JOURNAL OF ENVIRONMENTAL ECONOMICS AND MANAGEMENT **34,** 54–78 (1997)
ARTICLE NO. EE971003

EPA Effectiveness at Reducing the Duration of Plant-Level Noncompliance[1]

Louis W. Nadeau

Clark University and Eastern Research Group, Lexington, Massachusetts 02703

Received January 5, 1997; revised July 2, 1997

This paper looks at the effectiveness of the Environmental Protection Agency (EPA) in reducing the time that manufacturing plants spend in a state of noncompliance. Plants that are found in violation of EPA standards may remain in violation for a number of time periods. The EPA's policy of making a timely and appropriate response to noncompliance implies returning violators to compliance as quickly as possible. The effectiveness of the timely and appropriate response policy is tested by estimating parametric survival models for the pulp and paper industry. The results indicate that the EPA is effective at reducing the time plants spend violating standards. A 10% increase in EPA monitoring activity leads to a 0.6–4.2% reduction in violation time. The same increase in enforcement activity results in a 4–4.7% reduction in violation time. © 1997 Academic Press

I. INTRODUCTION

Laws designed to protect the environment are only the first step in an effective environmental policy. If the Environmental Protection Agency (EPA) does not enforce compliance with these laws, or the enforcement effort is ineffective at deterring violations, the laws will come to nothing more than empty words. It is clear the EPA enforces compliance, although some have called into question the adequacy of the level of enforcement [22]. A related question is whether the enforcement activity conducted is effective at inducing compliance.

EPA enforcement activity is concerned with the incidence and level of noncompliance with environmental laws. Clearly the agency would like to see complete compliance but will generally have to accept less than complete compliance due to resource constraints.[2] Since the incidence of noncompliance is not fully preventable the EPA will wish to minimize the harm caused by violations. Two ways to measure harm are the extent of violations (how far above a regulatory limit) and the time spent in violation. It is more natural to think in terms of the first of these measures, but some authors have pointed to violation time as another relevant measure [11, 29, 30].

This paper focuses on the length of time that plants in the pulp and paper industry spend in violation of EPA regulations. Once the EPA detects a plant in a state of noncompliance, it will take action to induce compliance as quickly as

[1] I thank Wayne Gray, Trudy Cameron, and E.C.H Veendorp for their insightful comments on earlier drafts. An earlier version of this paper was presented at the Western Economics Association's 70th Annual Meeting in San Diego, CA. This research was funded by the EPA Environmental Science Research Division (Grant R81-9843-010). Any and all remaining errors are mine.

[2] In the spirit of Becker [3].

0095-0696/97 $25.00
Copyright © 1997 by Academic Press
All rights of reproduction in any form reserved.

possible by making a *timely and appropriate response* [29]. The goal of such a response is to return the violator to compliance as quickly as possible. This paper looks at the effectiveness of the EPA at shortening the time plants spend in a state of noncompliance. Returning violators to compliance quickly is a measure of the EPA's success [29]. In this sense we can view the EPA as not only attempting to reduce the incidence of noncompliance, but also the length of noncompliance.

There are several reasons the EPA might wish to see shorter spells of noncompliance. First, longer spells of noncompliance are associated with increased environmental harm. Standards are set to protect the environment and violations of those standards imply an excessive harm. If the harm caused by noncompliance is cumulative over time then long spells of noncompliance are particularly harmful. Thus, following its mandate the EPA might try to shorten the length of noncompliance to reduce environmental harm.

Second, the existence of persistent violators is harmful to the EPA's reputation. The EPA can be viewed as maximizing net political support [21, 27]. Long-term violators indicate ineffective enforcement on the part of the EPA. Political support for the agency will fall if it is seen as ineffective at inducing compliance.

Finally, the existence of long-term noncompliant plants sends a signal that the EPA is ineffective. If compliant plants believe the EPA is ineffective they will lack incentives to remain compliant. Also, if the EPA has long-term noncompliant plants to deal with, the compliant plants might believe that they can violate standards with little EPA concern. Thus, long-term noncompliance by some plants may induce violations at others.

Previous empirical studies have demonstrated the effectiveness of regulatory actions. Bartel and Thomas [1] and Gray and Jones [7, 8] looked at the effectiveness of the Occupational Safety and Health Administration (OSHA) at enforcing compliance with workplace standards. They found that OSHA enforcement activity increases compliance reducing both penalties [1] and violations [7, 8]. Magat and Viscusi [16] and Gray and Deily [9] looked at the effectiveness of EPA enforcement. Magat and Viscusi [16] showed the incidence of an inspection in the previous quarter decreases both the emissions from the plant and the probability of noncompliance for water pollution in the pulp and paper industry. Gray and Deily [9] found that EPA activities increase the probability a firm will be compliant for air pollution regulations in the steel industry. This previous empirical work treats compliance as a point-in-time phenomenon. Compliance status is the dependent variable, measured by either a binary variable or a level of violations. None of the previous literature addresses the *time spent* in violation. For the reasons given above we might believe that the time spent out of compliance is an important aspect of the firm/regulator interaction.

Parametric survival models are estimated to look at EPA effectiveness at influencing the time spent in violation of standards. The effectiveness of the EPA's policy of making timely and appropriate responses to noncompliance is examined. If the EPA is effective at reducing the time out of compliance then plants experiencing more EPA activity should spend less time in violation, *ceteris paribus*. Two-stage models are estimated since the EPA's enforcement decision and the plant's compliance decision are made simultaneous to one another.

In contrast to most studies involving the pulp and paper industry which focus on water pollution [16], this paper focuses on air pollution. Air pollution concerns in the paper production process are not negligible. In 1989, 45% of all expenditures on environmental capital in the pulp and paper industry were for air pollution [17]. The EPA's air pollution data also provide us with regular information on compliance status through the 1980s, needed for the survival analysis.

This paper also attempts to discern the effects of different EPA activity. Russell [22] separates the EPA enforcement effort into monitoring activity and enforcement activity. Monitoring actions consist of inspections and tests. Monitoring aids the EPA in determining the compliance status of a plant or the extent of violations. Enforcement activities (e.g., administrative orders, legal actions, and penalties) are used to compel compliance from the regulated community. Previous work [1, 7, 8, 9, 16] measures regulatory activity as a single variable such as the number of inspections. This paper makes the first attempt at separating the effects of these two types of activity.

Section II discusses the pulp and paper industry and Section III lays out a simple model of the firm's compliance decision. In Section IV the econometric methodology is presented. Section V discusses the data used for the paper and Section VI presents the results of the analysis. Section VII concludes the paper.

II. THE PULP AND PAPER INDUSTRY

Paper production can be broken down into five stages. In the first stage, the pulping process, pulp is formed by separating fibers from lignin in the raw input, usually wood chips. This process can be chemical, mechanical, thermal, or some permutation of the three. Most chemical processes involve recovery of the process chemicals. Kraft, a form of chemical pulp production, must involve chemical recovery to be economical. After the pulping process, the fiber mixture is screened and washed. The mixture is bleached in the next stage to whiten the final product. After another stage of screening the fiber mixture is sent to the paper machine. The mixture enters the paper machine through the headbox at the "wet end" of the machine. The mixture, about 98% water at this point, is sprayed onto a moving screen and water is drawn off at high speed to form paper. The paper is then dried, refined, and cut for shipment or conversion into consumer products. Plants also produce much of their own electricity and provide treatment for the water used throughout the process.

Although noted for their effect on water quality [4, 6, 16], pulp and paper mills also create substantial amounts of air pollution. The production and associated processes result in the release of total reduced sulfur (TRS), volatile organic compounds (VOCs), SO_2, NO_x, particulate matter, fly ash, and organo-chlorine compounds. The chemical recovery process, pulping process, and energy production represent the major sources of air pollution from a pulp and paper mill [6]. Particulate matter and SO_2 are the major pollutants released in the process.

In 1991 the pulp and paper industry spent $1.5 billion on pollution abatement operating costs (PAOC) and another $1.2 on pollution abatement capital expenditures (PACE) [28]. This $2.9 billion total represented 2.2% of the value of shipments for the industry in 1991 and 11.6% of the pollution abatement outlays for all industries. The figure for capital expenditures represented 13.7% of the total for new capital expenditures in the industry. Spending on air pollution abatement in the pulp and paper industry was 30.7% of the $2.9 billion industry wide total.

The paper industry has come under close scrutiny by the EPA lately. On September 10, 1992 the EPA filed several actions in conjunction with the Department of Justice against persistent violators in pulp and paper, organic chemical, and metal manufacturing and processing industries [5]. In 1989, studies revealed that pulp and paper mills were the cause of high levels of dioxin in their water supplies due to the use of elemental chlorine in paper bleaching. This led the EPA to consider new standards for the use of chlorine and spurred the paper industry to develop new methods of bleaching [25, 26] The EPA has also targeted the pulp and paper industry as a testing ground for its multimedia enforcement approach known as ‘‘cluster’’ rules [26].

III. MODEL

EPA Activity

To protect air quality, the EPA sets rules and standards and then monitors and enforces compliance with those rules and standards. The EPA chooses a level of enforcement and monitoring activity to direct at the regulated plants. Monitoring consists primarily of inspections and tests. Monitoring actions are resources expended to ensure those covered by the laws and regulations are living up to their responsibilities [22, 30]. These actions provide information to aid sources in preventative and corrective activities, act as a method of evidence collection for the EPA, and determine the progress in correcting previous violations [30]. Enforcement activity is made up of administrative orders, penalties, civil actions, and criminal actions. These actions are designed to compel compliance from violators and deter noncompliance from compliant plants [22, 30].

Assume the EPA maximizes net benefits in its choice of enforcement and monitoring activity. Net benefits can be defined as the environmental benefits associated with a given level of EPA activity minus the costs associated with that activity. This can be written as

$$NB_t = B(a_t, m_t; H_t) - C_{\text{EPA}}(a_t, m_t; H_t), \tag{1}$$

where NB_t is the net benefit at time t. Enforcement and monitoring are represented by the vectors a_t and m_t, respectively. The frequencies of enforcement and monitoring activity conducted at any individual plant at time t are a_{it} and m_{it}, respectively. H_t is a set of exogenous factors that affect the net benefits to the EPA, all of which can measured in a plant-specific manner. The set of exogenous factors attributable to plant i can be written as h_{it}. $B(\ )$ is the environmental benefit from conducting a_{it} and m_{it} for all i, and $C_{\text{EPA}}(\ )$ is the cost of conducting that activity. The EPA maximizes (1) with respect to a_{it} and m_{it} for all i at each time period. A useful simplification of (1) is to assume that costs are linear in the frequencies of enforcement and monitoring and that the exogenous factors effect the unit cost of EPA activity. This can be written as

$$NB_t = B(a_t, m_t, H_t) - \sum_{i=1}^{n} [\phi_i(h_{it})a_{it} + \delta_{it}(h_{it})m_{it}], \tag{1a}$$

where $\phi_i(\ )$ and $\delta_i(\ )$ are unspecified functions of the exogenous factors. The first-order conditions for a maximum are, dropping the time subscript,

$$B_a - \phi_i(h_i) = 0 \tag{2a}$$

$$B_m - \delta_i(h_i) = 0, \tag{2b}$$

where the a and m subscripts denote partial derivatives with respect to those variables. The EPA will choose enforcement and monitoring frequencies up to the point where marginal benefits equal marginal costs. Assuming the necessary and sufficient conditions for a maximum are met, we can write the EPA optimizing functions as

$$a_{it} = a^*(H_{it}) + v_{it} \tag{3a}$$

$$m_{it} = m^*(H_{it}) + z_{it}, \tag{3b}$$

where v_{it} and z_{it} are random variables with zero expectations.

For simplicity's sake assume there is only one exogenous variable, h, and drop the i subscript. The effect of a change in h on enforcement activity is

$$\frac{\partial a}{\partial h} = \frac{(\phi_h - B_{ah})B_{mm} - (\delta_h - B_{mh})B_{am}}{\left(B_{aa}B_{mm} - B_{am}^2\right)} \tag{4}$$

where subscripts denote partial derivatives with respect to those variables.[3] If we assume the second-order condition is met ($B_{aa}B_{mm} > B_{am}B_{am}$), benefits rise at a decreasing rate in both enforcement and monitoring ($B_{aa}, B_{mm} < 0$), and one activity will increase the marginal benefits of the other ($B_{am} > 0$), then the effect of h can be found through assumptions about B_{ah}, B_{mh}, ϕ_h, δ_h, and their relative magnitudes. The cross partials B_{ah} and B_{mh} represent the effect of h on the marginal benefits of enforcement and monitoring, respectively. The two other cross partial, ϕ_h and δ_h, are the effects of h on the marginal costs.

Assuming h has a positive (negative) effect on marginal benefits and a negative (positive) effect on marginal costs implies h will have a positive (negative) effect on activity. In other words, if enforcement activity increases marginal benefits and decreases marginal costs, then increases in h will induce increases in EPA activity.

If h has the same directional effect on marginal costs and benefits, the effect on activity will depend on the signs of $(B_{ah} - \phi_h)$ and $(B_{mh} - \delta_h)$. If marginal benefits are more responsive than marginal costs ($|B_{ah}| > |\phi_h|$ and $|B_{mh}| > |\delta_h|$), then the effect of h will follow the signs of B_{ah} and B_{mh}. If costs are more responsive ($|B_{ah}| < |\phi_h|$ and $|B_{mh}| < |\delta_h|$), $\partial a/\partial h$ and $\partial m/\partial h$ will follow the signs of ϕ_h and δ_h, respectively.

For purposes of estimation, the set of exogenous factors is important. Dirtier technologies such as kraft pulping and pulp bleaching can be expected to raise the marginal benefits of EPA activity since increasing compliance at these sources will result in larger improvements in environmental quality [6]. It is also reasonable to assume dirtier technologies will result in increased marginal costs. Kraft and bleach

[3] A similar expression can be derived for monitoring activity by interchanging m and a.

plants employ more complex abatement technologies [6]. Russell *et al.* [23, p. 30] note that complex sources will result in higher surveillance costs. The effect of dirtier technologies will then depend on the relative magnitudes of two effects.

Plant size will also be important in determining the net benefits to the EPA. Larger plants have the potential to create larger amounts of pollution. This would imply that the marginal benefits of EPA activity will increase with plant size. It is unclear how marginal costs will vary with size though. Large plants may decrease marginal costs if the EPA can achieve an economy of scale in inspecting a plant. It might take four hours to inspect a 1000 ton per day plant, but only five to inspect a 2000 ton per day plant. On the other hand, marginal costs may increase with size if larger plants are more complex [23]. If marginal costs decrease with size ($\delta_h < 0$), then we expect size to have a positive effect on activity. If size increases marginal costs ($\delta_h > 0$), the direction of the effect will depend on the relative magnitudes of the two effects.

The history of a plant's compliance is also of concern to the EPA. The EPA has targeted plants with poor compliance histories for more enforcement and monitoring than those with cleaner records [29]. This targeting is a clear indication the EPA perceives the increased benefits of activity outweighing any increased cost.

The potential amount of emissions at a plant are also a factor. From time to time the EPA measures or estimates the potential emissions plants can produce. Higher emissions indicate more benefits can be reaped for bringing these plants into compliance. As with dirty technology, if plants with higher emissions are more complex the direction of the effect of emissions will depend on the relative increase in marginal benefits and costs. Intuitively we would expect that plants with a high level of potential emissions will be targeted for more activity.[4]

Attainment areas are those areas of the country the EPA wishes to protect from significant deterioration in quality.[5] Nonattainment areas are places the EPA has targeted for air quality improvements. In light of these goals the EPA might vary its frequency of enforcement and monitoring based on its perception of the marginal benefits and costs of activity in the two areas.

Besides factors that alter the marginal benefits and costs, we need to control for other factors. The state in which the plant is located will effect the EPA's choice of activity. States can decide on their own enforcement and monitoring policies as long as their policy is "no less effective" than the federal policy [22]. This allows some states to implement rules, monitor, and enforce more stringently than other states.[6] The time at which we are looking at the plant will also matter. Trends in EPA activity should be accounted for since an increase in EPA activity over time implies plants receive more actions on average toward the end of the sample

[4] It should be noted that the emissions variable in the CDS is measured infrequently. For some plants in the data, the measured level of emissions, whether it is for particulate matter, SO_2, or NO_x, was the same for the entire sample period. Therefore the emissions variable used here should be considered a measure of potential emissions. In other words, the emissions variable is the information the EPA has on the plant's level of pollution. If the emissions variable was continuous, like the Permit Compliance System's (PCS) effluent measure for water, then one could dispense with a binary measure of compliance and use the emissions data.

[5] The name "Attainment Area" refers to the fact that the area has achieved a certain level of air quality. In these are the EPA's official policy is to prevent significant deterioration (PSD).

[6] States that have a more frequent rate of monitoring and enforcement are referred to here as more stringent.

period. Also, the EPA Administrator might make a difference. Anne Gorsuch claimed she would reduce the level of activity that businesses faced as part of Reagan's policy of reducing regulatory burden [15]. After some problems at the EPA, William Ruckleshaus succeeded Gorsuch and claimed he would restore the credibility of the agency partly through increasing activity [15].

Compliance Decisions

Firms are assumed to maximize profits in their choice of production and environmental expenditures. Production is defined as the amount of pulp and paper produced at the individual plants. Environmental expenditures can be defined as the resources expended by the firm to abate or prevent pollution. These resources can take the form of the value of effort and time of employees or the money spent by the firm. It is also assumed that the EPA and the firm make their decisions simultaneously.[7]

Profits for the ith firm at time t can be written as

$$\pi_{it} = p_t q_{it} - d(q_{it}, e_{it}; S_{it}) - z(c(e_{it}, q_{it}), a_{it}, m_{it}; S_{it}), \tag{5}$$

where p_t is price at time t, q_{it} is production, e_{it} is environmental expenditures, $d(\ )$ is the production cost function, $z(\ )$ is the cost imposed (expected fine) on the plant from the regulatory agency, $c(\ )$ is the compliance function, S_{it} is a set of exogenous factors, and a_{it} and m_{it} are enforcement and monitoring resources directed at the firm by the EPA. Production costs are the costs that the plant incurs in the production of pulp and paper. The regulatory costs imposed on the firm are the costs that the firm pays because it produces pollution. These costs consist of reporting requirements, paperwork, self-monitoring, and expected fines. As the level of compliance, c, rises the expected fine will fall ($z_c < 0$) as the probability of being fined falls. The compliance function increases in environmental expenditures, $c_e > 0$, and falls in production, $c_q < 0$. As the expected number of enforcement and monitoring actions rise the regulatory costs will also rise since each of these is associated with an increase in the expected fine.

Enforcement and monitoring activity also impose direct costs on the plants they are directed toward. Even if an enforcement action does not result in a penalty being assessed, the plant must expend resources dealing with the EPA [23]. Russell *et al.* [23] provides a description of both the process once a violation is discovered and resources expended by the firm in dealing with the EPA action. Inspections and other forms of monitoring also occupy plant resources as they occur [23]. In general someone is usually with an inspector as he or she tours the plant.

The first-order conditions for a maximum with respect to q_{it} and e_{it} are

$$p - d_q - z_c c_q = 0 \tag{6a}$$

$$-d_e - z_c c_e = 0. \tag{6b}$$

[7]At the time the EPA is choosing frequencies of enforcement and monitoring, the firms are choosing production and environmental expenditures. Gray and Deily [9] make a similar assumption. The assumption is important for the empirical portion of the paper.

Firms choose production such that price equals marginal cost where marginal costs include both added production costs and added regulatory costs from increased production. Since $z_c c_q$ can be assumed to be positive, production would be larger in the absence of regulation. Environmental expenditures, e_{it}, are chosen by equating added production costs due to spending e_{it} with decreased regulatory costs associated with e_{it}. Implicitly solving the first-order condition for the choice variables gives

$$q_{it} = q^*(p, a_{it}, m_{it}, S_{it}) \tag{7a}$$

$$e_{it} = e^*(p, a_{it}, m_{it}, S_{it}). \tag{7b}$$

In this paper, the concern is with the interaction of EPA activity and plant level noncompliance.[8] The level of compliance will be determined by the level of EPA activity and the set of exogenous factors, S_{it}. EPA activity can be assumed to increase environmental expenditures and decrease production, both of which result in higher compliance. The compliance equation can be written more clearly, taking into account (7a) and (7b), as

$$c_{it} = c\big(e^*(a_{it}, m_{it}, S_{it}), q^*(a_{it}, m_{it}, S_{it})\big) + \varepsilon_{it}, \tag{8}$$

where e_{it} is a random error term with a zero expectation. The effect of EPA activity or any of the exogenous variables on compliance can be found by differentiation of (8). The effect of enforcement activity is, dropping the i and t subscripts,

$$\frac{dc}{da} = \frac{\partial c}{\partial e}\frac{\partial e^*}{\partial a} + \frac{\partial c}{\partial q}\frac{\partial q^*}{\partial a}. \tag{9}$$

We have assumed that environmental expenditures have a positive effect on compliance $(\partial c/\partial e > 0)$ and production has a negative effect $(\partial c/\partial q < 0)$. Assuming that enforcement has its desired effect of increasing environmental expenditures $(\partial e^*/\partial a > 0)$ or reducing production $(\partial q^*/\partial a < 0)$ implies (9) will be positive. A similar argument can be made for monitoring activity.[9] The effect of the exogenous variables is, dropping the subscripts and letting s be the exogenous variable in question,

$$\frac{dc}{da} = \frac{\partial c}{\partial e}\frac{\partial e^*}{\partial s} + \frac{\partial c}{\partial q}\frac{\partial q^*}{\partial s} + \frac{\partial c}{\partial s}. \tag{10}$$

Exogenous variables will have both a direct effect through the compliance equation $(\partial c/\partial s)$ and an indirect effect through (7a) and (7b). For some of the exogenous variables, the relative magnitudes of the effects may matter for the sign of (10).

To be considered "compliant" the plant must obtain a level c_s, while falling below c_s implies noncompliance. The level of compliance determined by (8) is not observable, but the plant is assumed to know their status in relation to the standard. The compliance level has a deterministic and a random component. The

[8]A full exposition of the comparative statics of the model will not be presented since the generality of the model results in the need to sign several cross partial derivatives. In what follows intuitive arguments will be presented to justify signs given to comparative static terms.

[9]The goal of this paper is to determine the significance and magnitude of dc/da and dc/dm.

function $c(\ )$ gives a mean level of compliance which itself is partly random since both a_{it} and m_{it} have random components.[10] The random component is added to capture factors beyond the control of the plant decision makers such as mechanical breakdowns, human error, and weather. The plant's level of compliance will vary around the mean level $c(\ )$ which is determined by optimal environmental expenditures and production.

A plant that wishes to ensure compliance with EPA regulations will set e_{it} such that expected compliance, $E[c_{it}]$, exceeds c_s and $\text{Prob}[c_{it} < c_s] \approx 0$. In other words it will choose environmental expenditures to make the deterministic portion of compliance larger than the acceptable level and far enough above the acceptable level to ensure violations occur rarely or not at all. Other plants might not be as concerned about remaining above c_s and choose expenditures such that $\text{Prob}[c_{it} < c_s] > 0$. This implies the plant violates the standard from time to time.

To see how (8) is useful in looking at durations of noncompliance consider how this function might move over time for an individual plant. First, consider a plant that chooses $E[c_{it}] = c_s$ or just greater than c_s. In this case a consecutive series of negative realized errors might produce a series of time periods where $c_{it} < c_s$. If this is reported to or observed by the EPA, then the plant is experiencing a duration of detected noncompliance. Due to the random nature of the errors, this situation might not last very long before a positive realization occurs.

A second case is more plausible. A plant might be going through time choosing e_{it} such that $\text{Prob}[c_{it} < c_s]$ is small, but might experience a shift in the exogenous factors, S_{it}, that effects the profits of the plant. If the exogenous factors change such that e_{it} falls or such that the same level of e_{it} results in lower compliance, the plant could end up in a situation where $E[c_{it}] < c_s$ and the $\text{Prob}[c_{it} > c_s]$ is low. This corresponds to a shift in the deterministic portion of (5). The plant will then be going along with its average compliance level below c_s and its actual realizations of c_{it} below c_s. Thus the plant will experience a period of noncompliance.

A final case to consider is if the EPA alters the standard c_s. The legal standard that a plant is required to comply with changes only at the renewal of a permit or when the law changes. A more likely source of a changing standard would be discretion on the part of the inspectors or enforcement agents. If there is room for discretion in the rules, then the standard to which the firm must comply is open for interpretation. One inspector or enforcement agent might hold the plant to a more stringent standard than another. A plant, compliant with c_s, might fall under a new standard, c_s', and have a low probability of realizing compliance above the new standard. Thus a change in the standard might generate a duration of noncompliance.

In all three cases there is the need for the plant to raise its level of environmental spending or lower production in order to return to compliance. To induce a return to compliance, the EPA will direct enforcement and monitoring activity at the noncompliant plant. Assuming that EPA activity increases e_{it} or decreases q_{it} implies EPA activity will have a positive effect on compliance. There are good reasons to believe both assumed relations will hold true. When faced with more frequent inspections, the plant will have an incentive to increase its environmental spending or lower it's production. First, more frequent inspections raise the

[10] The function $c(\ )$ will be referred to as the deterministic component in what follows since its randomness comes from the EPA's choice variables and not from the compliance process at the plant.

expected cost of noncompliance since the EPA can use inspections at noncompliant plants to build legal cases against the plant [29]. The more inspections a plant receives, the more likely it will lose any future legal action. Second, more frequent inspections cost the plant money since environmental personnel at the plant must spend time and effort preparing for inspections and conducting the inspection with the EPA. Finally more frequent inspections increase the probability of detecting other violations. To offset the increased costs of monitoring activity, the plant can raise its level of compliance through increased environmental spending, e_{it}, or decreased production, q_{it}. Both will raise the mean level of compliance and cause spells of noncompliance to end sooner.

Enforcement can also be expected to raise compliance at plants. Enforcement actions targeted at the plant directly raise the costs of noncompliance. Consent decrees and other administrative orders, penalties, and legal actions require the plant to spend money due to noncompliance. To offset the increased costs of enforcement actions, a plant can increase its level of environmental spending or produce less. Either will raise the mean level of compliance and end the violation time sooner.

In addition to EPA actions, the firm's compliance status will be affected by the technology used at the plant. Plants using a kraft pulping process or bleaching pulp might spend longer in violation due to air pollution problems associated with these processes [6]. The use of highly polluting technology implies that a given level of environmental expenditure and output will produce lower compliance than cleaner technology $(\partial c / \partial s < 0)$. Lower compliance makes it harder to leave a spell of noncompliance. On the other hand, taking into account the indirect effects through production and environmental expenditures might result in shorter spells of noncompliance. Assuming kraft production or bleaching increases both production and environmental expenditures $(\partial e^* / \partial s, \partial q^* / \partial s > 0)$, the effect on compliance through increased environmental expenditures may offset lower compliance from increased production and the direct effect on compliance. Another consideration is that kraft or bleach plants might spend less time in violation relative to plants using other processes if problems associated with the other processes create larger problems.

Size also determines compliance at a plant. There is some evidence of economies of scale in compliance [2, 18]. Plants with large capacities might spend less per unit of capacity on compliance. This implies that larger plants will find it easier to comply $(\partial c / \partial s > 0)$. Large plants will also have larger environmental expenditures $(\partial e / \partial s > 0)$ and produce more $(\partial q / \partial s > 0)$. This implies the effect of size on compliance is indeterminate. If $|(\partial c / \partial e)(\delta e^* / \partial s) + \partial c / \partial s| > |(\partial c / \partial q)(\partial^* / \partial s)|$ then larger plants will be more compliant and spend less time violating standards.

Two plants that are similar may fall out of compliance but have differing possibilities of returning if one plant has a higher level of emissions. The direct effect of emissions on compliance is negative $(\partial c / \partial s < 0)$: higher emissions result in lower compliance. Emissions will increase both environmental expenditures and production. Although the result is indeterminate, we would expect the negative effects on compliance (i.e., production and the direct effect) to outweigh the positive effect. This implies that emissions reduce compliance and increase the time spent violating regulations.

Compliance decisions of plants are also effected by the intensity of enforcement activity at the state level. The bulk of enforcement is done by states through their own environmental protection agencies. When a new standard is promulgated, states are required to develop plans, called State Implementation Plans (SIPS), documenting the strategies they will employ to implement and enforce the new standard. The states are allowed to develop strategies that are no less effective than the federal guidelines. This implies that states can opt for more stringent strategies to enforce the laws. States that enforce and monitor vigorously impose higher costs on violators. The value of increased environmental spending or reduced output to achieve compliance will be higher for plants in stringent states since the costs associated with noncompliance in these states is high. In terms of the model, we can assume $\partial e^*/\partial s, \partial c/\partial s > 0$, and $\partial q^*/\partial s < 0$. Therefore plants located in states that are more stringent will leave noncompliance sooner than those that are located in less stringent states.

The amount of demand in the industry will also affect compliance decisions at the plant. If the industry is experiencing an upswing in demand then plants will be producing a large amount of paper and subsequently a large amount of pollution. Increased production at a plant implies a high opportunity cost of diverting resources from productive purpose to compliance purposes.[11]

A final consideration is how the probability of returning to compliance varies over the course of a noncompliance spell. If plants expect harsh future EPA activity for continued noncompliance then the probability of returning to compliance might rise as the spell length increases. This would be the case where a plant has $E[c_{it}] < c_s$ but $E[c_{it}]$ rises over time, making it more likely to observe a return to compliance as the spell length increases. The probability of returning to compliance will fall as the spell increases if plants feel the EPA will not respond to future noncompliance. In this case $E[c_{it}] < c_s$ and $E[c_{it}]$ falls over time making a return to compliance less likely as spell length increases.

IV. ECONOMETRIC METHODOLOGY

Survival analysis is used to make inferences about the length of time plants spend out of compliance. In a survival model we estimate the probability of remaining in a state of existence for t periods. In this paper we are looking at the probability that a firm becomes compliant at time t, given it has been noncompliant for t periods. This method allows us to make inferences about how factors, such as EPA activity, affect the probability of becoming compliant. If EPA actions significantly increase the probability of exiting noncompliance we can say the agency is effective at reducing the duration of noncompliance.

Let the time of exit be a random variable T and let t be a realization of T. Let x be a set of regressors that explain the length of time until exit. Clearly it is possible that the values in x might vary over the course of the spell. Divide the time until exit, t, into j $(\leq t)$ distinct intervals during which no regressor changes. Denote the interval as t_k, for $k = 0, 1, \ldots, j$. The exit time is then t_j and the interval just prior

[11] Causation may also run in the opposite direction. The opportunity cost of an EPA imposed shutdown is large if demand in the industry is high. The plant will also have the money to spend on compliance when demand is large. These both imply that high demand for the product leads to shorter spells of noncompliance. Thus it appears that the effect of demand on violation times is an empirical issue. I thank an anonymous reviewer for pointing this out.

to the exit is then t_{j-1}. The regressors during the interval t_k are defined as $x(t_k)$. The probability that a plant becomes compliant at t_j given that it has been noncompliant for t_{j-1} periods is defined as

$$\Pr\left[t_{j-1} \leq T \leq t_j \mid x(t_j), T > t_{j-1}\right] = \frac{f\left(t_j \mid x(t_j)\right)}{1 - F\left(t_j \mid x(t_j)\right)}, \tag{11}$$

where $f(\ )$ and $F(\ )$ are the density and distribution function of T, respectively. This is referred to as the hazard rate and is denoted $\lambda(t_j \mid x(t_j))$. The function $1 - F(t_j \mid x(t_j))$ is referred to as the survivor function. It gives the probability that an individual remains in the state after t_j and is denoted $S(t_j \mid x(t_j))$. The survivor function is easier to work with analytically.[12]

The hazard rate used in this paper is of the proportional hazards form and can be specified as the product of two separable function as

$$\lambda\left(t_j \mid x(t_j)\right) = \lambda_0\left(t_j\right)\phi\left(x(t_j)\right). \tag{12}$$

The function λ_0 is referred to as the baseline hazard rate and is possibly, but not necessarily, a function of the regressors. ϕ is a function of the regressors only. Various assumptions can be made about the forms of λ_0 and ϕ in order to generate different estimable functions. In practice it is necessary to specify a functional form for $\phi(x(t_j))$. The most common form is

$$\phi\left(x(t_j)\right) = \exp\left(-x(t_j)'\boldsymbol{\beta}\right), \tag{13}$$

where $\boldsymbol{\beta}$ is a vector of coefficients to be estimated.

The estimation of survival models can be done using a fully parametric, semi-parametric, or nonparametric approach. This paper makes use of the fully parametric approach.[13] The fully parametric approach used is the accelerated failure time (AFT) model. Lancaster [14], Kiefer [13], and Kalbfleisch and Prentice [12] provide more extensive discussion and treatment of survival models.

The accelerated failure time model assumes that the regressors accelerate or decelerate the time spent in the state [12]. In this model the baseline hazard is a fully parametric function of both the regressors and the time in the state. The survivor function for a spell of length t_k is [19, 20]

$$S\left(t_k \mid x(t_k)\right) = \exp\left[-\sum_{j=1}^{k}\int_{t_{j-1}}^{t_j} \lambda\left(s \mid x(s)\right) ds\right]. \tag{14}$$

[12] See Keifer [13] and Lancaster [14] for more on the use of survivor functions.

[13] This does not imply that the nonparametric or semi-parametric approaches are invalid. Heckman and Taber [15] and Lancaster [14] provide extensive discussion and treatment of nonparametric models. Nonparametric approaches are used to account for the effect of unobservable variables on the probability of exit. This possibility was explored in the present context. In estimations not reported here the effect of unobserved variables were found to have a statistically insignificant effect on the estimated models. Semi-parametric models were also estimated but not reported since the estimates did not differ qualitatively from the fully parametric ones reported.

Specifying a functional form for $\lambda(\ )$ will allow the model to be estimated. The form chosen here is the Weibull distribution which can be written as

$$\lambda\left(t_j \mid x(t_j)\right) = \alpha t_j^{\alpha-1}\left[\exp\left(-x(t_j)'\boldsymbol{\beta}\right)\right]^{\alpha}, \qquad \alpha \geq 0, \tag{15}$$

where α is a shape parameter.[14] The Weibull distribution has been the most popular specification for survival models in economics [14].

The density function to be estimated through maximum likelihood (ML) is defined as the product of (14) and (15) with (15) substituted into (14). The existence of time-varying regressors complicates normal ML so a method developed by Petersen [19, 20] is used to estimate the model. This procedure uses a nonlinear least squares solution to a ML estimation.[15]

Some spells of noncompliance are incomplete at the end of the sample period. In other words, the plant has fallen out of compliance and not returned by the end of the sample period. This is referred to as *right-censoring*. If a spell is censored at t_j then all we know is that the spell lasted at least t_j periods. The probability that a spell lasted at least t_j is represented by the survivor function and not the density. To control for right-censoring an indicator variable, equal to one if the spell ends during the sample and zero if the spell is censored, is added to the data. The indicator variable is used in the maximum likelihood function to account for the fact that right-censored spells are represented by the survivor function.[16] The likelihood function is given as

$$L(\beta) = \prod_{i=1}^{n}\left[f\left(t_j \mid x_i(t_j)\right)\right]^{d_i}\left[S\left(t_j \mid x_i(t_j)\right)\right]^{(1-d_i)}, \tag{16}$$

where d_i is the indicator variable discussed above and $f(\ )$ and $S(\ )$ are given by (15) and (14), respectively.

Since we are concerned with the time that a state lasts we might also be concerned about how the probability of exiting that state changes over the course of the spell. If the probability of exit rises (falls) over the state we refer to this as a *positive* (*negative*) *state dependence*. The value of α in the AFT model will allow us to make inferences about how the probability of exit changes over the spell. In (15), $\alpha > 1$ implies that $\partial\lambda/\partial t > 0$ and the probability of exit rises over the spell. If $\alpha < 1$ then $\partial\lambda/\partial t < 0$ and the probability falls over the spell. A value of α greater than unity would imply a positive state dependence and a value less than unity implies a negative state dependence.

A potential problem occurs since the EPA and firms can be viewed as making decisions about enforcement and compliance simultaneously. If not accounted for, this may bias the results of the estimations. The EPA will direct more actions at troublesome plants. On the other hand, the behavioral relationship being tested is that more EPA activity induces plants to become less troublesome. Estimating a model without accounting for this observation implies the EPA activity variable

[14] It should be noted that independent variables enter the hazard function in an inverse manner. Thus a variable with a positive estimated coefficient has a negative effect on the hazard rate.

[15] See Petersen [19, 20] for the details of the procedure.

[16] It is also possible to have a problem of left-censoring. In this case we do not know in which quarter the spell begins. This was not a problem for the data used here. Spells that were left censored were not included in the data.

and the errors will be correlated. Plants that are more compliant than they are predicted to be (a positive error) will also receive less activity. Two-stage models are estimated to account for this simultaneity of decisions. In the first stage, an instrument for EPA activity is generated by estimating a model for EPA activity and obtaining the fitted values for that model. The fitted values are used as the EPA activity variable in the second stage survival model. This method will incorporate the EPA's allocation decisions into the EPA variable used in the second stage and remove the correlation with the errors in the survival model.

The models for EPA activity are assumed to follow a Poisson process. This assumption is made since the frequency of EPA activity for plant-quarters is low, often zero, and never negative. Greene [10] provides a discussion of count data models such as the Poisson. These models are estimated for both monitoring and enforcement actions. The estimations are done for two samples. The first sample is the full set of plant-quarters. The second sample is the set of noncompliant plant-quarters. The choice of the noncompliant plant-quarters is motivated by the idea that the EPA's enforcement and monitoring strategy may vary according to compliance status. If this is the case then only noncompliant plant-quarters will be relevant for explaining the length of violations.

V. DATA

The data for this paper is composed of 277 distinct spells of noncompliance in a sample of 175 plants in the pulp and paper industry. The 175 plants generate 7175 plant-quarters and the 277 spells account for 1452 quarters of noncompliance. The time frame ranged from 1979:3 to 1989:3, measured quarterly. Only 23 plants experience more than two spells, 89 experience only one, and 8 are compliant for the entire period. This implies 86.9% of the plants experience two or fewer spells. Based on this, each spell is treated as independent of the others. Thus methods for dealing with multiple spells are disregarded.[17]

Compliance status at the plant was obtained from the CDS. The plant's quarterly compliance status reported in the CDS was converted into a binary variable and the number of consecutive noncompliant quarters were counted. In cases where the plant did not have a compliance status, compliance at individual sources within the plant was used. The plant's compliance in these cases was specified as the worst compliance at all sources. Thus a plant with four compliant and one noncompliant source was labeled as noncompliant.

A potential problem occurs in the compliance variable since this information is self-reported by plants. A plant that misrepresents itself as compliant when it is noncompliant creates errors in the compliance variable. Two considerations minimize this concern. First, false reporting is a criminal offense. Thus the individual reporting the compliance status, usually a mill manager or an environmental director, has an incentive to accurately report. Second, this paper is concerned with the length of detected noncompliance. In other words, the focus is on EPA effectiveness at reducing noncompliance among plants that it knows are noncompliant.

[17] Multiple-state models were estimated using methods found in [14]. These estimations did not improve the results presented here.

EPA activity is measured by seven variables. ENF is the number of enforcement actions where enforcement actions are defined as actions taken to ensure compliance [22]. Enforcement actions are made up of administrative, civil, judicial, and penalty actions. Two first-stage estimations generate predicted values for ENF, which are measured in log form as LENFP and LENFPN.[18] MON is the number of monitoring activities. Monitoring activities are those EPA actions that monitor the compliance status of the plant [22]. Inspections and tests make up monitoring actions in this paper. The logs of the two predicted values for MON are LMONP and LMONPN. The variable LSTINT is the log of inspection activity at other plants in the state. LSTINT is used to control for the intensity of activity in the state. States that follow an intensive enforcement and monitoring strategy are considered more stringent in this paper. The monitoring, enforcement, and state level activity information are all taken from the CDS.

As stated in the model section, a number of factors will effect the frequency of EPA activity directed at plants. Two dummy variables represent technology used at pulp and paper mills. KRAFT is equal to one if the plant produces pulp using the kraft pulping process and BLEACH is one if the plant bleaches pulp. LCAP is the log of capacity at the plant and captures the variation in activity over different sized plants. The log of emissions, LEMIT, captures the effect of potential emissions.[19] The plant's compliance history is captured by TIME and LAGCOMP. TIME is the length of time the plant has been noncompliant. TIME was set equal to zero for all quarters in which the plants were compliant. LAGCOMP is the compliance status at the plant in the previous quarter.[20] Q is the quarter in which the activity took place and is used to capture time trends. The third quarter of 1979 was taken to be $Q = 1$. The geographic area of the plant was captured by ATTAIN and a set of 14 state dummy variables. ATTAIN equals one if the plant is located in an attainment area. GORSUCH equals one if the action occurs during Anne Gorsuch's tenure as EPA administrator. RUCK is similarly defined for William Ruckleshaus.

Besides EPA activity, a number of other factors will also effect a plant's compliance decision and ultimately their length of noncompliance. The effects of technology and size are captured by KRAFT, BLEACH, and LCAP. LEMIT captures the effect of potential emissions. The demand in the industry is proxied by the log of the capacity utilization rate, LUTIL. Commentary on the industry points to capacity utilization as an important variable for determining the level of demand [24–26].

Descriptive statistics for the data at various stages of aggregation appear in Tables I through III. The average plant has a capacity of 1207 tons per day. Forty-six percent of the plants use the kraft pulping process and 37% bleach pulp. The average spell of noncompliance was 5.04 quarters during which plants experienced 2.4 enforcement and 3.6 monitoring actions on average. Eighty-eight percent of the spells end during the sample period implying that 12% are right-censored.

[18] The first-stage estimations are explained in more detail below.

[19] The variable is measured in log form to mitigate the effect of large observations.

[20] Other formulations of the LAGCOMP were also used but none performed as well as "compliance in the previous quarter." Some of the other formulations were "compliance one year ago," "compliance two quarters ago," "compliance three quarters ago," and "average compliance during the last year."

Every year all plants averaged one enforcement action and four monitoring actions. Noncompliant plants averaged one enforcement action every half-year and one monitoring action every four to five months.

VI. RESULTS

As discussed above, the estimations are done in a two-stage process. In the first stage, Poisson models are estimated for EPA monitoring and enforcement activity. These models generate instruments used in the second-stage survival models. The discussion in this section begins with a look at the first-stage estimations and then turns to the second-stage models.

First-Stage Estimations

The results of the first-stage Poisson estimations appear in Table IV. The estimations show that plants employing a kraft pulping process (KRAFT) receive significantly more inspections, but significantly less enforcement activity. Bleaching pulp (BLEACH) results in significantly more activity except for monitoring activity in the noncompliant sample. The conflicting signs of the kraft variable can be

TABLE I
Descriptive Statistics by Plant and Spell

Variable	Mean	SD	Definition
		Plant level ($N = 175$)	
KRAFT	0.457	0.500	Equal to one if the plant employed kraft pulping process.
BLEACH	0.371	0.485	Equal to one if the plant bleaches paper.
CAP	1206.74	1231.73	Capacity of the plant in tons of paper per day.
ATTAIN	0.474	0.501	Equal to zero if the plant was in a nonattainment area for particulate matter.
EMIT	1763.37	6277.50	Emissions of particulate matter at the plant in tons.
		Spell level ($N = 277$)	
DURATION	5.057	5.692	Time spent in noncompliance.
KRAFT	0.516	0.501	See above.
BLEACH	0.430	0.496	See above.
ATTAIN	0.440	0.497	See above.
EMIT	2093.65	7365.48	See above.
ENF	2.408	4.877	Average number of enforcement actions directed at the plant.
MON	3.560	5.596	Average number of monitoring actions directed at the plant.
D	0.881	0.325	Equal to one if the spell ends during the sample, equal to zero if the spell is censored.

TABLE II
Descriptive Statistics of the Full Set of Quarters
(N = 7175)

Variable	Mean	SD	Definition
KRAFT	0.457	0.498	See Table I.
BLEACH	0.371	0.483	See Table I.
LCAP	6.364	1.450	= log(CAP); see Table I.
TIME	1.293	3.946	Time spent in noncompliance.
Q	21.00	11.833	Quarterly time trend.
LAGCOMP	0.797	0.403	One quarter lagged compliance.
ATTAIN	0.474	0.499	See Table I.
LEMIT	5.704	1.959	= log(EMIT); see Table I.
GORSUCH	0.220	0.414	Equal to one during Anne Gorsuch's tenure as EPA Administrator.
RUCK	0.171	0.376	Equal to one during William Ruckleshaus' tenure as EPA Administrator.
ENF	0.273	0.754	Enforcement action during the quarter.
ENFP	0.273	0.208	Predicted value of ENF from first stage equation using full sample.
LENFP	−1.586	0.794	= log(ENFP).
MON	1.069	1.784	Monitoring actions during the quarter.
MONP	0.610	0.794	Predicted value of MON from first stage equation using full sample.
LMONP	−0.764	0.762	= log(MONP).

explained with reference to the theoretical model. The benefits of increased inspections may outweigh the costs since kraft plants have the potential to create large amounts of pollution. If these pollution problems are easily fixed, the benefits of more enforcement activity might not outweigh the costs since fewer actions might be needed to induce compliance.

Larger plants (LCAP) are inspected more often and receive significantly more enforcement activity. These results verify the expectation of the model section that larger plants will receive more activity since they might create larger problems. As plant size increases, benefits begin to outweigh the costs of increased activity.

The level of enforcement activity remains constant over the spell length (TIME) while monitoring activity falls over the spell in the full sample estimation and rises in the noncompliant estimation. The disparity between the two samples for monitoring activity is caused by the definition of TIME in the full sample estimation. A compliant plant is given a value of zero for TIME, generating a truncation problem for TIME. The estimated values for Q are positive and significant indicating a rise in both monitoring and enforcement activity over the sample period.

Plants that were compliant in the previous quarter (LAGCOMP) receive less monitoring and enforcement activity. Those plants that were noncompliant in the previous quarter are likely to have compliance problems in the present. The EPA can reap increased benefits from increasing compliance at these sources since they

TABLE III
Descriptive Statistics of the Set of Noncompliant Quarters
($N = 1452$)

Variable	Mean	SD	Definition
KRAFT	0.399	0.490	See Table I.
BLEACH	0.398	0.490	See Table I.
LCAP	6.288	1.346	= log(CAP); see Table I.
LEMIT	5.870	1.885	= log(EMIT); see Table I.
LSTINT	7.155	0.789	Log of the number of inspections at other plants in the state. Measure of state intensity of enforcement.
LUTIL	4.532	0.033	Log of the industry capacity utilization rate.
ENF	0.459	1.067	Enforcement action during the quarter.
ENFP	0.399	0.262	Predicted value of ENF from first stage equation using full sample.
ENFPN	0.459	0.266	Predicted value of ENF from first stage equation using noncompliant quarters only.
LENFP	−1.160	0.737	= log(ENFP).
LENFPN	−0.981	0.697	= log(ENFPN).
MON	0.679	1.419	Monitoring actions during the quarter.
MONP	0.607	0.440	Predicted value of MON from first stage equation using full sample.
MONPN	0.679	0.469	Predicted value of MON from first stage equation using noncompliant quarters only.
LMONP	−0.739	0.710	= log(MONP).
LMONPN	−0.612	0.683	= log(MONPN).

are causing excessive harm. Also, given the plant's prior noncompliance, the EPA also faces decreased costs of directing actions at these sources in terms of evidence collection and identifying violations.

In the full sample estimation, plants in total suspended particulate (TSP) attainment regions (ATTAIN) receive significantly less enforcement actions but significantly more monitoring actions. The EPA's policies for attainment and nonattainment areas can provide an explanation for this disparity between the two types of actions. The goal in an attainment region is to avoid deterioration of ambient air quality. In this context the EPA monitors the plants to ensure they are not exceeding regulatory limits and causing deterioration. The goal in nonattainment regions is to raise the air quality. This would lead the EPA to direct more enforcement actions at plants in nonattainment regions since standards in these regions are stricter.

Plants that have a higher level of measured emissions (LEMIT) receive significantly more enforcement actions in both samples, but only more monitoring actions in the full sample estimation. The measured amount of emissions is an indication to the EPA that the plant has the potential to pose a significant threat to ambient air quality. The positive relationship between emissions and enforce-

TABLE IV
First-Stage Poisson Estimations for EPA Activity

Variable	ENF, all quarters in the sample ($N = 7175$)	MON, all quarters in the sample ($N = 7175$)	ENF, noncompliant quarters ($N = 1452$)	MON, noncompliant quarters ($N = 1452$)
Constant	−2.294***	−2.313***	−2.400***	−2.435***
	(0.206)	(0.143)	(0.332)	(0.307)
KRAFT	−0.199***	0.518***	−0.492***	0.578***
	(0.070)	(0.056)	(0.123)	(0.110)
BLEACH	0.458***	0.112***	0.210**	−0.037
	(0.052)	(0.036)	(0.092)	(0.078)
LCAP	0.136***	0.103***	0.145**	0.213***
	(0.032)	(0.020)	(0.060)	(0.048)
TIME	0.008	−0.243***	−0.010	0.032***
	(0.006)	(0.006)	(0.007)	(0.007)
Q	0.015***	0.019***	0.023***	0.009***
	(0.002)	(0.002)	(0.004)	(0.003)
LAGCOMP	−0.650***	−0.300***	·	·
	(0.061)	(0.047)	·	·
ATTAIN	−0.140**	0.071*	−0.042	0.078
	(0.055)	(0.040)	(0.094)	(0.082)
LEMIT	0.041**	0.093***	0.073**	0.019
	(0.019)	(0.012)	(0.035)	(0.027)
GORSUCH	0.060	−0.042	0.138	0.213
	(0.071)	(0.049)	(0.121)	(0.097)
RUCK	−0.006	0.134***	0.222**	0.532***
	(0.066)	(0.043)	(0.118)	(0.092)
LOG-L	−4684.47	−8012.35	−1382.48	−1686.88
Pred. value	ENFP	MONP	ENFPN	MONPN

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

ment and between emissions and monitoring at all plants indicates that the increased benefits of EPA activity outweigh the costs for plants having the potential to create large amounts of pollution. On the other hand, once a plant is found in violation the measured amount of emissions play an insignificant role in the level of monitoring done at the plant. If a large part of EPA monitoring of noncompliant plants is collection of evidence then this is sensible. Plants that are larger emitters need less evidence collected against them.

The policy of Anne Gorsuch was to decrease the level of EPA activity during her tenure as EPA administrator [15]. This was not verified; GORSUCH was insignificant in all the estimations. This does not contradict an EPA slowdown during her term since we are looking at only one industry. There might have been a slowdown for activity in general, but not activity directed at the paper industry since it is a significant polluter. Also, GORSUCH is measured against a base group which occurs mostly toward the end of the period. This result implies that she performed no more or less activity than her republican-appointed successors Lee Thomas and William Reilly. The term of Ruckleshaus (RUCK) shows a significant increase in all but the full sample estimation for enforcement. His policy was to restore the credibility of the EPA by increasing the level of activity [15]. The result says that he performed significantly more activity than his successors. The lack of an increase in enforcement for the full sample estimation might be indicative of President Reagan's pro-business stance.

The models for ENF and MON using the noncompliant sample assume that the EPA's strategy for violators differs from the strategy for compliant plants. This appears to be the stated policy of the EPA [29, 30]. To test this more formally, a specification test for differences between compliant and noncompliant plants is performed. COMP, a dummy variable equal to one when a plant is compliant, is added to both full sample estimations and is interacted with all the other variables.[21] A likelihood ratio test comparing the full sample estimations and this new estimation results in χ^2 statistics of 281.56 for ENF and 410.56 for MON, both of which are well above the critical value of 35.17. Thus, there is a significant difference between the EPA's policy for compliant versus noncompliant plants.[22]

Second-Stage Estimations

Before commenting on the results of the second-stage estimations, three points need to be discussed. First the x vector enters the hazard function inversely; therefore the signs in the estimations are reversed. In other words, a positive estimated coefficient implies a negative effect on the probability of exit. The second point is that the inverse of the hazard rate is equal to expected time in the spell [14]. Combined with the first point this implies that the sign of the estimated coefficients shows the direction of the effect on the expected violation time. A positive estimated coefficient means that an increase in this variable extends the time of violation.

Finally, since many of the variables are measured in natural logs we can derive the elasticity of expected time with respect to these variables. To see this note that expected time can be written as[23, 24]

$$E(T) = \frac{1}{\alpha t^{\alpha-1}[\exp(-x\beta)]^{\alpha}}. \tag{17}$$

Taking the natural log of (17) we get

$$\ln E(T) = -\ln(\alpha) - (\alpha - 1)\ln(t) + \alpha x'\beta. \tag{18}$$

If the ith variable, x_i, is measured in log form, the derivative of (18) with respect to x_i, equal to $\boldsymbol{\alpha\beta}_i$, is the elasticity of expected violation time with respect to x_i.

[21] Only the variable TIME is not interacted with COMP since, by its definition, the interaction term would be perfectly collinear with the variable itself.

[22] The full sample estimation in Table IV is considered the restricted estimation. The results of the estimation of the unrestricted model are available from the author upon request.

[23] Suppressing x's dependence on time.

[24] See Lancaster [14].

TABLE V
Second-Stage Accelerated Failure Time Models
($N = 1452$)

Variable	(A)	(B)	(C)
Constant	−10.488	−15.210*	−14.088
	(9.596)	(8.718)	(9.630)
KRAFT	−0.601***	−0.433**	−0.626***
	(0.190)	(0.192)	(0.189)
BLEACH	0.017	0.149	0.131
	(0.177)	(0.149)	(0.157)
LCAP	−0.050	0.153*	0.105
	(0.082)	(0.087)	(0.087)
LEMIT	0.067	0.060	0.070
	(0.046)	(0.045)	(0.046)
LENFP	0.093	·	·
	(0.146)	·	·
LMONP	−0.079	·	−0.041
	(0.115)	·	(0.116)
LENFPN	·	−0.352**	−0.427***
	·	(0.138)	(0.143)
LMONPN	·	−0.362***	·
	·	(0.132)	·
LSTINT	−0.147	−0.144	−0.227**
	(0.093)	(0.088)	(0.089)
LUTIL	3.001	3.611*	3.590*
	(2.079)	(1.901)	(2.089)
α	1.101	1.149	1.102
	(0.087)	(0.085)	(0.082)
LOG-L	−665.051	−656.749	−660.125

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

The estimates for the second-stage models appear in Table V.[25] Models (A) and (B) are straightforward, using predicted values for enforcement and monitoring activity from the full and noncompliant sample, respectively. Model (C) on the other hand is less intuitive. In this model enforcement activity is predicted from the noncompliant sample and monitoring activity from the full sample. The motivation for this model is simple: enforcement actions are usually taken in response to a violation while monitoring is done at all plants. The reverse is not a plausible policy since the combination of monitoring being done in a status-specific manner while enforcement is not is unlikely.

Plants that use the kraft pulping process (KRAFT) spend significantly less time out of compliance than plants employing other processes. This result could be

[25] The standard errors of the second-stage models are not adjusted to account for the fact that two of the variables, enforcement and monitoring activity, are taken from a first stage estimation. In other words, the variables are assumed to be fixed. This implies that the standard errors in the second-stage estimation will be biased downward. An adjustment is not made because the derivation of these standard errors is not straightforward in a system with two Poisson first-stage models and a survival model second stage. Also, methods that are available to deal with this circumstance (i.e., the delta method) may result in biased estimates [10].

considered consistent with the first-stage estimations which found that kraft firms receive significantly less enforcement activity. It appears that plants employing other forms of pulping, such as mechanical or thermal, experience larger compliance problems than kraft plants. In terms of the theoretical model, the positive effect of increased environmental spending outweighs the negative effect of increased production and kraft technology itself on compliance. The magnitude of the result is small; kraft plants spend 0.49 to 0.69% less time violating EPA air regulations. This implies that a kraft plant will spend 895 days in violation compared to a similar nonkraft plant expected to spend 900 days (approximately 10 quarters). Bleaching paper has no effect on the time spent in violation of EPA regulations. The estimates for BLEACH are all positive but insignificant.

The estimates for the effect of plant size appear to be sensitive to the choice of EPA activity variable. In models using monitoring activity predicted from the full sample, models (A) and (C), LCAP is insignificant. LCAP is negative in model (A) where both EPA activity variables are predicted from the full sample. Size has a positive effect in model (B) where activity is predicted from the noncompliant sample. This model implies that larger plants spend longer out of compliance, which is not indicative of economies of scale in compliance. There are three possible explanations of this result. First, there are no economies of scale in compliance in the pulp and paper industry. From the theoretical model, $\partial c / \partial s \leq 0$ and is not dominated by any positive effect on compliance. The second explanation is that there is no relationship between compliance and size.[26] This would imply that all terms add up to zero in (10). The third explanation is that there are economies of scale in compliance and the EPA takes this into account when setting the requirements for plants. This implies that larger plants are made to meet stricter requirements since they can abate pollution problems at a lower per unit cost.[27] The result in (B) says that a 10% increase in size leads to a 1.76% longer spell of noncompliance should a violation occur.

Plants that have a higher level of measured emissions (LEMIT) spend a longer time out of compliance but the effect is not significant. This sign of the result is expected since plants with a higher level of measured emissions in the CDS will probably have more serious violations. The magnitude of the result is small. A 10% increase in the emissions at the plant results in a 0.69–0.77% increase in the spell length.

Plants located in stringent states (LSTINT) spend less time in violation, but the effect is significant only in model (C). As with LEMIT, the results depend on the choice of activity variable. Holding the enforcement variable constant and comparing across models (B) and (C) we see that LSTINT gains explanatory power when monitoring is predicted from the full sample. A plant located in a more stringent state will have a higher expected cost of noncompliance than a plant in a less stringent one, *ceteris paribus*. Thus, plants in stringent states spend less time in violation. The significant models predict that a 10% increase in inspections at other plants in the state leads to a 2.5% decrease in violation time.

[26] The first and second reason are not the same. The first reason implies that large pulp and paper mills are unable to capture advantages due to their size. The second reason says that size does not matter for compliance.

[27] This is not to say larger plants receive more activity from the EPA. This was accounted for in the first stage. A “stricter requirement” means the EPA sets a standard for the plant that takes into account economies of scale in compliance.

As demand conditions in the industry improve, the length of noncompliance increases. LUTIL is positive in all the estimations and significant in models (B) and (C).[28] The opportunity costs of diverting resources from productive purposes are high during an upswing in demand and plants are unwilling to incur these costs. Since plants are less willing to spend for compliance reasons, the length of violation increases. The results indicate that a 1% increase in the industry capacity utilization rate will lead to a 3.3–4.15% increase in the expected spell length. If a plant is expected to spend 10 quarters in violation, an increase from 90 to 99% capacity utilization will increase the expected spell length by almost a year.

The value of α tells us how the probability of exit varies over the course of the spell. The estimates of α in Table V are greater than unity but not significantly. This implies that the probability of exit, conditional on being noncompliant until that point, remains constant over the course of the spell. As noted earlier, how the hazard varies over time might point to plant's expectations about future EPA actions. A rising hazard is consistent with plants expecting increased EPA action due to continued noncompliance. A falling hazard is consistent with plants expecting little EPA activity due to a perceived ineffectiveness. The result here has three interpretations. First, the two effects discussed above could be averaged in the estimations with some plants holding each type of expectation. Second, time in a state of noncompliance may have no effect on the conditional probability of exit. The final interpretation is that plants expect no increased future activity for continued noncompliance.

Enforcement activity predicted from the sample of noncompliant plant-quarters has a significant and negative effect on the length of noncompliance. Predicted from the full sample, enforcement is positive and insignificant. Considering the test for the appropriateness of splitting the sample this is not unexpected. Enforcement actions are generally directed at noncompliant plants; therefore we might expect enforcement activity predicted from the noncompliant sample to work better. The results imply that EPA enforcement activity significantly reduces the time plants spend in a state of noncompliance and is effective at reducing violation times. The estimated elasticities are -0.4 for model (B) and -0.47 for model (C). A 10% increase in the expected enforcement activity that a noncompliant plant faces will reduce a 10 quarter spell to a 5.3 to 6 quarter spell.

Monitoring activity is significant when predicted from the sample of noncompliant plants. If predicted from the full sample monitoring activity has a negative but insignificant effect. Plants that experience a larger number of inspections and tests during the spell tend to spend less time in violation. The elasticity of this effect ranges from -0.06 to -0.42, with the upper end being the significant result in (B). The significant result tells us that a 10% increase in monitoring activity reduces a 10 quarter spell to a 5.8 quarter spell.

When either monitoring or enforcement activity was predicted from the full sample, it was insignificant in the second stage. Given the result of the specification test done for the first-stage models this is not surprising. The test shows that the EPA uses different strategies for compliant and noncompliant plants. The variables predicted from the full sample are an average of the strategies. This is

[28] It should also be noticed that the coefficient of LUTIL is imprecisely measured in all three second-stage models. This is due to the lack of variation in LUTIL. From Table III we see the standard deviation of LUTIL is 0.033, which is much smaller than the standard deviation of any of the other variables.

troublesome in this case since we are explaining the variation in spells of noncompliance. The first stage that uses only noncompliant quarters provides better instruments for the second-stage estimations.

VII. CONCLUSIONS

This paper has examined the EPA's policy of making a timely and appropriate response to violations. An effective enforcement effort on the part of the EPA will result in sources returning to compliance quicker than in the absence of agency activity. Survival models were estimated to examine the effectiveness of EPA activity in the pulp and paper industry. The results show that the EPA is effective at reducing the time that plants violate standards. A 10% increase in monitoring activity leads to a 4.2% reduction in the time that plants violate EPA regulations. A 10% increase in enforcement responses implies a 4–4.7% reduction in the length of violation. This result implies that the EPA's policy of making a timely and appropriate response to noncompliance is effective at achieving its goal of returning violators to compliance quickly.

The effectiveness of EPA actions is seen by allowing the agency's policy to vary between compliant and noncompliant plants. If the agency is viewed as not having separate policies for compliant and noncompliant plants the agency is seen as ineffective. A specification test shows that the EPA follows separate strategies based on compliance status, validating the result that the EPA is effective at reducing the duration of noncompliance.

The effectiveness of EPA actions in this paper does not imply that an increase in EPA activity is desirable. The benefits of increased compliance is a reduction in harm done to the environment and the subsequent health and aesthetic benefits that follow. Increased activity, on the other hand, would have a positive cost in terms of both increased compliance costs to plants and increased EPA activity costs. If the benefits of the increased compliance were to outweigh the additional costs then more actions would be warranted. A full cost–benefit assessment is clearly beyond the scope of this paper.

The extent to which this is applicable to other industries depends on their view of EPA effectiveness. It is possible that plants in less-polluting industries may be induced to become or remain compliant if the EPA is effective at inducing compliance in a highly polluting industry such as pulp and paper. If this is true then the results here imply that the EPA effectively induces compliance for other industries.

Environmental policy, administered by the EPA, is well served by the agency's ability to reduce the time of noncompliance. Less harm is caused and the EPA does not suffer the associated political support and reputation consequences of ineffective enforcement. Upon detection of a violation, the EPA effectively causes the time until compliance is achieved to be shorter than in its absence. This results in a higher rate of compliance, a step toward complete compliance which is the ultimate goal of regulatory enforcement.

REFERENCES

1. A. P. Bartel and L. G. Thomas, Direct and indirect effects of OSHA regulations, *J. Law Econom.* **28**, 1–25 (1985).

2. W. A. Brock and D. S. Evans, ''The Economics of Small Business: Their and Regulation in the U.S. Economy,'' Holmes and Meier, New York (1985).
3. Gary Becker, Crime and punishment: An economic approach, *J. Polit. Econom.* March/April, 169–217 (1968).
4. The Council on Economic Priorities, ''Paper Profits: Pollution in the Pulp and Paper Industry,'' MIT Press, Cambridge, MA (1972).
5. Council on Environmental Quality, ''Environmental Quality 1992,'' U.S. Government Printing Office, Washington DC (1993).
6. Environmental Protection Agency (EPA), Office of Compliance, ''Profile of the Pulp and Paper Industry,'' Sector Notebook Project, U.S. Government Printing Office, Washington, DC, September, (1995).
7. Wayne B. Gray and Carol Adaire Jones, Are OSHA health inspections effective? A longitudinal study in the manufacturing sector, *Rev. Econom. Statist.* **73** (3), 504–508 (1991).
8. Wayne B. Gray and Carol Adaire Jones, Longitudinal patterns of compliance with OSHA in the manufacturing sector, *J. Human Resour.* **26** (4), 623–653 (1991).
9. Wayne B. Gray and Mary E. Deily, Compliance and enforcement behavior: Air pollution regulation in the U.S. steel industry, May (1995).
10. William H. Greene, ''Econometric Analysis,'' Macmillan, New York (1993).
11. Winston Harrington, ''The Regulatory Approach to Air Quality Management: A Case Study of New Mexico,'' Research Paper R-25, Resources for the Future, Washington, DC (1981).
12. J. D. Kalbfleisch and R. L. Prentice, ''The Statistical Analysis of Failure Time Data,'' Wiley, New York (1980).
13. N. M. Kiefer, Econometric duration data and hazard functions, *J. Econom. Lit.* **26**, 646–679 (1988).
14. Tony Lancaster, ''The Econometric Analysis of Transition Data,'' Cambridge Univ. Press, Cambridge, UK (1990).
15. M. K. Landy, M. J. Roberts, and S. R. Thomas, ''The Environmental Protection Agency: Asking the Wrong Questions, From Nixon to Clinton,'' Oxford Univ. Press, New York (1994).
16. W. A. Magat and W. K. Viscusi, Effectiveness of the EPA's regulatory enforcement: The case of industrial effluent standards, *J. Law Econom.* **33**, 331–360 (1990).
17. National Council of the Paper Industry for Air and Stream Improvement, ''A Survey of Pulp and Paper Industry Environmental Protection Expenditures—1989,'' Special Report No. 90-12, November (1990).
18. B. Peter Pashigian, The effect of environmental regulation on optimal plant size and factor shares, *J. Law Econom.* **37** (1), 1–28 (1984).
19. T. Petersen, Estimating fully parametric hazard rate models with time-dependent covariates, *Sociol. Meth. Res.* **14** (3), 219–246 (1986).
20. T. Petersen, Fitting parametric survival models with time-dependent covariates, *J. Amer. Statist. Assoc. Appl. Statist.* **35** (3), 281–288 (1986).
21. Sam Peltzman, Toward a more general theory of regulation, *J. Law Econom.* **19** (2), 211–240 (1976).
22. Clifford Russell, Monitoring and enforcement, *in* ''Public Policies for Environmental Protection'' (Paul R. Portney, Ed.), Resources for the Future, Washington, DC (1990).
23. C. S., Russell, W. Harrington, and W. J. Vaughn, ''Enforcing Pollution Control Laws,'' Resources for the Future, Washington, DC (1986).
24. Standard and Poors, Building and forest products, *in* ''Standard and Poors' Industry Reports,'' Standard and Poors Corporation, New York (1983).
25. Standard and Poors, Building and forest products, *in* ''Standard and Poors' Industry Reports,'' Standard and Poors Corporation, New York (1989).
26. Standard and Poors, Building and forest products, *in* ''Standard and Poors' Industry Reports,'' Standard and Poors Corporation, New York (1994).
27. George J. Stigler, The theory of economic regulation, *Bell J. Econom. Management Sci.* **2** (1), 3–21 (1971).
28. U.S. Bureau of the Census, ''Pollution Abatement Costs and Expenditures, 1992,'' Current Industrial Reports; MA200(92)-1, U.S. Government Printing Office, Washington, DC (1994).
29. Cheryl Wasserman, ''Improving the Efficiency and Effectiveness of Compliance Monitoring and Enforcement of Environmental Policies, United States: A National Review,'' prepared on behalf of the Organization for Economic Cooperation and Development, Group of Economic Experts (1984).
30. Cheryl Wasserman, Federal enforcement: Theory and practice, *in* ''Innovation in Environmental Policy: Economic and Legal Aspects of Recent Developments in Environmental Enforcement and Liability'' (T. H. Tietenberg, Ed.) Elgar, Aldersot, UK (1992).