DRAFT - JULY 11, 2000
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When is Enforcement Effective - or Necessary?

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for presentation at the
NBER Environmental Economics Workshop
August 8, 2000

Financial support for the research from the National Science Foundation (grant # SBR-9809204) and the Environmental Protection Agency (grant #R-826155-01-0) is gratefully acknowledged, as is access to Census data at the Boston Research Data Center. We benefitted greatly from comments by Suzi Kerr and other participants at the AERE 2000 Summer Workshop, and also wish to thank the many people in the paper industry who were willing to share their knowledge of the industry with us. Capable research assistance was provided by Bansari Saha, Aleksandra Simic, Nadezhda Baryshnikova and Melanie Lajoie. The opinions and conclusions expressed are those of the authors and not the Census Bureau, EPA, or NSF. All papers using Census data are screened to ensure that they do not disclose confidential information. Any remaining errors or omissions are the authors'.

Abstract

This paper examines differences in plant-level compliance with air pollution regulation for U.S. pulp and paper mills. We test a variety of plant- and firm-specific characteristics, to see which plants are more likely to comply with regulation. We also test how effective regulatory enforcement is in inducing compliance, and whether different types of plants are more sensitive to the level of enforcement activity directed towards them.

Our analysis is based on confidential, plant-level Census data from the Longitudinal Research Database for 116 pulp and paper mills, covering the 1979-1990 period. The LRD provides us with data on shipments, investment, productivity, age, and production technology. We also have plant-level pollution abatement expenditures from the Pollution Abatement Costs and Expenditures (PACE) survey. Using ownership data, we link in firm-level financial data taken from Compustat, identifying firm size and profitability. Finally, we use several regulatory data sets. From EPA, the Compliance Data System provides measures of air pollution enforcement activity and compliance status during the period, while the Permit Compliance System and the Toxic Release Inventory provide information on other pollution media. OSHA's Integrated Management Information System provides data on OSHA enforcement and compliance.

We find significant effects of some plant characteristics on compliance: plants which include a pulping process, plants which are older, and plants which are larger are all less likely to be in compliance. In general, firm-level characteristics are not significant determinants of compliance at the plant level. Plants in violation of water pollution or OSHA regulations are significantly less likely to be in compliance with air pollution regulations than plants in compliance with those other regulations.

Measuring the impact of regulatory enforcement on compliance is complicated by the targeting of enforcement towards plants that are out of compliance (i.e. enforcement is not exogenous). Enforcement targeting has often resulted in past research finding a negative relationship between enforcement and compliance. We also find a negative relationship between enforcement and compliance when we use the actual value of enforcement and even when we use lagged values of enforcement to account for the endogeneity of enforcement. However, once we use a predicted value of enforcement, based on variables clearly exogenous to the plant's compliance decision, we find the expected positive relationship between enforcement and compliance. We also find some differences across different types of plants in their responsiveness to enforcement: pulp mills, which are already less likely to be in compliance, are also less sensitive to inspections. Furthermore, firm characteristics are found to be more strongly related to enforcement sensitivity than plant characteristics. 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.

1. Introduction

For government regulation to be successful, a regulatory agency must achieve some degree of compliance on the part of regulated firms. 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 firms to optimally choose compliance). However, in practice the number of inspectors is small relative to the regulated population and the penalties are limited, so there seems to be a limited incentive for compliance - yet most firms seem to comply.

This puzzle of 'excessive' compliance has led to several strands of literature. On the theoretical side, 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 would be assumed to behave well and be rarely inspected. 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 OSHA and EPA enforcement, using a variety of estimation techniques. These include studies of environmental enforcement at steel mills for air pollution (Gray and Deily 1996); at paper mills for air pollution (Nadeau 1997) and water pollution [Magat and Viscusi (1990), Laplante and Rilstone (1996), and Helland (1998)]; and of OSHA regulation at manufacturing plants (Gray and Jones(1991), and Gray and 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 finds that more profitable firms have fewer violations, and Gray and Deily 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 either compliance or enforcement behavior.

In this paper we examine differences in plant-level compliance with air pollution regulations, looking at a sample of U.S. pulp and paper mills. In particular, we test a variety of plant- and firm-specific characteristics, to see which plants are more likely to comply with regulation. We also compare the plant's air pollution compliance with its performance on other regulatory dimensions (water pollution and toxic chemicals). Finally, we test how effective regulatory enforcement is at inducing compliance, and whether some plants are more sensitive to the level of enforcement activity they face.

We use confidential, plant-level Census data from the Longitudinal Research Database for 116 pulp and paper mills, covering the 1979-1990 period. The LRD provides us with data on each plant's shipments, investment, productivity, age, and production technology. We also have plant-level pollution abatement expenditures from the Pollution Abatement Costs and

Expenditures (PACE) survey. We link in ownership information, based on the Lockwood Directory, which allows us to identify the number of paper mills owned by the firm, and also link in firm-level financial data taken from Compustat, identifying firm size and profitability. Finally, we add compliance and enforcement information from several regulatory data sets, although our focus is on the EPA's Compliance Data System, which provides measures of air pollution enforcement activity and compliance status during the period.

We use a relatively simple model of compliance with air pollution regulation, using a logit analysis: compliance is a function of enforcement activity directed towards the plant and various plant and firm characteristics. Because regulators target their enforcement activity towards plants that are out of compliance, the simple correlation between enforcement and compliance is negative - naively indicating that enforcement activity decreases compliance. To address this targeting issue, we try two alternative ways of measuring enforcement. First, we try using lagged enforcement as an explanatory variable, in principle purging the equations of any contemporaneous endogeneity. Second, we try 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 use this predicted value in a second-stage compliance equation. Models using lagged enforcement find an apparently negative 'impact' of enforcement on compliance, while predicted values yield more positive results.

We find significant effects of plant characteristics on compliance rates: plants which include a pulping process, plants which are older, and plants which are larger are all less likely to be in compliance. We also find that plants in violation of other regulations (water pollution or OSHA regulations) are more likely to be in violation of air pollution regulations. In general, firm-level characteristics are not significant determinants of compliance at the plant level. Furthermore, we find some differences across different types of plants in their responsiveness to enforcement; pulp mills, which are already less likely to be in compliance, are also less sensitive to inspections. Finally, firm characteristics are found to be more strongly related to enforcement sensitivity than plant characteristics. 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.

Section 2 provides some background on environmental regulation and compliance issues in the paper industry. Section 3 describes a simple model of the compliance decision faced by a plant. Section 4 describes the data used in the analysis, Section 5 describes some econometric issues with the analysis, Section 6 presents the results, and Section 7 contains the concluding comments.

2. Paper Industry Background

Environmental regulations have grown substantially in stringency and enforcement activity over the past 30 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 has taken the lead in developing stricter regulations, and encouraging greater enforcement (much of which is still done by state agencies, 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.

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 them down into wood fiber, which are then used to make paper. A number of pulping techniques are currently in use in the U.S. currently. 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 may also involve hazardous chemicals, raising the issue of toxic releases.

The paper-making process is much less pollution intensive than pulping. Non-pulping mills either buy pulp from other mills, or recycle wastepaper. During paper-making, the slurry (more than 90% 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 30 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.

3. 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 enforcement activity of the 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 enforcement activity to maximize their objective function (political support, compliance levels, efficiency), taking into account the expected reactions of the firms to that enforcement.

Simple versions of the socially optimal pollution abatement at a single paper mill are based on the social marginal benefits and marginal costs of cleanup. Here we anticipate an upward sloping marginal cost curve, especially as cleanup nears 100%, and a marginal benefits curve that is either flat or decreasing, depending on the dose-response function of the affected population (at least not rising faster than the marginal cost curve). Given continuous curves, this suggests that an optimal/efficient interior solution would equate the marginal benefits and marginal costs from an additional unit of abatement. A plant for which the marginal costs of abatement are lower (or the marginal benefits higher) should choose a higher degree of abatement.

Looking at the issue from the plant's point of view, the concern shifts to the private benefits and costs realized by the plant. Recognizing that the compliance process is a stochastic one, with accidents being a primary cause of being out of compliance, the plant can increase the probability that it will be in compliance at any given time by increasing its pollution abatement efforts (increasing the size of its water treatment plant to deal with spills, increasing the efforts to find and repair any leaks, and increasing the training provided to operators). This increased probability of compliance is costly, and probably rises quickly as the plant attempts to approach 100% compliance, given the possibility of large and rare 'shocks' to the production process. The result is a rising marginal cost of compliance curve, similar to the rising marginal cost of abatement curve for the social optimum.

The direct benefits to the firm from increasing compliance come in terms of reduced penalties for being found in violation of pollution regulations. These penalties are usually associated with the behavior of regulators in terms of legal sanctions and monetary fines, but could also be 'imposed' by customers who avoid 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 plant would get a constant marginal benefit from increasing its probability of compliance. Thus we get a rising marginal cost, and constant marginal benefit, so we would again expect an interior solution, equating the marginal costs and marginal benefits of compliance - to the firm, rather than to society.

As mentioned earlier, there are 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, the impact of some of these plant characteristics on compliance could go either way: older plants might find it harder to comply, but could be grandfathered; and larger plants might enjoy economies of scale, but could also have more places that something could go wrong, raising their probability of non-compliance.

The chief expected direct benefit the plant receives from compliance is the avoidance of penalties. Therefore a plant's decision to comply depends on both the magnitudes of the penalties that would be imposed for violations and the probability of getting caught, which depends in turn on the amount of enforcement activity that the mill expects to face. We have no information on penalties imposed, so all of our analysis concentrates on the probability of being caught. The deterrent effect of enforcement can be described as including both specific and general deterrence components, depending on how the plant forms its expectation of the probability of being caught. General deterrence refers to the overall expected probability of being caught, similar to a speeding motorist gauging the risk of detection by the overall number of police cars monitoring traffic. Specific deterrence refers to actually having been caught in violation in the past. Specific deterrence may be important if firms have limited information about the amount of enforcement going on at other plants, but have a good memory for the actual inspections they received in past years. Alternatively, specific deterrence may be important if firms face higher penalties for repeated violations, so that once caught a violator will make an extra effort to comply in the future. Scholz and Gray (1990) examine the impact of OSHA inspections on injury rates and find significant evidence for both types of deterrence.

Compliance behavior may also depend on characteristics of the firm which 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 raise - 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, 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. In sum, a plant's compliance decision depends on its age and production technology, its firm size and profitability, and the enforcement activity directed towards it.

Based on the above discussion, we estimate a model of compliance behavior as follows:

(1) $\text{COMPLY} = f(\text{ENFORCE}, X_p, X_f, X{*}\text{ENFORCE}, \text{YEAR}_t, \text{OCOMPLY})$.

COMPLY is the plant's compliance status with air pollution regulations, taken from the CDS. ENFORCE is the enforcement activity faced by the plant, which could be either in terms of expected probability of enforcement (general deterrence) or actual past enforcement directed towards the plant (specific enforcement). The model includes characteristics of the plant (X_p) and firm (X_f), either of which could be interacted with enforcement activity to test for differences in the responsiveness of plants and firms to enforcement, and year dummies (YEAR_t) to allow for changes in enforcement, or its definition, over time. Finally, we include the compliance status of the plant in other regulatory areas (OCOMPLY).

Now consider the regulator's decision. 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 which 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, et. al. (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 due to the severity of pollution problems or to the political makeup 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.[1]

4. 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 Manufactures and Annual Survey of Manufacturers over time (for a more detailed description of the LRD data, see McGuckin and Pascoe (1988)). From the LRD we extracted information for 116 pulp and

[1] 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.

paper industry plants with continuous data over the 1979-1990 period. We capture differences in technology across plants with a PULP dummy variable, indicating whether or not the plant incorporates a pulping process. Our control for plant age, OLD, is a dummy variable, indicating whether the plant was in operation before 1960[2]. We control for the plant's efficiency using TFP, an index of the total factor productivity level at the plant, which we developed in Gray and Shadbegian (1994), when we tested for the impact of regulation on productivity. Possible economies of scale in compliance are captured by SIZE, the log of the plant's real value of shipments. Finally, 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 use the Census Bureau's annual Pollution Abatement Costs and Expenditures (PACE) survey. The PACE survey 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 we took FIRMEMP, the log of firm employment, and FIRMPROF, the firm's profit rate (net income divided by capital stock). We also include 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 excluded from Compustat, we also include a MISSFIRM dummy to control for those observations with missing Compustat data.

Our regulatory measures come 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 use information from three other regulatory data sets: the EPA's Permit Compliance System (PCS) and Toxic Release Inventory (TRI), and the Occupational Safety and Health Administration's (OSHA) Integrated

[2] 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.

Management Information System (IMIS). The EPA's PCS provides information on water pollution regulation. Unfortunately, this data set does not begin until the late 1980s, near the end of our period, so we cannot include its variation over time in the model. Instead, we create 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 also does not provide useful time series variation for our model. Thus, we calculate 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. Finally, OSHA conducts inspections and imposes penalties to try to ensure safe working conditions. We use 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 can include the annual values directly in our model.

5. Econometric Issues

Several econometric issues arise when we proceed to the estimation of equation (1). The key econometric issue that any study of enforcement and compliance must face is the endogeneity of enforcement: regulators 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 which 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 focussing long-run enforcement activity on a few non-complying 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).[3] 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

[3] Note that these two variables (lagged enforcement and lagged predicted enforcement) could also be interpreted as corresponding to the general and specific deterrence effects discussed earlier.

(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 is not used in the final analyses shown here. Finally, we include a variable measuring the political support for environmental regulation within the state, VOTE, which is the percent 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 is then used in the second-stage compliance models.

Another concern for the estimation of equation (1) is that the dependent variable in our compliance equations (COMPLY) is discrete: a plant is either in compliance or not in compliance. Thus we need to use an estimation method that is appropriate to a binary dependent variable. In this case, we choose the logit model. We also estimate the model using a (theoretically inappropriate) OLS regression model partly as a consistency check on the logit results, but mostly so that we can easily include fixed effects into the analysis.[4]

A final concern for the analysis is the limited time-series variation available for key variables. Some plant characteristics (being in operation in 1960 and incorporating a pulping process) never change in our data set, while other characteristics (being large, spending heavily on pollution control, being part of a large multi-plant firm) change only slightly over time. Therefore, moving to a fixed-effects model would completely eliminate OLD and PULP (variables which never change over time), and greatly reduce the explanatory variation available for the other explanatory variables, which may adversely affect the explanatory power of these variables. Also, if there is substantial measurement error over time, using fixed-effects estimators may also result in a sizable bias in the estimated coefficients (Griliches and Hausman (1986)). Thus, our data limits our ability to use fixed-effects to distinguish unobservable plant-specific effects from the effects of the observed variables. Therefore, aside from a brief exploration of the effect of introducing fixed-effects into an OLS model of compliance, we do not pursue fixed-effects models in our analysis.

6. 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 operations in 1960 or before, with slightly less than half including pulping facilities. The last two columns (%CS and

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[4] The fixed-effects version of the logit analysis would require estimating a conditional logit model, which in our data set would probably raise disclosure concerns, making it unlikely that we could report the resulting coefficients.

%TS) show the fraction of total variation in the variable accounted for by plant and year dummies. 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.[5] Air pollution enforcement activity is greater at plants which 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. Finally, air enforcement is negatively correlated with compliance evidence that the tendency to target enforcement towards non-complying 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. 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 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% less likely to be in compliance, while doubling a plant's size reduces its compliance rate by 6% -- the transformed logit effects are nearly identical.

Table 4 considers 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 due to 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. The magnitudes of the water and OSHA impacts could be substantial, for

[5] A few of the dummy variables in our data set (OLD, NONPAPER, and MISSFIRM) are not 'disclosable' in some of our analyses. For these variables, we have indicated the sign of the relationship, and doubled the sign (e.g. '--') when the results are significant at the 10% level or better.

example in model 4D, a plant with 100% water compliance has an expected air compliance rate 11 percentage points higher than one with 0% water compliance; a similar shift for OSHA compliance is associated with a 14 percentage point higher expected air compliance rate.[6]

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 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.[7] 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.[8] On the other hand, 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 $P(INSPECT)_{-2}$ by one inspection raises the probability of being in compliance by roughly 10%. However, once we include $P(OTHERACT)_{-2}$ along with $P(INSPECT)_{-2}$ (model 5E), the coefficient on $P(INSPECT)_{-2}$ becomes a bit smaller and is nolonger significant, while the coefficient on $P(OTHERACT)_{-2}$ is positive and significant. The magnitude of the two coefficients implies that increasing either by one inspection/other action leads to an approximate 10% increase in the probability of being in compliance -- although this increase is only significant for other actions.

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 models which 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 and have similar signs. 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 $P(INSPECT)_{-2}$ by one inspection at a paper mill without pulping facilities increases the likelihood of compliance by approximately 20%, whereas if the paper mill does have a pulping facility the likelihood of compliance only rises by 5% -- although the interactive effect is not quite significant.

Table 7 presents similar results, using firm characteristics: profit rate, employment, and

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[6] These calculations are based on the logit model's derivative of the probability of compliance with respect to the explanatory variables equal to .1824, evaluated at COMP's mean value of .76.

[7] 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 .143, so we are only explaining a relatively small part of the variation in enforcement.

[8] 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).

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 on inspections and other actions. Plants owned by larger firms, whether measured as 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 firms. For example, in model 7D, increasing the log of firm employment from 2.5 (its mean value) to 3.0 -- only about 1/3 its standard deviation -- completely eliminates any positive effect $P(INSPECT)_{-2}$ have on the likelihood of compliance. On the other hand, $P(OTHERACT)_{-2}$ will 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%. 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 in states where regulators put more effort into other enforcement activity.

7. Conclusions

We have examined plant-level data on enforcement and compliance with air pollution regulation to: 1) test whether enforcement is effective in inducing plants to comply; 2) test whether certain types of plants are more influenced by enforcement behavior; 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 which are larger are all less likely to be in compliance. Unlike Helland (1998), we find that firm-level characteristics are not significant determinants of compliance at the plant level. 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, but 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% reduction in compliance; a plant with pulping has 17% lower compliance than one without pulping; a plant in violation of water pollution regulations is 13% 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 account for the endogeneity of enforcement using lagged predicted values of enforcement, based on variables that are clearly exogenous to the plant's compliance decision, we find the expected positive significant relationship between enforcement and compliance. We also find 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. For example, increasing $P(INSPECT)_{-2}$ by one inspection at a paper mill without pulping facilities increases the likelihood of compliance by approximately 20%, whereas if the paper mill does have a pulping facility the likelihood of compliance only rises by 5%. Finally, even though firm characteristics are not found to be related to plant-level compliance, we find them to be more strongly related to enforcement sensitivity than plant characteristics. 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 $P(INSPECT)_{-2}$ have 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%.

What lessons can be drawn by policy-makers from these results? First (and no surprise), there are observable characteristics of plants which are strongly associated with their compliance behavior. To the extent that regulators want to concentrate their enforcement activity on those plants which 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 compliance. 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. Finally, there is some evidence that those plants which are likely to be out of compliance seem to be somewhat less responsive to enforcement activity, so that optimal targeting of enforcement must weigh the greater opportunity for compliance improvement against the greater enforcement effort needed to achieve that improvement.

We are planning to overcome some of the limitations of the current paper in future work. Most importantly, we anticipate extending the data set 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 would allow us to look more closely at the interactions between the compliance decision for one pollution medium with decisions on other media. We also 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 state-level enforcement activity and federal enforcement.

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Table 1

Summary Statistics
(N=1392)

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)

%CS = percent of variation explained by plant dummies
%TS = percent 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 .08 are significant at the .05 level.
(--) indicates significant negative correlation.

Table 3

Basic Compliance Models

(Dep Var = COMP; N=1160)

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

Regressions also include a constant term and year dummies.
Firm variables include MISSFIRM.

(-) indicates negative coefficient; (--) indicates significant negative.

Table 4

Compliance - Cross-Regulation Effects
Logit Models

(Dep Var = COMP; N=1160)

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

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

Table 5

Compliance - Enforcement Measures
Logit Models

(Dep Var = COMP; N=1160)

	(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 (1.85)		0.429 (1.40)	
$INSPECT_{-2}$				-0.080 (-0.54)		0.045 (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

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

Table 6

Enforcement * Plant Characteristics
Logit Models

(Dep Var = COMP; N=1160)

	(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

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

Table 7

Enforcement * Firm Characteristics
Logit Models

(Dep Var = COMP; N=1160)

	(7A)	(7B)	(7C)	(7D)	(7E)	(7F)
P(INSPECT)$_{-2}$	0.458 (1.18)	0.458 (1.67)	0.685 (1.47)	1.311 (2.55)	0.829 (1.32)	1.604 (2.35)
P(OTHERACT)$_{-2}$		0.402 (1.00)		-0.713 (-1.84)		-0.862 (-1.65)
PROF*P(INSPECT)$_{-2}$	2.464 (0.38)	0.529 (0.07)				
PROF*P(OTHERACT)$_{-2}$		0.644 (0.14)				
EMP*P(INSPECT)$_{-2}$			-0.062 (-0.37)	-0.445 (-2.29)		
EMP*P(OTHERACT)$_{-2}$				0.488 (3.89)		
PLANTS*P(INSPECT)$_{-2}$					-0.142 (-0.50)	-0.643 (-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

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