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When is Enforcement Effective - or Necessary?

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Abstract

This paper examines differences in plant-level compliance with air pollution regulation for U.S. 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 datasets. 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. Enforcement targeting generally results in a negative relationship between enforcement and compliance, even when we use lagged values of enforcement or when we instrument for enforcement based on variables exogenous to the plant's compliance decision. As an alternative, we consider changes in compliance and find that plants facing more enforcement are more likely to move into compliance. We do not generally find significant differences across different types of plants in their responsiveness to enforcement, although there is some hint that those types of plants which tend to have lower compliance rates overall also tend to be less responsive to enforcement.

1. Introduction

For government regulation to be successful, a regulatory agency must achieve some degree of compliance on the part of regulated firms. This is usually accomplished by having inspectors visit plants to identify violations, then impose penalties on violators. 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, as demonstrated by Becker (1968). In the case of many regulatory programs dealing with business decisions, 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 would therefore be willing to invest in compliance at the start of the game, more than 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), 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: 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.

This paper examines differences in plant-level compliance with air pollution regulations, looking at a sample of U.S. paper mills. We test a variety of plant- and firm-specific characteristics, to see which plants are more likely to comply with regulation. We compare the plant's air pollution compliance with its performance on other regulatory dimensions (water pollution and toxic chemicals). We also 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 datasets, 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 begin with 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. We try predicting enforcement from a tobit model on a set of clearly exogenous variables (state political support for environmental regulation and year and state dummies). We then use this predicted value in a second-stage compliance equation. Second, we try using lagged enforcement as an explanatory variable, in principle purging the equations of any contemporaneous endogeneity. Most of these models continue to find an apparently negative 'impact' of enforcement on compliance.

Since neither of these methods gives consistently sensible results, we look for an alternative method of modelling the connection between enforcement and compliance. Our new model involves transforming the compliance variable into a change in compliance from one year to the next. This results in a multi-valued dependent variable (newly out of compliance, no change, and newly in compliance), requiring alternative estimation methods. We consider multinomial logit and ordered probit models. For both models we find evidence that greater enforcement activity is associated with a significantly higher probability of being 'newly in compliance'.

We also 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 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. Finally, we do not find significant differences across plants in their responsiveness to enforcement, although there is some hint that types of plants which tend to have lower compliance rates (large, old, pulping mills) are less responsive to enforcement.

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, 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 benefits 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. Some of these plant characteristics might go either way: older plants might find it harder to comply, but could be grandfathered; larger plants might enjoy economies of scale, but could have more places that something could go wrong, raising their probability of non-compliance.

The chief expected benefit from compliance is the avoidance of penalties. Therefore a plant's decision 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 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) find significant evidence for both types of deterrence, looking at the impact of OSHA inspections on injury rates.

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:

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

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 paper industry plants with continuous data over the 1979-1990 period. We capture differences in technology across plants with a PULP dummy indicating whether or not the plant incorporates a pulping process. Our control for plant age is an OLD dummy, 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 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

[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.

[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.

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. 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 included FIRMPLANT the log of the number of other paper mills owned by the firm (in a large file of 758 paper mills) and NONPAPER, a dummy variable indicating that the firm's primary activity as identified on 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 datasets. The Compliance Data System (CDS) provides annual measures of enforcement and compliance directed towards each plant. COMPLY is a dummy, 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). Because of our concerns about targeting of enforcement mentioned earlier, we also look at DCOMP, the change in compliance status, which takes on values of +1, 0, and -1, with 0 (no change in compliance) being the most common.

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 CDS actions 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 datasets. The EPA's Permit Compliance System (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 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 Toxic Release Inventory (TRI) dataset provides information on the disposal of toxic substances from manufacturing plants. It was first collected in 1987, so it also isn't providing useful time series variation for our model. 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, the Occupational Safety and Health Administration (OSHA) conducts inspections and imposes penalties to try to ensure safe working conditions. We use data from OSHA's Integrated Management Information System (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. This data does span 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.

This targeting behavior on the part of regulators can cause problems for estimating the determinants of compliance. If we assume that there is some heterogeneity in compliance across plants, not captured by the explanatory variables but observable by the regulator, then the estimated coefficient on enforcement would be biased downwards and could even change sign. This endogeneity bias is examined in more detail in Gray and Scholz (1993), who test for an impact of OSHA enforcement on workplace injuries. Since OSHA targets inspections towards high-injury sectors, inspected plants tend to be have higher injuries, pushing the estimation towards a conclusion that OSHA enforcement increased injuries. Using a Chamberlain analysis, they show that this endogeneity bias is significant for injury levels, but when the analysis is modified to look at changes in injuries from year to year, the endogeneity bias disappears.

Initially 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 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. Thus either method used to overcome the endogeneity of enforcement is likely to result in insignificant coefficients on enforcement in the compliance equation.

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; 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 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 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. This is partly as a consistency check on the logit results, but mostly so that we can easily include fixed effects into the analysis.[4]

A different type of limited dependent variable problem arises when we consider our third solution for the problem of endogenous enforcement: switching the dependent variable from 'compliance' to the 'change in compliance'. In the change form of the model, we have three possible values for the dependent variable, DCOMP: moving from compliance into non-compliance (DCOMP=-1), no change in compliance (DCOMP=0), and moving from non-compliance into compliance (DCOMP=+1). We consider two possible models, ordered probit and multinomial logit.

The ordered probit model assumes that the three choices for DCOMP can be ordered, in this case

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

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

from -1 to 0 to +1, so that the same explanatory factors (Xb) that make a plant more likely to move from state 0 to +1 also make it more likely to move from state -1 to 0. On the other hand, the multinomial logit model makes no assumptions about the ordering of the three outcomes. Instead it picks one of the outcomes as the 'base', and estimates the impact of the explanatory variables on the relative probability of each of the other outcomes, relative to the base outcome. Thus the multinomial logit model gives two full sets of coefficients, which are not constrained by any ordering. For example, one variable might make it less likely that the base category would occur by increasing the probabilities of both of the other two categories. In this case, the base outcome is the 'no change' (DCOMP=0) category. Since this category falls in between the other two 'change' outcomes (according to the ordered probit), we would expect the two sets of coefficients to have the opposite sign: any factor that makes it more likely that you would 'become compliant' must also make you less likely to 'become non-compliant'. This seems reasonable for most variables, but certainly need not be true for all variables. For example, a small plant might have more variance in its compliance status, making small plants more likely to have either of the 'compliance change' outcomes, relative to the base outcome of no change, without specifically indicating in which direction the change would occur.

A final concern for the analysis is the limited time-series variation available for key variables. Some plant characteristics (being in operation in 1960, incorporating a pulping process) never change in our dataset, while other characteristics (being large, spending heavily on pollution control, being part of a large multi-plant firm) change only slightly over time. Thus our data limits our ability to use fixed-effects type of analyses to distinguish unobservable plant-specific effects from the effects of the observed variables. Moving to a fixed-effects model eliminates the variables which do not change over time, and reduces the explanatory variation available for the other explanatory variables. This may adversely affect the explanatory power of these variables. 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)). 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 %TS) show the fraction of total variation in the variable accounted for by plant and year dummies. Nearly all of the variables in our dataset 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 first, 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

[5] A few of the dummy variables in our dataset (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

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. As noted earlier, this 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. 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 drop out of the fixed effects model. Interpreting the magnitude of the Table 3 effects is easiest from the OLS run (and the transformed logit effects are similar) - a pulp mill is 17% less likely to be in compliance, while doubling a plant's size reduces its compliance rate by 6%.

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: a plant with 100% water compliance has an expected air compliance rate 13 percentage points higher than one with 0% water compliance; a similar shift for OSHA compliance is associate with a 15 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 predicted enforcement and actual 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 tend to have a higher probability of being out of compliance. There is some variation in sign across the different measures, and many of the coefficients are not significant, but the strongest coefficients tend to be negative (on $ACTION_{-2}$ and $OTHERACT_{-2}$). We believe that these results say more about the targeting of enforcement towards violators, and do not indicate completely counterproductive enforcement.

In Tables 6 and 7 we turn our attention to the change in compliance, DCOMP. Although we include all of the plant and firm characteristics from the earlier tables, they are generally insignificant here, and we do not report them (results available from authors upon request). The results for predicted enforcement measures tend to be insignificant in both tables. The only exception is the significant positive

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sign (e.g. '--') when the results are significant at the 5% level.

[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.

coefficient on $P(ACTION)_{-2}$ in Table 7, which does not fit the model since both compliance changes (going into and out of compliance) are positive, and there is no significant difference between them. The actual lagged enforcement measures do much better in most cases. The ordered probit models show a positive impact of enforcement on compliance changes. The multinomial logit models show that enforcement significantly increases moves from non-compliance into compliance, but its ability to reduce the number of moves from compliance into non-compliance is essentially zero. Together, these results provide some support for the multinomial logit model rather than the ordered probit, since the latter implicitly assumes that the impacts on the two 'change' outcomes are symmetric. Interpreting the magnitude of the coefficients in terms of their impact on the probability changing compliance is complicated by the multinomial nature of the dependent variable (and some disclosure issues).[8] Note that when we combine both inspections and other actions into the same equation, we find that an additional inspection raises the probability of moving into compliance by more than an additional other action.

In Tables 8 and 9 we continue examining the effectiveness of enforcement activity, by looking at whether enforcement has different impacts for different types of plants. We test for possible interactive effects, using the three plant characteristics that were significantly related to compliance: plant age (OLD), plant size (SIZE) and having pulping operations. All three of these characteristics are associated with lower compliance rates. When we interact these variables with enforcement measures, we see little evidence of differences in response to enforcement activity between these groups, although larger plants are a bit less sensitive to enforcement activity (significant in model 9G).[9] More generally, though not significantly, the signs of the direct effect for each of the enforcement variables are reversed on the interaction terms, indicating a smaller effect of enforcement for the large/old/pulping plants in nearly all cases. This suggests, albeit weakly, that those plants which have an especially difficult time in complying with regulations may also be less likely to respond to regulatory enforcement.

7. Conclusions

We have examined plant-level data on enforcement and compliance of air pollution regulation, testing whether enforcement is effective in inducing plants to comply, whether certain types of plants are more influenced by enforcement behavior, and 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. 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.

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

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[8] The calculation depends heavily on the distribution of the DCOMP variable. For example, if 10% of the sample observations experienced a movement into compliance, the derivative at that point would be p(1-p), or .1*.9=.09, so the coefficient on $INSPECT_{-2}$ of .529 would result in an impact of .529*.09 = 4.8%. If 30% of the sample experienced a movement into compliance, the derivative would be .3*.7=.21, so the effect of $INSPECT_{-2}$ would be .529*.21 = 11.1%, over twice as large.

[9] Finding a smaller impact of regulatory enforcement for large plants is consistent with Gray and Sholz (1991), who found that small and medium-sized manufacturing plants showed a greater responsiveness to OSHA inspections than large plants did, measured in reductions in injuries after an inspection.

relationship between enforcement and compliance, even when using lagged values of enforcement or predicted enforcement, based on variables exogenous to the plant's compliance decision. As an alternative, we consider whether enforcement results in changes in the plant's compliance level, and do indeed find that plants facing more enforcement are more likely to move into compliance. Finally, we do not generally find significant differences across plants in their responsiveness to enforcement, based on either plant- or firm-level characteristics, although the pattern of the results suggests that plants which have an especially difficult time in complying with regulations may also be less likely to respond to regulatory enforcement.

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. We measure the impact of enforcement on compliance using a 'compliance change' model. We find smaller effects on compliance than we do for plant characteristics, and these effects are only significant for the change from non-compliance to compliance. More specifically, having one more inspection raises the probability of moving into compliance by 3.6%; having one more 'other action' raises the probability by 2.4%. However, enforcement does not seem effective in reducing the probability of moving from compliance into non-compliance.

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 firms to move into compliance, but not effective in discouraging movement out of compliance. Finally, 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 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 dataset 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.

REFERENCES

Bartel, Ann P. and Lacy Glenn Thomas, "Direct and Indirect Effects of Regulations: A New Look at OSHA's Impact," Journal of Law and Economics, 28, 1-25 (1985).

Becker, Gary, "Crime and Punishment: An Economic Approach," Journal of Political Economy , 76, 169-217 (1968).

Deily, Mary E. and Wayne B. Gray, "Enforcement of Pollution Regulations in a Declining Industry," Journal of Environmental Economics and Management, 21, 260-274 (1991).

Gollop, Frank M. and Mark J. Roberts, "Environmental Regulations and Productivity Growth: The case of Fossil-fueled Electric Power Generation," Journal of Political Economy , 91, 654-674 (1983).

Gray, Wayne B. "Environmental Compliance at Paper Mills: The Role of Regulatory Enforcement and Corporate Restructuring," presented at AERE Winter Meetings, Boston, January 2000.

_____ and Mary E. Deily, "Compliance and Enforcement: Air Pollution Regulation in the U.S. Steel Industry," Journal of Environmental Economics and Management, 31, 96-111 (1996).

_____ and Carol A. Jones, "Longitudinal Patterns of Compliance with OSHA in the Manufacturing Sector," Journal of Human Resources, 26 (4), 623-653 (1991).

_____ and John T. Scholz, "Analyzing the Equity and Efficiency of OSHA Enforcement," Law and Policy, 13, 185-214 (1991).

_____ and Ronald J. Shadbegian, "Pollution Abatement Costs, Regulation, and Plant-Level Productivity," NBER Working Paper 4994 (1995).

Griliches, Zvi and Jerry A. Hausman, "Errors in Variables in Panel Data," Journal of Econometrics, 31 (1), 93-118, 1986.

Harrington, Winston, "Enforcement Leverage when Penalties are Restricted," Journal of Public Economics, 37, 29-53 (1988).

Helland, Eric, "The Enforcement of Pollution Control Laws: Inspections, Violations, and Self-Reporting," Review of Economics and Statistics, 80 (1), 141-153 (1998).

Laplante, Benoit and Paul Rilstone, "Environmental Inspections and Emissions of the Pulp and Paper Industry in Quebec," Journal of Environmental Economics and Management, 31, 19-36 (1996).

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

McGuckin, Robert H. and George A. Pascoe, "The Longitudinal Research Database: Status and Research Possibilities," Survey of Current Business (1988).

Nadeau, Louis W., "EPA Effectiveness at Reducing the Duration of Plant-Level Noncompliance," Journal of Environmental Economics and Management, 34 (1), 54-78 (1997).

Scholz, John T., "Cooperation, Deterrence, and the Ecology of Regulatory Enforcement," Law & Society Review, 18, 179-224 (1984).

______ and Wayne B. Gray, "OSHA Enforcement and Workplace Injuries: A Behavioral Approach to Risk Assessment," Journal of Risk and Uncertainty, 3, 283-305 (1990).

Shadbegian, Ronald J., Wayne B. Gray, and Jonathan Levy, "Spatial Efficiency of Pollution Abatement Expenditures," presented at NBER Environmental Economics session, April 13, 2000.

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	0.01	0.01	78	<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	0.596	-0.009	0.034	0.507	0.025	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:	(A) Logit	(B) Logit	(C) Logit	(D) OLS	(E) F.E.
			Plant Characteristics		
PAOC	1.001		0.361	0.059	0.899
	(0.07)		(0.02)	(0.02)	(0.18)
PULP	-0.918		-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

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)

	(A)	(B)	(C)	(D)	(E)	(F)
	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)	(-3.77)	(-3.97)
	Plant characteristics					
PAOC	0.384	4.672	-1.877	1.374	2.136	
	(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	
	(-0.49)	(-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	2.466	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

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)

	(A)	(B)	(C)	(D)	(E)	(F)
			Enforcement Measures			
$P(ACTION)_{-2}$	-0.230 (-1.51)					
$ACTION_{-2}$		-0.294 (-3.18)				
$P(INSPECT)_{-2}$			0.503 (1.70)		0.500 (1.68)	
$INSPECT_{-2}$				-0.092 (-0.63)		0.045 (0.30)
$P(OTHERACT)_{-2}$					0.012 (0.09)	
$OTHERACT_{-2}$						-0.296 (-3.56)
LOG-L	-604.40	-600.48	-604.03	-605.32	-604.03	-599.52
pseudo-R^2	0.072	0.078	0.072	0.071	0.073	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

Change in Compliance
Ordered Probit Models

(Dep Var = DCOMP; N=1160)

	(A)	(B)	(C)	(D)	(E)	(F)
$P(ACTION)_{-2}$	-0.003 (-0.03)					
$ACTION_{-2}$		0.135 (2.50)				
$P(INSPECT)_{-2}$			0.122 (0.78)		0.130 (0.83)	
$INSPECT_{-2}$				0.140 (1.68)		0.101 (1.18)
$P(OTHERACT)_{-2}$					-0.033 (-0.39)	
$OTHERACT_{-2}$						0.083 (1.64)
k_1	-1.424	-1.711	-1.425	-1.473	-1.378	-1.699
k_2	1.466	1.195	1.467	1.423	1.514	1.205
LOG-L	-618.38	-615.23	-618.07	-616.96	-617.99	-615.48
pseudo-R^2	0.022	0.027	0.023	0.024	0.023	0.027

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

Table 7

Change in Compliance
Multinomial Logit Models

(Dep Var = DCOMP; N=1160)

	(A)		(B)		(C)	
DCOMP value:	-1	+1	-1	+1	-1	+1
$P(ACTION)_{-2}$	0.529 (2.34)	0.553 (2.37)				
$P(INSPECT)_{-2}$			0.203 (0.46)	0.710 (1.64)	0.147 (0.33)	0.698 (1.57)
$P(OTHERACT)_{-2}$					0.163 (0.73)	0.034 (0.15)
LOG-L	-563.37		-566.72		-566.45	
pseudo-R^2	0.109		0.104		0.104	

	(D)		(E)		(F)	
DCOMP value:	-1	+1	-1	+1	-1	+1
$ACTION_{-2}$	-0.073 (-0.49)	0.426 (2.86)				
$INSPECT_{-2}$			-0.043 (-0.19)	0.529 (2.21)	-0.047 (-0.20)	0.395 (1.62)
$OTHERACT_{-2}$					-0.001 (-0.01)	0.269 (2.03)
LOG-L	-563.71		-565.50		-563.31	
pseudo-R^2	0.109		0.106		0.109	

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

Table 8

Change in Compliance
Ordered Probit Models
(Dep Var = DCOMP; N=1160)

	(A)	(B)	(C)
$ACTION_{-2}$	0.139		
	(1.89)		
$INSPECT_{-2}$		0.182	0.157
		(1.65)	(1.33)
$OTHERACT_{-2}$			0.054
			(0.68)
$PULP*ACTION_{-2}$	-0.009		
	(-0.09)		
$PULP*INSPECT_{-2}$		-0.096	-0.106
		(-0.58)	(-0.62)
$PULP*OTHERACT_{-2}$			0.043
			(0.44)
k_1	-1.710	-1.449	-1.635
k_2	1.196	1.448	1.270
LOG-L	-615.23	-616.79	-615.42
pseudo-R^2	0.027	0.025	0.027

	(D)	(E)	(F)
$ACTION_{-2}$	0.174		
	(1.33)		
$INSPECT_{-2}$		0.051	-0.096
		(0.25)	(-0.43)
$OTHERACT_{-2}$			0.192
			(1.53)
$OLD*ACTION_{-2}$	-0.046		
	(-0.33)		
$OLD*INSPECT_{-2}$		0.107	0.229
		(0.48)	(0.94)
$OLD*OTHERACT_{-2}$			-0.127
			(-0.94)
k_1	-1.637	-1.559	-1.706
k_2	1.269	1.338	1.201
LOG-L	-615.18	-616.85	-615.01
pseudo-R^2	0.027	0.025	0.028

Table 8 (cont.)

Change in Compliance
Ordered Probit Models

(Dep Var = DCOMP; N=1160)

	(G)	(H)	(I)
$ACTION_{-2}$	0.736		
	(1.07)		
$INSPECT_{-2}$		1.298	1.268
		(1.13)	(1.06)
$OTHERACT_{-2}$			0.213
			(0.30)
$SIZE*ACTION_{-2}$	-0.057		
	(-0.87)		
$SIZE*INSPECT_{-2}$		-0.111	-0.112
		(-1.01)	(-0.97)
$SIZE*OTHERACT_{-2}$			-0.012
			(-0.19)
k_1	-1.076	-0.642	-0.780
k_2	1.831	2.257	2.127
LOG-L	-614.85	-616.45	-615.06
pseudo-R^2	0.028	0.025	0.027

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

Table 9

Change in Compliance
Multinomial Logit Models
(Dep Var = DCOMP; N=1160)

	(A)		(B)		(C)	
DCOMP value:	-1	+1	-1	+1	-1	+1
ACTION$_{-2}$	-0.019 (-0.08)	0.639 (2.95)				
INSPECT$_{-2}$			-0.152 (-0.43)	0.803 (2.35)	-0.250 (-0.67)	0.553 (1.48)
OTHERACT$_{-2}$					0.196 (0.83)	0.382 (1.70)
PULP*ACTION$_{-2}$	-0.096 (-0.33)	-0.379 (-1.33)				
PULP*INSPECT$_{-2}$			0.166 (0.36)	-0.520 (-1.11)	0.288 (0.61)	-0.331 (-0.67)
PULP*OTHERACT$_{-2}$					-0.277 (-0.99)	-0.193 (-0.72)
LOG-L	-562.81		-564.77		-562.29	
pseudo-R^2	0.110		0.107		0.111	

	(D)		(E)		(F)	
DCOMP value:	-1	+1	-1	+1	-1	+1
ACTION$_{-2}$	-0.151 (-0.37)	0.541 (1.63)				
INSPECT$_{-2}$			0.645 (1.06)	0.836 (1.49)	0.911 (1.31)	0.589 (0.96)
OTHERACT$_{-2}$					-0.413 (-1.07)	0.265 (0.83)
OLD*ACTION$_{-2}$	0.089 (0.20)	-0.142 (-0.38)				
OLD*INSPECT$_{-2}$			-0.793 (-1.21)	-0.377 (-0.60)	-1.068 (-1.46)	-0.225 (-0.34)
OLD*OTHERACT$_{-2}$					0.468 (1.13)	-0.006 (-0.02)
LOG-L	-563.61		-564.68		-562.06	
pseudo-R^2	0.109		0.107		0.111	

Table 9 (cont.)

Change in Compliance
Multinomial Logit Models

(Dep Var = DCOMP; N=1160)

	(G)		(H)		(I)	
DCOMP value:	-1	+1	-1	+1	-1	+1
$ACTION_{-2}$	0.588	4.382				
	(0.27)	(2.17)				
$INSPECT_{-2}$			-1.458	5.695	-2.310	4.486
			(-0.43)	(1.53)	(-0.65)	(1.15)
$OTHERACT_{-2}$					1.866	2.570
					(0.89)	(1.42)
$SIZE*ACTION_{-2}$	-0.062	-0.373				
	(-0.31)	(-1.96)				
$SIZE*INSPECT_{-2}$			0.133	-0.489	0.212	-0.388
			(0.42)	(-1.39)	(0.64)	(-1.05)
$SIZE*OTHERACT_{-2}$					-0.173	-0.216
					(-0.89)	(-1.28)
LOG-L	-561.75		-564.36		-561.26	
pseudo-R^2	0.112		0.108		0.113	

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