An Empirical Examination of EPA Administrative Penalties

Kelly Kristen Lear
Kelley School of Business
Indiana University
March, 1998

Abstract

Becker's classic 1968 article argues that enforcement costs can be minimized by setting fines as high as possible and lowering resources proportionately to maintain the same level of deterrence. Other scholars propose that the optimal fine should reflect the harm to the victim or the gain to the offender. This paper tests alternative theories by examining the U.S. Environmental Protection Agency's (EPA) implicit enforcement policy. Employing new data on federal, administrative enforcement actions and regional enforcement spending, I characterize the EPA's use of its enforcement tools and find weak evidence of a trade-off between fines and resources. In addition, I estimate a model for administrative fines and present evidence that the EPA applies different criteria when fining small and large firms. Fines for large firms depend strongly and positively on firm size, while fines for small firms reflect the violator's expected gain and the victim's harm.

The author is grateful to Heejoon Kang and Eric Rasmusen for helpful comments and to the U.S. Small Business Administration for financial support (Contract No. SBAHQ-95-0026). Any remaining errors are the sole responsibility of the author. Contact information: 1309 E. 10th Street, Bloomington, Indiana 47405; Tel: 812/855-9219; Email: klear@indiana.edu; Internet: http://php.indiana.edu/~klear.

1 Introduction

The economic literature on enforcement aims to determine the optimal combination of fines, prison terms, and detection resources in order to control activities that generate an externality. It is well recognized that these enforcement tools are not equivalent in terms of their cost to society. Fines are costless transfers between parties, while prison terms and detection resources impose an external cost. In view of this, Becker (1968) argued that enforcement costs could be minimized by raising fines as high as possible, and lowering detection resources proportionately, while still maintaining the same level of deterrence.[1] The optimal fine is presumably equal to the offender's wealth.

Becker's classic theory implies substitutability between fines and resources, which is limited by the offender's ability to pay. He suggests that fines should be set equal to the offender's wealth and that detection resources should be allocated to achieve the desired level of deterrence. This raises two important questions. First, what is the "desired" level of deterrence, and second, why are fines equal to the offender's wealth rarely observed in practice? Subsequent research has identified conditions under which maximal fines are not optimal. In addition, alternative theories suggest that the optimal magnitude of the fine should reflect the harm imposed on the victim or the gain to the offender.

The primary objective of this paper is to provide insight into the U.S. Environmental Protection Agency's (EPA's) enforcement policy. I employ new data on administrative fines assessed by the EPA in 1995 and EPA regional spending on compliance monitoring and enforcement to empirically test and measure the trade-off between fines and detection resources.[2] In addition to characterizing the EPA's use of fines and resources, I examine the relevance of alternative penalty models in determining fines assessed by the EPA. Specifically, I consider models based on the harm to the victim, the gain to the offender, and the offender's ability to pay.

The difference between harm- and gain-based penalties is rooted in the deterrence objective. Deterrence theory assumes that illegal acts are discouraged by the threat of

[1] This conclusion assumes risk-neutral agents.

[2] Detection resources are defined in terms of monetary spending on compliance monitoring and enforcement.

punishment. However, Posner (1976) points out that the purpose of deterrence may be either "conditional" or "unconditional." "Conditional" deterrence aims to prevent only those activities in which the cost (harm) to the victim exceeds the gain to the offender. In this case, complete deterrence is not desired. A harm-based penalty achieves conditional deterrence by setting the fine equal to the marginal damages imposed by the activity at the optimal level.[3] The penalty is said to "fit the crime" because it reflects the (marginal) harm imposed by the violation. Individuals engage in the activity if and only if the gain from the illegal act exceeds the harm to the victim.

Alternatively, the law may wish to prohibit some externality creating activities entirely. "Unconditional" deterrence aims to prevent all violations, even those for which the gain exceeds the harm. A gain-based penalty achieves unconditional deterrence by fining the violator his expected gain, thus eliminating any benefit from the act. One potential danger with gain-based penalties is that they may lead to over-enforcement. Individuals for whom the gain from the illegal act exceeds the harm to the victim are completely deterred. As a result, an activity that is socially desirable up to a point may no longer take place. Cohen (1992, 10) provides an example: "In the case of oil spills, we do not want to raise the 'price' of causing an oil spill so high that we deter firms from engaging in the socially beneficial practice of oil transportation."

While the theoretical debate ensues over whether fines should reflect the harm or the gain, there is only weak evidence that fines are harm- or gain-based. Cohen (1992) finds that fines for environmental crimes are significantly and positively related to harm, while Waldfogel (1995) finds no such relationship between harm and fines levied for fraud offenses.[4] With respect to gain-based penalties, the General Accounting Office (1991, p.1) reports that in nearly two out of three penalty cases concluded in fiscal year 1990 there was no evidence that an economic benefit component had been calculated or assessed.

Conversely, the empirical literature presents strong evidence that fines are related to ability to pay or firm size. Several studies report that fines for fraud offenses by individuals

[3] The optimal level of an activity which imposes an external cost is the level at which the marginal social damage from the activity equals the marginal private benefit.

[4] Instead, Waldfogel (1995) reports that prison terms are strongly and positively related to harm variables.

depend strongly and positively on the offender's preconviction income (see Lott, 1992; Weisburd, et al., 1991; Waldfogel, 1995).[5] Furthermore, Cohen (1992) finds that fines for environmental crimes are higher for large firms with more than 500 employees or over $50 million in sales. He notes that courts often do not impose penalties on firms that are bankrupt or that have insufficient assets to pay the fine. Note that this study lacks a continuous measure of the violator's financial condition and therefore is only able to distinguish between large and small firms.

Evidence that fines are increasing in the violator's ability to pay or is troublesome for two reasons. First, this finding may support the often criticized "deep pockets theory," which posits that firms that can afford to pay higher fines are fined more for the same violation. In Cohen's (1992) study, large firms incur higher fines, while small firms incur lower fines that are supplemented with imprisonment. Moreover, Cohen (1992) finds that the conviction rate for individuals in cases involving large firms was only 9 percent, compared to 25 percent for small firms. Cohen's (1992) results are consistent with the theory that prison terms are prescribed when the optimal fine exceeds the offender's ability to pay (Segerson and Tietenberg, 1992). While this theory applies to criminal actions, which are punishable by imprisonment, it does not apply to administrative actions, which are *not* punishable by imprisonment.

Unlike previous studies of environmental crimes (Cohen, 1992) or fraud offenses (Lott, 1992; Waldfogel, 1995), this study uses data on administrative enforcement actions.[6] This eliminates the use of imprisonment as a possible enforcement mechanism and allows me to determine if, controlling for other factors, fines are higher for large firms.

Moreover, fines based on ability to pay or firm size is troublesome for reasons identified by Lear and Maxwell (1997). The authors show that limiting fines to affordable levels can result inefficient regulatory spending on monitoring and enforcement. When financial constraints limit fines to low levels, the regulator's best resource allocation response may fail to achieve a socially beneficial level of compliance. Constraints on the magnitude of the

[5]It is interesting to note that both Lott (1992) and Waldfogel (1995) find that income is negatively related to the length of the prison sentence.

[6]See Chapter 1 of this dissertation for a discussion of the difference between administrative, civil and criminal penalties.

fine may elicit inefficient spending on enforcement. Under these circumstances, regulation makes society worse off. This may indicate that fines should not be limited by the firm's ability to pay.

In addition to economic theory and empirical evidence, it is important to consider existing EPA penalty policies. The Policy on Civil Penalties (EPA, 1984a) establishes three goals: (1) deterrence; (2) fair and equitable treatment of the regulated community; and (3) swift resolution of environmental problems. This policy outlines a general process for assessing penalties. The first step involves calculating a preliminary deterrence amount which includes both an economic benefit component and a gravity component. The economic benefit component should reflect the benefits from delayed or avoided costs and any competitive advantage that results from non-compliance. The gravity component should take into consideration actual or possible harm inferred by the amount of the pollutant, the toxicity of the pollutant, the sensitivity of the surrounding environment, the duration of the violation, and the size of the violator. The preliminary deterrence figure is then adjusted for the degree of willfulness and/or negligence, the degree of cooperation or noncooperation, history of non-compliance, ability to pay, and other unique factors. Finally, the initial penalty target is reassessed periodically during negotiations to reflect any new information. The policy should also provide for alternative payment schedules and pre-settlement corrective action.

The EPA has developed computer models known as BEN and ABEL to assist in computing the economic benefit and the firm's ability to pay, respectively. In addition to these penalty guidelines, most environmental statutes specify penalty maximums. Appendix A gives a brief description of the major environmental statutes and their specified penalty maximums. While these policies provide general guidelines for setting penalties, final assessment is left to the discretion of states, regions, and civil and administrative courts.

This paper examines fines assessed administratively by the EPA to determine the significance of alternative penalty theories. I employ enforcement case data retrieved from the EPA's new Integrated Data for Enforcement Analysis (IDEA) System. The sample includes a cross-section of 158 EPA administrative fines assessed in 1995, financial and industry data on the parent company of the violating facility, and the legislation that was violated. The enforcement case data are supplemented with data on EPA regional spending on compliance monitoring and enforcement for 1990 through 1995 and industry data on pollution abatement and control expenditures. I test for evidence of substitution between fines and resources and estimate a model for administrative fines.

This paper advances the existing literature in several ways. First, I employ more recent and more comprehensive data on environmental enforcement actions. Relative to previous studies, the data include a slightly larger sample of violators with a continuous measure of firm size. Second, I am the first to empirically test and measure the trade-off between fines and resources. I focus on the EPA's choice of enforcement weapons and therefore employ data on administrative enforcement actions handled within the Agency. Among other things, I am interested in determining whether or not fines are higher in EPA regions with lower levels of spending on compliance monitoring and enforcement. Third, I test the implications of economic theories which suggest that the optimal fine is based on harm, gain, and ability to pay. Finally, I test for evidence of different penalty models for small and large firms.

The remainder of this paper proceeds as follows. Section 2 discusses alternative penalty theories using a simple model of enforcement. A regulatory objective of enforcement cost minimization is then imposed to examine the impact of the firm's ability to pay on the optimal fine and level of resources. The predictions of the model are compared with the prediction of Lear and Maxwell (1997), who examine the impact of financial constraints (ability to pay) in a model with a different regulatory objective. The two models have different implications for the predicted relationship between the optimal fine and the violator's ability to pay. Section 3 discusses the data and provides descriptive statistics of the sample. Section 4 formally states the hypotheses that are tested and estimates a model of administrative fines for the full sample. Split sample estimates are also provided to test for structural differences in penalty models for small and large firms. Concluding remarks and areas for future research are discussed in Section 5.

2 The Model

This section illustrates the different penalty theories using a simple model of enforcement.

First, I present gain- and harm-based penalty models which differ in their deterrence objectives. Next, I impose a regulator who simply minimizes detection resources, as suggested by Becker (1968). The model predicts that the optimal fine is increasing in the violator's ability to pay. I then compare this model with one in which the regulator is concerned with enforcement activity. I assume that this concern manifests itself in the regulator's objective function, so that the regulator minimizes detection resources *net* of expected penalty revenues. I discuss how penalty policies that restrict fines to affordable levels affect the optimal fine-resource combination under this alternative regulatory objective.

2.1 A Simple Model of Enforcement

Consider a risk-neutral firm's decision of whether or not to comply with a costly environmental regulation. Compliance is assumed to reduce firm profits below the level achieved under non-compliance, giving the firm an incentive to violate. Let $E\delta$ denote firm i's expected gain from non-compliance. $E\delta$ is the difference between firm i's expected profit under non-compliance and its expected profit under compliance. In other words, $E\delta$ represents firm i's foregone profit under compliance.[7]

Let p denote the probability of being caught and fined for non-compliance, herein referred to as the probability of detection. Consistent with the existing literature (Becker, 1968; Polinsky and Shavell, 1979, 1991; Malik, 1990), I assume that detection is costly so that the probability of detection is determined by the level of resources r devoted to detection; $p(r) \in [0, 1)$ and $p(0) = 0$.[8] An increase in resources devoted to monitoring and

[7] Lear and Maxwell (1997) show that in a Cournot oligopoly, the expected gain from non-compliance is a function of both the compliance strategy chosen by all other firms in the industry and the number of firms in the industry. Moreover, the impact of a change in the number of firms in the industry on the equilibrium probability compliance depends on the rate at which the expected gain falls relative to the simultaneous decline in the expected penalty. In this essay, I present a more generalized model and assume that the expected gain from non-compliance is constant in order to focus on the relationship between the expected gain and the optimal fine, apart from changes in industry structure. This approach is consistent with most of the theoretical literature which assumes a constant expected gain or expected benefit (see Polinsky and Shavell (1979), Malik (1990)).

[8] I exclude $p(r) = 1$. There may exist a level of resources which ensures that each violation is detected with certainty; however, it is unrealistic that such an endowment of regulatory resources will be appropriated given fiscal budget constraints. Garvie and Keeler (1994) cite a number of authors who address the severity of resource constraints facing environmental regulators [Melnick (1983), DiMento (1986), Hawkins (1984), Yeager (1991)].

enforcement raises the probability of detection for any given firm ($p_r > 0$) and there are diminishing returns to regulatory spending ($p_{rr} < 0$). Monitoring is assumed to be error free: the probability of mistakenly fining a compliance firm is zero. The expected fine is given by $p(r)F$ where F is the fine for non-compliance.

The order of play is as follows. The regulator sets r and F and the firm responds by either complying or violating the regulation. I consider two alternative regulatory objectives in the analysis that follows. Using backward induction, I start with the firm's compliance decision.

The firm decides whether or not to comply with a costly environmental regulation. Firm i chooses its compliance strategy to minimize the expected cost of compliance, C_i. Let $\alpha_i \in [0,1]$ represent firm i's probability of compliance. The firm's problem is

$$\min_{\alpha_i} C_i = \alpha_i(E\delta) + (1-\alpha_i)[p(r)F]. \tag{1}$$

Maximizing Equation (1) with respect to α_i and rearranging terms gives the first order condition,

$$E\delta - p(r)F = 0. \tag{2}$$

Firm i's optimal compliance strategy is then,

$$\hat{\alpha} = \begin{cases} 0 & \text{if } E\delta > p(r)F, \\ \in (0,1) & \text{if } E\delta = p(r)F, \\ 1 & \text{if } E\delta < p(r)F. \end{cases}$$

Firm i violates the regulation if the expected gain from non-compliance exceeds the expected penalty. For $E\delta = p(r)F$, firm i mixes between complying and violating if it is indifferent between compliance and non-compliance. Firm i complies if the expected gain from non-compliance is less than the expected penalty.

Applying the theory of production, I treat fines and resources as inputs in an enforcement production function.[9] The iso-compliance locus represents all possible combinations of fines and resources that deter crimes with an expected gain equal to $E\delta$. Along the iso-compliance locus the following condition holds,

[9]Waldfogel (1995) takes a similar approach in his analysis of fines and imprisonment as enforcement weapons.

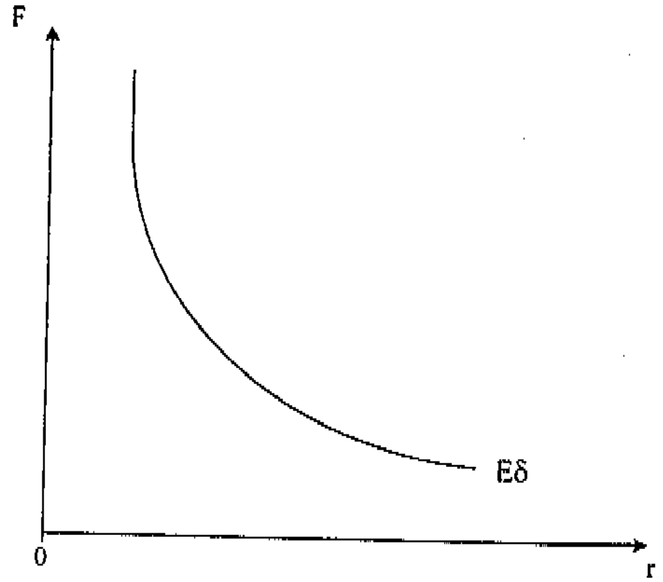

Figure 1: The Iso-Compliance Locus

$$F = \frac{E\delta}{p(r)}. \tag{3}$$

Equation 3 represents a gain-based penalty where the fine is a multiple of the expected gain. F is the minimum fine that induces some degree of compliance.

The iso-compliance locus is illustrated in Figure 1, which plots the fine on the vertical axis and the level of detection resources on the horizontal axis. Differentiating Equation (3) with respect to r confirms that the iso-compliance locus is downward sloping as shown below,

$$\frac{\partial F}{\partial r} = -\frac{E\delta}{(p_r)p(r)^2} < 0. \tag{4}$$

The slope represents the marginal rate of substitution between fines and resources. Note that the iso-compliance locus is undefined at $r = 0$, given $p(0) = 0$, and $F \to \infty$ as $r \to 0$. If the regulator devotes no resources to monitoring and enforcement, the probability of detection is zero and all firms violate in equilibrium. In addition, the iso-compliance locus is bounded below by $F = E\delta$ since as r increases, $p(r) \to 1$ and $F \to E\delta$.

The comparative statics of the model are straight forward. An increase in the expected gain, ceteris paribus, shifts the iso-compliance locus up increasing the minimum fine that induces compliance for a given level of resources. All combination of (r, F) that lie in the area to the right of $E\delta$ result in universal compliance and over-deterrence. Conversely, all combinations of (r, F) that lie in the area to the left of $E\delta$ result in universal non-compliance and under-deterrence.

2.2 A Harm-Based Penalty Model

The gain-based penalty model presented above sets the fine equal to a multiple of the expected gain from non-compliance. It aims to achieve "unconditional" deterrence by eliminating the expected gain, therefore making violations unprofitable. In the context of environmental regulation, this approach may be used in command and control regulation where *all* violations of a predetermined emissions standard are prohibited, with no concern for the relationship between the marginal environmental (social) damage and the firm's marginal private benefit (the expected gain from non-compliance). At the emissions level prescribed by the standard, the marginal benefit from reduced social damage may be greater than, less than, or equal to the firm's marginal private benefit.

Alternatively, consider the case where "conditional" deterrence is desired. Conditional deterrence aims to prevent acts for which the marginal net private benefit to the violator is less than the marginal social damage at the optimal level of the activity.[10] To achieve this objective in pollution control, a fine equal to the marginal social damage at the optimal level of emissions is imposed on the generator of the activity (Baumol and Oates, 1988, 23). This is the traditional Pigovian tax solution. All firms pollute up to the point where their marginal net private benefit equals the marginal social damage at the optimal level of emissions. However, Polinsky and Shavell (1979, 880) point out that "if it were costless to 'catch' or 'observe' individuals (or firms) when they engage in an externality creating activity, presumably everyone would be caught and fined an amount equal to the external cost of the activity." Since it is costly to catch firms in non-compliance, the *expected* fine is the relevant consideration.

[10]Recall, footnote 4 explains that the optimal level of the externality generating activity is that which equates the marginal social damage from the activity with the marginal private benefit.

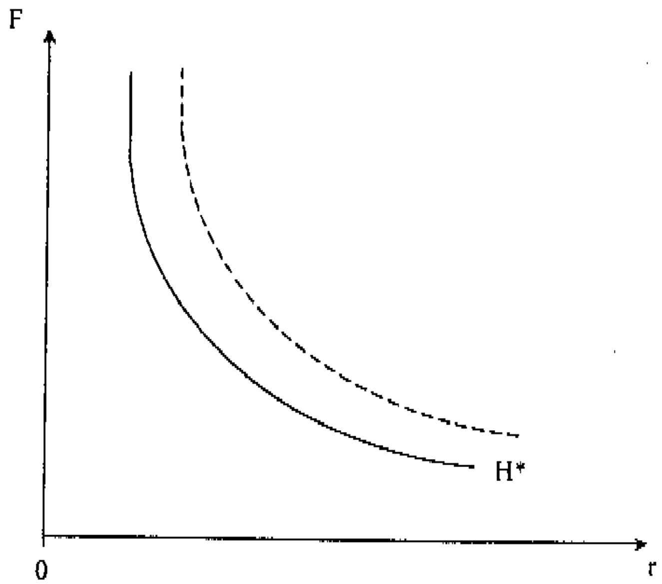

Figure 2: The Iso-Damage Locus

Let H^* denote the monetary value of the marginal harm (environmental damage) at the optimal level of emissions. In the model presented above, the firm's marginal net private benefit from non-compliance is measured in profits as $E\delta$. "Conditional" deterrence therefore aims to prevent all acts with an expected gain that is less than marginal social damage at the optimal level of emissions: $E\delta < H^*$. A harm-based penalty model sets the expected fine equal to the marginal social damage at the optimal level. In this model, the minimum fine that achieves unconditional deterrence is

$$F = \frac{H^*}{p(r)}. \tag{5}$$

Equation 5 reveals that the fine is a multiple of the harm.

Again, I apply the theory of production and treat fines and resources as inputs in an enforcement production function. For a given H^*, the appropriate combination of fines and resources that satisfies Equation (5) is given by the iso-damage locus: $p(r)F = H^*$. Activities for which marginal damages are higher than H^* at the optimal level of emission are deterred by either higher fines, higher detection resources, or both. The harm-based penalty regime is illustrated in Figure 2 which plots the fine on the vertical axis and the level of enforcement resources on the horizontal axis.

Figure 2 is similar to Figure 1 except it illustrates the iso-damage locus, rather than the iso-compliance locus. A given iso-damage locus represents all combinations of fines and resources that produce an expected fine equal to the marginal social damage at the optimal level of emissions. The slope of the iso-damage locus, $\frac{\partial F}{\partial r} = \frac{H^*}{p_r p(r)^2}$, represents the trade-off (marginal rate of substitution) between fines and resources. Like the iso-compliance locus, the iso-damage locus is downward sloping and undefined at $r = 0$. $F \to \infty$ as $r \to 0$. Moreover, as r increases, $p(r) \to 1$ and $F \to H^*$. F is therefore bounded below by H^*.

The comparative statics in model suggest that the fine is increasing in the harm. An increase in the marginal harm at the optimal level of the activity, ceteris paribus, raises the fine necessary to achieve conditional deterrence: $\frac{\partial F}{\partial H^*} = \frac{1}{p(r)} > 0$.

Substituting Equation (5) into the firm's compliance decision reveals that the harm-based penalty regime elicits compliance, $\alpha = 1$, if the marginal social damage at the optimal level of emissions exceeds the firm's expected gain: $H^* > E\delta$. For any given resource allocation, a higher fine is prescribed under the harm-based penalty regime than under the gain-based penalty regime. The iso-damage locus lies above the iso-compliance locus, creating a situation of over-deterrence. The reverse is true if $H^* < E\delta$. In this case, a harm-based penalty induces non-compliance, $\alpha = 0$. For any given level of resources, a lower fine is prescribed under the harm-based penalty regime than under the gain-based regime. The iso-damage locus lies below the iso-compliance locus, creating a situation of under-deterrence. Firms violate and pay $F = \frac{H^*}{p(r)}$ if caught violating the regulation. Firm i mixes between compliance and non-compliance, $\alpha \in (0, 1)$, if $H^* = E\delta$. In this situation, the harm- and gain-based penalties are equivalent.

2.3 The Impact of Financial Constraints on the Regulator's Resource Allocation Decision

If the regulator's objective is to minimize spending on monitoring and enforcement subject to attaining an expected penalty that achieves the desired level of deterrence (conditional or unconditional), then it is optimal to set the fine as high as possible and allocate resources to achieve the necessary expected penalty (Becker, 1968). This suggests that the fine is restricted by the offender's ability to pay the fine. In fact in practice, the EPA's

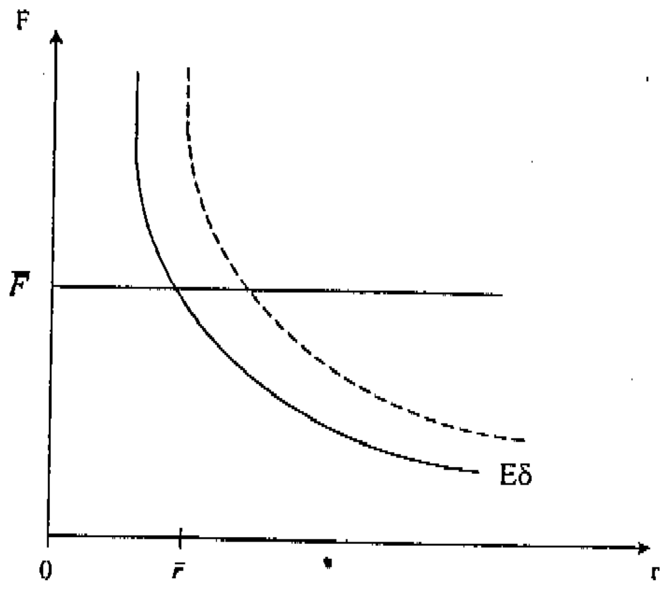

Figure 3: The Impact of Financial Constraints

civil penalty policy requires consideration of a firm's ability to pay when setting fines for environmental violations. The penalty is often adjusted if the violator claims paying the penalty would cause "extreme financial hardship." To assess a firm's ability to pay, the Agency may request financial information from the violator including tax returns and financial statements such as balance sheets, income statements, and retained earnings statements. Fines are also restricted by statutory limitations, such as penalty maximums specified under the Clean Water Act, the Safe Drinking Water Act and the Toxic Inventory Control Act (see Appendix A).

Assume that limiting the fine to either the maximum amount the firm can afford to pay or a predetermined maximum restricts the fine to $\bar{F}$. I impose this assumption on the gain-based penalty model as illustrated in Figure 3. The cost-minimizing resource allocation that induces compliance is given by $\bar{r}$.

The comparative statics with respect to the expected gain function are as follows. An increase in the firm's ability to pay, ceteris paribus, raises the optimal fine and lowers the optimal resources allocation, $\bar{r}$. This simple model illustrates the implied trade-off between fines and resources. It predicts a negative relationship between the fine and the level of resources, and a positive relationship between the fine and the firm's ability to pay. Conversely, an increase in the expected gain, ceteris paribus, leaves the optimal fine unchanged, while increasing the optimal resource allocation.

Similarly, in a harm-based penalty regime with constraints on the magnitude of the fine, the combination of fines and resources that achieves *conditional* deterrence and minimize enforcement costs is given by the intersection of the iso-damage locus and the maximum affordable fine. Again, an increase in the firm's ability to pay, ceteris paribus, raises the optimal fine. Moreover, an increase in the harm imposed by the violation, ceteris paribus, has no impact on the optimal fine, but raises the optimal resource allocation.

2.4 Prediction Under an Alternative Regulatory Objective

In this section, I consider the impact of financial constraints on the optimal fine when the regulator is concerned with enforcement activity. I assume that this concern manifests itself in the regulator's cost minimization objective. As a result, the regulator is concerned with minimizing spending on monitoring and enforcement, r, net of expected penalty revenue, $(1-\alpha)np(r)F$.[11]

In this era of tight regulatory budgets and threatened enforcement programs, I believe this objective is more realistic. Regulatory agency concerns with enforcement activity arise in response to threatened budget cuts. Moreover, activity is often viewed as justification for the Agency's existence. Most recently, reports indicate that harassment activity at the Internal Revenue Service was driven by the organization's preoccupation with enforcement activity indicators including dollar collections per hour, number of seizures, and number of liens (Schlesinger, 1997). Similarly, Pendergrass of the Environmental Law Institute, Washington, D.C., states that existing federal EPA oversight of states' environmental protection programs places "more emphasis on administrative actions and capacity than on environmental quality" (Lepkowski 1995, 47). I assume that these concerns are reflected in the regulator's objective function.

Under this regulatory objective, Lear and Maxwell (1997) show that policies which limit fines to affordable levels may induce ineffective spending on enforcement. The fine

[11]This is analogous to a penalty revenue maximization problem.

and cost-minimizing resource combination fail to achieve a socially beneficial level of compliance. The result is that the private cost of compliance to firms and consumers (in the form of reduced output), in addition to the public cost of regulatory enforcement, outweigh the benefit of reduced environmental damage under low or zero levels of compliance. Our results imply that it may not be optimal to base fines on ability to pay.

2.5 Penalty Model Predictions

This section provides a brief summary of the predictions given by the different models presented above. The strictly gain-based penalty model predicts that the optimal fine is increasing in the expected gain from non-compliance, while the strictly harm-based model predicts that the optimal fine is increasing in the marginal social harm at the optimal level of the activity. Both models also predict substitutability between fines and detection resources. Similarly, if the regulator minimizes spending on monitoring and enforcement, as Becker proposed, a negative relationship is predicted between fines and resources. In this model, an increase in the offender's ability to pay raises the optimal fine; however, an increase in the marginal harm or the expected gain has no effect on the optimal fine when financial constraints are binding. Finally, if the regulator cares about minimizing enforcement costs net of penalty revenues, the model presented by Lear and Maxwell (1997) predicts that the optimal fine is either zero or the maximum affordable amount. I now test these theoretical predictions using data on administrative fines assessed by the EPA in 1995.

3 The Data

In this section, I identify the sources of data, provide descriptive statistics of the sample and discuss the data's limitations. Testable hypotheses are formally stated in Section 4.

3.1 Data Sources

In the past, EPA enforcement and compliance data were managed independently by responsible program office (e.g. air, water, etc.) and limited to summary statistics released by the Justice Department's Environmental Crimes Section or the EPA's Office of Compliance. This may explain why empirical studies of environmental crimes to date are scant and there is no research on administrative fines assessed by the EPA. However, in 1990, the Enforcement Management Council of EPA recognized the need for a database system that linked enforcement and compliance data for a given facility across the program office databases. The result was the development of the Integrated Data for Enforcement Analysis (IDEA) System.

Data on federal, EPA administrative enforcement actions were extracted from the IDEA system. The data include the following information for each enforcement case: the dollar amount of the assessed fine; the violated EPA legislation; the pollutant involved in the violation; the EPA region responsible for enforcement; and sales volume, total employees, and 2-digit SIC industry group for the parent company of the violating facility. After eliminating 36 cases that lacked sales volume or industry group data, I was left with a sample of 158 federal administrative enforcement actions that resulted in non-zero penalties in 1995.

In addition to the enforcement case data I collected from the EPA, I obtained EPA data on regional spending on compliance monitoring and enforcement for 1990 through 1995 from the EPA's Budget Division. Other data sources include the Current Industrial Reports on *Pollution Abatement Costs and Expenditures: 1994* from the U.S. Department of Commerce, County Business Patterns Report from the Census Bureau, and Gross State Product from the Bureau of Economic Analysis. The description of my use of this data follows.

3.2 Descriptive Statistics

Firm size is measured by the parent company's total number of employees, *EMPL*. Firms with more than 50 employees are considered large. Those with 50 or fewer employees are considered small.[12] The full sample is split according to firm size in order to test the hypothesis of structural differences in penalty models for large and small firms. Table 1

[12] This split was decided through conversations with people at the U.S. Small Business Administration (SBA). The SBA's definition of a small business varies across industry and is identified by either the number of employees or the sales volume; however, for the purpose of this study, 50 employees was deemed to be an acceptable measure of small firm size.

reports the summary characteristics of the distribution of employees for the full sample, as well as for the large and small firm subsamples.

Table 1: Distribution of Employees

	Sample		
	Full (n=159)	Large (n=76)	Small (n=82)
Mean	700	1,437	16
Standard Deviation	3,054	4,297	15
Minimum	1	58	1
1st Percentile	1	58	1
5th Percentile	2	62	1
10th Percentile	4	65	2
25th Percentile	12	99	5
Median	50	195	12
75th Percentile	170	762	25
90th Percentile	1,188	3,400	42
95th Percentile	3,400	5,122	50
99th Percentile	21,510	29,437	50
Maximum	29,437	29,437	50
Skewness	7.62	5.28	0.91

Table 1 reveals that the total number of employees in the full sample ranges from one employee to 29,437 employees. The mean number of employees for the full sample is 700, as compared with 1,437 for the large firms and 17 for the small firms. However, the median number of employees is 50 for the full sample, 195 for the large sample and 12 for the small sample. All three samples are skewed right and the skewness is significantly different from zero, even for the small firm sample. Over 75 percent of the firms in the full samples have fewer than 200 employees.

Table 2 reports the summary characteristics of the distribution of fines for the three samples. Fines in the sample range from \$50 to \$125,000. The mean fine for all firms is \$10,181, as compared with \$16,284 and \$4,524 for the large and small firm subsamples, respectively. Thus, fines for violations by small firms are, on average, only one-fourth the magnitude of fines for violations by large firms. The median fine for each sample is less than the mean fine and the distributions are skewed right. The skewness, though small, is significantly different from zero. The median fine for the full sample is $4,000, while the median fine for the large and small firms are $7,625 and $1,000, respectively. Note, half the firms in the small firm sample were assessed fines of $1,000 or less, as compared with only 10 percent of the large firms. The log of the dollar amount of the assessed fine is given by *LFINE*.

Table 2: Distribution of Fines ($)

	Sample		
	Full (n=159)	Large (n=76)	Small (n=82)
Mean	10,181	16,284	4,524
Standard Deviation	17,989	23,389	7,304
Minimum	50	200	50
1st Percentile	50	200	50
5th Percentile	200	500	100
10th Percentile	200	1,000	200
25th Percentile	750	3,000	350
Median	4,000	7,625	1,000
75th Percentile	10,800	19,786	6,000
90th Percentile	26,250	56,995	12,000
95th Percentile	56,995	65,450	16,875
99th Percentile	97,930	125,000	36,000
Maximum	125,000	125,000	36,000
Skewness	3.54	2.60	2.74

The parent company's total sales volume in 1995, *SALES*, measures firm size as well as providing some indication of the violator's ability to pay. While financial databases such as COMPUSTAT and CRSP contain better measures of ability to pay (such as total assets or earnings before interest and taxes), these databases are limited to public corporations. As a result, use of such databases requires dropping privately held firms from the sample. Since a major objective of this study is to examine fines assessed on both small and large firms, I opted to use parent company sales volume, which was included in the EPA data and was not limited to public firms. Other issues arising from this measure of ability to pay are discussed in the next section.

Table 3: Distribution of Sales ($000)

	Sample		
	Full (n=159)	Large (n=76)	Small (n=82)
Mean	233,591	482,767	2,646
Standard Deviation	1,612,829	2,307,372	4,513
Minimum	62	1,000	62
1st Percentile	63	1,000	62
5th Percentile	120	3,600	97
10th Percentile	220	4,629	130
25th Percentile	1,000	8,000	250
Median	4,664	21,446	1,000
75th Percentile	20,000	119,840	2,697
90th Percentile	127,340	419,810	4,900
95th Percentile	419,810	918,000	16,067
99th Percentile	9,373,700	17,846,10	22,000
Maximum	17,846,10	17,846,10	22,000
Skewness	9.60	6.63	3.00

Table 3 reports the summary characteristics of the distribution of sales for the three samples. The maximum sales volume for all firms in the sample is $17.85 billion and the minimum sales volume is $62,000. Sales average $233.59 million for all firms in the sample, as compared with $482.77 million for large firms and $2.65 million for small firms. The median sales volume is $4.7 million for the full sample, $21.45 million for large firms, and $1 million for small firms. Again the distributions are skewed right and the skewness is significantly different from zero. Indeed, more than 75 percent of all firms in the sample had sales of less than $50 million in 1995. The log of sales, *LSALES*, serves as an independent variable in the log-linear model.

As mentioned in the Introduction, administrative penalty guidelines are statute specific. I therefore control for differences across statutes. ACT^H is a vector of the following zero-one dummy variables which control for the violated legislation: CAA, CWA, EPCRA, FIFRA, RCRA, SDWA, and TSCA.[13] Table 4 provides a comparison of the full sample distribution across the major statutes with the distribution of all 1995 EPA enforcement actions.

Table 4: Comparison of Sample to Total EPA Administrative Actions, 1995*

Distribution of Enforcement Actions by Act

	1995		SAMPLE	
	TOTAL #	% TOTAL	TOTAL #	% TOTAL
CAA (air)	127	12	5	3
CWA (water)	210	20	17	11
EPCRA (right-to-know)	201	19	59	37
CERCLA (superfund)	28	3	0	0
FIFRA (pesticides)	105	10	18	11
RCRA (hazardous waste)	104	10	36	23
SDWA (drinking water)	55	5	3	2
TSCA (toxics)	239	22	20	13
TOTAL	1,069	100	158	100

Distribution of Penalty Revenues by Act

	1995		SAMPLE	
	TOTAL $	% TOTAL	TOTAL $	% TOTAL
CAA (air)	2,366,859	7	50,219	3
CWA (water)	5,462,329	16	374,646	23
EPCRA (right-to-know)	4,084,188	12	646,541	40
CERCLA (superfund)	194,534	1	0	0
FIFRA (pesticides)	1,630,039	5	52,340	3
RCRA (hazardous waste)	13,076,989	38	88,922	6
SDWA (drinking water)	255,191	1	4,900	0
TSCA (toxics)	7,042,884	21	391,010	24
TOTAL	$34,113,013	100	$1,608,578	100

*Note: Six CERCLA cases were discarded from the sample due to difficulties in identifying responsible parties.

[13] CERCLA cases were thrown out of the sample since CERCLA cases may involve several potentially responsible parties and the degree of liability is at issue.

The legislation may provide some insight into the harm caused by the pollutant. If fines reflect the harm imposed by the violation, then fines may be higher for violations of TSCA, which deals with toxics, than for violations involving hazardous wastes (RCRA), pesticides (FIFRA) or reporting requirements (EPCRA). The harm imposed by an environmental violation on the surrounding environment (e.g. water quality, air pollution) and/or on the surrounding populations is often difficult to quantify. In a similar study of environmental crimes, Cohen (1992) measured harm monetarily as the sum of cleanup costs and any residual environmental damage. He used the legislation to infer the type of pollutant, e.g. toxic substance (TSCA), hazardous waste (RCRA), etc. For the enforcement actions examined in this study, data on cleanup costs were not available from the IDEA system. However, I did obtain the pollutant for 47 of the 158 enforcement cases and use this data to analyze the relationship between fines and harm.

Table 5: Subsample with Pollutant Data

Hazardous Substance	Rank	Inverted Rank	Number of Observations
PCBs	7	269	10
Manganese	50	226	1
Toluene	53	223	3
Chromium	61	215	1
Aluminum	63	213	1
Asbestos	74	202	2
Xylene	79	197	3
Copper	98	178	1
Acetone	144	132	1
Ammonia	151	125	1
2-Butanone	168	108	1
Chlorine	208	68	1
Styrene	241	35	1
Number of Cases Involving Listed Pollants			27
Total Number of Cases with Pollutant Data			47

For the 47 cases with pollutant information, 20 cases involved non-hazardous substances and 27 cases involved hazardous substances that are listed on the 1995 CERCLA

Priority List of 275 Hazardous Substances. The variable $HAZSUB$ represents the harm imposed the pollutant. Listed hazardous pollutants were assigned a harm-based ranking according to the 1995 CERCLA Priority List, which ranks 275 hazardous substances from most to least harmful. The substances and their respective rankings are given in Table 5. For purposes of estimating the regression, I inverted the ranking so that it is increasing in harm. For the hazardous pollutants, $HAZSUB$ equals the inverted ranking. For example, the inverted ranking for PCBs, the most hazardous substance in the sample, is 269 (275-7+1). $HAZSUB = 0$ for non-listed pollutants. Note, this subsample does not include any FIFRA violations.

Table 6: Distribution of Employees, Fine, and Sales for Pollutant Subsample (n=47)

	Employees	Fine ($)	Sales ($000)
Mean	1,435	13,276	656,940
Standard Deviation	4,530	22,682	2,903,500
Minimum	1	150	63
1st Percentile	1	150	63
5th Percentile	3	200	250
10th Percentile	4	200	650
25th Percentile	21	1,000	1,600
Median	75	5,000	12,199
75th Percentile	724	15,000	118,730
90th Percentile	3,800	35,000	419,810
95th Percentile	5,122	65,100	850,000
99th Percentile	29,437	125,000	17,850,000
Maximum	29,437	125,000	17,850,000
Skewness	5.49	3.38	5.32

Table 6 gives summary characteristics of the distribution of employees, fines, and sales for the subsample that includes the pollutant data. The distribution of employees indicates that half of the firms in this subsample have fewer than 75 employees. In fact, 43 percent of the firms in this subsample have 50 or fewer employees.. As a result, this sample more closely resembles the large firm sample discussed above. The average fine is roughly $3,000 less than the average fine for the large firm sample and $3,000 more than the average fine for the full sample. However, the average sales volume for this subsample is greater than that of the large firm sample, $656.9 million as compared with $482.8 million for the large firms. The three distributions are skewed right and the skewness is significantly different from zero.

As presented in Section 2, the expected gain from non-compliance is the avoided cost of compliance. It is generally accepted that the costs of compliance are higher for firms in manufacturing industries than for firms in non-manufacturing industries. I therefore distinguish manufacturing firms from non-manufacturing firms. Higher fines for manufacturing firms imply that fines are set to recover the greater gain from non-compliance which accrues to manufacturing firms in the form of avoided compliance costs. Manufacturing is industry groups 20 through 39 at the 2-digit level (Standard Industrial Classification codes). Table 7 gives the distribution of enforcement actions by major industry group.

Furthermore, within the manufacturing industries, compliance is more costly for some industries than others. To identify manufacturing industries with high costs of abatement, I use historical data from the U.S. Department of Commerce's Current Industrial Reports on *Pollution Abatement Costs and Expenditures: 1994*. This report contains 1990 through 1994 data on pollution abatement operating costs (PAOC) and pollution abatement capital expenditures (PACE) for Major Groups 20-39.[14] Specifically, firms are classified as having high expected gains from non-compliance if they operate in industries that incurred PAOC of more than $1,100 per employee and PACE of more than $250 per employee in 1993 and 1994, consecutively.[15] The following five major groups are high abatement cost industries based on this classification: Paper and Allied Products (Major Group 26), Chemicals and Allied Products (28), Petroleum Refining and Related Industries (29), Stone, Clay, Glass, and Concrete Products (32), and Primary Metals (33). The expected gain variable, $E\delta$, is a vector of dummy variables which distinguish between non-manufacturing firms, $NONMAN$, manufacturing with low abatement costs, $MANLOW$, and manufacturing firms with high abatement costs, $MANHIGH$. There are 76 non-manufacturing firms,

[14]This report, which has since been discontinued, excludes Apparel and Other Textile Products (23) since firms in this industry operate primarily in rented quarters where abatement control is arranged by the landlord.

[15]The total number of employees per 2-digit SIC is given by the Census Bureaus' County Business Patterns Report.

Table 7: Penalized Firms by Industry Classification

Two-digit SIC Code	Industry Group	Number of Firms	% of Full Sample
20-39	**Manufacturing**		
20	Food	5	3.2
22	Textile mill products	1	0.6
24	Lumber-wood products	4	2.5
25	Furniture-fixtures	3	1.9
26	Paper-allied products	3	1.9
28	Chemicals-allied products	23	14.6
29	Petroleum refining	3	1.9
30	Rubber, plastics	4	2.5
31	Leather	1	0.6
32	Stone, clay, glass, concrete products	7	4.4
33	Primary metals	5	3.2
34	Fabricated metal products	9	5.7
35	Machinery and computer equipment	5	3.2
36	Electronics	2	1.3
37	Transportation equipment	2	1.3
39	Miscellaneous manufacturing	5	3.2
	Total manufacturing	82	51.9
	Non-manufacturing		
1-2	Agricultural production	2	1.3
13	Mining-oil & gas extraction	1	0.6
17	Construction	5	3.2
40-49	Transportation, communication, electric, gas, sanitary services	7	4.4
50-51	Wholesale trade	14	8.9
52-59	Retail trade	27	17.1
65	Real estate	1	0.6
70+	Services, public administration	19	12.0
	Total non-manufacturing	76	48.1
	Total	158	100.0

41 manufacturing firms with low abatement costs, and 41 manufacturing firms with high abatement costs.

Finally, to empirically examine the EPA's use of fines and monitoring and enforcement resources, I use two different measures of EPA spending on compliance monitoring and enforcement. I obtained data on EPA spending on compliance monitoring and enforcement by region for 1990 through 1995 from the EPA's Budget Division. Nominal and real (1992$) spending levels given in Table 8 indicate that spending on monitoring and enforcement varies across regions. In 1995 dollars, Region 5 (Chicago) spent the most on monitoring enforcement, $40.7 million, while Region 7 (Kansas City) spent the least on monitoring enforcement, $16.2 million. However, absolute levels of spending are somewhat misleading. Lower spending in Region 7 relative to Region 5 may indicate that Region 7 has fewer facilities to monitor. Furthermore, for a given region, one cannot infer from 1995 data whether regional spending is high or low relative to prior spending by that region. For example, 1995 spending on monitoring and enforcement by Region 10 (Seattle) totaled $19,676 thousand which is low relative to spending by Region 5. However, this represents an average annual growth in spending on enforcement of 4.51 percent over the period 1990 through 1995. In view of this and the lack of data on the number of regulated facilities by region, I use two alternative measures of regional enforcement spending.

Table 8: U.S. Environmental Protection Agency Regional Spending on Enforcement and Compliance Monitoring
(Thousands of Dollars)

Region	City	1995 Nominal	1995 Real (92$s)	1990 Nominal	1990 Real (92$s)	Average Annual Real Growth (%)
1	Boston	19,158	17,927	16,792	18,063	-0.15
2	NY	29,458	27,565	24,187	26,019	1.16
3	Philadelphia	30,664	28,694	25,458	27,386	0.94
4	Atlanta	32,052	29,992	26,381	28,379	1.11
5	Chicago	40,724	38,107	34,715	37,344	0.41
6	Dallas (1)	24,434	22,863	18,708	20,124	2.58
7	Kansas City (2)	16,184	15,143	15,173	16,322	-1.49
8	Denver	19,443	18,193	15,839	17,039	1.32
9	San Francisco (3)	28,269	26,452	22,511	24,216	1.78
10	Seattle (4)	19,676	18,412	13,727	14,767	4.51

Notes:
(1) Excludes $1139.9 in site remediation under CERCLA.
(2) Excludes $100.0 in site remediation under CERCLA.
(3) Excludes $620.9 in site remediation under CERCLA.
(4) Excludes $424.9 in site remediation under CERCLA.

First, I use the average annual real rate of growth in regional spending on enforcement as an independent variable to test the predicted trade-off between fines and resources. Substitutability between fines and resources predicts that, controlling for differences across legislation, industry, and firm size, fines should be higher in regions that have cut-back spending on monitoring and enforcement. Average annual growth in real spending on compliance monitoring and enforcement between 1990 and 1995 is given for each region in the last column of Table 8. The mean average growth rate is 1.49 percent for the entire sample, 1.26 percent for the large firm sample, and 1.69 percent for the small firm sample. This average annual growth in spending on monitoring and enforcement is represented by the independent variable $RGROWTH$. Note, $RGROWTH$ takes the same value for each region and indicates the rate of change in spending on monitoring and enforcement by the EPA region responsible for the action. I test for a negative relationship between growth in spending on enforcement and fines.

I also employ a second measure of regional spending on compliance monitoring and enforcement: regional spending on enforcement per dollar of regional output. Regional spending on enforcement is adjusted for regional output by dividing 1995 nominal spending by an estimate of 1995 nominal gross "regional" product.[16] Gross regional output and regional spending on enforcement and compliance monitoring per dollar of gross regional product, *GRP*, is detailed in Table 9. I employ the log of enforcement spending per dollar of regional output, *LGRP*, as an independent variable in the log-linear models. As with *RGROWTH*, *LGRP* takes the same value for each region.

[16] Gross regional product was computed by first projecting 1995 gross state product (GSP) for each of the fifty state and gross domestic product for Puerto Rico and the U.S. Virgin Islands, since this data was not available. Regional totals were computed by summing gross state product and gross domestic product for the states in each of the respective EPA regions. Appendix B contains a map which identifies the states and U.S. territories in each region. I used the most current estimates of gross state product (GSP) available from the Bureau of Economic Analysis (1977-1994) to project 1995 nominal GSP for each of the fifty states. An estimate of gross domestic product for Puerto Rico was obtained from the Puerto Rico Planning Board, *Economic Report of the Governor, 1994-95.* I estimated 1995 gross domestic product for the U.S. Virgin Islands using historical data obtained from the Bureau of Economic Research, U.S.V.I. Department of Tourism, *Annual Economic Indicators.*

Table 9: Projected 1995 Gross Regional Product
(million of dollars)

Region	State	Projected 1995 GSP/GDP	Gross Regional Product	Region	State	Projected 1995 GSP/GDP	Gross Regional Product
Region 1	ME	$27,221		Region 6	NM	$40,000	
	NH	28,904			TX	429,959	
	VT	14,073			OK	80,514	
	MA	197,175			AR	59,016	
	RI	25,010			LA	95,139	
	CT	115,789		Total			$704,628
Total			$408,172				
Region 2	NY	599,271		Region 7	NE	46,639	
	NJ	270,153			KS	69,817	
	PR	28,371			IA	77,763	
	VI	1,862			MO	138,267	
Total			899,657	Total			332,486
Region 3	PA	308,643		Region 8	MT	28,358	
	DE	28,399			ND	20,128	
	DC	48,909			WY	16,748	
	MD	139,730			SD	22,376	
	VA	189,966			UT	43,739	
	WV	36,709			CO	114,064	
Total			752,355	Total			245,413
Region 4	KY	92,343		Region 9	CA	735,545	
	TN	135,307			NV	35,642	
	NC	198,635			AZ	97,005	
	SC	86,007			HI	29,992	
	MS	53,412		Total			898,184
	AL	94,049					
	GA	197,353					
	FL	338,004					
Total			1,195,110				
Region 5	MN	132,104		Region 10	WA	149,610	
	WI	132,802			OR	91,456	
	MI	252,102			ID	31,881	
	IN	146,350			AK	16,916	289,863
	IL	350,097		Total			
	OH	289,084					
Total			1,302,540				
				Grand Total		$7,028,408	$7,028,408

3.3 Data Limitations

This section discusses a limitation that results from using sales volume as an indicator of ability to pay, while lacking data on the size of the violation (the release amount). Sales volume is often used as a measure of firm size. Large firms produce more and therefore have greater total sales volumes. In addition, large firms generally have greater resources with which to pay higher fines, such as higher profit levels or a larger asset base. However, it may also be the case that large firms pollute more than small firms and therefore may be assessed higher fines due to the extent of the violation.

Since I do not have data on the size of the violation, I cannot determine whether large firms are assessed higher fines because they violate more or because they can afford to pay more. However, it is important to note that the sales volume data used in this study is at the parent company level, not the facility level. Thus, the argument that large firms are fined more because they violate more depends on the relationship between the size of the facility and the size of the parent company. The violating facility may in fact be small, while the parent company is large. Moreover, Magat and Viscusi (1990) point out that while large firms may produce more pollution, there is no evidence that they are more likely to be in or out of compliance. If there are economies of scale with respect to pollution control, large firms may be less likely to be out of compliance.

If there is no positive relationship between the size of the violation and the size of the parent company, then evidence that fines are increasing in sales volume suggests fines are related to the violator's ability to pay. This would provide support for the deep pockets theory, which states that fines are higher for firms that can afford to pay more. However, if large firms violate more than small firms, then I can only conclude that fines are higher for large firms. Without information on the relationship between the size of the facility's release amount and the size of the parent company as measured by sales volume, my conclusions are reserved to the relationship between the magnitude of the fine and firm size.

4 Analysis

This section formally states the three hypotheses tested in this study. Ordinary least square (OLS) estimates of the penalty models are presented for the full sample, as well as for the subsamples of large and small firms. The results are interpreted in terms of the predictions of the harm-, gain-, and firm size (ability to pay) penalty theories presented above. Particular attention is given to the relationship between fines and resources implied by the data. Penalty models for small and large firms are examined to determine structural differences.

4.1 Formal Hypotheses and Tests

Three penalty models are presented in this section. The first model tests for evidence of firm size (ability to pay) and gain-based penalties, controlling for differences across EPA legislations. In addition, I examine the relationship between fines and resources. The model is estimated using both measures of regional enforcement spending: $RGROWTH$ and $LGRP$. The regression equations are

$$LFINE_i = \beta_0 + \beta_S LSALES_i + \beta_G RGROWTH_i + \beta_\delta E\delta_i + \beta_H ACT_i^H + u_i, \quad (6)$$

$$LFINE_i = \beta_0 + \beta_S LSALES_i + \beta_R LGRP_i + \beta_\delta E\delta_i + \beta_H ACT_i^H + v_i, \quad (7)$$

where β_δ represents the vector of coefficients (β_{MANLOW}, $\beta_{MANHIGH}$) and β_H represents the vector of coefficients (β_{CAA}, β_{CWA}, β_{EPCRA}, β_{FIFRA}, β_{RCRA}, β_{SDWA}). Error terms are given by u_i and v_i. Note, TSCA and NONMAN dummy variables are dropped from both equations to avoid the dummy variable trap. As a result, the constant term, β_0, represents the intercept for non-manufacturing firms fined under TSCA.

The null hypothesis is $\beta_S = \beta_R = \beta_G = \beta_\delta = \beta_H = 0$. A simple model in which the regulator minimizes spending on enforcement and penalties are restricted by the offenders ability to pay predicts a positive relationship between fines and ability to pay: $\beta_S > 0$; but, negative relationship between fines and regulatory spending on monitoring and enforcement: $\beta_R, \beta_G < 0$. Gain-based penalty theory predicts that fines are positively related to the expected gain from non-compliance: $\beta_\delta > 0$. Furthermore, the coefficient for manufacturing firms with high abatement costs should be greater than the coefficient for manufacturing firms with low abatement costs, since firms with high abatement costs face greater expected gains: $\beta_{MANHIGH} > \beta_{MANLOW}$. If harm can be implied by the legislation, I would expect fines for violations of all other legislations to be lower than fines for TSCA so that $\beta_H < 0$.

Note, linear specifications of Equations (6) and (7) were also estimated and tested against the log-linear specifications using the P_E test (Greene, 1993, 322). However, the P_E test indicated that the log-linear specifications provide a better fit.[17] I therefore focus on the log-linear specifications in the analyses that follow.

To test for significant differences in penalty models applied to small and large firms, I split the sample in two: one of "large" firms with more than 50 employees and one of "small" firms with 50 or fewer employees. There are 76 large firms and 82 small firms. The model presented Equations (6) and (7) is estimated for both the large and small firm samples. The Chow test is used to test for structural differences. Formally, the restriction is $\beta_k^L = \beta_k^S$ for all $k = (0, S, G, \delta, H)$, where β_k^L represents the coefficients for the large firm sample and β_k^S represents the coefficients for the small firm sample.

Finally, for the subsample of the full sample that contains pollutant data, I estimate Equations (6) and (7) with $HAZSUB$. Recall, $HAZSUB$ assigns hazardous pollutants a harm-based ranking. $HAZSUB$ equals zero if the pollutant is not listed on the 1995 CERCLA Priority List of 275 Hazardous Substances or $HAZSUB$ equals the inverted CERCLA Priority List Ranking, which is increasing in harm. The following equations are estimated:

$$LFINE_i = \beta_0 + \beta_S LSALES_i + \beta_G RGROWTH_i + \beta_\delta E\delta_i + \beta_H ACT_i^H + \beta_Z HAZSUB_i + \epsilon_i, \tag{8}$$

$$LFINE_i = \beta_0 + \beta_S LSALES_i + \beta_R LGRP_i + \beta_\delta E\delta_i + \beta_H ACT_i^H + \beta_Z HAZSUB_i + \omega_i, \tag{9}$$

where ϵ_i and ω_i represent error terms. Note, the constant term represents the intercept for non-manufacturing firms fined for a violation of TSCA involving a non-listed pollutant.

[17] I esimated the log-linear models presented in Equations (6) and (7) with and without controlling for differences across EPA legislation (ACT^H), as well as linear versions of these models. This yielded four models for each specification (linear and log-linear). Using P_E test, I reject the linear specification in favor of the log-linear specification at the 5 percent significance level for *all four* models. Conversely, I reject the log-linear specifications in favor the linear specifications at the 5 percent level in only *two* of the four models. In addition, the linear model results in negative predicted values of the fine and lower adjusted R^2s. In a similar study, Cohen (1992) also finds that the log-linear model provides a better fit.

The null hypothesis is $\beta_S = \beta_R = \beta_G = \beta_6 = \beta_H = \beta_Z = 0$. If fines reflect the harm imposed by the pollutant, then I expect $\beta_Z > 0$.

4.2 Results

Table 10 reports the OLS estimates of the log-linear regressions presented in Equations (6) and (7) using the full sample. The first two columns report the models without control variables for the EPA legislation, while the last two columns report the models with control variables for the EPA legislation. The adjusted R^2 indicates that controlling for differences across EPA legislations greatly improves the fit under both measures of enforcement spending. The adjusted R^2 increases from .3590 to .5003 for the model including *RGROWTH* and from .3858 to .4738 for the model including *LGRP*. This represents an improvement over past research.

The constant term in the Columns 1 and 2 of Tables 10 represents the intercept for fines assessed on non-manufacturing firms, while the constant term in Columns 3 and 4 represents the intercept for fines assessed on non-manufacturing firms that violated TSCA. The estimated coefficients of *MANLOW* and *MANHIGH* indicate that fines for manufacturing firms are significantly greater than fines for non-manufacturing firms. However, the magnitude of the coefficients is not as predicted. The gain-based model predicts higher fines for manufacturing firms with high abatement costs, since they face greater expected gains from non-compliance. Yet, my results for the full sample suggest that fines are higher for manufacturing firms with low abatement costs: $\hat{\beta}_{MANLOW} > \hat{\beta}_{MANHIGH}$. The split sample regression estimates, discussed later, provide some insights into these results.

My results for the full sample provide strong evidence that fines are positively related to the size of the parent company, *LSALES*. Controlling for differences across EPA legislations reduces the impact of *LSALES* on the fine. Columns 3 and 4 indicate that a one percent increase in sales results in roughly a .20 percent increase in the fine. This represents an average increase of \$19.34 in the fine for every \$2.34 million increase in the parent company's annual sales.

Table 10: Ordinary Least Squares Estimation of EPA Administrative Penalties

Full Sample (n=158)
(Standard Errors in Parentheses)

Variable	LFINE		LFINE		LFINE		LFINE	
Intercept	3.1081	***	-2.3664		5.9838	***	4.2254	**
	(0.7579)		(1.6030)		(0.8504)		(2.1707)	
Ability to pay:								
LSALES	0.2983	***	0.2965	***	0.1946	***	0.1977	***
	(0.0491)		(0.0481)		(0.0477)		(0.0490)	
Enforcement Spending:								
RGROWTH	-0.1994	**	-		-0.2210	***	-	
	(0.0837)				(0.0766)			
LGRP	-		-0.9824	***	-		-0.2448	
			(0.2770)				(0.3462)	
Expected gain:								
MANLOW	1.1643	***	1.0402	***	0.9905	***	1.1723	***
	(0.2870)		(0.2849)		(0.3144)		(0.3179)	
MANHIGH	0.9700	***	0.5844	**	0.7184	***	0.7177	***
	(0.2875)		(0.3000)		(0.2748)		(0.2899)	
Act:								
CAA	-		-		-0.3098		-0.0653	
					(0.6513)		(0.6622)	
CWA	-		-		-0.0937		-0.1602	
					(0.4225)		(0.4342)	
EPCRA	-		-		-1.1160	***	-1.1996	***
					(0.3629)		(0.3712)	
FIFRA	-		-		-1.3365	***	-1.4412	***
					(0.4210)		(0.4324)	
RCRA	-		-		-2.2387	***	-2.0132	***
					(0.3824)		(0.4666)	
SDWA	-		-		-1.5419	*	-1.7567	**
					(0.8244)		(0.8452)	
Adjusted R^2	0.3590		0.3858		0.5003		0.4738	

*** = .01 significance level.
** = .05 significance level.
* = .10 significance level.

In addition, both measures of enforcement spending provide evidence of a negative relationship between fines and resources. The coefficient of $RGROWTH$ is consistently significant at the one percent level, supporting the hypothesis of a negative relationship between fines and resources. These results suggest that fines are higher in EPA regions that have cut spending on compliance monitoring and enforcement over the last five years. However, the coefficient of $LGRP$, while consistent with the predicted sign, is only significant in the regression which does not control for differences across EPA legislation. The negative coefficient of $LGRP$ provides weak evidence that fines are higher in regions with low levels of spending on enforcement per dollar gross regional product. My results suggest some degree of substitutability between fines and resources.

The estimated coefficients of the ACT^H dummy variables reveal that fines for violations of TSCA are higher than fines for violations of any other statute. Moreover, fines for EPCRA, FIFRA, and RCRA are different from fines for TSCA at the 1 percent significance level, while fines for SDWA violations are different from TSCA violations at the 5 and 10 percent significance levels. My findings are consistent with those of Cohen (1992), who reports that fines for CWA and TSCA violations are higher than those for RCRA, EPCRA, and FIFRA. However, my results concerning fines for violations of the CAA contradict Cohen's (1992). This may be explained by the fact that my sample of CAA violations includes a violation of the National Emission Standards for Hazardous Air Pollutants (NESHAPS) which addresses air toxics and therefore may command a higher fine.

In summary, the full sample results imply that EPA administrative fines are positively related to firm size and to the expected gain from non-compliance. There is strong evidence of differences in fines across EPA legislations, which may suggest that fines reflect the harm imposed by the pollutant. Finally, there is weak evidence of a negative relationship between fines and regional spending on compliance monitoring and enforcement.

Tables 11 and 12 present the subsample estimations. My results indicate that fines for small firms are harm- and gain-based, while fines for large firms are primarily based on firm size (ability to pay). The estimated regressions consistently provide a better fit for the small firms than for the large firms, as measured by an increase in the $\bar{R}^2$. However, the $\bar{R}^2$ is again improved by controlling for differences across EPA legislations. I therefore focus on the OLS estimates for Equations (6) and (7) presented in Columns 3 and 4.

Table 11: Ordinary Least Squares Estimation of EPA Administrative Penalties

Large Firm Sample (n=76)
(Standard Errors in Parentheses)

Variable	LFINE		LFINE		LFINE		LFINE	
Intercept	3.1460	**	-0.5676		4.7581	***	3.4701	
	(1.5532)		(2.9050)		(1.6584)		(3.2059)	
Ability to pay:								
LSALES	0.3192	***	0.3079	***	0.2686	***	0.2571	***
	(0.0856)		(0.0869)		(0.0859)		(0.0887)	
Enforcement Spending:								
RGROWTH	-0.2091	**	-		-0.2096	**	-	
	(0.0993)				(0.0967)			
LGRP			-0.6612		-		-0.2050	
			(0.4621)				(0.4809)	
Expected gain:								
MANLOW	0.8233	**	0.9175	**	0.2368		0.3892	
	(0.3978)		(0.3994)		(0.4944)		(0.5061)	
MANHIGH	0.1823		0.0847		-0.1694		-0.1300	
	(0.4070)		(0.4280)		(0.4257)		(0.4536)	
Act:								
CAA	-		-		-0.5848		-0.3467	
					(0.8606)		(0.8832)	
CWA	-		-		0.2345		0.2087	
					(0.5499)		(0.5717)	
EPCRA	-		-		-0.1592		-0.1336	
					(0.4942)		(0.5139)	
FIFRA	-		-		-0.9824	*	-1.0884	*
					(0.5619)		(0.5835)	
RCRA	-		-		-1.7216	***	-1.5910	***
					(0.5776)		(0.6335)	
Adjusted R^2	0.1801		0.1532		0.2660		0.2159	

$***$ = .01 significance level.
$**$ = .05 significance level.
$*$ = .10 significance level.

Table 12: Ordinary Least Squares Estimation of EPA Administrative Penalties

Small Firm Sample (n=82)
(Standard Errors in Parentheses)

Variable	LFINE		LFINE		LFINE		LFINE	
Intercept	3.6635	**	-2.3162		8.2059	***	3.7523	
	(1.6124)		(2.3579)		(1.5405)		(3.4860)	
Ability to pay:								
LSALES	0.2504	**	0.2468	**	0.0785		0.0988	
	(0.1158)		(0.1109)		(0.1003)		(0.1019)	
Enforcement Spending:								
RGROWTH	-0.2290		-		-0.2047		-	
	(0.1534)				(0.1292)			
LGRP	-		-1.0829	***	-		-0.6932	
			(0.3534)				(0.5175)	
Expected Gain:								
MANLOW	1.2127	**	0.7045		1.2249	**	1.2733	***
	(0.5839)		(0.5576)		(0.4994)		(0.5064)	
MANHIGH	1.6493	***	1.0546	**	1.6497	***	1.5654	***
	(0.4173)		(0.4293)		(0.3741)		(0.3812)	
Act:								
CAA	-		-		-0.5873		-0.3764	
					(0.9673)		(0.9608)	
CWA	-		-		-0.6851		-0.7197	
					(0.6292)		(0.6309)	
EPCRA	-		-		-2.3652	***	-2.5912	***
					(0.5320)		(0.5274)	
FIFRA	-		-		-2.7156	***	-2.7854	***
					(0.6517)		(0.6511)	
RCRA	-		-		-3.0138	***	-2.4281	***
					(0.5231)		(0.6858)	
SDWA	-		-		-2.4835	***	-2.7108	***
					(0.8838)		(0.8848)	
Adjusted R^2	0.2232		0.2876		0.5167		0.5119	

$***$ = .01 significance level.
$**$ = .05 significance level.
$*$ = .10 significance level.

Turning first to the large firm sample, firm size is the most significant determinant of administrative fines assessed by the EPA. A one percent increase in sales raises fines for large firms by roughly .26 percent. On average, fines increase by \$42.34 for every \$4.83 million increase in sales. In addition, the trade-off between fines and regulatory resources continues to hold for the model estimated using average annual growth in enforcement spending, *RGROWTH*. The coefficient is negative and significant at the five percent level. As with the full sample estimation, the coefficient of *LGRP* is the predicted sign, but is no longer statistically significant. Finally, there is only weak evidence that fines for large firms are affected by legislative differences. Only fines for violations of RCRA are lower than those for TSCA violations and the difference is significant at the 1 percent level. Violations of FIFRA are also lower than TSCA violations; however, the difference is significant only at the ten percent level.[18] In summary, my results suggest that firm size is the most significant determinant of fines levied on large firms by the EPA. Furthermore, there is weak evidence of a trade-off between fines and resources or of differences across EPA legislations.

The results for the small firm sample are presented in Table 12. Contrary to large firms, the results suggest that firm size is not significant in explaining variations in fines assessed on small firms. The OLS estimates of Equations (6) and (7) are presented in Columns 3 and 4. The results indicate that the estimated coefficient of *LSALES* is not significantly different from zero. Furthermore, both measures of regulatory spending on enforcement provide no evidence of substitutability between fines and resources. However, the models provide strong evidence for gain-based penalties and differences across legislations.

Fines for small firms appear to be positively related to the expected gain from non-compliance. The estimated coefficients vector of the expected gain variables indicate that fines for manufacturing firms are significantly higher than fines for non-manufacturing firms. Moreover, the magnitude of the coefficients of *MANLOW* and *MANHIGH* in 3 of the 4 regression models is consistent with the theory that fines are higher for manufacturing firms with high abatement costs (high expected gains), than for manufacturing firms with low abatement costs (low expected gains).

[18] No large firms in the sample violated SDWA.

In addition, differences across EPA legislations are significant in determining the magnitude of fines for small firms. Fines for TSCA are higher than fines for violations of all other legislations. Moreover, the difference between fines for TSCA and fines for EPCRA, RCRA, FIFRA, and SDWA violations is significant at the 1 percent level. The results suggest that fines for small firms are gain- and harm-based, but not related to firm size.

I employ the Chow test to test the hypothesis that the coefficients in the small and large firm subsamples are the same. Formally, the null hypothesis is that $\beta_k^L = \beta_k^S$ for all $k = 0, S, G, R, \delta, H$, where β_k^L represents the coefficients for the large firm sample and β_k^S represents the coefficients for the small firm sample. The F statistics for the regressions shown in Equations (6) and (7) is 1.82 and 2.00, respectively. Given a critical value of 1.79 for 5 percent significance, I reject the hypothesis that the coefficients are the same in the two subsamples. This provides strong evidence that EPA considers different factors when fining small and large firms.

Table 13 presents the OLS estimates of the log-linear regression models presented in Equations (8) and (9) using the sample of 47 enforcement cases that include pollutant data. For this subsample, the expected gain variables (*NONMAN*, *MANLOW*, and *MANHIGH*) are omitted since inclusion worsened the fit. Table 13 gives the coefficient estimates both with and without the hazardous substance ranking, *HAZSUB*, using each measure of enforcement spending. Recall, the sample does not include violations of FIFRA. Furthermore, there is only one RCRA violation, one CAA violation, and two SDWA violations. As a result, analysis of variation in the fine across acts is limited to variation across TSCA, EPCRA and the CWA.

Table 13: Ordinary Least Squares Estimation of EPA Administrative Penalties

subsample with Pollutant Data (n=47)
(Standard Errors in Parentheses)

Variable	LFINE		LFINE		LFINE		LFINE	
Intercept	6.6198	***	5.5630	***	24.4498	***	20.3272	***
	(1.5435)		(1.5294)		(5.1577)		(5.2650)	
Ability to pay:								
LSALES	0.1847	**	0.1640	**	0.1688	**	0.1526	*
	(0.0833)		(0.0794)		(0.0819)		(0.0785)	
Enforcement Spending:								
RGROWTH	-0.4703	***	-0.3839	***	—		—	
	(0.1292)		(0.1278)					
LGRP	—		—		3.2409	***	2.6721	***
					(0.8116)		(0.8163)	
Act:								
CAA	-0.9914		-0.7309		-0.5524		-0.3867	
	(1.3553)		(1.2881)		(1.3255)		(1.2668)	
CWA	0.3342		1.433	*	0.3265		1.3505	*
	(0.5936)		(0.7318)		(0.5786)		(0.7218)	
EPCRA	-1.998	**	-0.4335		-1.2972	***	-0.5752	
	(0.4786)		(0.5562)		(0.4689)		(0.5546)	
FIFRA	—		—		—		—	
RCRA	-0.4546		0.2073		0.0046		0.5400	
	(1.3670)		(1.3249)		(1.3393)		(1.3007)	
SDWA	-0.9132		0.1637		-1.051		-0.0246	
	(1.0897)		(1.1294)		(1.0621)		(1.1154)	
Harm:								
HAZSUB	—		0.0054	**	—		0.0050	**
			(0.0023)				(0.0023)	
Adjusted R^2	0.4358		0.4942		0.4635		0.5117	

*** = .01 significance level.
** = .05 significance level.
* = .10 significance level.

Columns 1 and 2 in Table 13 reveal that the harm imposed by the pollutant does impact the magnitude of the fine. The estimated coefficient of *HAZSUB* is significant at the 5 percent level. The interpretation is that a 1 unit increase in the pollutant's harm ranking yields roughly a 0.0054 percent in the fine. This implies that fines for violations involving PCBs are 1.09 percent higher than fines for violations involving chlorine.

Moreover, inclusion of *HAZSUB* slightly reduces the significance, as well as the magnitude of the estimated coefficients of *LSALES* and *RGROWTH*, while improving the adjusted R^2 from .4358 to .4942. Controlling for the pollutant's harm reduces the constant term, which represents the intercept for TSCA violation. Only fines for CWA violations are significantly different from fines for TSCA violations. I employ the F-test to test the restriction that $\beta_Z = 0$. The computed F-statistic for the restricted and unrestricted regressions presented in Columns 1 and 2 is 5.50. Given a critical value of 4.10, I reject the null hypothesis that $\beta_Z = 0$ at the 5 percent significance level and conclude that the harm imposed by the pollutant is a significant determinant of the magnitude of the fine.

Columns 3 and 4 presented in Table 13 present the estimated regression equation which includes the log of the ratio of EPA enforcement spending to gross regional product, *LGRP*, as a measure enforcement resources. These results also provide evidence that the harm imposed by the pollutant impacts the magnitude of the fine. Inclusion of *HAZSUB* improves the adjusted R^2 from .4358 to .4942. The estimated coefficient of *HAZSUB* is significant at the 5 percent level and roughly the same magnitude as the estimate presented in Column 2. Again, inclusion of *HAZSUB* reduces both the significance and the magnitude of the firm's ability to pay, *LSALES*, and enforcement spending, *LGRP*; however, the sign of the estimated coefficient of *LGRP* is positive, rather than negative. This contradicts the prediction of substitutability between enforcement resources and fines. Fines for CWA violations are statistically greater than fines for TSCA violations.

The computed F-statistic for the restricted and unrestricted regressions presented in Columns 3 and 4 is 4.85. Given a critical value of 4.10, I again reject the null hypothesis that $\beta_Z = 0$ at the 5 percent significance level and conclude that fines reflect the harm imposed by the pollutant.

5 Conclusions

This paper presents strong evidence that the EPA applies different criteria when fining small and large firms. Fines for large firms depend significantly and positively on the size of the violator's parent company, while fines for small firms depend significantly and positively on the expected gain to the violator from non-compliance. Moreover, fines for small firms differ across legislation. Fines for violations of TSCA, CAA, and CWA are greater than for violations of SDWA, EPCRA, RCRA, and FIFRA. This may suggest that fines for small firms also reflect the harm imposed by the violation. Analysis of a small subsample of the data implies that the fines are increasing in the harm and that EPA consideration of harm may reduce the importance placed on other factors, including the firm's ability to pay or regulatory enforcement spending.

I provide evidence of substitutability between EPA enforcement weapons (fines and resources) when fining large firms, but not when fining small firms. There is a strong negative relationship between fines for large firms and the growth rate of EPA regional spending on monitoring and enforcement. This suggests that fines for large firms are higher in regions that have recently cut spending on monitoring and enforcement. There is little evidence of a relationship between fines for small firms and regional spending on enforcement.

My results provide further evidence that fines are higher for large firms. This finding may support the "deep pockets" theory, provided there is not positive relationship between the size of the violation and the size of the parent company. Otherwise, I must reserve my conclusions to the finding that fines are higher for large firms. Examination of the relationship between firm size and violation size is a fruitful area for future research.

The major obstacle to empirical studies of regulatory enforcement policy like this one continues to be lack of data. While the development of IDEA marks considerable progress in EPA's efforts to provide the public with a centralized source of enforcement data, there is room for improvement. This study could have been enhanced with information on historical non-compliance, the amount of the release, and the number of days in violation. Hopefully, more widespread use of the system will lead to further improvement in both the quantity and quality of available data.

References

[1] Arbuckle, J. G. (1993), "Liabilities and Enforcement," *Environmental Law Handbook, Twelfth Edition,* Arbuckle et al., eds., Government Institutes (Rockville, MD).

[2] Baumol, W. J. and W. E. Oates (1988), *The Theory of Environmental Policy*, Cambridge University Press (Cambridge).

[3] Becker, G. S. (1968), "Crime and Punishment: An Economic Approach," *Journal of Political Economy, 76*, 169-217.

[4] Bureau of Economic Research (1997), "U.S. Virgin Islands Annual Economic Indicators," U.S. Virgin Islands Department of Tourism (U.S. Virgin Islands).

[5] Cohen, M. A. (1992), "Criminal Law, Environmental Crime and Punishment: Legal/Economic Theory and Empirical Evidence on Enforcement of Federal Environmental Statutes," *The Journal of Criminal Law and Criminology, 82*, 1054-1108.

[6] DiMento, J. F. (1986), *Environmental Law and American Business*, Plenum Press (New York).

[7] Garvie, D. and A. Keeler (1994), "Incomplete Enforcement with Endogenous Regulatory Choice," *Journal of Public Economics, 55*, 141-162.

[8] Greene, W. H. (1993), *Econometric Analysis*, Second Edition, Macmillan Publishing (New York).

[9] Hawkins, K. (1984), *Environment and Enforcement: Regulation and the Social Definition of Pollution*, Clarendon Press (Oxford).

[10] Kennedy, P. (1996), *A Guide to Econometrics, Third Edition*, MIT Press (Cambridge).

[11] Lear, K. K. and J. W. Maxwell (1997), "The Impact of Industry Structure and Penalty Policies on Incentives for Compliance and Regulatory Enforcement," *Journal of Regulatory Economics* (forthcoming).

[12] Lee, R. T. (1993), "Comprehensive Environmental Response, Compensation, and Liability Act," *Environmental Law Handbook, Twelfth Edition*, Arbuckle et al., eds., Government Institutes (Rockville, MD).

[13] Lepkowski, Wil. 1995. "Delegating Authority: Government Seeks New Balance in Environmental Protection." *Chemical & Engineering News* 73(44), 44-49.

[14] Lott, J. R. (1992), "Do We Punish High Income Criminals Too Heavily?" *Economic Inquiry, 30*, 583-608.

[15] Magat, W. A. and W. K. Viscusi (1990), "Effectiveness of the EPA's Regulatory Enforcement: The Case of Industrial Effluent Standards," *Journal of Law & Economics, 33*, 331-360.

[16] Malik, A. S. (1990), "Avoidance, Screening and Optimum Enforcement," *Rand Journal of Economics, 21(3)*, 341-353.

[17] Melnick, R. S. (1983), *Regulation and the Courts: The Case of the Clean Air Act*, Brookings Institutions (Washington, DC).

[18] Miller, M. L. (1993), "Federal Regulation of Pesticides," *Environmental Law Handbook, Twelfth Edition*, Arbuckle et al., eds., Government Institutes (Rockeville, MD).

[19] O'Leary, R. (1993), *Environmental Change*, Temple University Press (Philadelphia).

[20] Polinsky, A. M. and S. Shavell (1979), "The Optimal Tradeoff between the Probability and Magnitude of Fines," *American Economic Review, 69*, 880-891.

[21] Polinsky, A. M. and S. Shavell (1991), "A Note on Optimal Fines When Wealth Varies Among Individuals," *American Economic Review, 81*, 618-621.

[22] Posner, R. A. (2nd ed. 1976), *Economic Analysis of Law*, Little, Brown and Company (Boston).

[23] Puerto Rico Planning Board (1996), "Economic Report of the Governor, 1994-95," *Statistical Abstracts of the United States, 1996*.

[24] Schlesinger, J. M. (1997), *The Wall Street Journal*, September 22, Dow Jones & Company, Inc. (New York).

[25] Segerson, K. and T. Tietenberg (1992), "The Structure of Penalties in Environmental Enforcement: An Economic Analysis" in *Innovations in Environmental Policy*, T. Tietenberg, Ed., Edward Elgar Publishing (Cheltenham, U.K.).

[26] Sullivan, T. F. P. (1993), "Basics of Environmental Law," *Environmental Law Handbook, Twelfth Edition*, Arbuckle et al., eds., Government Institutes (Rockeville, MD).

[27] U.S. Bureau of the Census (1996), "Pollution Abatement Costs and Expenditures, 1994," *Current Industrial Reports, MA200(94)-1*, U.S. Government Printing Office (Washington, DC).

[28] U.S. Environmental Protection Agency (1984), "Policy on Civil Penalties," *EPA General Enforcement Policy, #GM-21* (Washington, DC).

[29] U.S. Environmental Protection Agency (1984), "A framework for Statute-Specific Approaches to Penalty Assessments: Implementing EPA's Policy on Civil Penalties,"*EPA General Enforcement Policy, #GM-22* (Washington, DC).

[30] U.S. Environmental Protection Agency (1995), *Integrated Data For Enforcement Analysis, IDEA User's Guide*, Office of Enforcement and Compliance Assurance (Washington, DC).

[31] U.S. Environmental Protection Agency (1996), *Enforcement and Compliance Assurance Accomplishments Report FY 1995*, Office of Enforcement and Compliance Assurance (Washington, DC).

[32] U.S. General Accounting Office (1991), "Environmental Enforcement: Penalties May Not Recover Economic Benefits Gained by Violators," *Report to Congressional Requesters*, Resources, Community, and Economic Development Division (Washington, DC).

[33] Waldfogel, J. (1995) "Are Fines and Prison Terms Used Efficiently? Evidence on Federal Fraud Offenders," *Journal of Law and Economics*, *38*, 107-139.

[34] Weisburd, D. S. Wheeler, E. Waring, and N. Bode (1991), *Crimes of the Middle Classes*, Yale University Press (New Haven, CT).

[35] Yeager, P.C. (1991), *The Limits of Law: The Public Regulation of Private Pollution*, Cambridge University Press (New York).

Appendix A
Major EPA Statutes

The following environmental statutes are examined in this paper (acronyms are given in parentheses): the Clean Air Act (CAA), the Clean Water Act (CWA), the Emergency Planning and Community Right-to-Know Act (EPCRA), the Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA), the Federal Insecticide, Fungicide and Rodenticide Act (FIFRA), the Resource Conservation and Recovery Act (RCRA), the Safe Drinking Water Act (SDWA), and the Toxic Substances Control Act (TSCA). A brief statement of the overall objective of each act follows. The accepted pronunciation of associated acronyms are provided for those statutes that are commonly referred to by their acronym.

The **CAA** established National Ambient Air Quality Standards (NAAQS) for six "criteria pollutants" (nitrogen dioxide, sulfur dioxide, lead, ozone, carbon monoxide, and particulate matter), as well as National Emission Standards for Hazardous Air Pollutants (NESHAPS) for 149 air toxics. The NAAQS are implemented through source specific emissions limitations established by states in State Implementation Plans (SIPs). Each state is responsible for assuring that air quality within its borders meets the levels prescribed by the NAAQS.

The **CAA** applies to all new, existing and mobile sources of air pollution. A field citation program allows agency inspectors to issue "environmental traffic tickets" up to \$5,000 per day per violation. Criminal penalty maximums range between \$100,000 to \$250,000 per day and up to as many as fifteen years in jail for individuals and between \$200,000 to \$1million per day for corporations, depending on the violation. The highest penalty maximums are those for knowing releases of hazardous air pollutants.

Arbuckle (1993, p. 155) states that the objective of the **CWA** is "to restore and maintain the chemical, physical and biological integrity of the nation's waters." The CWA regulates new and existing direct dischargers, privately and publicly owned pretreatment facilities and non-point sources including five categories of municipal and industrial storm water dischargers. Pollutants regulated by this act include conventional pollutants (e.g.

suspended solids, fecal coliform, pH, Biochemical Oxygen Demand, oil and grease), toxics (chlorinated organic chemicals, heavy metals, and pesticides), and select nonconventional pollutants (ten substances listed to date). All dischargers to the surface are required to obtain permits which meet technology based performance standards and require dischargers to report violations of these standards.

The CWA provides for two classes of administrative penalties. Class I penalty limits are $25,000 total for the proceeding and $10,000 per violation. Class II penalty limits are $125,000 total for the proceeding and $10,000 per violation. Civil penalty limits were increased under the 1987 amendments from $10,000 per day of violation to $25,000 per day of violation. The amendments set forth a number of factors to be considered in setting penalties including the seriousness of the violation, the economic benefit from the violation, and any history of non©compliance.

EPCRA, pronounced *ep kra*, deals with emergency situations, as well as reporting requirements. It requires facilities to plan for chemical emergencies and to notify of chemical accidents and releases. In addition, it requires annual reporting of the use of hazardous substances and/or toxic chemicals in the work place.

Like the CWA, EPCRA also provides for two classes of administrative penalties. Class I penalties are up to $25,000 per violation and Class II penalties are up to $25,000 per day for each day during which the violation continued. Penalty limits for repeat violation are up to $75,000 per day the violation continues. Ô Civil penalties limits range from $10,000 to $25,000 per day per violation.

CERCLA, pronounced *ser kla*, addresses issues of *past* disposal of hazardous substances. Section 104 authorizes EPA to investigate releases or substantial threats of release of hazardous substances or pollutants or contaminants into the environment which may present an imminent and substantial danger to public health or welfare. Lee (1993, p. 277) notes that sites are scored using EPA criteria which considers toxicity of the substance, location of potential receptors, exposure pathways, threats to the human food chain, and threats to ambient air and ground water. Sites are place on the National Priorities List when this score exceeds a benchmark level (28.5). Once listed, the site is eligible for removal or remediation actions. The Record of Decision sets forth EPA's selected remedy and the factors considered to reach this decision. Parties potentially liable for the clean-up costs include current owners/operators (regardless of their involvement in the handling, disposal or treatment of the relevant hazardous waste), former owners/operators, generators, and transporters.[19] CERCLA enforcement actions were discarded from the sample due to difficulties in obtaining financial information for all responsible parties.

FIFRA, pronounced *fif ra*, regulates the registration, use, cancellation and suspension of pesticides. It controls both general use, as well as restricted use by private and commercial certified applicators. Miller (1993, p. 417) states FIFRA requires that the pesticide will perform its intended function without "unreasonable adverse effects on the environment."

RCRA, pronounced *rick ra*, governs companies that reduce their inventories or discard hazardous wastes, as well as accidental spills of hazardous wastes. It is considered a "cradle to grave" policy since it applies to active generators, transporters, and treatment/storage/disposal (TSD) facilities that deal with hazardous waste. TSDs are required to obtain a permit for operating conditions. Subtitle I of RCRA addresses existing and new underground storage tanks containing hazardous substances (not wastes), petroleum or petroleum-based substances. Violations of Subtitle C or Subtitle I can result in civil penalties of up to $25,000 per day of violation.

The **SDWA** has two primary purposes. The first is to ensure that tap water is fit to drink. The second is to prevent contamination of ground water which serves as the principal source of drinking water for a large majority of the population.

With respect to the first objective, the SDWA regulates public water systems which are defined as any system that provides piped water for human consumption and has at least fifteen service connections or serves at least twenty-five individuals on a regular basis. This statute establishes health-based National Primary Drinking Water Regulations (NPDWRs), in addition to aesthetically-based National Secondary Drinking Water Regulations (NSDWRs). The NPDWRs set Maximum Contaminant Levels (MCLs) for 83 contaminants and requires public water systems to notify the proper regulatory authority and its customers when the MCLs or other SDWA requirements are violated.

[19] A transporter is only liable if it selected the disposal or treatment site.

With respect to the second objective, the SDWA establishes two ground water protection programs: the Underground Injection Control (UIC) Program, which regulates the disposal of liquid wastes underground through a permit system, and Wellhead Protection Programs, which are developed by the states to prevent contamination of areas surrounding wells that supply drinking water to public water systems. Violators are not required to give public notice under the UIC program.

If EPA finds a violation of an MCL, it must notify the State and the public water system and provide advice for meeting compliance. If the state does not take appropriate enforcement action within 30 days, EPA is obligated to either issue a compliance order to the public water system or begin a civil action. This initial compliance order may not assess penalties. However, if the order is violated, EPA may asses administrative penalties of up to $5,000 per violation. If the action proceeds through court, EPA may assess penalties of up to $25,000 per day per violation. Violations of public notification and monitoring requirements are also subject to administrative penalties of $5,000 per violation or civil penalties of $25,000 per day per violation. EPA may issue compliance orders for violation of the UIC program. These compliance orders may include administrative penalties of $10,000 per day per violation up to $125,000. Civil penalties range up to $25,000 per day and prison terms of up to three years.

TSCA pronounced *tos ka*, gives EPA the authority to limit or prohibit the manufacture, process, use, distribution and disposal of chemical substances listed on the Toxic Inventory to the extent necessary to protect against risk.

TSCA authorizes EPA to issue administrative subpoenas to require the attendance and testimony of witnesses, the production of reports, papers, documents or other such information as it deems necessary. Civil penalties under TSCA are determined in a two-stage process. First a gravity based penalty is calculated based on the nature, extent, and circumstances of the violation. Second, the gravity based penalty is adjusted upward or downward taking into account nine factors including ability to pay, good faith efforts to comply, and history of prior non©compliance. Penalties are adjusted up 25 percent for willful violation and up or down 15 percent depending on the extent of "good faith" efforts to comply.