0.30 (0.46)
Generated 2005	Log of the tons of hazardous waste generated in 2005	-1.53 (5.65)
Managed 2005	Log of the tons of hazardous waste managed in 2005	-6.61 (7.32)
Employees	Number of employees at facility, in thousands	3.15 (13.21)
Urban population	Total percentage of urban population	69.77 (26.02)
Republican	Percentage of voters that voted republican in 2000 Presidential Election	48.66 (10.82)
Income	Per capita income in 1999, in thousand dollars	21.40 (4.11)
House value	Median value of specified owner-occupied housing units, in thousand dollars	111.25 (31.96)
Manufacturing Employed	Percentage of civilian population 16 years and over that are employed in manufacturing industries	23.84 (5.95)
Education	Percentage of population 25 years and over with educational attainment	83.54 (4.02)
White population	Total percentage of white population	83.67 (14.11)

Table 92 Estimation results

Variable	RCRA compliance	Inspection
RCRA inspection 1	-0.11 (0.16)	0.22* (0.05)
RCRA inspection 2	0.17** (0.08)	
RCRA penalty 1	-0.28 (0.22)	
RCRA penalty 2	0.06* (0.03)	
CAA inspection 1	0.47* (0.27)	
CAA inspection 2	-0.09 (0.29)	
CAA penalty 1	0.009* (0.005)	
CAA penalty 2	0.003** (0.001)	
TRI	0.57* (0.31)	
Urban population	0.01 (0.008)	
Republican	0.01 (0.01)	
House value	0.008 (0.01)	
Education	0.006 (0.05)	
Employees	0.008 (0.005)	0.0006 (0.001)
Generated 2005	-0.03 (0.06)	0.002 (0.009)
Managed 2005	-0.08 (0.05)	0.02* (0.01)
Manufacturing	-0.41 (0.37)	-0.08 (0.07)

** Significant at the 95% level, * significant at the 90% level.

Table 103 Marginal effects

Variable	Marginal effects
RCRA inspection 2	0.066
RCRA penalty 2	0.023
CAA inspection 1	0.177
CAA penalty 1	0.004
CAA penalty 2	0.001

VITA

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