When and Why do Plants Comply? Paper Mills in the 1980s*

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This paper uses census data for 116 pulp and paper mills over the period 1979–1990 to examine the determinants of compliance with air pollution regulations. Several plant characteristics are significant: large plants, old plants, and pulp mills comply less frequently, as do plants with water pollution or OSHA violations, but firm characteristics generally are not significant. Enforcement activity increases compliance, but in a heterogeneous way: pulp mills are less sensitive to inspections, while plants owned by larger firms are less sensitive to inspections and more sensitive to "other" enforcement actions, consistent with the authors' expectations and prior research results.

I. INTRODUCTION

In most economic models of government regulation, a regulatory agency establishes standards with which regulated firms are required to comply. Compliance is usually accomplished by having inspectors visit plants to identify violations and to impose penalties on violators. Becker (1968) demonstrated that if both the probability of being caught and the penalty for violations are high (relative to the costs of compliance), we would expect profit-maximizing firms to optimally choose compliance. However, for many regulatory agencies, the number of inspectors is small relative to

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the regulated population and the penalties are limited, so there seems to be a limited incentive for compliance—yet most firms still seem to comply.

This puzzle of "excessive" compliance has led to several strands of literature. Outside economics, researchers have emphasized the importance of social norms and a corporate culture that encourages compliance, and have conducted interviews to identify how corporate decisions are affected by pressures from both regulatory agencies and the general public. Within economics, a model by Harrington (1988) shows that in a repeated game, a regulator could substantially increase the expected long-run penalty for non-compliance by creating two classes of regulated firms—cooperative and non-cooperative. The cooperative firms are assumed to behave well and to be inspected only rarely. The non-cooperative firms would face much heavier enforcement. Since facing enforcement is costly, firms would be anxious to be placed in the cooperative group initially, and therefore would invest more in compliance at the start of the game, than would be predicted from the expected penalty in a one-period model.

On the empirical side, there have been several studies on the effectiveness of Occupational Safety and Health Administration (OSHA) and Environmental Protection Agency (EPA) enforcement, using a variety of estimation techniques. These include studies of environmental enforcement at steel mills for air pollution (Gray & Deily 1996); at paper mills for air pollution (Nadeau 1997) and water pollution (Helland 1998; Laplante & Rilstone 1996; Magat & Viscusi 1990); and of OSHA regulation at manufacturing plants (Gray & Jones 1991; Gray & Scholz 1993). These studies generally find that enforcement has some effect on compliance, or the goals of compliance (reduced emissions or injuries). Since enforcement and compliance tend to be defined at the plant level, most of these studies do not incorporate firm-level variables. However, Helland (1998) finds a weak tendency for more profitable firms to have fewer violations, and Gray and Deily (1996) find that compliance status is correlated across plants owned by the same firm, though they find insignificant effects of firm size and profitability on compliance. Gray (2000) finds little effect of corporate ownership change or restructuring on compliance and enforcement.

For this paper, we used a sample of U.S. pulp and paper mills to examine differences in plant-level compliance with air pollution regulations. In particular, we tested a variety of plant- and firm-specific characteristics, to see which plants are more likely to comply with regulation. We also compared the plant's air pollution compliance with its performance in other dimensions (water pollution, toxic chemicals, and worker health and safety). Lastly, we tested how effective regulatory enforcement was at inducing compliance, and whether plants differed in their sensitivity to enforcement activity.

We used confidential, plant-level census data from the Longitudinal Research Database (LRD)[1] for 116 pulp and paper mills, covering the 1979–1990 period. The LRD provided us with data on each plant's shipments, investment, productivity, age, and production technology. We also had plant-level pollution abatement expenditures from the Pollution Abatement Costs and Expenditures (PACE) survey (U.S. Bureau of the Census, various years). We linked in ownership information, based on the *Lockwood Directory*, which allowed us to identify the number of paper mills owned by the firm, and also linked in firm-level financial data taken from Compustat, identifying firm size and profitability. Lastly, we added compliance and enforcement information from several regulatory datasets, although our focus was on the EPA's Compliance Data System, which provides measures of air pollution enforcement activity and compliance status during the period.

We use a logit model of compliance with air pollution regulation: compliance depends on regulatory activity directed towards the plant, as well as various plant and firm characteristics. Regulatory activity is endogenous—regulators target enforcement activity towards plants that are out of compliance—so a simple correlation between enforcement and compliance would be negative, indicating (naïvely) that enforcement decreases compliance. To address this targeting issue, we tried two alternative ways of measuring enforcement. First, we used lagged enforcement as an explanatory variable, in principle purging the equations of any contemporaneous endogeneity. Second, we tried predicting enforcement from a tobit model on a set of variables, which are clearly exogenous to the plant's compliance decision (state political support for environmental regulation and year and state dummies). We then used this predicted value in a second-stage compliance equation. Models using lagged regulatory activity continue to find a negative "impact" of enforcement on compliance (which we attribute to remaining endogeneity), while models using predicted activity yield positive coefficients, with regulatory activity increasing compliance.

We found significant effects of plant characteristics on compliance rates: plants that included a pulping process, plants which were older, and plants which were larger were all less likely to be in compliance. In contrast, firm-level characteristics are not significant determinants of plant-level compliance rates. Plants violating other regulations (water pollution or OSHA regulations) were more likely to violate air pollution regulations.

We also found differences across plants in their responsiveness to enforcement. Pulp mills, already less likely to be in compliance, were also less sensitive to inspections. Lastly, firm characteristics did seem to matter for a plant's inspection sensitivity (though they did not for the overall compliance rate). Plants owned by larger firms, whether measured in terms of firm employment or the number of paper mills owned by the firm, were less sensitive to inspections and more sensitive to other enforcement actions than plants owned by smaller firms.

Section II provides some background on environmental regulation and compliance issues in the paper industry. Section III describes a simple model of the compliance decision faced by a plant. Section IV describes the data used in the analysis, Section V describes some econometric issues with the analysis, Section VI presents the results, and Section VII contains the concluding comments.

II. PAPER INDUSTRY BACKGROUND

Environmental regulations have grown substantially in stringency and enforcement activity over the past thirty years. In the late 1960s the rules were primarily written at the state level, and there was little enforcement. Since the early 1970s, the Environmental Protection Agency (EPA) has taken the lead in developing stricter regulations, and encouraging greater enforcement, much of which is still done by state agencies via state implementation plants (SIPs), following federal guidelines. This expanded regulation has imposed sizable costs on traditional "smokestack" industries, with the pulp and paper industry being one of the most affected, given its substantial generation of air and water pollution.

During the 1980s, pulp and paper mills faced air pollution regulations drafted by state regulators as part of SIPs designed to ensure that the county in which the plant was located could meet the National Ambient Air Quality Standards (NAAQS) set by the 1970 Clean Air Act Amendments (CAAAs). Certain kraft pulp mills that made significant modifications to their facility after 1976 could also have been subject to the more stringent New Source Performance Standards (NSPS) set by the CAAAs, but we have no way of identifying which plants were subject to these regulations (new plants are also affected, but we have hardly any post-1976 plants in our sample).[2]

Plants within the pulp and paper industry can face very different impacts of regulation, depending in part on the technology being used, the plant's age, and the regulatory effort directed towards the plant. The biggest determinant of regulatory impact is whether or not the plant contains a pulping process. Pulp mills start with raw wood (chips or entire trees) and break it down into wood fiber, which is then used to make paper. A number of pulping techniques are currently in use in the U.S. The most common one is kraft pulping, which separates the wood into fibers using chemicals. Many plants also use mechanical pulping (giant grinders separating out the fibers), while others use a combination of heat, other chemicals, and mechanical methods. After the fibers are separated out, they may be bleached, and mixed with water to form a slurry. After pulping, a residue remains, which was historically dumped into rivers (hence water pollution), but now must be treated. The process also takes a great deal of energy, so most pulp mills have their own power plant, and therefore are significant sources of air pollution. Pulping processes involve hazardous chemicals, raising issues of toxic releases.

The papermaking process is much less pollution intensive than pulping. Non-pulping mills either buy pulp from other mills, or recycle wastepaper. During papermaking, the slurry (more than 90 percent water at the start) is set on a rapidly-moving wire mesh which proceeds through a series of dryers in order to extract the water, thereby producing a continuous sheet of paper. Some energy is required, especially in the form of steam for the dryers, which can raise air pollution concerns if the mill generates its own power. There is also some residual water pollution as the paper fibers are dried. Still, these pollution problems are much smaller than those raised in the pulping process.

Over the past thirty years, pollution from the paper industry has been greatly reduced, with the installation of secondary wastewater treatment, electrostatic precipitators, and scrubbers. In addition to these end-of-pipe controls, some mills have changed their production process, more closely tracking material flows to reduce emissions. In general, these changes have been much easier to make at newer plants, which were designed at least in part with pollution controls in mind. (Some old pulp mills were deliberately built on top of the river, so that any spills or leaks could flow through holes in the floor for "easy disposal.") These rigidities can be partially or completely offset by the tendency for regulations to include grandfather clauses, exempting existing plants from most stringent air pollution regulations.

III. COMPLIANCE AND ENFORCEMENT DECISIONS

An individual paper mill faces costs and benefits from complying with environmental regulation, which may depend on characteristics of the plant itself, the firm which owns the plant, and the activity of environmental regulators. Given these constraints, the firm operating the mill is presumed to maximize its profits, choosing to comply if the benefits (lower penalties, better public image) outweigh the costs (investment in new pollution control equipment, managerial attention). Regulators, in turn, allocate their activity to maximize some objective function (political support, compliance levels, economic efficiency), taking into account the reactions of firms to that activity.

The objective function for mill i owned by firm j at time t includes the usual revenues and costs of production, but these are extended to include the penalties associated with being found in violation (*PENALTY*), the probability of being found in violation (*VPROB*), and the costs of coming into compliance (*COMPCOST*):

$$\begin{aligned} PROFIT_{ijt}(COMPLY) = P_{ijt} * Q_{ijt} - COST_{ijt} - COMPCOST_{ijt}(COMPLY) \\ - PENALTY_{ijt} * VPROB_{ijt}(COMPLY) \qquad (1) \end{aligned}$$

Plants can vary their level of compliance (*COMPLY*) to maximize their profits (this assumes that the underlying compliance decision is in fact continuous, although we only observe a 0-1 compliance status in our data). Assuming that the benefits and costs of compliance are captured in the last two terms of equation (1), the plant will set its marginal cost of compliance equal to the marginal benefit from compliance, measured here in terms of reductions in expected penalties.

$$d(-PENALTY_{ijt} * VPROB_{ijt})/dCOMPLY = d(COMPCOST_{ijt})/dCOMPLY \quad (2)$$

This implicitly determines an optimal level of compliance, $COMPLY^*$.

The benefits to the firm from increasing compliance come in terms of reducing the probability of being found in violation of pollution regulations, thus reducing the expected penalties for violations. These penalties are usually associated with regulators in terms of legal sanctions and monetary fines, but could also be "imposed" by customers boycotting the firm's products in the future. In some circumstances, customers might also be willing to pay more for products that have been certified to have especially environmentally friendly production processes, although this is currently more common in Europe than in the U.S. If we make the usual assumption that the firm is risk-neutral, the expected benefits of compliance should be linear in the probability of being in non-compliance, so the marginal benefit to the plant from increasing its probability of compliance would be constant. Because of the difficulties associated with ensuring 100 percent compliance, we expect a rising marginal cost curve. Rising marginal costs along with constant marginal benefits should lead to an interior $COMPLY^*$ solution, equating the marginal costs and marginal benefits of compliance to the firm.

We focus on differences in compliance behavior across different mills, based on plant and firm characteristics. As mentioned earlier, there are likely to be substantial differences in pollution problems across different types of paper mills. We expect to see differences in compliance behavior being related to the production technology at the plant (especially the use of pulping) and related to the plant's age. There may also be economies of scale in complying with regulations, so larger plants might find it easier to comply with a given level of stringency. However, some of these plant characteristics on compliance could go either way: older plants might find it harder to comply with a given standard, but they could be subject to less strict standards due to grandfathering. Larger plants might enjoy economies of scale, but could also have more places that something could go wrong, raising their probability of non-compliance.

Compliance behavior may also depend on characteristics of the firm that owns the mill (e.g., the financial situation of the firm may matter). Pollution abatement can involve sizable capital expenditures, which may be easier for profitable firms to fund—either through retained earnings or through borrowing in capital markets. A firm in financial distress may not feel the full threat of potential fines in an expected value sense, if they would just go bankrupt if they happened to be caught. Firms with reputational investments in the product market may face an additional incentive not to be caught violating environmental rules, if their customers would react badly to the news.

Firms might also differ in the quality of the environmental support that they offer their plants. A large firm, or one specializing in the paper industry, is likely to have economies of scale in learning about what regulations require, and may be in a better position to lobby regulators on behalf of their plants. We cannot measure the strength of a company's environmental program, but may observe a correlation in compliance behavior across plants owned by the same firm. We may also see some effect of the firm size, either in absolute magnitude or in terms of the number of mills they operate.

The regulatory activity faced by a plant is also expected to affect its compliance behavior. A higher rate of inspections by regulators should increase *VPROB*(*COMPLY**) for any given *COMPLY** value, increasing the benefits from compliance. This inspection effect could be described in terms of specific deterrence (plants who had been inspected in the past are more careful) or general deterrence (plants with a high probability of being inspected are more careful).[3] Other enforcement actions might encourage compliance by raising the costs of being found in violation (*PENALTY*) without increasing the probability of being caught (*VPROB*).

We test for differences across plants in their sensitivity to regulatory activity. Such differences could arise for a variety of reasons. Plants owned by larger firms that sell on a national market might be more concerned about bad publicity from environmental violations, raising their *PENALTY*, and hence their benefits from compliance.[4] Larger plants may be used to having regular inspections so that inspections have less of a "shock effect" (specific deterrence) than might be experienced by a smaller plant, reducing the benefits from compliance. Plants may also differ in the cost of increasing their compliance, giving them different impacts from the same increase in regulatory activity.

Some of these different possibilities are shown in the three panels of Figure 1. These panels all assume upward-sloping marginal costs and unchanging marginal benefits from compliance. Each panel compares the impact on optimal compliance rates of an increase in the benefits from compliance (such as might be induced by increased regulatory activity) on two different plants. Figure 1a shows that, even if the two plants differ in their initial level of compliance, they could have the same change in compliance for a given increase in regulation if the slopes of their marginal cost curves are the same. Figure 1b shows that differences in the slopes of the marginal cost of compliance can result in very different impacts from the same increase in regulation—here the plant with high and steep compliance costs has both lower initial compliance and a smaller impact from the increased regulation. Lastly, Figure 1c shows that plants with the same marginal cost of compliance can respond differently if the same increase in regulation has different marginal benefits for them, as might happen if the larger firm felt a greater desire to avoid adverse publicity (*MB*1′).

$$MB = MB(X_p, X_f, \text{REGS}, \text{X*REGS})$$
$$MC = MC(X_p, X_f)$$

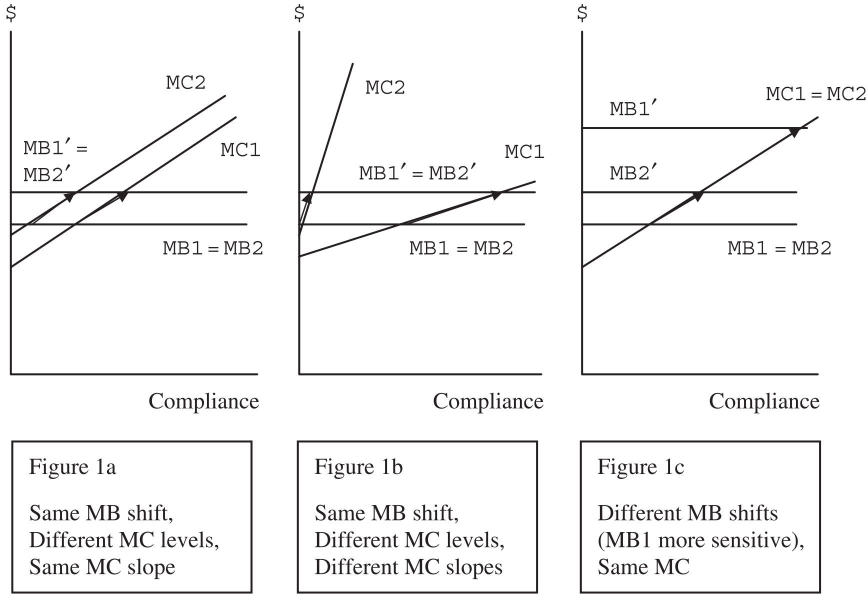

Figure 1. Impact of Shift in Regulation on Optimal Compliance.

In sum, a plant's compliance decision depends on its age and production technology, its firm size and profitability, and the regulatory activity directed towards it, with the possibility of some differences across plants in their sensitivity to that regulatory activity. We estimate a model of compliance behavior as follows:

$$COMPLY^*_{ijt} = f(REGS_{ijt}, X_i, X_j, X_{ijt} * REGS_{ijt}, OCOMPLY_{ijt}, YEAR_t) \tag{3}$$

COMPLY is the plant's observed compliance status with air pollution regulations. *REGS* is the regulatory activity faced by the plant, which could be either inspections or other enforcement actions. This activity could affect either the probability of being caught in violation or the negative consequences associated with being caught. The model includes characteristics of the plant (X_i) and firm (X_j), either of which could be interacted with enforcement activity to test for differences in the responsiveness of plants and firms to enforcement. The plant's compliance status with other regulatory areas is measured by *OCOMPLY*. Lastly, year dummies ($YEAR_t$) allow for changes in enforcement, or its definition, over time.

Now consider the regulator's decision about how to allocate its regulatory activity. If enforcement were costless, regulators could use "infinite" enforcement, catching all violators, in which case setting a fine equal to the environmental damages from pollution would be optimal. Becker (1968) notes that in a world with costly and uncertain enforcement, higher penalties might be substituted for some of the enforcement effort, to raise the expected penalty for violations. In fact, given limitations on the size of penalties under existing regulations, and the high costs of controlling some pollutants, it seems puzzling why any firms would comply with regulation. However, Harrington (1988) showed that a regulator could substantially raise the effectiveness of enforcement, by making future enforcement conditional on past compliance. In this model, non-compliance today not only raises expected penalties today, but the plant risks being treated much more severely for years to come (or forever, depending on the regulator's behavior).

If regulators are using the Harrington strategy, we would expect enforcement at a plant to be greater in plants that have violated the standards in the past. On the other hand, if most of the differences in compliance behavior across plants are driven by fixed plant or firm characteristics, those plants which are out of compliance may be more resistant to enforcement pressures, because they face higher costs of compliance. Therefore regulators might have to balance the greater opportunity for compliance improvement against the greater enforcement effort needed to achieve that improvement.

Regulators may also respond to differences in the potential environmental harm caused by pollution, with plants in more rural areas facing less enforcement activity. In fact, Shadbegian, Gray, and Levy (2000) find evidence that plants with greater benefits per unit of pollution reduction wind up spending more on pollution abatement, suggesting that regulators are indeed being tougher on those plants.

Observed differences in enforcement across plants and over time may also be strongly influenced by the amount of resources allocated to regulatory enforcement in a particular state and a particular year. During the 1980s the budgets of most regulatory agencies tended to increase, so there were likely to be more inspections over time. There are also significant differences in the political support for regulation across different states as a result of the severity of pollution problems or to the political make-up of each state's population. On a more pragmatic note, states may differ in the extent to which they enter all of their enforcement activity into the regulatory databases we use.[5]

IV. DATA DESCRIPTION

Our research was carried out at the Census Bureau's Boston Research Data Center, using confidential Census databases developed by the Census's Center for Economic Studies. The primary Census data source is the Longitudinal Research Database (LRD), which contains information on individual manufacturing plants from the Census of Manufacturers and Annual Survey of Manufacturers over time (for a more detailed description of the LRD data, see McGuckin & Pascoe 1988). From the LRD we selected those pulp and paper mills (from SIC 2611 and 2621) with continuous LRD data from 1972–1990 and with adequate data to construct a capital stock measure, dropping a few mills with implausible values for key variables. Our final sample contains 116 pulp and paper mills, which account for 60 percent of total industry shipments from SIC 2611 and 2621. We capture differences in technology across plants with a *PULP* dummy variable, indicating whether or not the plant incorporates a pulping process.[6] Our control for plant age, *OLD*, is a dummy variable, indicating whether the plant was in operation before 1960.[7] We control for the plant's efficiency using TFP, an index of the total factor productivity level at the plant, which we calculated earlier when testing for the impact of regulation on productivity in Gray and Shadbegian (1995, 2003). Possible economies of scale in compliance are captured by *SIZE*, the log of the plant's real value of shipments. Lastly, we include *IRATE*, the ratio of the plant's total new capital investment over the past three years to its capital stock, to identify those plants with recent renovations.

In addition to these Census variables taken directly from the LRD, we used data from the Census Bureau's annual Pollution Abatement Costs and Expenditures (PACE) survey. The PACE survey (various years) provides us with the annual plant-level pollution abatement operating cost data from 1979 to 1990. We divide this by a measure of the plant's size (the average of its largest two years of real shipments over the period) to get a measure of the pollution abatement expenditure intensity at the plant, PAOC.

To the Census data we linked firm-level information taken from the Compustat database. The ownership linkage was based on an annual industry directory (the *Lockwood Directory*), capturing changes in plant ownership over time, which allowed us to calculate *FIRMPLANT*, the log of the number of other paper mills owned by the firm. From the Compustat data we took *FIRMEMP*, the log of firm employment, and *FIRMPROF*, the firm's profit rate (net income divided by capital stock). We also included *NONPAPER*, a dummy variable indicating that the firm's primary activity as identified by Compustat was outside SIC 26 (paper products). Since some (not a large fraction) of our plants are privately owned and hence are excluded from Compustat, we also included a dummy variable, *MISSFIRM*, to control for those observations with missing Compustat data.

Our regulatory measures came from EPA's Compliance Data System (CDS). The CDS provides annual measures of enforcement and compliance directed towards each plant. Our compliance measure, *COMPLY*, is a dummy variable indicating whether the plant was in compliance throughout the year (based on the CDS quarterly compliance status field—if a plant was out of compliance in any quarter, *COMPLY* was zero). To measure air pollution enforcement, we use *ACTION*, the log of the total number of actions directed towards the plant during the year. We also split *ACTION* into *INSPECT*, the log of the total number of "inspection-type" actions (e.g., inspections, emissions monitoring, stack tests), and *OTHERACT*, the log of all non-inspection actions (e.g., notices of violation, penalties, phone calls). These different types of actions may have different impacts on compliance, and may have different degrees of endogeneity with compliance.

To supplement the air pollution data, we also used information from three other regulatory datasets: the EPA's Permit Compliance System (PCS) and Toxic Release Inventory (TRI), and the Occupational Safety and Health Administration's (OSHA) Integrated Management Information System (IMIS). The EPA's PCS provides information on water pollution regulation. Unfortunately, this dataset does not begin until the late 1980s, near the end of our period, so we could not include its variation over time in the model. Instead, we created *WATERVIOL*, the fraction of years in which the plant had at least one reported water pollution emission that was in violation of its permit. The EPA's TRI data set provides information on the disposal of toxic substances from manufacturing plants. The TRI was first collected in 1987, so it does not provide useful time series variation for our model either. Thus, we calculated the average discharge intensity for the plant, *TOXIC*, as the annual pounds of environmental releases, averaged over the 1987–1990 period, divided by the average real shipments of the plant in the same time period. Lastly, OSHA conducts inspections and imposes penalties to try to ensure safe working conditions. We used data from OSHA's IMIS to measure the fraction of inspections during each year that were in violation, *OSHAVIOL*, which is set to zero for those plants with no OSHA inspections during the year. The OSHA data spans our entire period, so we could include the annual values directly in our model.

V. ECONOMETRIC ISSUES

Several econometric issues arise when we proceed to the estimation of equation (3). The key econometric issue that any study of enforcement and compliance must face is the endogeneity of enforcement: regulators are likely to direct more of their attention towards those plants which they expect to find in violation. The explanation of this targeting behavior could be as simple as a desire to avoid wasting limited regulatory resources by inspecting those plants that are almost certain to be in compliance (so probably no corrective action would result from an inspection). A more complicated explanation comes from the work of Harrington (1988), who showed that an optimal regulatory strategy could involve focusing long-run enforcement activity on a few noncomplying plants to punish them for not cooperating with regulation. In any event, it is the case that past research has little trouble identifying a negative relationship between enforcement activity and compliance behavior: non-complying plants get more enforcement.

We tried two methods to overcome the endogeneity of enforcement: lagging the actual enforcement faced by the firm and generating a predicted value of enforcement (which we also lagged) to use in a second-stage estimation (an instrumental variables method).[8] The possible problem with both of these methods is that some endogeneity may remain: for lagging, if there is serial correlation in both the enforcement and compliance decisions, and for predicting, if the explanatory variables used in the first stage are not completely exogenous. In addition, if the lags are long enough, or the first-stage equation performs weakly enough, there will be little correlation between the instrument and the actual value of enforcement.

We use a relatively simple first-stage model to predict enforcement activity, focussing on variables that are clearly exogenous with respect to the plant's compliance decision: year dummies, state dummies, and *VOTE*. Year dummies account for changes in enforcement activity over time, while state dummies allow for cross-state differences in enforcement activity (or differences in reporting of that activity in the CDS). We also tested an alternative control for state-year differences in enforcement: the overall air-pollution enforcement activity rate (looking at manufacturing industries, and dividing overall actions in the year by the number of plants in the state's CDS database). The state enforcement rate was highly significant and had the expected positive sign, but proved less powerful than the state dummies, and was not used in the final analyses shown here. Lastly, we include a variable measuring the political support for environmental regulation within the state, *VOTE*, which is the percentage of votes in favor of environmental legislation by the state's congressional delegation, as measured by the League of Conservation Voters. The lagged predicted value from this first-stage model was then used in the second-stage compliance models.

Another concern for the estimation of equation (3) is that the dependent variable in our compliance equations (*COMPLY*) is discrete: a plant is either in compliance or not in compliance. Thus we needed to use an estimation method that is appropriate to a binary dependent variable. In this case, we chose the logit model. We also estimated the model using a (theoretically inappropriate) OLS regression model, partly as a consistency check on the logit results, but mostly so that we could easily include fixed effects into the analysis.[9]

A final concern for the analysis is the limited time-series variation available for key variables. *OLD* and *PULP* never change in our data set, while other characteristics change only slightly over time. Going to a fixed-effects model would completely eliminate *OLD* and *PULP*, and reduce the explanatory power of the other variables. If there is substantial measurement error over time, using fixed-effects estimators could also result in a sizable bias in the estimated coefficients (Griliches & Hausman 1986). We briefly explored introducing fixed-effects into an OLS model of compliance, but did not otherwise use fixed-effects models.

VI. RESULTS

Now we turn to the empirical analysis. Table 1 presents summary statistics and variable definitions. Looking at the regulatory variables, compliance with air pollution regulations is common, with about three-quarters of the observations in compliance. Enforcement activity is also common, with plants averaging more than one enforcement action per year. Turning to other regulatory programs, few plants show violations of either water pollution (16 percent) or OSHA regulations (13 percent). Most of our plants (87 percent) were in operation in 1960 or before, with slightly less than half (46 percent) including pulping facilities. The last two columns (%CS and %TS) show the fraction of total variation in the variable accounted for by plant and year dummies respectively. Nearly all of the variables in our data set are primarily cross-sectional in nature, with only the productivity measure and firm profit rates showing significant time-series variation. In any event, all of our models include year dummies, to account for changes in overall compliance rates and definitions of compliance over the period.

In Table 2 we examine the correlations between key variables, using Spearman correlation coefficients, because they tend to be more robust to outliers. Examining plant characteristics, we find that pulp mills are larger and spend more on pollution abatement, old mills are less productive and are less likely to incorporate pulping, and large mills are more productive and spend more on pollution abatement. Air pollution compliance is lower for plants that are large, old, incorporate pulping, and spend more on pollution abatement.[10] Air pollution enforcement activity is greater at plants that are large, incorporate pulping and spend more on pollution abatement. Performance on other regulatory measures tends to be worse for large plants, those incorporating pulping, and those that spend more on pollution abatement. Within the set of regulatory measures, there is weak evidence for similar compliance behavior across different regulatory programs: air compliance is negatively correlated with water pollution violations, OSHA violations, and TRI discharges. Lastly, air enforcement is negatively correlated with compliance, evidence that the tendency to target enforcement towards noncomplying plants may make it difficult to observe empirically the ability of enforcement to increase compliance.

Table 3 concentrates on the basic logit model of the compliance decision, based solely on plant and firm characteristics. Most of the relationships are similar to those seen in the earlier correlations. Compliance rates are significantly lower at old mills, pulp mills, and large mills. However, there is little evidence for any impact of firm characteristics on compliance. Switching to an OLS model makes no noticeable difference in the results. However, a model incorporating plant-specific fixed effects does give substantially different results—not surprisingly, since Table 1 showed us that most of the variables are primarily determined by cross-sectional differences, and two of the key plant characteristics (pulping and old) are purely cross-sectional and

Table 1. Summary Statistics (n = 1,392)

Variable	Mean	Std Dev	%CS	%TS	Description
			Plant Characteristics		
PULP	0.46	0.50	100	.	dummy, 1 = pulping operations
OLD	0.87	0.34	100	.	dummy, 1 = operating before 1960
TFP	0.89	0.22	33	33	total factor productivity (level)
SIZE	10.30	0.81	93	<10	real value of shipments (log)
IRATE	0.13	0.17	20	<10	real investment (last 3 years/real capital stock)
PAOC	0.004	0.005	77	<10	pollution abatement operating expenses / value of shipments
			Firm Characteristics		
FIRMEMP	2.49	1.43	70	<10	firm employment (log)
FIRMPROF	0.05	0.04	48	11	firm profit rate (net earnings/capital stock)
FIRMPLANT	2.29	0.85	80	<10	firm number of paper mills (log)
NONPAPER	0.20	0.40	.	.	firm's primary SIC not papermaking
MISSFIRM	0.19	0.39	.	.	plant not owned by Compustat firm
			Air Pollution Regulation		
COMPLY	0.76	0.43	31	<10	dummy, 1 = in compliance during year
ACTION	1.17	0.84	52	<10	total air enforcement actions (log) (mean # actions = 3.79)
INSPECT	0.72	0.50	34	<10	air inspections (log) (mean # inspections = 1.34)
OTHERACT	0.71	0.91	52	<10	other air enforcement actions (log) (mean # other actions = 2.45)
			Other Regulatory Measures		
TOXIC	2.48	2.86	100	.	TRI air & water discharges/value of shipments (1987–90 avg pounds/$000)
WATERVIOL	0.16	0.29	100	.	% water violations (1985–90 avg)
OSHAVIOL	0.13	0.32	<10	18	% OSHA inspections w/penalty (79–90)

Notes: %CS = percentage of variation explained by plant dummies.
%TS = percentage of variation explained by year dummies.

Table 2. Spearman Correlation Coefficients (N = 1392)

	PULP	***OLD***	***TFP***	***SIZE***	***IRATE***	***PAOC***
PULP	1.000					
OLD	(--)	1.000				
TFP	0.036	−0.130	1.000			
SIZE	0.538	−0.011	0.235	1.000		
IRATE	−0.048	0.065	0.015	0.042	1.000	
PAOC	0.515	0.012	0.006	0.396	−0.001	1.000
COMPLY	−0.230	(--)	−0.006	−0.179	−0.062	−0.178
ACTION	0.300	−0.071	0.050	0.372	0.006	0.324
TOXIC	0.310	−0.105	0.046	0.255	0.045	0.320
WATERVIOL	−0.025	0.149	−0.027	0.288	0.010	0.151
OSHAVIOL	0.039	0.013	−0.090	0.092	0.046	0.056
	COMPLY	***ACTION***	***TOXIC***	***WATERVIOL***	***OSHAVIOL***	
COMPLY	1.000					
ACTION	−0.295	1.000				
TOXIC	−0.094	0.210	1.000			
WATERVIOL	−0.075	0.093	0.115	1.000		
OSHAVIOL	−0.116	0.099	0.034	0.143	1.000	

Correlations exceeding about 0.08 are significant at the 0.05 level.
(--) indicates significant negative correlation.

therefore drop out of the fixed-effects model. Interpreting the magnitude of the Table 3 effects is easiest from the OLS model (3D)—a pulp mill is 17 percent less likely to be in compliance, while doubling a plant's size reduces its compliance rate by 6 percent—but the transformed logit effects are nearly identical.

Table 4 adds measures of the plant's performance on other regulatory measures. The different regulatory measures are included separately, and then combined into a single model. In all cases the results are similar: a plant's compliance behavior with regards to water pollution or OSHA regulation is similar to its compliance for air pollution. The TRI results are much weaker, and more sensitive to model specification. The weaker connection to TRI may be as a result of the different regulatory structure: the TRI provides an information-driven incentive to reduce discharges, while the other three regulatory programs follow the traditional command-and-control model, and might therefore be more affected by a plant having a "culture of compliance" for regulation in general. The magnitudes of the water and OSHA impacts could be substantial. In Model 4D, for example, a plant with 100 percent water compliance has an expected air compliance rate 11 percentage points higher than one with 0 percent water compliance; a similar shift for OSHA compliance is associated with a 14 percentage point higher expected air compliance rate.[11]

Table 5 provides a first look at the relationship between a plant's compliance with air pollution regulations and a variety of measures of the enforcement

Table 3. Basic Compliance Models (Dep Var = *COMPLY*; n = 1,160)

model:	(3A) Logit	(3B) Logit	(3C) Logit	(3D) OLS	(3E) F.E.
			Plant Characteristics		
PAOC	1.064		0.427	0.072	0.879
	(0.07)		(0.03)	(0.02)	(0.18)
PULP	−0.919		−0.912	−0.170	
	(−5.07)		(−4.73)	(−4.94)	
OLD	(–)		(--)	(--)	
TFP	0.237		0.190	0.024	0.126
	(0.59)		(0.46)	(0.35)	(1.11)
IRATE	−0.328		−0.219	−0.039	0.019
	(−0.75)		(−0.50)	(−0.50)	(0.24)
SIZE	−0.303		−0.365	−0.055	0.011
	(−2.61)		(−2.81)	(−2.57)	(0.12)
			Firm Characteristics		
FIRMEMP		−0.042	0.120	0.018	−0.057
		(−0.38)	(1.01)	(0.88)	(−1.53)
FIRMPROF		2.970	2.468	0.451	−0.029
		(1.25)	(0.97)	(1.01)	(−0.06)
FIRMPLANT		0.127	0.052	0.011	−0.073
		(1.09)	(0.42)	(0.51)	(−2.09)
NONPAPER		(–)	(–)	(–)	(+)
LOG-L	−609.72	−645.96	−605.97		
pseudo-R^2	0.064	0.008	0.070	0.075	0.341

Notes: Regressions also include a constant term and year dummies.
Firm variables include *MISSFIRM*.
(–) indicates negative coefficient; (--) indicates significant negative.

effort it faces. We use both actual enforcement and predicted enforcement measures, each lagged two years, in an attempt to reduce within-period endogeneity of enforcement.[12] Based on the correlations seen in Table 2, it is not surprising that we find evidence that plants which face greater enforcement activity, as measured by lagged actual enforcement, tend to have a higher probability of being out of compliance. We strongly believe that these results say more about the targeting of enforcement towards violators, and do not indicate completely counterproductive enforcement. In an earlier version of the paper, we examined the impact of enforcement on changes in compliance status. These results indicated that enforcement activity was most effective in moving plants from violation into compliance, rather than in preventing plants from falling out of compliance (results available from the authors).

Once we account for the endogeneity of enforcement by using lagged predicted enforcement, we find the expected positive significant relationship between enforcement and compliance. In particular, in Model 5C, we find that increasing inspections by one raises the probability of being in

Table 4. Compliance—Cross-Regulation Effects Logit Models
(Dep Var = *COMPLY*; n = 1,160)

	(4A)	(4B)	(4C)	(4D)	(4E)	(4F)
			Cross-Regulation Effects			
TOXIC	−0.000			0.009	0.005	−0.031
	(−0.02)			(0.35)	(0.17)	(−1.33)
WATERVIOL		−0.713		−0.618	−0.670	−0.601
		(−2.73)		(−2.32)	(−2.54)	(−2.58)
OSHAVIOL			−0.836	−0.788	−0.765	−0.774
			(−4.14)	(−3.87)	(−3.76)	(−3.97)
			Plant Characteristics			
PAOC	0.450	4.694	−1.793	1.429	2.184	
	(0.03)	(0.30)	(−0.12)	(0.09)	(0.14)	
PULP	−0.911	−1.070	−0.941	−1.086	−1.092	
	(−4.68)	(−5.30)	(−4.82)	(−5.26)	(−5.62)	
OLD	(--)	(–)	(--)	(–)	(–)	
TFP	0.190	0.118	−0.002	−0.054	−0.011	
	(0.46)	(0.28)	(−0.01)	(−0.13)	(−0.03)	
IRATE	−0.219	−0.321	−0.194	−0.292	−0.401	
	(−0.50)	(−0.72)	(−0.43)	(−0.65)	(−0.90)	
SIZE	−0.366	−0.245	−0.324	−0.220	−0.154	
	(−2.81)	(−1.78)	(−2.45)	(−1.58)	(−1.23)	
			Firm Characteristics			
FIRMEMP	0.120	0.099	0.108	0.095		−0.071
	(1.00)	(0.82)	(0.90)	(0.78)		(−0.63)
FIRMPROF	2.467	2.152	2.587	2.384		2.917
	(0.97)	(0.83)	(1.00)	(0.90)		(1.19)
FIRMPLANT	0.052	0.060	0.073	0.077		0.103
	(0.42)	(0.49)	(0.59)	(0.62)		(0.87)
NONPAPER	(–)	(–)	(–)	(–)		(–)
LOG-L	−605.97	−602.26	−597.68	−594.99	−598.54	−632.17
pseudo-R^2	0.070	0.075	0.082	0.086	0.081	0.029

Notes: Regressions also include year dummies, a constant term, and *MISSFIRM*.
(–) indicates negative coefficient; (--) indicates significant negative.

compliance by roughly 10 percent. However, once we include other actions along with inspections (Model 5E), the coefficient on inspections becomes a bit smaller and is no longer significant, while the coefficient on other actions is positive and significant. The magnitude of the two coefficients implies that increasing regulatory actions, either by one inspection or one other action, leads to approximately a 10 percent increase in the probability of being in compliance—although this increase is only statistically significant for other actions. This is a large impact, given that only 24 percent of our observations are out of compliance.

In Tables 6 and 7 we consider differences in the impact of enforcement, based on plant and firm characteristics. We focus our attention on those

Table 5. Compliance—Enforcement Measures Logit Models
(Dep Var = *COMPLY*; n = 1,160)

	(5A)	(5B)	(5C)	(5D)	(5E)	(5F)
			Enforcement Measures			
$P(ACTION)_{-2}$	−0.213					
	(−1.40)					
$ACTION_{-2}$		−0.291				
		(−3.14)				
$P(INSPECT)_{-2}$			0.551		0.429	
			(1.85)		(1.40)	
$INSPECT_{-2}$				−0.080		0.045
				(−0.54)		(0.30)
$P(OTHERACT)_{-2}$					0.483	
					(2.20)	
$OTHERACT_{-2}$						−0.296
						(−3.56)
LOG-L	−605.01	−601.03	−604.18	−605.82	−601.75	−599.52
pseudo-R^2	0.071	0.077	0.072	0.070	0.076	0.079

Note: All models include the complete set of plant and firm characteristics from earlier models, along with year dummies and a constant term.

models that found the most positive impacts of enforcement activity on compliance—models which use $P(INSPECT)_{-2}$ and $P(OTHERACT)_{-2}$. These models include all of the plant and firm characteristics found in Table 3, which have similar signs and magnitudes to those found earlier. Table 6 considers possible interactive effects using the three plant characteristics that were significantly related to compliance: plant age (*OLD*), plant size (*SIZE*), and having pulping operations (*PULP*). Recall all three of these characteristics are associated with lower compliance rates. When we interact these three variables with enforcement measures (separately), we see some differences in response to enforcement activity by plant type: pulp mills are less sensitive to enforcement activity. In particular, in Model 6A, increasing inspections by one at a paper mill without pulping facilities increases the likelihood of compliance by approximately 20 percent, whereas if the paper mill does have a pulping facility the likelihood of compliance only rises by 5 percent—although the interactive effect is not quite significant.

Table 7 presents similar results, using firm characteristics: profit rate, employment, and number of plants (the latter two measured in log form). Although firm characteristics seemed unrelated to compliance levels in Table 3, they appear to be strongly related to sensitivity to enforcement, with opposite effects seen for sensitivity to inspections and to other enforcement actions (such as notices of violation or enforcement orders). Plants owned by larger firms, whether measured by firm employment or by the number of other paper mills owned by the firm, are less sensitive to inspections, and more sensitive to other enforcement actions, than those owned by smaller

Table 6. Enforcement * Plant Characteristics Logit Models
(Dep Var = *COMPLY*; n = 1,160)

	(6A)	(6B)	(6C)	(6D)	(6E)	(6F)
$P(INSPECT)_{-2}$	1.047	1.145	−0.065	−0.033	3.827	7.051
	(2.24)	(2.28)	(−0.14)	(−0.07)	(0.99)	(1.51)
$P(OTHERACT)_{-2}$		0.123		0.171		−1.314
		(0.33)		(0.41)		(−0.51)
$PULP{*}P(INSPECT)_{-2}$	−0.792	−1.124				
	(−1.46)	(−1.89)				
$PULP{*}P(OTHERACT)_{-2}$		0.490				
		(1.26)				
$OLD{*}P(INSPECT)_{-2}$			(++)	(+)		
$OLD{*}P(OTHERACT)_{-2}$				(+)		
$SIZE{*}P(INSPECT)_{-2}$					−0.309	−0.628
					(−0.85)	(−1.42)
$SIZE{*}P(OTHERACT)_{-2}$						0.175
						(0.72)
LOG-L	−603.08	−599.76	−602.89	−600.62	−603.82	−600.75
pseudo-R^2	0.074	0.079	0.074	0.078	0.073	0.078

Note: All models include the complete set of plant and firm characteristics from earlier models, along with year dummies and a constant term.
(+) indicates positive coefficient; (++) indicates significant positive.

firms. For example, in Model 7D, increasing the log of firm employment from 2.5 (its mean value) to 3.0—only about one-third its standard deviation—completely eliminates any positive effect that inspections have on the likelihood of compliance. In contrast, other actions have a positive impact on the likelihood of being in compliance for any firm with a log of employment greater than 1.5. Furthermore, for the same increase in log employment (2.5 to 3.0), an additional other action raises the likelihood of being in compliance by roughly 5 percent. Perhaps larger firms have better-developed regulatory support programs and are less likely to be “surprised” by routine inspections, but are at the same time more able to focus compliance resources on plants with serious problems or plants in states with aggressive follow-up through other enforcement actions, raising the costs of non-compliance. Smaller firms might be more surprised by (and responsive to) routine inspections, but less able to put additional resources into plants with serious problems and less bothered by bad publicity associated with other enforcement actions.

VII. CONCLUSIONS

We have examined plant-level data on enforcement and compliance with air pollution regulation to: (1) test whether enforcement is effective in

Table 7. Enforcement * Firm Characteristics Logit Models
(Dep Var = *COMPLY*; n = 1,160)

	(7A)	(7B)	(7C)	(7D)	(7E)	(7F)
$P(INSPECT)_{-2}$	0.458	0.458	0.685	1.311	0.829	1.604
	(1.18)	(1.67)	(1.47)	(2.55)	(1.32)	(2.35)
$P(OTHERACT)_{-2}$		0.402		−0.713		−0.862
		(1.00)		(−1.84)		(−1.65)
$PROF{*}P(INSPECT)_{-2}$	2.464	0.529				
	(0.38)	(0.07)				
$PROF{*}P(OTHERACT)_{-2}$		0.644				
		(0.14)				
$EMP{*}P(INSPECT)_{-2}$			−0.062	−0.445		
			(−0.37)	(−2.29)		
$EMP{*}P(OTHERACT)_{-2}$				0.488		
				(3.89)		
$PLANTS{*}P(INSPECT)_{-2}$					−0.142	−0.643
					(−0.50)	(−2.00)
$PLANTS{*}P(OTHERACT)_{-2}$						0.587
						(2.94)
LOG-L	−604.11	−601.73	−604.11	−593.39	−604.05	−596.80
pseudo-R^2	0.072	0.076	0.072	0.089	0.072	0.084

Note: All models include the complete set of plant and firm characteristics from earlier models, along with year dummies and a constant term.

inducing plants to comply; (2) test whether certain types of plants are more influenced by enforcement behavior; and (3) determine what other firm and plant characteristics are associated with compliance. We find significant effects of some plant characteristics on compliance: plants which include a pulping process, plants which are older, and plants that are larger are all less likely to be in compliance. We do not find significant effects of firm characteristics, unlike Gunningham, Kagan, and Thornton (2003) and Helland (1998), but both of those studies examined compliance in the 1990s, while Deily and Gray (1991) found results more consistent with ours for U.S. steel mills in the 1980s. Perhaps an increase in the stringency of regulatory pressures in the 1990s, or the emergence of other external pressures on firms, increased the impact of firm characteristics on compliance. On the other hand, plants with violations of other regulatory requirements, either in water pollution or OSHA regulation, are significantly less likely to comply with air pollution regulations. We do not see the same sort of effect for "voluntary compliance" as represented by TRI emissions. The magnitudes of the effects of plant-level characteristics on compliance are non-trivial, at least for large changes in plant characteristics and enforcement activity. In particular, doubling the size of a plant is associated with a 6 percent reduction in compliance; a plant with pulping has 17 percent lower compliance than one without pulping; a plant in violation of water pollution regulations is 11 percent less likely to be in compliance with air pollution regulations.

Measuring the impact of regulatory enforcement on compliance is complicated by the targeting of enforcement towards plants that are out of compliance. This targeting effect generally results in a negative relationship between enforcement and compliance. However, when we accounted for the endogeneity of enforcement by using lagged predicted values of enforcement, based on variables that are clearly exogenous to the plant's compliance decision, we found the expected positive significant relationship between enforcement and compliance.

We also found some differences across plants in their responsiveness to enforcement, based on plant characteristics. Pulp mills, which have difficulties in complying with regulations, are also less likely to respond to regulatory enforcement (Figure 1b). For example, increasing $P(INSPECT)_{-2}$ by one inspection at a paper mill without pulping facilities increases the likelihood of compliance by approximately 20 percent, whereas if the paper mill does have a pulping facility the likelihood of compliance only rises by 5 percent. Lastly, even though firm characteristics are not found to be related to the level of compliance, we find them to be more strongly related to a plant's sensitivity to enforcement (Figure 1c). Plants owned by larger firms, whether measured in terms of their employment or by the number of other paper mills they own, are less sensitive to inspections and more sensitive to other enforcement actions. For example, increasing the log of firm employment from 2.5 (its mean value) to 3.0 completely eliminates any positive effect $P(INSPECT)_{-2}$ has on the likelihood of compliance. On the other hand, for the same increase in log employment, one more $P(OTHERACT)_{-2}$ raises the likelihood of being in compliance by roughly 5 percent.

What lessons can be drawn by policymakers from these results? First, and no surprise, there are observable characteristics of plants that are strongly associated with their compliance behavior. To the extent that regulators want to concentrate their enforcement activity on those plants that are likely to be in violation, knowing which characteristics are important for a particular industry could be useful. Second, firm characteristics seem much less important than plant characteristics in determining a plant's compliance rate. Third, a plant's behavior in one regulatory area appears to carry over into others, so that knowing a plant's compliance with water pollution regulations (or even OSHA regulations) provides an indication of whether it is likely to be in compliance with air pollution regulations. Fourth, enforcement is at least somewhat effective in encouraging compliance.

Lastly, there is evidence that plants differ in their responsiveness to enforcement activity, and these differences are related to firm as well as to plant characteristics. In particular, plants owned by larger firms are less responsive to inspections, and more responsive to other enforcement actions (the effects of plant size are similar, though not statistically significant). This is consistent with other research on regulatory impacts: Gunningham, Thornton, and Kagan (2003) find a greater effect of EPA inspections for smaller firms, and Gray and Mendeloff (forthcoming) find a greater impact of OSHA inspections on smaller workplaces.

We are planning to overcome some of the limitations of the current paper in future work. Most importantly, we anticipate extending the dataset into the 1990s. This will enable us to include more years of data for other environmental regulatory measures, water compliance and toxic discharges. The expanded data set will allow us to look more closely at the interactions between the compliance decision for one pollution medium and compliance on other media. It will also allow us to test for changes in the importance of firm characteristics over time. We plan to expand our definition of compliance to allow us to distinguish among different levels of compliance, ranging from paperwork violations to excess emissions, and to distinguish between the impacts of state and federal enforcement activity. Lastly, we plan to examine the impact of regulation on compliance for plants in other industries, including steel and oil, to see if regulatory effects differ across industries.

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NOTES

1. Confidential data files, which can be accessed at secure census facilities by researchers on approved research projects. Further details are given later in the data section of the paper.
2. NSPS are uniform engineering-based standards set by EPA for each source type within an industry. For more details see 40 CFR Parts 50-99.
3. Scholz and Gray (1990) examine the impact of OSHA inspections on injury rates and find significant evidence for both general and specific deterrence effects.
4. Conversations with people in the paper industry suggested that most large firms had strong policies encouraging 100 percent compliance as much as possible, perhaps because of these concerns with adverse publicity.
5. Of course the latter difference would cause problems for our estimation of the model, since seeing one "observed" enforcement action in a low-reporting state might mean the same thing as seeing several actions in a high-reporting state.
6. Census Bureau disclosure rules preclude our further differentiating pulp mills by their pulping process (kraft, mechanical etc), since our sample contains too few plants to release coefficients for specific pulping types.
7. We would like to thank John Haltiwanger for providing the plant age information. In our analysis we used a single dummy to measure plant age (*OLD* = open

before 1960) for two reasons: our sample includes some very old plants, likely to heavily influence any linear (or non-linear) age specification, and concern with environmental issues was not prominent before the 1960s.

8. Note that these two variables (lagged actual enforcement and predicted enforcement) could also be interpreted as corresponding to the specific and general deterrence effects mentioned earlier.
9. The fixed-effects version of the logit analysis would require estimating a conditional logit model, which in our Census data set would probably raise disclosure concerns, making it unlikely that we could report the resulting coefficients.
10. Some dummy variables in our data set (*OLD*, *NONPAPER*, and *MISSFIRM*) are not "disclosable' in our analyses. For these variables, we indicate the sign of the relationship, and double the sign (e.g. "--") for results significant at the 10 percent level or better.
11. These calculations are based on the logit model's derivative of the probability of compliance with respect to the explanatory variables equal to 0.1824, evaluated at *COMPLY*'s mean value of 0.76.
12. Predicted enforcement values come from a first stage tobit, explaining the log of each type of enforcement activity using state and year dummies, as well as the *VOTE* variable. The pseudo-r-square of the tobits is 0.143, so we are only explaining a relatively small part of the variation in enforcement.

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