Monitoring and enforcement

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1 Introduction

Monitoring and enforcement of agents' degree of compliance with regulations is necessary for environmental policy instruments to work as intended. Although important for any regulation, this is particularly the case for market based instruments. The primary reason for this is that without any checks on the compliance level, the information provided by these instruments will be misleading. Recall that any resource allocation mechanism in the modern game theory sense (Campbell, 1987; Romstad 2005) is a communication device.

From an environmental perspective compliance is also important. Without the necessary compliance, environmental standards would not be maintained. Under the presumption that the environmental standards were set optimally, lack of compliance would make the resulting emissions or provisioning level of a public good sub optimal. Malik (1990) stresses the importance of compliance for emissions; any system seeking optimal emission level needs a mechanism for inducing firms to comply with the standards.

Vis-a-vis optimality, it is also important that the monitoring and enforcement scheme delivers the desired level of compliance at the least social costs.[1] A monitoring and enforcement system that does not satisfy this criterion cannot maximize social welfare. Consequently, more resources than necessary are spent on achieving the desired compliance level. By the first theorem of welfare economics this implies that one forfeits the opportunity of taking the "wasted" resource and redistributing to someone without making anyone worse off (Varian, 1984).

Along the same reasoning it follows that the optimal compliance level rarely is 100 %. The reason for this is that optimal compliance occurs where the expected marginal benefits of compliance equals the expected marginal costs of the effort to achieve compliance.

The reminder of this note is structured as follows. Section two deals with the stochastic nature of agents' environmental performance. In section three I present the notion of the penalty function, i.e., how a penalty for noncompliance should be designed to create more correct incentives for avoiding excess emissions. The following two sections present models for monitoring and enforcement. Section four presents the standard basic model, while section five extends the analysis going into reputation based models for monitoring and enforcement.

2 The stochasticity of emissions

Emissions usually has a stochastic element. This is commonly accepted in agriculture or similar productions where the weather adds some variation around the targeted emission level. However, even for productions where weather does not play a role, emissions are likely to have a stochastic element due to measurement errors, machinery not configured correctly, accidents, or by human mistakes. A common term for these events is *lack of process control*.

The stochastic nature of emissions could be captured by a bar chart over frequency of observed emissions where one scales the bars so that the sum of their height equals one. Making the width of each bar infinitely small, we get the probability density as shown in Figure 1.

[1] The dual formulation of this is to get the maximum compliance for a given expenditure (budget to be used on monitoring and enforcement).

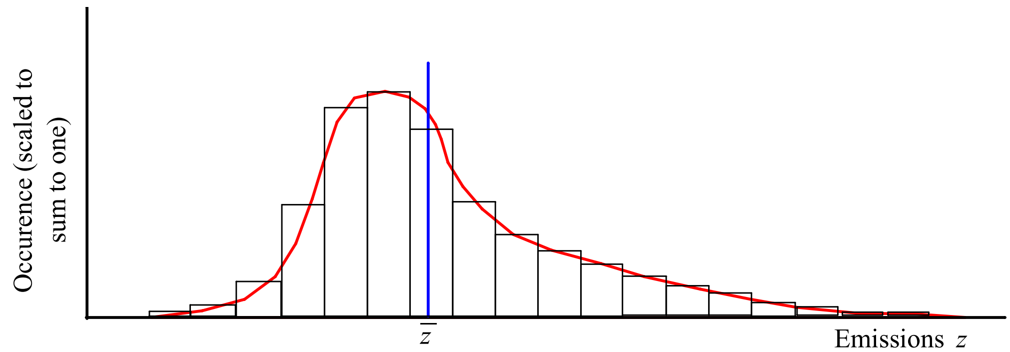

Figure 1: The probability distribution of emissions (mean emissions marked as $\bar{z}$) .

From the bar chart over emissions one can estimate a *probability density function* of emissions, $f(z)$, that fully describes the emission process so that the area underneath the red line equals one. This implies that the integral of the probability density function also has the value of one, i.e., $F(z) = \int_{-\infty}^{\infty} f(z)\, dz = 1$. $F(z)$ is denoted the *cumulative density function* of z.

Suppose that a firm targets its mean emission level at $\bar{z}$. It is then easy to see from Figure 1 that the firm will quite frequently have emissions in excess of the target level. If there are fines or penalties levied for having emissions over the allowed level, the firm will adjust its target level downward, so that it only exceeds the allowed emission with a frequency that maximizes its expected profit maximizing level. Denote this emission level z_1^*. Let there be another firm that has a narrower probability distribution. Assume that the owners of both firms have the same risk preferences and the same preference for not breaking the law. The second firm, with the better *process control*, can then allow its mean emissions ($\bar{z}_2$)to be higher than the first firm ($\bar{z}_1$). Figure 2 contains a graphical illustration.

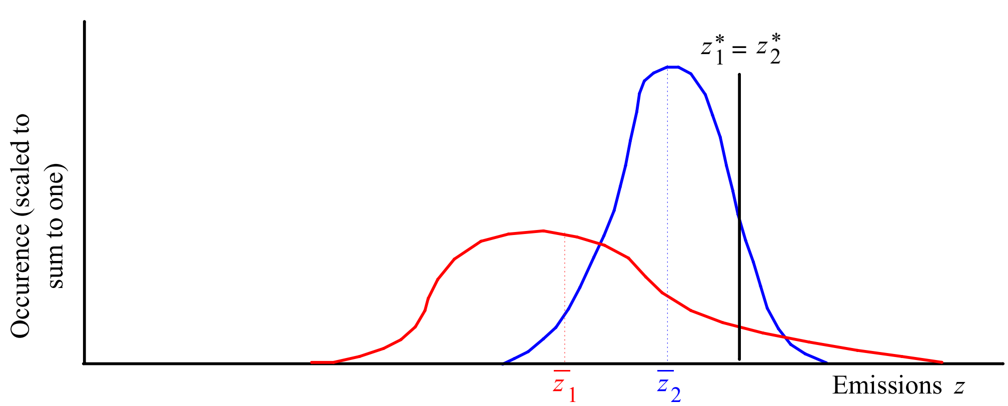

Figure 2: The probability distribution of emissions for a firm with poor (red line) and better process control (blue line).

Suppose that gaining process control, and hence a higher mean emission level to have the same risk of violating the emission standard, entails some extra investment. This investment is profitable if the discounted stream of profits from the higher emission level exceeds the investment costs.

From an environmental perspective, the expected increase in the damages from the higher mean emission level may be offset by less frequent emissions in the high end of the probability distribution. This is clearly demonstrated in Figure 2, where firm 2 has less occurrence of emissions to the right of the point where the blue line intersects the red line from above.

3 The penalty function

High emission levels are usually more damaging to the environment than smaller emissions. The penalties levied against large violation of the allowed emission level should reflect this. Hence, the penalty function should be increasing. Moreover, environmental damages increase with increasing emissions. This should be reflected in the penalty function by making it increasing at an increasing rate. Figure 3 provides an illustration.

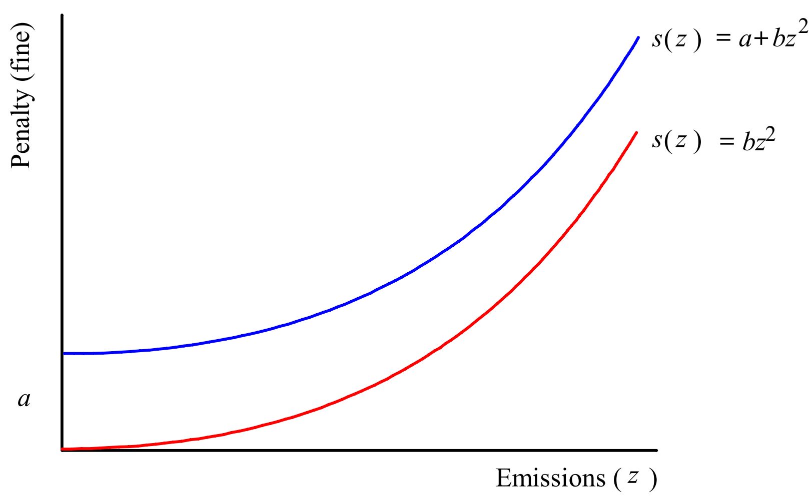

Figure 3: The penalty function of emissions
(red line: without fixed term, blue line: with fixed term).

Several functional form satisfies the criteria of increasing at an increasing rate. Figure 3 shows two second order polynomial for demonstration purposes, one with a fixed effect, $s(z) = a + bz^2$, and one without a fixed effect, $s(z) = bz^2$. There are two obvious reasons for including a fixed effect in the penalty function. First, it provides an extra incentive for firms not to exceed the allowed emission level. Second, it the penalties paid provide extra revenues to cover the costs of the regulator's extra work when a firm violates the allowed emission level.

4 The basic monitoring and enforcement model

An agent's degree of conformity to regulations depends upon the relative profits of compliance and noncompliance. Using principal-agent models makes it possible to find necessary changes in these payoffs to get the desired level(s) of compliance. The task of the principal (the regulatory agency) is to choose the appropriate policy variables so that the agents when maximizing their objective functions under the modified payoffs, thereby maximize the principal's objective function (Laffont, 1988; Rasmusen, 1989). In the case of pollution control the regulatory agency chooses monitoring and penalty schemes such that the firms' expected profits from noncompliance are less than those for compliance.

4.1 Monitoring and enforcement without uncertainty

For compliance to occur for a standard norm-less self regarding agent, the expected payoff off conforming to the regulation must exceed the expected payoff of noncompliance. Let $U_c(z)$ denote the payoff of compliance, and $U_n(z)$ denote the payoff of noncompliance. Moreover, let $S(z)$ denote the penalty paid (with certainty)[2] if a firm is monitored, and let p denote the monitoring probability. Let z denote the size of the emission level, and $\bar{z}$ denote the legal emission level. A violation occurs when $z-\bar{z}>0$. Mathematically, this can be expressed as follows:

$$U_c(z) \geq p[(U_n(z)-S(z-\bar{z}))]+(1-p)U_n(z) \qquad [1]$$

$$\Downarrow$$

$$U_c(z) \geq pU_n(z)-pS(z)+U_n(z)-pU_n(z) \;\; (=-pS(z)+U_n(s))$$

$$\Downarrow S(z-\bar{z}) \neq 0$$

$$p \geq \frac{U_n(z)-U_c(z)}{S(z-\bar{z})} \qquad [2]$$

[2] Certainty in this case implies that if a agent is in noncompliance and monitored, the agent is levied the fine S. In this "certain" setting, there are no type-I (wrongfully finding a compliant agent in noncompliance) or type-II (wrongfully finding a noncompliant agent in compliance) errors.

Equation [2] is denoted the basic equation for monitoring and enforcement. It says that for compliance to be assured, the monitoring probability must exceed the difference in payoffs between noncompliance (U_n) denote and compliance (U_c) divided by the penalty (S) if monitored and found in noncompliance. Examination of [2] yields several interesting insights:

(1) As the penalty, S, increases, the needed monitoring probability to ensure compliance decreases. If the penalty is infinitely large, the necessary monitoring probability is zero. Mathematically,

$$\lim_{S \to \infty} p = \lim_{S \to \infty} \frac{U_n(z) - U_c(z)}{S(z - \bar{z})} = 0 \qquad [3]$$

Equation [3] is known as the "hang the prisoner with probability zero" proposition (Becker, 1968). In terms of reducing the resources spent on monitoring and enforcement (recall that the basic purpose of monitoring and enforcement is to achieve the desired level of compliance at the least effort), it certainly has some appealing features in a completely certain world (see footnote 2). These properties no longer holds if there is uncertainty, in particular with possibilities of false positives (an agent is monitored and wrongly found in noncompliance, see Shavell, 1987, for details).

(2) The necessary monitoring probability depends on the difference between the noncompliance and compliance payoffs. Provided that the regulator has reliable estimates of these payoffs for various agents, the regulator has a (Bayesian)[3] prior estimate of the necessary monitoring probabilities for various agents. This enables the regulator to differentiate the monitoring probability between agents, reducing monitoring effort to achieve the desired compliance level.

4.2 Monitoring and enforcement when there is uncertainty

Uncertainty can come in two major forms: (i) measurement error on behalf of the regulator, and (ii) measurement error or insufficient process control on behalf of the agents. In the first case, there is a possibility of conducting a type-I error, i.e., wrongfully finding an agent in violation when the agent in reality has complied to the regulation. Type-I errors are particu-

[3] See any intermediate text book in statistics to read more about Bayesian statistics.

larly serious in the cases where the penalty levels are high, as the consequences of wrongly finding someone in noncompliance are large. This has given rise to some basic principles of modern law. The first, and most well known principle, is that no one is judged as guilty unless it can be proven they are guilty without reasonable doubt. This does not imply that wrongful convictions do not occur, but that the burden of providing the evidence rests on the accuser, not the defendant.

The second, and far less known principle, is that as the consequences of making a type-I error increase with increasing penalties, so should the necessary evidence of finding the accused guilty. In brief, if the state attorney goes for a higher penalty (for example murder with intent rather than involuntary manslaughter), the burden of proof increases. This further emphasizes the problems with Becker's (1968) "hang the prisoner with probability zero" proposition (Shavell, 1987). This can be extended to popular demands of increased penalties for certain crimes – in any society adhering to democratic principles, it should also increase the burden of proof on the accuser (the state attorney). From criminal psychology it is well known that for some criminals it is not the severity of the penalty, but the probability of being found guilty that matters. As such, there is an asymmetry not visible in the basic equation of monitoring and enforcement [2].

Given that the purpose of monitoring and enforcement is to achieve the desired level of compliance at the least cost, regulators need to tradeoff catching as many violators as possible without having those being monitored challenging the results of the monitoring process in costly litigation. Most regulatory regimes therefore operate with some safety margin in the monitoring process.

Let k denote the safety margin (fudge factor), and retain the notation used in the previous section. A violation then occurs if

$$z - (\bar{z} + k) > 0, \tag{4}$$

and the revised basic equation of monitoring and enforcement is written as:

$$p \geq \frac{U_n(z) - U_c(z)}{S(z - (\bar{z} + k))} \tag{5}$$

The basic difference from [2] is that the safety margin is subtracted when assessing the safety margin in [5].

5 Reputation based models for monitoring and enforcement

The basic logic behind reputation based models is that agents' past records of compliance determines the monitoring probability they face. The rationale for this is that unobservable agent characteristics may reveal themselves in agents' actions over time. A long record of compliance may indicate that an agent has lower relative payoffs from noncompliance (as indicated by equations [3] or [5], or that the agent is law abiding by nature. The regulator cannot know which of these, or any alternate reason, that govern the agent's behavior, but the agent's revealed behavior suffices for the regulator to adjust the monitoring probabilities.

The basic intuition behind reputation based models is:

> *By making monitoring probabilities and penalties depend on past compliance performance creates a compliance rent that reduces the monitoring probabilities needed for incentive compatibility to hold.*

Most of the early enforcement literature deals with static models (see for example Downing and Watson, 1974; Harford, 1978; Viscusi and Zeckhauser 1979; Linder and McBride, 1984). The disadvantage of atemporal models is that the agency and the firms cannot react to each other's actions. Dynamic models allow for such interaction. Some of the first applications of dynamic principal-agent models have been undertaken on tax-cheating (Greenberg, 1984).

Reputation based models use a dynamic principal-agent formulation to model firm behavior with respect to pollution control, where the relative profits of compliance and noncompliance are incorporated explicitly. The firms' relative profits are influenced by three factors; (i) the cost of abatement, (ii) the probability of being caught if in noncompliance, and (iii) the penalty levied if found in noncompliance.

The basic setup of a reputation based system is that firms are divided into three groups according to their past compliance record:

(1) *Group 1 – habitual compliers* (*"heaven"*): Firms in this group has the lowest monitoring probability and do not pay monitoring costs.

(2) *Group 2 – uncertain status ("purgatory")*: Firms in this group have just been caught after having complied in the previous monitoring round, and are moved to group 1 if they are found in compliance, and to group 3 if the are found in noncompliance.

(3) *Group 3 – habitual noncompliers ("hell")*: Firms in this group have to pay the monitoring costs themselves, and must be found in compliance in repeated (q) periods before they are moved to group 2.

The ranking of the monitoring probabilities between the groups (indexed by subscript for group) is:

$$p_1 < p_2 < p_3 \leq 1 \qquad [6]$$

Figure 4 shows the basic structure of such models.

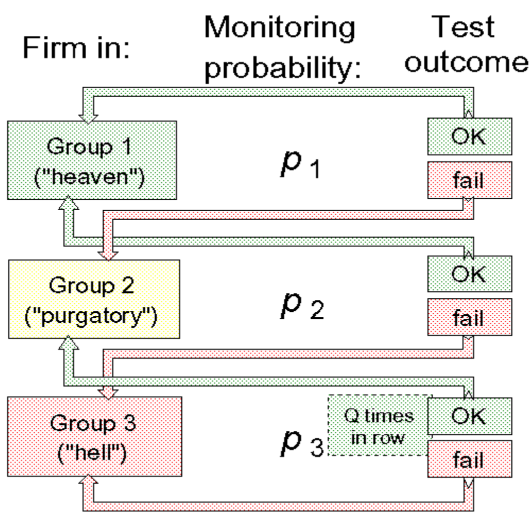

Figure 4: Structure of a reputation based model of monitoring and enforcement.

Group 3 firms ("hell") pay the monitoring costs themselves. This is justified by the fact that these firms have ended up in this group by their own past actions. As such, the participation constraint is met.[4] Let $c = U_n(z) - U_c(z)$. Paying monitoring costs, m, reduces the necessary monitoring probability in this group as indicated by the rewritten version of [5]. Simplifying $S(z-(\bar{z}+k))$ to S, the following condition for compliance in group 3 emerges:

[4] For models where entrant firms are started in group 3, the participation constraint may not be met. However, starting all new firms in group 3 in mobile industries (shipping, brokering houses, etc.) where the emissions are not easily linked to a physical location (like a large industrial site), creates some odd entry-exit incentives that may ruin the main intuition of reputation based monitoring systems. Starting entrants in group 3 reinforces the compliance rent aspects of reputation based models, but will inhibit entry to some extent.

$$p_3 \geq \frac{c-m}{S} \qquad [7]$$

The conditions for compliance in group 2 ("purgatory") is given by [8]:

$$\sum_{t=0}^{T_2+1+KT_3} \beta^t (c - p_2 S) > \sum_{t=0}^{T_2} \beta^{T_2}(-S) + \sum_{t=T_2+1}^{T_2+1+KT_3} \beta^t (c - m - p_3 S) \qquad [8]$$

compliance in group 2 OK — caught in group 2 — group 3 OK

The conditions for compliance in group 1 ("heaven") is given by [9] below:

$$\sum_{t=0}^{T_1+1+T_2} \mathrm{b}^t (c - p_1 S) > \sum_{t=0}^{T_1} \mathrm{b}^{T_1}(-S) + \sum_{t=T_1+1}^{T_1+1+T_2} \mathrm{b}^t (c - p_2 S) \qquad [9]$$

compliance in group 1 OK — caught in group 1 — group 2 OK

The basic structure of equations [7]-[9] is the same in all reputation based models (a net present value formulation of the payoffs of compliance versus noncompliance). However, the details may vary depending upon the specific rules of the chosen monitoring and enforcement regime.

Seeing reputation based systems in conjunction with prior monitoring probabilities is a promising avenue of research in this area. If the (Bayesian) priors suggest that entrant firms should be started in group 3, that will most likely enhance overall welfare gains from such monitoring systems.

6 Concluding remarks

The main purpose of monitoring and enforcement is to achieve the desired level of compliance to regulations at the least social costs. In general, monitoring and enforcement is needed to induce agents to comply to regulations by making the expected payoffs from compliance larger than the expected payoffs from noncompliance. The optimal compliance level is rarely 100 %.

Reputation based models are informationally more demanding than the standard uniform monitoring and enforcement regimes, but they also provide more compliance for a given set of expenditures.

7 Literature

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