Why Do Plants Comply with Environmental Regulations?
The Importance of Enforcement Activity, Abatement Costs, and Community Pressure.

(EPA Agreement Number RD-83215501-0)
(2/10/2005 - 2/09/2009)

Final Report
July 6, 2009

Wayne B. Gray
Clark University

Disclaimer

Table of Contents

1. Research Objectives

This study examined factors affecting environmental performance (both compliance status and emissions for air, water, and toxic pollutants) in paper mills, oil refineries, steel mills, and electric utilities. We began with data on each plant, its owning firm and traditional regulatory activity. We then added information on community pressures and political pressures faced by the plant at both the state and local level. We also examined the spatial impacts of regulation on all manufacturing plants in four cities: Los Angeles, Houston, Boston and Columbus. We addressed four questions: (1) How do corporate environmental culture and government regulatory interventions influence a plant's environmental performance? (2) Do community and political pressures at the state and local level significantly affect performance? (3) Why do firms and plants differ in their responsiveness to government interventions? (4) Is environmental performance at one plant related to the performance of nearby plants?

2. Executive Summary

This project continued and extended what has been a sizable data collection effort. Our past research work required the creation of a large plant-level database, linking records from EPA regulatory databases and Census databases for the steel, oil, and paper industries. We extended these data with information from more recent years and added additional variables from various sources. We also developed a plant-level database for coal-fired electric utilities, focusing on the impact of SO2 allowance trading in the 1990s, specifically the spatial distribution of emissions and the population affected by those emissions. Finally, we created a 4-city dataset containing all manufacturing plants in the areas surrounding Los Angeles, Houston, Boston, and Columbus, again linking EPA regulatory datasets with Census plant-level data. Those datasets which do not involve confidential material (e.g. non-Census data) are being made available at my web page at Clark University (http://www.clarku.edu/faculty/wgray). For more information about any of the datasets, including help in working with the merged Census datasets through the Census Research Data Center network, contact me directly (wgray@clarku.edu; 508-793-7693).

During the grant period, we have written eight papers based on these databases and we anticipate that the databases will continue to prove useful for a wide range of research projects, both by ourselves and by other researchers, in years to come. The wide range of research work we carried out under this project makes it difficult to provide a single unified summary of the overall project results. Instead, we first identify what we consider to be the key findings of the research, particularly those connected to the four questions identified in our research objectives. We then discuss the research results on a paper-by-paper basis, identifying the most important research outcomes and their connections to the objectives of the overall project. Later in the report we present the most recent versions (as of this writing) of each of the papers, for those who wish to see the details of the research and connections to the existing literature.

2A. Key Findings

Most of our papers examine the importance of various determinants of environmental performance. These include plant and firm characteristics, as well as regulatory pressures and local neighborhood demographics, which address questions 1 and 2 from our research objectives. The papers vary in terms of the industries and pollutants being examined, as well as the focus of the analysis, and our results also show some variation across these dimensions. Our "Assessing Multi-Dimensional Performance: Environmental and Economic Outcomes" paper [5A] addresses this variation directly, by analyzing a total of 15 models - three industries (paper, oil, and steel) and five pollutants (including air, water, and toxic media) - with consistent data and models, as well as comparing environmental and economic performance. We found some consistent patterns, but most factors had differing impacts across the 15 models. This should raise a cautionary note for policy makers (and researchers) about generalizing from the results of isolated analyses.

One key finding from [5A] is that plants with better economic performance (higher productivity) also tend to have better environmental performance (lower emissions). Given the model being used, this suggests that some unmeasured plant characteristics (perhaps related to the quality of plant management) tend to improve both environmental and economic performance. Older plants had poorer economic performance, but their environmental performance was mixed – somewhat worse for oil and steel, but better for paper (especially for water pollution). Our "The Environmental Performance of Polluting Plants: A Spatial Analysis" paper [5D] looks at plants from all manufacturing industries, finding somewhat poorer environmental performance (lower compliance and higher emissions) for older plants, while our "Regulatory Regime Changes under Federalism: Do States Matter More" paper [5E] focuses on the paper industry, and finds lower water toxic releases for older plants. Note that the differences in results from [5D] and [5E] "line up" with the differences in [5A] (paper vs. other industries), providing some cross-study validation of those differences across industries.

We find some evidence of the effectiveness of regulatory interventions, although these aren't always significant. In both [5A] and [5E] we find that plants in non-attainment areas show lower emissions of air pollutants, consistent with the greater regulatory pressure expected in those areas. We find in [5A] (particularly for paper mills) and [5E] that states with greater regulatory stringency (as proxied by their Congressional delegations' pro-environment voting record, collected by the League of Conservation Voters) tend to have lower emissions of a variety of pollutants.

Looking more closely at direct measures of regulatory activity (inspections and other enforcement actions), [5A] finds evidence that regulatory enforcement actions are associated with better environmental performance, but this result is coupled with an anomalous finding of regulatory inspections being associated with worse environmental performance, for which we have no satisfactory explanation – we would not interpret those results as calling for a switch in regulatory activity away from inspections and toward other actions. [5D] uses a spatial econometric analysis to test whether regulatory inspections at a plant (or at neighboring plants) influence environmental performance. We find that compliance is significantly higher at plants that have been inspected recently (reflecting "specific" deterrence) – and also at plants that have had recent inspections at neighboring plants (reflecting "general" deterrence). However, the "neighboring plant" effect does not hold for neighboring plants that are in another state, consistent with the federal nature of U.S. environmental regulation.

[5E] also addresses the federal structure of regulation, with its focus on how a change in regulatory stringency at the federal level (EPA's adoption of the Cluster Rule, designed to reduce toxic air and water emissions from paper mills) affects environmental performance at paper mills in different states, based on their state's overall stringency levels. We find (as noted above) that plants located in states with greater stringency tend to have lower toxic emissions, and that those emissions tended to drop after the adoption of the Cluster Rule, but that the drop in emissions was greater for plants located in less stringent states. This supports the hypothesis that federal regulations tend to "level the playing field" across states (rather than providing a mechanism for stringent states to become even more stringent).

Several of our papers examine whether local demographic variables are related to differences in environmental performance across plants, potentially related to "Environmental Justice" concerns, but generally find limited effects. [5D] tests whether being located near poor or minority neighborhoods affects compliance and emissions, finding no significant effects (aside from marginally higher compliance near minority neighborhoods). [5E] finds significantly higher emissions near poor neighborhoods for toxic pollutants, though not for conventional pollutants. Our "Spatial Patterns in Regulatory Enforcement: Local Tests of Environmental Justice" paper [5F] uses our 4-city dataset to examine whether local demographic variation within cities influences the regulatory activity directed towards manufacturing plants, considering inspections and other enforcement actions separately. We find significant impacts of several factors on regulatory activity, including political activism (high voter turnout and pro-Democrat voting are associated with greater regulatory activity), but local demographic variables show little consistent impact.

All of the above papers address environmental performance in manufacturing industries. We also wrote two papers examining environmental performance at electric utilities, "Benefits and Costs from Sulfur Dioxide Trading: A Distributional Analysis" [5G] and "A Spatial Analysis of the Consequences of the SO_2 Trading Program" [5H]. These papers focus not on command-and-control regulation but on a more flexible instrument: the sulfur allowance trading program, using data from the mid-1990s. We use models of the spatial dispersion of pollution to calculate the distribution of the benefits and costs of the reductions in SO2 emissions that resulted from SO2 allowance trading. [5G] considers the differences across demographic groups in terms of the benefits and costs that they received, finding that all demographic groups gained from the SO2 reductions, and that both African-American and Hispanic groups received a substantially greater share of the benefits associated with SO2 reductions than they did of the costs. [5H] considers spatial variation in benefits and costs, finding that allowance trading did significantly reduce costs, but that the geographic shift of SO2 emissions that resulted from allowance trading also tended to reduce the benefits of the SO2 reductions – plants that bought allowances tended to have higher per-ton-benefits than plants that sold allowances. We examined whether the adverse impact on benefits could be corrected using a "trading zones" approach (where trades would be limited to plants in the same region), but we found that trading zones would only achieve a modest improvement, in part because much of the variation across plants in benefits is due to their stack height rather than their regional location.

Our "Do Firms Shift Production across States to Avoid Environmental Regulation?" paper [5C], addresses question 3 in our objectives, providing evidence about why firms differ in their responsiveness to government intervention. This analysis considers the decision by paper firms to allocate their production across their plants in different states. Our analysis includes reallocations due to plant openings and closings, but we find that changes in the allocation of production within existing plants represent the majority of all reallocations, despite plant openings and closings having been much more heavily studied. We relate the shifting of production across states to a variety of state characteristics (e.g. factor prices, unionization, tax rates), but focus on the results for a series of seven measures of state regulatory stringency. We find evidence that some firms shift production away from states with more stringent environmental regulation, but this shift is concentrated among those firms with relatively low compliance rates – high-compliance firms are less sensitive to state regulatory stringency. Based on the theoretical model developed in the paper, we conclude that differences in firm-level compliance are driven by differences across firms in their costs of compliance, rather than differences in their benefits from compliance.

Our [5D] paper uses spatial econometrics to answer question 4 in our objectives, testing whether (and how) environmental performance at one plant is related to the performance of nearby plants. We used data for all manufacturing plants near 3 cities located near state borders, so we could test for differences in spatial effects across state borders. We found significant spatial correlations in compliance: if one plant is in compliance, nearby plants also tend to be in compliance. This correlation is stronger among plants that are in the same industry, and even stronger for plants that are in both the same industry and the same state. When we account for spatial correlations in plant characteristics (productivity, age, pollution abatement spending, and size), we find that they can explain about one-third of the spatial correlations in compliance.

2B. Paper-by-Paper Summary

The first paper published under this project, ("Assessing Multi-Dimensional Performance: Environmental and Economic Outcomes") examined economic performance, environmental performance, and regulatory activity for plants in the pulp and paper, oil, and steel industries. Because we had access to both EPA and Census data for these plants, we could compare productive efficiency with emissions performance, using a stochastic frontier production function model and a seemingly unrelated regression model. Our measures of environmental performance included air pollution emissions, water pollution discharges, and toxic releases, all measured relative to the plant's production level. Our measures of regulatory activity included both inspections and enforcement actions related to air and water pollution.

We found some variation in coefficients across models, which is not surprising given that we were estimating fifteen models (with three industries and five pollutants), but it raises a cautionary note to policy-makers and other researchers: results from one narrowly-focused study may not carry over to other areas. Our production function estimates showed significant evidence of production inefficiency, with plants producing at about 70%-80% of their potential. Some of this inefficiency could be explained by plant characteristics, e.g. older plants were 10-15% less efficient than newer plants. Firm characteristics seemed less important, although firms with a larger presence in the industry seemed to have more efficient plants, while being more profitable or larger overall did not consistently raise efficiency.

Environmental activity seems to have some impact on production efficiency. Facilities spending more on pollution abatement had lower efficiency, with a large and significant negative effect for steel mills. Greater state-level political support for environmental regulations was associated with lower efficiency in paper and steel mills (but surprisingly higher efficiency in oil refineries). Finally, plants facing more regulatory inspections seemed to have lower efficiency, while plants facing more regulatory actions other than inspections had higher efficiency.

In models of both production efficiency and pollution emissions, plants using dirtier production technologies had greater emissions, but older plants did not always emit more pollution. Plants in non-attainment areas showed lower emissions of air pollutants, and plants in states with greater pro-environment voting also showed lower emissions (only occasionally significant), providing evidence that stricter regulatory policy tends to reduce emissions. Finally, plants getting more inspections had poorer environmental performance and plants getting more other regulatory actions had better environmental performance.

Examining the correlations across equations, we found a positive relationship of emissions within a given pollution medium (e.g. plants emitting more PM2.5 also emitted more SO2) and positive correlations between environmental and economic performance, especially for steel mills. This contrasts with the tradeoffs in performance (negative correlations) expected from a standard economic model. This suggests the importance of some unmeasured plant characteristics that improved both environmental and economic performance.

More recently, we wrote a paper ("What Determines the Opportunity Cost of Pollution Abatement? A Production Function Approach") that also examined the relationship between economic performance and environmental regulation. In this paper we investigated the impact of environmental regulation on the opportunity cost of pollution abatement, measured as the reduction in output associated with pollution abatement activities, using Census data for pulp and paper mills. We then examined whether or not the stringency of environmental regulation (the number of regulatory actions at the plant in a year), the age of plant, and the technology in place at the plant (whether or not the plant has a pulping facility) was related to the opportunity cost of pollution abatement. We found that regulatory actions had no significant impact on opportunity costs of pollution abatement, but plants with pulping facilities had significantly higher opportunity costs of pollution abatement.

A third paper dealing with the relationship between economic decisions and environmental regulation ("Do Firms Shift Production across States to Avoid Environmental Regulation?") examined the decision faced by firms trying to allocate their production across plants in several states, based in part on the regulatory stringency in those states, as well as other state characteristics affecting production costs. We found that states with stricter regulations received smaller production shares, even after controlling for a variety of other state characteristics - but this sensitivity to regulation differed across firms, and was concentrated among firms with relatively low compliance rates. In fact, firms with high compliance rates appeared to be slightly more likely to produce in more stringent states. This suggests that compliance decisions are driven by differences in compliance costs across firms - with high-compliance-cost firms avoiding high-stringency states - and provides evidence that firms differ in their responsiveness to government intervention.

Another paper ("The Environmental Performance of Polluting Plants: A Spatial Analysis") was based on a spatial econometric analysis of the environmental performances of neighboring plants, considering both compliance and emissions behavior. Our analysis incorporated spatially-based information in three new ways. First, in addition to the usual demographic and political information about those living near the plant, we constructed a measure of regulatory activity at nearby plants that distinguished between plants in the same state and plants in different states, allowing us to test for general deterrence effects and to test whether those deterrence effects end at jurisdictional borders. Second, we tested for spatial correlations in the explanatory variables, in the performance measures, and in the residuals from non-spatial models. Comparing the magnitudes of these correlations allowed us to see whether spatial correlations in plant characteristics (possibly driven by industry agglomeration effects) contributed to correlations in environmental performance. Finally, we used spatial econometric techniques to allow explicitly for correlations with the performance of nearby plants, to see whether (and how much) omitted spatial effects biased the results of non-spatial models.

Our results indicated a significant role for spatial factors in environmental performance, without seriously biasing the effects of other factors. Compliance status was positively correlated at nearby plants in the same state, but this correlation did not carry across state borders. The residuals from a compliance model showed weaker spatial correlations, so spatial correlations in explanatory variables could explain a sizable part (but not all) of the correlation in compliance across nearby plants. In spatial econometric models we found that spatially-lagged compliance terms were small and usually not significant, confirming that the explanatory variables captured most of the spatial effects. Our analyses of air pollution emissions, for both conventional and toxic pollutants, showed no evidence of spatial correlations – in fact few variables in our model showed significant impacts on air pollutant emissions, perhaps due to the smaller sample sizes involved or due to the heterogeneity of the plants included in our sample (in order to obtain sufficient numbers of nearby plants for the spatial econometric analysis, we included all manufacturing plants, not just those from a single industry as most prior research had done).

Much of the explanatory power of the compliance models came from plant-specific characteristics, with larger, older, and more pollution-abatement-intensive plants having lower compliance rates. Local demographic characteristics mattered – having more elderly or minority residents nearby was associated with greater compliance – but political activity had little impact. We found the expected effects of regulatory enforcement (although not always significant): more inspections at the plant, at nearby plants, and at all other plants in the state, were associated with greater compliance. The latter two results demonstrated the importance of general deterrence effects. Inspections at nearby plants in other states did not seem to increase compliance, showing a significantly different effect from inspections at nearby plants in the same state, and reinforcing the message that the federal nature of regulatory enforcement in the U.S., and the resulting jurisdictional borders, matter for environmental performance.

A more recent paper ("Regulatory Regime Changes Under Federalism: Do States Matter More?") also demonstrates the importance of accounting for the federal nature of regulatory activity, examining the impact of the EPA's Cluster Rule on the pulp and paper industry. The Cluster Rule (CR) was designed to reduce toxic releases into air and water, and was relatively novel in its multi-media focus (covering air and water pollution in one rulemaking). We found significant reductions in toxic air (but not water) releases around the time that the CR was implemented, although those plants which faced stricter CR rules did not generally show larger reductions in toxics. Emissions of conventional pollutants did not seem to fall around the CR implementation date, but there were significant positive correlations in emissions across the different pollutants, suggesting the presence of unmeasured factors that could improve (or worsen) a plant's environmental performance across the board - similar to our results in the "Multidimensional Performance" paper. Differences across states in regulatory stringency may have fallen after EPA's adoption of the CR, since plants located in states with more support for stringent regulation had lower toxic releases on average throughout the period, but had a smaller decline in toxic releases over time. This suggests that some reductions required by the CR had already been implemented by plants in high-stringency states, and the CR had more impact on plants in lower-stringency states - so different levels of state stringency may help explain differences across plants in their responsiveness to federal regulatory interventions.

Our initial paper using the 4-city dataset ("Spatial Patterns in Regulatory Enforcement: Local Tests of Environmental Justice") examined the determinants of environmental regulatory activity (inspections and enforcement actions) for all manufacturing plants located near Los Angeles, Boston, Columbus, and Houston. We sought to examine whether or not regulators treat different segments of the population differently, by directing more regulatory activity at plants in rich, white, and homogeneous neighborhoods and less in poor, minority, and heterogeneous neighborhoods, controlling for characteristics of the plant (size, age, and industry), and the plant's past environmental performance. Earlier tests of the 'Environmental Justice' hypothesis tended to focus either on whether polluters were disproportionately likely to be located in neighborhoods with high poor/minority populations, or on whether polluters located in those neighborhoods emitted disproportionately high levels of pollution. By focusing on the allocation of enforcement activity across neighborhoods within a city, we can test a key mechanism through which discrepancies in pollution exposure across neighborhoods could arise and persist.

We found that plant characteristics and political activity significantly affected the amount of regulatory activity directed at a plant. In particular, bigger plants and plants with high fuel consumption faced significantly more regulatory activity, as did plants which had been out of compliance with regulatory requirements. Furthermore, plants surrounded by politically active and more liberal populations also received more attention from regulators. However, regulatory attention did not seem to be affected by nearby demographics. Plants with more elders nearby did face more inspections (though not more enforcement), while the results for plants with more children nearby were mixed, but all these effects were insignificant.

We found little statistical evidence for 'Environmental Justice' concerns. Plants located in minority neighborhoods were inspected somewhat less often and faced fewer enforcement actions, but both these effects were statistically insignificant, and plants located in poor neighborhoods tended to face more regulatory activity. Plants in homogeneous neighborhoods, as measured by educational attainment, received more regulatory attention, but this wasn't true for measures of racial homogeneity. 'Environmental Justice' concerns could still arise: a politically well-connected population could intervene in permit renewals, organize community action against the plant, or encourage regulators to pursue qualitatively different avenues (e.g. the use of criminal penalties for violations) that we could not observe in our data. Still, we might have expected to see some evidence of differences in the intensity of regulatory activity if 'Environmental Justice' concerns had large effects.

We also wrote two papers using the data on electric utilities, examining the impact on facility emissions and production costs of a market-based regulatory intervention: the sulfur allowance trading program. In one paper ("Benefits and Costs from Sulfur Dioxide Trading: A Distributional Analysis") we focused on the distribution of benefits and costs from the trading across different socio-economic groups. We found that the benefits of the program (based on reductions in mortality) greatly exceeded the costs of the program (based on higher electricity prices) for everyone affected by the program, given the considerable reductions in SO2 emissions. Comparing the relative shares in benefits and costs for different demographic groups, we found that both blacks and Hispanics received a higher share of the benefits than they paid of the costs; the poor seemed to receive a slightly lower share of the benefits than they paid of the costs, but the benefits still greatly outweighed the costs. This lack of evidence for 'Environmental Justice' concerns is similar to the results from our "Spatial Patterns" paper.

In our second paper on electric utilities ("A Spatial Analysis of the Consequences of the SO2 Trading Program"), we examined the spatial distribution of sulfur dioxide emissions, based on the allowance trading that followed the enactment of the 1990 Clean Air Act Amendments. We considered the benefits and costs of the trading under two scenarios: one where the alternative emissions at each plant were their actual emissions before 1995, and the other that assumed the same overall reduction in emissions, but with the reduction assumed to be allocated proportionately to each plant. Allowance trading saved a substantial fraction of the abatement costs (in either of the scenarios), but the geographic shift in SO2 emissions induced by allowance trading shifted abatement spatially in an adverse direction: plants that bought allowances (and hence emitted more SO2) tended to be plants with high benefits of abatement and plants that sold allowances (and hence emitted less SO2) tended to be have moderate or low benefits.

This raised the question of whether a spatially-based approach to trading would improve the results. We found that alternative trading zone models (using either 2 or 6 trading zones) resulted in only modest reductions in the overall performance of the model (reducing the shortfall in benefits by about 11-14%). This arose from the considerable heterogeneity of marginal benefits across plants within the same region: even within narrowly-defined regions there were both buyers and sellers of allowances, and the purchasers tended to be older facilities located near urban centers (with correspondingly high abatement benefits). Given the increase in complexity needed to implement a multi-region trading system, the modest improvements in benefits may not be sufficient justification for making a change.

3. Quality Assurance Activities

The overall goal of this research project was to increase our understanding of the factors affecting environmental performance, examining a wide range of factors including regulatory enforcement activity, state and local political and community pressures, and plant-specific factors such as pollution abatement costs. Four specific research areas were examined, as described above in the "Research Objectives" section. The project involved collecting and combining plant-level data from a variety of sources, including EPA databases, industry directories, Compustat, and Census Bureau datafiles. These databases were analyzed using a variety of statistical models. None of this involved making direct measurements on environmental variables, so issues related to preparing a physical sampling design, handling samples, and calibrating measurement equipment were not relevant. Nevertheless, when preparing and analyzing data, it was important to pay attention to data quality.

The first step in preparing a plant-level database was to define the sample of plants to be considered. For the paper, oil, and steel industries (created in earlier research) we relied on industry directories to identify plants, but then examined directories from multiple years and compared the plant lists to lists of plants in those industries from EPA databases, to try to get as complete a list as possible. We also attempted to get as accurate an address as possible for each plant, again by comparing different sources for consistency in address information. For the electric utility industry data, we relied on a database prepared by Economic Sciences Corporation. This database has been prepared for commercial sale and use in litigation (as well as research), so we judge that its quality level is fairly high, though we compared the data to other sources where possible.

We used the industry directories to identify certain characteristics of the plants (age, production technology, capacity). We also identified the company which owns each plant, using multiple years of directories to identify ownership changes. This enabled us to link each plant to the Compustat database to gather financial information on the owning company. The Compustat database is prepared by Standard & Poors, Inc, and is the standard source of data from financial returns filed by publicly held companies. Given the legal requirements associated with these filings, and the intensive scrutiny paid to this database by investors and companies, we believe the data is of good quality, but still checked variation over time in key Compustat variables, to insure that changes in ownership or mergers and acquisitions did not adversely affect the data. Plants which were privately owned were indicated with a 'missing data' dummy variable, to allow their inclusion in the later analysis without biasing the results for the firm variables.

Information from EPA databases was linked in, based on the plant-level name and address information. Past experience with EPA datasets taught us the importance of examining data closely, especially in the earlier years of the database, as occasional typing errors or misreporting of units is not unknown, and much of the data is self-reported by plants. Recently EPA has put substantial resources into the Facility Registry System (FRS) database, designed to link together all of the EPA data records referring to the each individual facility, which should reduce such errors. To the extent that we have multiple data sources or multiple years of observation for a particular piece of information, we compared them to identify any discrepancies (e.g. both the Compliance Data System and the National Emissions Data System contain air pollution emissions data for the 1980s) - few problems of this type were observed. Simple tests of ratios (e.g. comparing emissions to plant capacity) can help identify potential outliers. In general, errors in measuring an explanatory variable tend to bias its estimated coefficient towards zero, leading the model to understate its true impact. Therefore we were sensitive to problems of data quality, to ensure unbiased results.

Information at the Census Bureau was linked to the other data, working at the Boston Research Data Center, using name and address information. The Census data was provided by firms, as required by law, under strict confidentiality conditions. This was expected to minimize any inclination for misreporting. However, experience with Census data indicates that some data quality concerns are appropriate, particularly relating to imputed fields (in some cases, missing data is filled in by a Census Bureau imputation program). We examined year-to-year variation in key data fields to identify potential errors in the data, and omitted from the analysis sample any observation with a large part of its data imputed, or with other obvious data quality problems.

These steps were also followed to create the database for the 4-city analysis, with a few adjustments: we included all plants in all manufacturing industries for each city, making it impractical to collect sufficient industry directory data. Instead we took the plant identifiers for the external version of the data from EPA regulatory datasets, relying on the presence of data for several different types of pollution (air, water, and toxics) to reduce the likelihood of missing an important plant. This data was then matched to the internal Census files for manufacturing and non-manufacturing establishments using name-address matching, relying on Census geo-coding to identify the set of plants in a particular local area. This data has the particular advantage (in Economic Census years) of allowing us to identify all the plants in an area. We used this data to examine whether there was any selectivity in which of those plants were being included in the EPA regulatory datasets, and found no evidence of such selectivity.

Once the database was created, we analyzed the determinants of a variety of measures of environmental performance (absolute levels of air, water, and toxic emissions, as well as compliance status), using standard statistical methods in statistical packages including Stata, SAS, and Matlab. Since we used well-known statistical packages, we did not see any need to test the validity of the statistical routines themselves.

A multiple regression estimator was used to model the dependence of each performance measure on a set of plant and firm characteristics, along with measures of government regulatory interventions and community and political pressures at the local and state levels. We used a seemingly unrelated estimation model to test for unobserved factors affecting performance on a variety of pollutants. We interacted some plant and firm characteristics with the measures of government interventions, to test for differential sensitivity to interventions across observed characteristics. Spatial econometric methods were used in the 4-city analysis.

For each of these statistical analyses, we tested a variety of different sets of explanatory variables, to see whether the results from a particular model were sensitive to the specification. More generally, the different industries, different pollution media, and the 4-city analysis were all designed to provide an internal check on the validity of any particular model, by seeing whether it is consistent with the other results. This is not to say that all models must give the same result - enforcement actions may have more impact on air pollution than on water pollution, or more impact at paper mills than at steel mills - but we were sensitive to comparisons across models.

Finally, we took advantage of the outside quality control provided by interactions with other researchers. We presented preliminary results at professional conferences, and circulated preliminary versions of the papers for comment. Some of the research results have already gone through the peer-review process and been published in academic journals - we expect eventually to publish all of the papers generated in this project, either in peer-reviewed journals or in conference volumes.

4. Publications and Presentations

"Assessing Multi-Dimensional Performance: Environmental and Economic Outcomes" by Ronald Shadbegian and Wayne Gray. Published in Journal of Productivity Analysis, December 2006, pp. 213-234.

"The Environmental Performance of Polluting Plants: A Spatial Analysis" by Wayne Gray and Ronald Shadbegian. Presented at Census Research Data Center Conference (October 2005), Regional Science Association Meetings (November 2005), and Southern Economic Association Meetings (November 2005). Published in Journal of Regional Science, February 2007, pp. 63-84.

"Benefits and Costs from Sulfur Dioxide Trading: A Distributional Analysis" by Ronald Shadbegian, Wayne Gray, and Cynthia Morgan. Presented at Connecticut College's "Acid in the Environment: Lessons Learned and Future Prospects" conference (April 2005). Published in Acid in the Environment: Lessons Learned and Future Prospects (Gerald R. Visgilio and Diana M. Whitelaw, eds), Springer Science+Business Media: New York, 2007.

"Do Firms Shift Production across States to Avoid Environmental Regulation?" by Wayne B. Gray and Ronald J. Shadbegian. Presented at CAED conference in Chicago (September 2006). Being revised for journal resubmission.

"A Spatial Analysis of the Consequences of the SO2 Trading Program" by Ronald J. Shadbegian, Wayne B. Gray, and Cynthia Morgan. Presented at Third World Congress of Environmental and Resource Economists, Kyoto (July 2006) in session (organized by Gray) on "Spatial Variation in Benefits and Costs for Environmental Policy Making"; International Atlantic Economic Society meeting in Philadelphia (October 2006); EPA's Market Mechanisms and Incentives Progress Review Workshop in Washington, DC (October 2006). Being prepared for journal submission.

"Regulatory Regime Changes Under Federalism: Do States Matter More?" by Wayne B. Gray and Ronald J. Shadbegian. Presented at Environmental Economics and Policy Seminar, Harvard University (May 2007); EPA-ORD Science Day conference in Boston (October 2007); Brandeis University (November 2007); Yale University (November 2007); University of New Hampshire (December 2007); EPA Environmental Behavior and Decision-Making Conference in New York (January 2008). Being prepared for journal submission.

"What Determines the Opportunity Cost of Pollution Abatement? A Production Function Approach" by Ronald Shadbegian and Wayne Gray. Presented at Asia-Pacific Productivity Conference, Taipei (July 2008). Being prepared for journal submission.

"Spatial Patterns in Regulatory Enforcement: Local Tests of Environmental Justice" by Wayne B. Gray and Ronald J. Shadbegian. Presented at Markets for Land and Pollution: Implications for Environmental Justice Workshop, Big Sky, Montana (October 2008) and AERE/ASSA meetings in San Francisco (January 2009). Expected to be published in conference volume based on Montana conference.

5. Project Details

Rather than trying to summarize the eight papers produced under this project, I present here the papers in their entirety - this enables the reader to see the full range of information used in all the analyses, as well as putting the results into the context of the existing literature.

5A. "Assessing Multi-Dimensional Performance: Environmental and Economic Outcomes"

1. Introduction

During the past 30 years there have been substantial improvements in U.S. air and water quality due in large part to increasing stringency of regulation which has caused continuous declines in emissions from industrial sources. This study examines the determinants of both environmental and economic performance for plants in three traditional smoke-stack industries – pulp and paper, oil, and steel. We measure environmental performance based on a plant's air, water, and toxic emissions per unit of output and economic performance based on its technical efficiency.

Much of the empirical research on the impact of environmental regulation has concentrated on the impact of reported pollution abatement costs on productivity. [1] However, there have been a few studies which examine the environmental performance of polluting plants including Magat and Viscusi (1990), Gray and Deily (1996), Laplante and Rilstone (1996), Nadeau (1997), Gray and Shadbegian (2005) and Shadbegian and Gray (2003). These studies have primarily focused on the efficacy of EPA enforcement in terms of raising compliance rates or lowering emissions. Gray and Deily, and Gray and Shadbegian show that plants which receive more air enforcement activity by regulators have higher compliance rates, Nadeau finds they have shorter spells in non-compliance, while both Magat and Viscusi and Laplante and Rilstone find that water pollution enforcement activity reduces water discharges. Shadbegian and Gray (2003) examine data for a cross-section of 68 pulp and paper mills, finding that emissions are significantly lower at plants with a larger air pollution abatement capital stock, which face more stringent local regulation, and with higher production efficiency. They also test for residual correlations between emissions and efficiency, concluding that plants which are more efficient in production are also more efficient in pollution abatement.

Our current study examines the determinants of both environmental and economic performance using plant-level data in three traditional smoke-stack industries. This study extends Shadbegian and Gray (2003) by using a stochastic frontier model to estimate an output-oriented measure of technical efficiency rather than using growth-accounting efficiency measures, by covering additional industries (oil refineries and steel mills) and additional media (water pollution and toxic releases), and by using more recent data (1990-2000). These extensions allow us to determine how consistent the earlier results are across time and industries. Using confidential plant-level Census data, we identify each plant's output, its use of labor, capital, and materials, its age, and its pollution abatement spending. We merge Census data to several EPA datasets with plant-level emissions of air, water, and toxic pollutants and enforcement activity. We also add characteristics of the plant's production technology taken from industry directories, and firm financial data from Compustat.

Our results include 18 different equations (3 industries * (5 pollutants + efficiency)), so our discussion focuses more on patterns of coefficient signs and significance across equations than on individual coefficients. The most consistent results we find are for plant age and technology – older plants are significantly less efficient in production, while plants that use the dirtier production technology are somewhat more efficient. Plants owned by firms that focus on the plant's industry are usually more efficient, but being owned by a larger or more profitable firm does not seem to matter much.

We use Seemingly Unrelated Regressions (SUR) models to examine the determinants of environmental performance and its relationship to economic performance. Plants spending more on pollution abatement tend to have lower measured production efficiency. Local regulatory stringency shows mixed results, with oil refineries showing (surprisingly) higher efficiency in high-stringency areas, while paper and steel mills show the expected lower efficiency. We find a

[1] See Denison (1979), Gollop and Roberts (1983), Gray (1986, 1987), Boyd and McClelland (1999), Berman and Bui (2001), and Gray and Shadbegian (2002, 2003a).

surprising difference between inspections and other enforcement actions, with both environmental performance and production efficiency being lower for plants facing more inspections and higher for plants facing other enforcement actions.

The SUR cross-equation residual correlations show a positive relationship within a given pollution medium (e.g. plants emitting more $PM_{2.5}$ emit more SO_2). There are some positive correlations across different media, but they are less often significant. Finally, when significant, we find positive correlations between environmental and economic performance, especially for steel mills. This is contrary to the tradeoffs in performance (negative correlations) expected from our model, and suggests the importance of some as yet unmeasured characteristics that improve a plant's performance along both environmental and economic dimensions.

Section 2 provides some information about the generation of air and water pollution in the paper, oil, and steel industries. Section 3 discusses the stochastic frontier production function model and its application here. Section 4 describes the data used in the analysis. In section 5 we describe the major econometric issue with our analysis – endogeneity of environmental regulation. Section 6 presents the results, and section 7 concludes the paper.

2. Air and Water Pollution in the Paper, Oil and Steel Industries

The three industries we study in this paper – paper, oil and steel – are all heavy emitters of both air and water pollution. For example, in 1996 each of these industries ranks in the top six of all 2-digit SIC industries in terms of fine particulate and sulfur dioxide (SO_2) emissions per dollar of output (see Aiken and Pasurka (2003)). These three industries are also among the top users of industrial process water and thus have major water pollution concerns as well. Now we describe in a little more detail the pollution concerns of each of our three industries.

Pulp and paper mills are a major emitter of both air pollution – particulates ($PM_{2.5}$), SO_2, and nitrogen oxides (NO_X) – and water pollution – biological oxygen demand (BOD) and suspended solids (TSS). The majority of air pollution is created during the pulping stage of paper production. Pulp mills and integrated mills (paper mills that incorporate a pulping process) have large boilers which burn fossil fuels, liquor waste solids, and wood wastes to generate power, thus creating the potential for air pollution problems. Similarly, considerable water and toxic pollution is created during the pulping process, especially with bleached pulp. A typical pulp and integrated mill uses between 4,000-12,000 gallons of water to produce one ton of pulp, and bleached kraft pulping mills were identified in the 1980s as a source of dioxin, a highly toxic pollutant.

Oil refineries use numerous process heaters to heat process streams or to generate steam (boilers) for heating or steam stripping. Incomplete combustion or heaters fired with refinery fuel pitch or residuals are a significant source of air pollution, including carbon monoxide (CO), SO_2, NOX, and $PM_{2.5}$. Of the many production techniques employed at oil refineries, catalytic cracking is one of the most significant sources of air pollutants – producing heater flue gas emissions, fugitive emissions, and emissions generated during regeneration of the catalyst. Water pollution concerns are mainly with wastewaters which consist of cooling water, process water, sanitary sewage water, and storm water run-off. Many refineries have had issues with unintentional releases of liquid hydrocarbons to ground water and surface waters. The actual volume of hydrocarbons released are relatively small, however there is the potential to contaminate large volumes of ground water and surface water, possibly posing a substantial risk to human health and the environment.

The main processes for steel production use either traditional blast furnaces (integrated mills) or the newer, cleaner electric arc furnaces. The use of blast furnaces is necessarily preceded by two additional production stages: coke-making (coke is produced from coal) and iron-making (molten iron is produced from iron ore and coke). The coke-making process is one of the steel industry's areas of greatest environmental concerns, producing both air and water emissions. Air emissions include both fine particles of coke and various sulfur compounds. Water is used to reduce or cool the gases to temperatures at which they can be effectively treated by the gas abatement equipment (roughly 1,000 gallons of water per ton of steel are used for a wet scrubber). On the other hand, the primary raw material for electric arc furnace mills is scrap metal. Since scrap metal is used instead of molten iron, there are no coke-making or iron-making operations associated with steel production, which makes it a much cleaner process than that of blast furnaces. However this process does still produce fine particles and gaseous byproducts which need to be abated.

3. Determinants of Environmental and Economic Performance

We model the decisions of optimizing plants, rather than firms. Our information on environmental and economic performance is defined at the plant-level, and we do not have data for all the firm's plants, so we cannot aggregate up to the firm level, although we do know which firm owns the plant, and our dataset includes some firm characteristics.

We assume the plant operates as a price-taker in both product and factor markets. A plant chooses its level of inputs (K, L, M) to maximize profits (π_{it}), while facing constraints to achieve a given level of environmental performance for each of a set of pollutants (ENV_j^*) and a per-unit cost of improving environmental performance on that pollutant ($Penv_j$):

(1) $\pi_{it} = (Py_{it} * Y_{it}) - (P_l L_{it} + P_k K_{it} + P_m M_{it}) - \sum(Penv_j * ENV_{ijt})$
s.t. $Y_{it} = f(L_{it}, K_{it}, M_{it}) * g(ENF_{it}, X_{it}, XF_t, YEAR_t)$
and $ENV_{ijt} \geq ENV^*_{ijt}(ENF_{it}, X_{it}, XF_t, YEAR_t)$.

Here both output and required environmental performance levels depend on a set of explanatory variables including regulatory enforcement (ENF), plant characteristics (X_i), firm characteristics (XF), and time. For ease of interpretation, we assume that the impact of these explanatory variables on output, g(), is separable from the contribution of the productive inputs, affecting overall plant efficiency without biasing the input choices.

Plant characteristics include plant age and production technology. Older plants are expected to be less productive, and are likely to find it more costly to achieve a given level of environmental performance. Certain technologies may be more or less efficient, and may also differ in their pollution emission levels. Existing facilities may remain in operation in these capital-intensive industries, even though no longer on the production frontier, as long as they're able to cover their operating costs.[2]

[2] Regulatory pressures can be related to plant closings, as shown by Deily and Gray (1991) for the steel industry in the early1980s, but there were fewer closings in our industries during the current period.

Firm characteristics include firm size, industry focus, and profitability. Larger firms may face economies of scale in providing technical assistance to their plants to improve production efficiency or reduce emissions. If this technical assistance is industry-specific, a firm whose expertise is concentrated on a single industry will have an advantage. A more profitable firm will have more internally-generated funds available to invest, allowing its plants to invest more in both productive and environmental capital, improving its performance on both dimensions.

From (1) we obtain the usual marginal conditions on productive inputs K, L, and M, with plants equating their marginal revenue products with input prices. However, there are two potential sources of differences across plants in their profitability. The plant's production function is affected by plant, firm, and regulatory variables, and could shift over time. In addition, achieving environmental performance (abating emissions) is costly, so that higher environmental performance should be associated with lower profitability, all else equal. Note that equation (1) includes only productive inputs in K, L, and M (abatement inputs are implicitly counted in Penvj*ENVj). To the extent that our measures of K, L, and M include abatement inputs, we will tend to overstate the plant's productive inputs, leading to the appearance of lower efficiency at plants with high abatement costs (Gray (1987)).[3]

Plants are expected to achieve their required levels of environmental performance (ENV^*), but the required performance levels can vary across plants, based on plant and firm characteristics as well as regulatory pressures (ENF_{it}). These regulatory pressures may include differences in the stringency of regulations applicable to a particular plant. They may also include the intensity of enforcement activity directed at the plant. Some variations across plants in "required" performance may be self-imposed and tied to firm characteristics: large, well-known firms selling in national consumer markets may feel more market pressures to avoid adverse publicity associated with poor environmental performance. Other variations in regulatory constraints may be tied to plant characteristics, if grandfathering exempts some older plants from strict regulations.

Our ability to estimate an optimizing plant's decision process in (1) is constrained by missing information. We do not have data on input price variation across plants, so we estimate a production function rather than a cost function. While we have some information about the plant's pollution abatement expenditures, past research shows the possibility of measurement error (Gray and Shadbegian (2002), Shadbegian and Gray (2005)). Finally, the information on environmental performance is only available for subsamples of the dataset, and these subsamples differ by pollution media, so very few observations have complete data for all three media.

Because we do not have the data to estimate the full optimization model (1), we focus initially on economic performance in terms of production efficiency. We allow a plant's observed efficiency (Y/f(L,K,M)) to be a function of the explanatory variables X_i, XF, and ENF. One drawback of this reduced form approach is that we are not able to identify whether a variable is reducing efficiency directly by reducing g(.), or indirectly by increasing ENV^* and the plant's resources devoted to pollution abatement: our estimated coefficients will be a combination of these two effects.

The measure of economic performance we use in this study is closely associated to the efficiency measures developed by Farrell (1957), which can be disaggregated into technical

[3] Shadbegian and Gray (2005) used annual data on abatement costs for detailed inputs (not available for the 1990s) to make such adjustments to production function estimation.

efficiency (TE) and allocative efficiency.[4] Technical efficiency is the ability of a plant to obtain the maximum amount of output for any given level of inputs. Allocative efficiency is the ability of the plant to use its inputs in the correct proportion given input prices. Because our data sets do not include input price variation across plants, we concentrate on TE. We measure TE from an output-based perspective as the proportional amount by which a plant could increase its output while holding constant its level of inputs, by moving onto its production frontier.

We estimate a stochastic frontier (SF) production function, measuring TE by how far each plant is from the frontier. The SF production function model we use was developed by Battese and Coelli (1995) for panel data and it allows for time-varying plant effects.[5] The model may be written as:

(2) $y_{it} = x_{it}\beta + v_{it} - u_{it}$

where y_{it} is the plant's output and x_{it} is a vector of inputs, both measured in logarithms making the underlying production function Cobb-Douglas. The error term in (2) is divided into two components, v_{it} and u_{it}. v_{it} is the usual error term arising from measurement error and other random events, i.i.d. normal with mean=0, variance σ_v^2, and independent of u_{it}. u_{it} is a non-negative random variable, which captures technical inefficiency, reflecting the extent to which the plant's output is less than expected, given its inputs. We assume a truncated normal distribution for u_{it}, though the half normal and exponential distributions can also be used. The TE of the ith plant at time t in this model is given by $TE_{it} = \exp(-u_{it})$ [see Coelli et al. (1998)].

The purpose of our study is not to estimate technical efficiency measures for their own sake, but to explain the variation in technical efficiency across plants within a given industry (paper, steel, and oil). In particular, we are interested in the potential impact of environmental regulation on TE. We could begin by estimating TE measures based on a first stage analysis, using equation (2). In a second stage we would then regress TE on a set of plant specific characteristics z (including measures of environmental regulation), in an attempt to explain how these factors contribute to the variation in TE:

(3) $TE_{it} = \exp(-u_{it}) = z_{it}\delta + \varepsilon_{it}$.

This sort of two-stage approach has been employed in several empirical studies, including Pitt and Lee (1981) and Bernstein et al (1990).

We instead estimate the two stages jointly, using an alternate SF model proposed by Battese and Coelli (1995) to improve on the usual two-stage estimator.[6] The technical

[4] It is also possible to decompose TE into two parts (1) pure technical inefficiency (i.e., not producing on the isoquant) and (2) deviations from constant returns to scale (i.e., producing under diminishing or increasing returns). By assuming constant returns, Farrell excluded the second part from his calculations.

[5] This is an extension of the SF approach first proposed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977).

[6] In the two-stage estimation procedure, the first stage estimates the efficiency effects assuming they are independently distributed, while the second stage models them as a function of the plant's characteristics (so the efficiencies for any two observations of the same plant would be

inefficiency effects [u_{it}'s from equation (2)] are assumed to be distributed independently (but not identically) according to the truncated normal distribution with mean m_{it} and variance σ_u^2,

(4) $$m_{it} = z_{it}\delta,$$

where z_{it} are variables (X_i, XF, and ENF) explaining the variation in technical inefficiency and δ is a vector of parameters to be estimated.[7] In other words, in the Battese and Coelli model the technical inefficiency effects are conditioned on the characteristics of each plant.

Our estimation is carried out using a Maximum Likelihood routine provided in FRONTIER version 4.1. FRONTIER provides three measures of the extent of technical inefficiency in the model. One is the mean level of efficiency achieved by the plants. Another is $\gamma = \sigma_u^2/(\sigma_v^2+\sigma_u^2)$, the fraction of the combined error term attributed to TE (the one-sided part of the error term). Finally, a Likelihood Ratio test measures whether the complete two-stage model with each observation's inefficiency depending on the explanatory variables does significantly better than a simple one-stage model with no inefficiency term.

We perform a second set of analyses based on a seemingly unrelated regression (SUR) model incorporating separate equations for each of our measures of environmental performance, in addition to a measure of economic performance. Environmental performance is measured by the plant's annual emissions of five pollutants across three media: fine particulate matter (air), sulfur dioxide (air), biological oxygen demand (water), total suspended solids (water), and total toxic releases (toxics), each measured as emissions per unit of plant output. For each of the three pollution media, we estimate a separate SUR model, corresponding to the distinct subsamples of data with emissions information from each medium. The SUR model includes one equation for production inefficiency along with additional equations for each of that medium's pollutants. The measure of economic performance is generated once for each industry, using a first-stage SF index of production inefficiency applied to the entire sample for the industry, with the appropriate subsample of observations included in each SUR model. Note that for both measures of performance higher values mean poorer performance.

Estimating separate equations for environmental and economic performance may help resolve ambiguities of interpretation of the initial analyses that concentrate on production efficiency, where we noted that we could not distinguish between the impact of a variable on g(.) or on ENV^* in equation (1). The environmental equations in the SUR help show whether a variable affects ENV^*, along with the magnitude and direction of that effect.

In addition, the SUR model allows us to examine the correlation in plant performance across the various economic and environmental performance measures. There are competing explanations for the expected correlations across the different outcome measures. Equation (1) emphasizes a tradeoff in performance, with greater expenditures on pollution abatement coming at the expense of economic efficiency. On the other hand, there could be omitted plant characteristics, such as having an excellent manager, that result in both higher economic

---

correlated). Jointly estimating both stages is more efficient and removes this inconsistency in assumptions.

[7] Note that FRONTIER estimates inefficiency measures (1/TE), not efficiency measures.

efficiency and lower emissions. Similar arguments could be made for positive or negative correlations among the environmental measures.

4. Data Description

Research for this study was done at the Census Bureau's Boston Research Data Center, using confidential Census databases developed by the Census's Center for Economic Studies. The principal Census data source is the Longitudinal Research Database (LRD), which contains information on individual manufacturing establishments from the Census of Manufactures and Annual Survey of Manufacturers linked together over time (for a more details concerning LRD data, see McGuckin and Pascoe (1988)). From the LRD we selected 327 pulp and paper mills (mainly SIC 2611 and 2621), 121 oil refineries (SIC 2911), and 83 steel mills (SIC 3312). We gathered the data for 1990-2000; our sample is not completely balanced, however most plants are present in most years over the time period.

The Census data is the primary information used for estimating the frontier production function. We measure OUTPUT as the log of the real value of shipments from the plant.[8] We use three inputs in the production function: LABOR, CAPITAL, and MATERIALS. Our measure of LABOR input is the log of production worker hours. CAPITAL is the log of the real gross book value of the plant's capital stock and MATERIALS is the log of the plant's real spending on materials inputs.

We capture differences in technology across plants (high-polluting versus low-polluting) with a technology dummy variable, DIRTY TECH, indicating that the plant incorporates the higher-polluting production process.[9] Therefore DIRTY TECH=1 for paper mills incorporating a pulping process, for oil refineries using catalytic cracking, and for integrated steel mills.[10] Our control for plant age, OLD, is a dummy variable, indicating whether the plant was in operation before 1972.[11] We control for plant size with the log of plant employment (production workers), PLANTEMP. We also include a dummy variable, MULTIUNIT, indicating whether a plant is part of a firm that owns more than one manufacturing plant.

To our LRD data we add data from Census Bureau's annual Pollution Abatement Costs and Expenditures (PACE) survey. The PACE survey provides annual plant-level pollution abatement operating cost data for air and water pollution. We divide pollution abatement operating costs for air and water by a measure of the plant's capacity (where plant capacity is the

---

[8] 4-digit SIC deflators discussed in Bartelsman and Gray (1996) were used to put nominal values into real terms.

[9] We categorize each plant's technology based on information from their respective industry directories: Lockwood-Post Pulp and Paper Directory; Oil and Gas Journal; and Directory of Iron and Steel Plants.

[10] DIRTY TECH for oil refineries is mostly connected to air pollution, but for consistency we include it in the water pollution models as well.

[11] 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 1972) 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 1970s.

average of the plant's peak two years of real shipments in \$1000s [12]) to get a measure of the pollution abatement expenditure intensity at the plant, AIR PAOC and WATER PAOC respectively.[13]

To our Census data we merge firm-level information from the Compustat database. The ownership linkage between firms and plants was based on industry directories capturing changes in plant ownership over time. From the industry directories we calculated FIRMPLANTS, the log of the number of other plants owned by the firm in that particular industry. From Compustat data we calculate the log of firm employment, FIRMEMP, and FIRMPROF, the firm's profit rate (net income divided by capital stock). We also include a dummy variable, FIRMSIC, indicating that the firm's primary activity, as identified by Compustat, was in the same industry as the plant's primary activity.[14]

Our environmental performance measures come from several EPA databases: National Emissions Inventory (NEI), Permit Compliance System (PSC), Toxic Release Inventory (TRI), and Compliance Data System (CDS). Our air emissions data come from the NEI database. The emissions data is provided separately for the major criteria air pollutants. In our analysis we focus on fine particulate matter[15] ($PM_{2.5}$) and sulfur dioxide (SO_2), since they are common across all three industries and were the major focus of air pollution regulation for these industries during in the 1990's.[16] We measure the emissions of $PM_{2.5}$ and SO_2 in log intensity form (the log of emissions in tons per year relative to plant capacity).

Our measures of water pollution are derived from EPA's PCS data set. We use two common measures of water pollution, biological oxygen demand (BOD) and total suspended solids (TSS). As with our air emissions we measure the emissions of each pollutant, BOD and TSS, in log intensity form (the log of emissions in tons per year, relative to capacity). Our final measure of emissions comes from EPA's TRI data set. The TRI provides detailed information on the disposal of toxic waste from manufacturing plants. We calculate the total TRI discharge intensity for each plant, TOXIC, as the log of annual pounds of toxic environmental releases relative to capacity.[17]

The CDS and PCS also provide annual measures of air and water pollution enforcement activity, respectively, directed towards each plant. To measure air/water pollution enforcement, we use two variables XACT and XINSP (where X = AIR and WATER). XACT is the log of the

---

[12] All variables below that are measured relative to plant capacity are measured in this way.
[13] For the TRI analysis we use total pollution abatement operating costs relative to plant size (PAOC).
[14] Regressions include a dummy variable for missing Compustat data, MISSFIRM, which cannot be reported due to Census Bureau disclosure rules.
[15] Particles of 2.5 micrometers or less in diameter.
[16] Relatively few of our emissions reports are based on actual monitored emissions; the majority of emission reports are based on calculated emissions or engineering estimates, based on the capacity of the production process and the design efficiency of the installed pollution abatement equipment.
[17] TRI chemicals are limited to those included in the 'core chemical' list for the 1988 TRI (found at http://www.epa.gov/triexplorer/list-chemical-core-88.htm).

total number of non-inspection actions (e.g. notices of violation, penalties, phone calls) directed towards the plant during the year. XINSP is the log of the total number of 'inspection-type' actions (e.g. inspections, emissions monitoring, stack tests). These two different measures of enforcement activity may have different impacts on emissions and may have different degrees of endogeneity with emissions.[18]

Other regulatory pressures expected to influence the level of environmental performance at a plant are NONATTAIN and GREEN VOTE. NONATTAIN, a measure of local regulatory stringency specific to air pollution, is a dummy variable indicating whether the plant is located in a county that failed to attain the National Ambient Air Quality Standards for PM or SO_2. The attainment status of each county is published each year in the Federal Register.[19] Plants located in non-attainment areas face stricter regulations than similar plants in attainment areas. For the plants in our sample, non-attainment status is almost always due to excessive fine particulates; sulfur dioxide non-attainment is much less common. Therefore, we consider a plant to be in a non-attainment area if the area is violation of either the ambient air quality standard for PM or SO_2.

We proxy for the state-level regulatory climate with GREEN VOTE, a measure of support for environmental legislation by that state's Congressional delegation. The League of Conservation Voters calculates the fraction of votes favoring environmental issues each year for each member of Congress. GREEN VOTE is the average score for the state's House of Representative delegation.

5. Econometric Issues

Several econometric issues arise in the estimation of equation (1). First, our emissions data are far from being a balanced panel: the air emissions data is from 1990, 1996, and 1999, while the water emissions data is for 1994-2000 and the toxic release data is for 1990-2000, though not all plants are present in all years. Our Census data, by contrast, is relatively balanced. The sparse emissions data complicates the estimation process for multi-equation models: sample sizes would diminish rapidly if we required the plant to have simultaneous data for multiple emissions measures across different media. Rather than estimating a multi-equation model directly, we concentrate on single-equation models. Even when we use an SUR model to allow for correlations in the residuals across equations, we only examine one pollution medium at a time: estimating two air pollutants and efficiency, two water pollutants and efficiency, and toxic releases and efficiency, rather than requiring water, air, and toxic data simultaneously. We then calculate pairwise correlations in residuals across all of the equations to see whether the unexplained portions of the different pollutants are related to each other, without trying to calculate an SUR model across all pollutants at once.

The sparseness of the data also influences the variable construction. Where necessary, we rely heavily on 'average' or 'most recent' values, rather than insisting on simultaneous data. For example, the pollution abatement cost data ends in 1994, while the water pollution data does

[18] Gray and Shadbegian (2005) found some evidence that compliance with air pollution regulations by plants which are owned by larger firms is less sensitive to inspections and more sensitive to enforcement actions than those owned by smaller firms.
[19] We would like to thank Randy Becker, who created this dataset and graciously made it available to us for this project. The data is described in more detail in Becker (2001).

not start until 1995 for many plants; to fill in the missing values, we lag the most recent abatement cost values for PAOC in the models.[20]

Finally, any study of enforcement and environmental performance must address the issue of the endogeneity of enforcement. Harrington (1988) suggests a sophisticated explanation of regulator behavior in which an optimal regulatory strategy may well involve focusing on long-run enforcement activity on the few non-compliant plants to punish them for not complying with environmental regulation. Whatever the reason, previous research has had little difficulty identifying an inverse relationship between regulatory activity and compliance behavior: non-complying plants get more enforcement.

We use an instrumental variable (IV) estimator to overcome the potential endogeneity of enforcement activity. In the first stage, we use a relatively simple model to predict enforcement activity, focusing on variables that are clearly exogenous with respect to the plant's environmental performance: year dummies, state dummies, DIRTY TECH, OLD, NONATTAIN, and GREEN VOTE. Year dummies allow for changes in enforcement activity over time, while state dummies allow for cross-state differences in enforcement activity (and/or for differences in reporting of enforcement activity in the CDS and PCS). NONATTAIN controls for different regulatory stringency in different areas, while DIRTY TECH and OLD provide plant characteristics. GREEN VOTE controls for changes over time in the political support for environmental regulation within the state. The lagged predicted values from these first-stage models are then used in the second-stage environmental performance models. One potential problem with any IV method is a weak performance by the first stage models: here we have first-stage R-squares of about 0.05 for water pollution activity and about 0.25 for air pollution activity.

6. Results

Table 1 lists the definitions of the variables used in the analysis, along with their means and standard deviations. We also present the fraction of the variation in each variable that is cross-sectional (CS) and time-series (TS), to get a better understanding of our ability to control for plant-specific and time-specific variation. As often happens with plant-level data, much of the variation in our key variables is cross-sectional, and several variables of interest are fixed over time (making it impossible to estimate their coefficients through a fixed-effect model).

As noted earlier, the pollution variables are measured relative to plant capacity. Most of these measures are relatively high for paper mills, which has the highest values for all the pollutants except BOD. Steel mills have twice as many employees as oil and paper, while oil refineries have especially high values of output, due to the high cost of the crude oil used in production. About three-quarters of all plants were in operation before 1972 and nearly all are owned by multi-unit firms, with the average plant having 4 other plants in the industry owned by the same company.

Tables 2-4 present the results for the frontier production function model for the three industries: oil in Table 2, paper in Table 3, and steel in Table 4. The first part of the model is a

[20] A revised version of the PACE survey was done in 1999, but it was not longitudinally consistent with the pre-1999 PACE data so it is not used here (see Becker and Shadbegian (2005) for more information).

3-factor Cobb-Douglas production function that generates a measure of the plant's inefficiency, which is in turn explained in the second part of the model by a set of plant, firm, and regulatory characteristics.

The production function estimates in the first part of the model are significant, and reasonably consistent when estimated with different specifications in the second part of the model. The contribution of labor and materials inputs to production varies across industries in the expected way, with production in the oil industry being the most materials-intensive, while the steel industry is the most labor intensive. The estimated contribution of capital to output is significantly positive for only one industry, steel, with an elasticity of about 6%, while the capital coefficients for oil and paper are less than 1% (and surprisingly negative for paper mills).[21] Most of the models show some degree of inefficiency in production. This can be seen in several ways. The mean efficiency measures are in the range of 70-80%, well below 100%. The gamma values, reflecting the importance of the one-sided component of the error as a fraction of the total error variance, show large contributions for oil and paper mills. The likelihood ratio tests for the additional explanatory power contributed by the second (inefficiency-explaining) stage of the model are significant in all models.[22]

The variations in the second part of the model involve adding different sets of variables related to environmental regulation to a basic set of plant and firm characteristics. Recall that the coefficients in the second part are predicting a plant's inefficiency, so positive coefficients are associated with reductions in efficiency. While the coefficients on any given variable remain consistent across the different models for each industry, we do find considerable variations across the industries. The only variables with consistent signs across all three industries are the plant characteristics. Older plants are significantly less efficient, with inefficiency effects on the order of 10-15%. Plants utilizing a dirtier production technology tend to be more efficient from a purely productive viewpoint, though the effects are small (typically 5% or less) and insignificant for oil refineries - this analysis also neglects any negative consequences for the plants from the additional pollution these technologies generate.

The firm characteristics show mixed results, though some patterns emerge when we concentrate on coefficients that are significant in the more general models (3 and 4). Recall that we intend to measure three firm-level attributes: the firm's focus on this industry (FIRMSIC and FIRMPLANTS), the firm's overall size (MULTIUNIT and FIRMEMP), and the financial performance of the firm (FIRMPROF). Firm financial performance has little impact, except in the steel industry, where plants owned by more profitable firms have higher production efficiency (perhaps due to better corporate management decisions, or greater availability of internal funding for investment). Being owned by a firm focused on the industry tends to improve efficiency; only oil has both industry-focus measures significantly negative, but for paper and steel the larger or more significant coefficient is negative. The two firm size measures are truly mixed, getting opposite signs in each industry. For paper and steel mills, multi-unit firms are less efficient and firms with greater employment are more efficient, while the opposite is true for oil refineries.

---

[21] Estimating small and insignificant contributions of capital to output is common in empirical results, as discussed in Griliches and Mairesse (1995).

[22] See Kodde and Palm (1986) for a table of critical values for this test.

The remaining variables in the models provide measures of the regulatory pressures the plant faces to improve its environmental performance, possibly at the expense of its production efficiency. Plants with higher pollution abatement operating costs have lower efficiency, although this effect is only significant for steel mills. Recall that in Gray and Shadbegian (2002), the impact of pollution abatement spending on efficiency was highest for steel mills and smallest for oil refineries, consistent with these results and with Berman and Bui (2001). Measures of stricter local regulatory pressures (VOTE at the state level, and NONATT at the county level) show mixed results, with oil refineries showing (surprisingly) that greater regulatory stringency is associated with improvements in production efficiency. Paper and steel tend to show the expected positive coefficients, though the effects are not always significant. We distinguish between two types of regulatory activity, inspections and other enforcement actions (using predicted values and lags to reduce endogeneity concerns). We find that inspections are associated with lower efficiency and other actions are associated with higher efficiency – results that are consistent across the three industries, but were not predicted by our model.

We also estimate SUR models that include pollution emissions as well as production efficiency as dependent variables. The results are shown separately for each industry in Tables 5-7. Note that the estimation is done on media-specific subsets of the data, combining estimates for air pollutants (SO_2 and $PM_{2.5}$) and efficiency in the first SUR model, water pollutants (BOD and TSS) and efficiency in the second SUR model, and toxic releases (TRI) and efficiency in the third SUR model. The sample sizes vary substantially across media, with the toxic release models having many more observations as compared to the air and water pollution models. The lack of overlap in the media subsamples, alluded to earlier, makes it impossible to estimate a multi-media model in a single subsample. In order to minimize the effects of shifts in sample size on the efficiency part of the model, we estimate a single first-stage frontier model on the full-sample datasets used in Tables 2-4 and use those results to calculate one set of plant inefficiency measures for use in all the SUR runs for that industry.[23]

Comparing the SUR results for production efficiency with the earlier models, we see some similarities, despite the greater diversity in results across the three subsamples of data in each industry. Older plants are significantly less efficient; steel and paper mills using the dirtier technology show greater efficiency, but this does not carry over to oil, and is often insignificant. The coefficients on the firm characteristics show patterns of sign and significance that are similar to those noted earlier in Tables 2-4, though with some variability across data subsamples. On the regulatory variables, plants with greater pollution abatement spending have lower efficiency, GREEN VOTE and NONATTAIN show mixed results, and we continue to find that inspections are associated with reduced production efficiency and other actions are associated with more efficiency.

We now consider the determinants of pollution emissions, as estimated in these SUR models, though fewer of the coefficients are significant. The dirty technology dummy does show the expected positive association with pollution emissions. We find that plants with high abatement spending have greater emissions, though this may reflect reverse causality, with high-emissions plants needing to spend more on abatement. Surprisingly, we find little evidence that older plants emit more – in fact, the evidence for paper mills suggests that older paper mills are

[23] The estimated production function coefficients from that estimate are similar to those in the first part of the simultaneously estimated models in Tables 2-4; results available from authors.

less polluting than newer paper mills, showing no sign of regulatory grandfathering for the older plants. The firm characteristics show fewer consistent effects across pollutants than they had for efficiency. Plants located in non-attainment areas generally have lower emissions of air pollutants. Finally, plants facing fewer inspections and more other enforcement actions tend to have lower emissions.

Of course, a key benefit of the SUR model is being able to examine the correlations in the residuals across the equations. Breusch-Pagan tests generally show significant overall correlations among the set of residuals for each SUR model. For those SUR models examining pollution media with two pollutants (air and water), we find significant positive correlations in the residuals for the two pollutants. The pairwise correlations in emissions residuals across pollutants in different media are usually positive for TRI releases, while SO_2 emissions are negatively related (and $PM_{2.5}$ emissions positively related) to water pollution discharges. The correlations between economic and environmental performance differ in sign across industries, being negative for paper and positive for oil and steel, but all of the statistically significant correlations are positive, and primarily for steel mills.

7. Concluding Remarks

This paper examines plant-level performance using a broad range of data, covering 3 industries and 5 pollutants, estimating the impact of various factors on both economic performance (production efficiency, measured using a stochastic frontier production model) and environmental performance (pollution emissions, measured per unit of plant output). The paper also checks for correlations across the different performance measures. The results do not show perfectly consistent patterns in coefficients across all the different industries and pollutants. This is not surprising given the range of models involved, but it raises a cautionary note to policy-makers (and other researchers): it may be difficult to apply results from a narrowly-focused study to other areas. Constraints on data availability for the pollution measures limit the range of analyses available: different pollution media have data available in different years, ruling out estimating a single simultaneous-equation model that includes all 5 pollutants and production. Instead, analyses of production efficiency are carried out on the full data sample, while other analyses relate economic and environmental performance within specific pollution media.

The basic production function estimates in the stochastic frontier model give sensible results. In all three industries, labor and materials inputs contribute significantly to output, with their relative contributions consistent with their input shares; on the other hand, capital's contribution is significantly positive only for steel mills. We find significant evidence of production inefficiency, with plants producing at about 70%-80% of their potential. Some of the inefficiency can be explained by plant characteristics, e.g. older plants are 10-15% less efficient than newer plants. Firm characteristics seem less important, although firms with a larger presence in the industry seem to have more efficient plants, while being more profitable or larger overall does not consistently raise efficiency.

Factors connected to environmental regulation have some impact on production efficiency. Facilities spending more on pollution abatement have lower efficiency, with a large and significant effect for steel mills. Greater political support at the state level for environmental regulations is associated with lower efficiency in paper and steel mills, but (surprisingly) higher efficiency in oil refineries. Finally, plants facing more regulatory inspections seem to have lower efficiency, while plants facing more of other regulatory actions have higher efficiency.

The SUR models show roughly similar effects for the efficiency equations to those found earlier with the full sample. In the emissions equations, plants using the dirtier technology have greater emissions, but older plants do not always emit more pollution, raising some questions about the importance of grandfathering, at least for the industries, pollutants, and time period being studied. Plants in non-attainment areas show lower emissions of air pollutants, and plants in states with greater pro-environment voting also show somewhat lower emissions (only occasionally significant), providing some indirect evidence for the effectiveness of stricter regulatory policy in reducing emissions. Finally, we find again that regulatory inspections are associated with poorer performance and other regulatory actions with better performance, this time for environmental performance. Combined with the results for production efficiency, this might suggest a policy prescription: do fewer inspections and more other actions. However these results, while consistent across models, must be considered quite tentative, given the complications involved in estimating distinct coefficients for (predicted) inspections and other actions, and given the lack of a clear explanation for this divergence in impacts.

The SUR cross-equation residual correlations show a positive relationship within a given pollution medium (e.g. plants emitting more $PM_{2.5}$ emit more SO_2). This holds less often across media – plants with high toxic releases tend to have higher air and water pollution, but this may reflect the presence of both air and water toxics in the overall TRI numbers. Finally, when significant, we find positive correlations between environmental and economic performance, especially for steel mills, rather than the tradeoffs in performance (negative correlations) expected from our model. This suggests the importance of some unmeasured characteristics that improves both a plant's environmental and economic performance.

We anticipate pursuing extensions of this line of research with a more narrowly defined sets of analyses (one industry or one pollution medium), given the complications found here in estimating and summarizing such a wide range of models. We also plan to further analyze some of the anomalous results we found in this paper. In particular, the substantial difference in coefficients between inspections and other regulatory actions, which may be connected to differences across states in their regulatory strategies, deserves further research. We will also pursue other approaches to identify the as yet unmeasured factors that seem to be driving both environmental and economic performance at the plant level.

REFERENCES

Aigner, Dennis, C.A.Knox Lowell, and Peter Schmidt. (1977). "Formulation and Estimation of Stochastic Frontier Production Function Models," *Journal of Econometrics* 6, 21-37.

Aiken, Deborah Vaughn and Carl A. Pasurka. (2003). "Adjusting the Measurement of US Manuracturing Productivity for Air Pollution Emissions Control." *Resource and Energy Economics*, 25, 329-351.

Bartelsman, Eric J. and Wayne B. Gray. (1996). "The NBER Manufacturing Productivity Database." *NBER Technical Working Paper 205*.

Battese, George E. and Timothy J. Coelli. (1995). "A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function Model for Panel Data," *Empirical Economics*, 20, 325-332.

Becker, Randy A. (2001). "Air Pollution Abatement Costs Under the Clean Air Act: Evidence from the PACE Survey." *Center for Economic Studies Working Paper no. 01-12.*

Becker, Randy A. and Ronald J. Shadbegian. (2005). "A Change of PACE: A Comparison of the 1994 and 1999 Pollution Abatement Costs and Expenditures Survey", *Journal of Economic and Social Measurement*,30, 63-95.

Berman, Eli and Linda Bui. (2001). "Environmental Regulation and Productivity: Evidence from Oil Refineries," *Review of Economics and Statistics*, 83, 498-510.

Boyd, Gale A. and John D. McClelland. (1999). "The Impact of Environmental Constraints on Productivity Improvement in Integrated Paper Plants," *Journal of Environmental Economics and Management*, 38, 121-142.

Coelli, Timothy J. (1996). "A Guide To DEAP Version 2.1: A Data Envelopment Analysis (Computer) Program," CEPA Working Paper 96/08.

Coelli, Timothy J., D.S. Prasada Rao, and George E. Battese. (1998). *An Introduction to Efficiency and Productivity Analysis*, Kluwer Academic Publishers.

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

Denison, Edward P. (1979). *Accounting for Slower Economic Growth: The U.S. in the 1970s*, Washington: The Brookings Institution.

Directory of Iron and Steel Plants, Association for Iron and Steel Technology (various issues).

Farrell, Michael J. (1957). "The Measurement of Productivity," *Journal of the Royal Statistical Society*,120, 253-290.

Gray, Wayne B. (1987). "The cost of regulation: OSHA, EPA and the Productivity Slowdown," *American Economic Review*, 77, 998-1006.

____, (1986). Productivity Versus OSHA and EPA Regulations,UMI Research Press, Ann Arbor, MI.

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

Gray, Wayne B. and Ronald J. Shadbegian. (2005). "When and Why do Plants Comply? Paper Mills in the 1980s," *Law and Policy*, 27, 238-261.

____, (2003a). "Plant Vintage, Technology, and Environmental Regulation," *Journal of Environmental Economics and Management*, 46, 384-402.

_____, (2003b). "The Environmental Performance of Polluting Plants: A Spatial Econometric Approach", presented at Association of Environmental and Resource Economics workshop in Madison, Wisconsin.

____, (2002). "Pollution Abatement Costs, Regulation, and Plant-Level Productivity," in Economic Costs and Consequences of Environmental Regulation, Wayne B. Gray, ed., Ashgate Publishing.

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

Griliches, Zvi and Jacques Mairesse. (1995). "Production Functions: The Search for Identification," *NBER Working Paper 5067*.

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

Kodde, David A. and Franz C. Palm. (1986). "Wald Criteria for Jointly Testing Equality and Inequality Restrictions," *Econometrica*, 54, 1243-1248.

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

Lockwood-Post Pulp and Paper Directory, Miller-Freeman Publishing Company, various issues.

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

McGuckin, Robert H. and George A. Pascoe. (1988), "The Longitudinal Research Database: Status and Research Possibilities." *Survey of Current Business*, 68, 30-37.

Meeusen, Wim and Julien van den Broeck. (1977). "Efficiency Estimation from Cobb-Douglas Production Functions With Composed Error," *International Economic Review* 18, 435-444.

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

Oil and Gas Journal, PennWell Corporation (various issues).

Shadbegian, Ronald J. and Wayne B. Gray. (2005). "Pollution Abatement Expenditures and Plant-Level Productivity: A Production Function Approach," *Ecological Economics*, 54, 196-208.

____, (2003). "What Determines the Environmental Performance of Paper Mills? The Roles of Abatement Spending, Regulation, and Efficiency," *Topics in Economic Analysis & Policy* 3, http://www.bepress.com/bejeap/topics/vol3/iss1/art15

U.S. Bureau of the Census, "Pollution Abatement Costs and Expenditures," U.S. Govt. Printing Office, Washington, DC, various issues.

Table 1 – Summary Statistics

VARIABLE	PAPER MEAN	SD	%CS	%TS	OIL MEAN	SD	%CS	%TS	STEEL MEAN	SD	%CS	%TS
BOD	7.66	52.36	0.17	0.00	22.70	438.42	0.16	0.01	0.12	0.38	0.54	0.01
Log(BOD)	1.48	0.92	0.83	0.01	0.11	0.50	0.22	0.02	0.09	0.21	0.70	0.01
TSS	11.16	28.43	0.60	0.01	0.49	5.31	0.15	0.01	1.35	4.17	0.47	0.02
Log(TSS)	1.78	1.08	0.89	0.01	0.15	0.35	0.49	0.01	0.48	0.67	0.86	0.00
SO_2	7.80	17.03	0.95	0.00	3.56	6.08	0.57	0.02	1.50	4.09	0.64	0.02
Log(SO_2)	1.47	1.13	0.81	0.00	1.09	0.85	0.79	0.01	0.50	0.74	0.79	0.02
$PM_{2.5}$	0.97	1.67	0.64	0.01	0.20	0.28	0.72	0.01	0.53	0.93	0.75	0.00
Log($PM_{2.5}$)	0.50	0.53	0.79	0.01	0.16	0.18	0.70	0.02	0.33	0.39	0.69	0.01
TOXIC	2.10	4.07	0.75	0.00	0.47	1.24	0.92	0.01	0.65	0.36	0.55	0.00
Log(TOXIC)	0.79	0.76	0.85	0.02	0.28	0.36	0.83	0.02	0.28	0.48	0.58	0.01
OUTPUT	173.56	145.54	0.87	0.07	746.50	688.06	0.88	0.05	500.92	595.65	0.94	0.02
Log(OUTPUT)	11.65	1.03	0.93	0.06	13.01	1.22	0.92	0.02	12.55	1.08	0.92	0.03
DIRTY TECH	0.65	0.48	1.00	0.00	0.76	0.43	0.89	0.01	0.38	0.49	1.00	0.00
OLD	0.78	0.42	1.00	0.00	0.79	0.41	1.00	0.00	0.68	0.47	1.00	0.00
LABOR	948.35	750.49	0.92	0.00	761.37	685.96	0.96	0.00	2577.96	3178.64	0.97	0.00
Log(LABOR)	6.54	0.85	0.95	0.00	6.22	1.01	0.96	0.01	7.26	1.07	0.95	0.00
CAPITAL	77.56	191.64	0.16	0.35	110.39	253.22	0.41	0.31	126.70	367.13	0.37	0.19
Log(CAPITAL)	8.70	2.80	0.37	0.44	10.35	1.90	0.67	0.21	10.37	1.79	0.61	0.27
MATERIALS	89.39	74.64	0.87	0.07	631.70	598.78	0.87	0.05	292.46	324.74	0.94	0.02
Log(MATERIALS)	10.97	1.09	0.92	0.64	12.81	1.26	0.91	0.02	12.06	1.06	0.90	0.03
MULTIUNIT	0.97	0.16	0.71	0.01	0.99	0.08	0.87	0.01	0.92	0.27	0.96	0.00
FIRMSIC	0.44	0.50	0.74	0.01	0.61	0.49	0.79	0.04	0.69	0.46	0.75	0.02
Log(FIRMEMP)	5.70	5.01	0.67	0.02	6.08	5.01	0.64	0.10	6.30	4.04	0.67	0.05
FIRMPROF	0.89	26.48	0.12	0.01	2.22	3.57	0.39	0.08	-0.05	5.79	0.29	0.15
FIRMPLANTS	12.27	11.44	0.86	0.00	5.99	4.49	0.86	0.00	5.36	4.28	0.95	0.00
Log(WATERACT)	2.36	2.65	0.72	0.26	4.97	3.00	0.81	0.18	2.91	2.61	0.73	0.26
Log(WATERINSP)	0.79	1.88	0.66	0.31	1.94	1.87	0.69	0.28	1.13	2.36	0.79	0.21
Log(AIRACT)	4.56	3.17	0.82	0.21	6.37	3.52	0.87	0.16	4.85	3.88	0.88	0.10
Log(AIRINSP)	1.62	0.67	0.89	0.06	2.08	0.99	0.95	0.03	2.02	1.07	0.95	0.01
WATER PAOC(%)	1.77	2.68	0.14	0.00	0.32	1.67	0.23	0.00	0.37	0.65	0.89	0.00
AIR PAOC(%)	0.41	1.59	0.21	0.00	0.47	0.89	0.37	0.01	0.56	0.63	0.84	0.00
PAOC(%)	3.41	3.97	0.19	0.00	1.31	3.96	0.10	0.01	1.29	1.28	0.85	0.00
GREEN VOTE	48.90	18.96	0.79	0.08	38.47	16.71	0.73	0.11	46.01	16.46	0.76	0.11
NONATTAIN	0.22	0.41	0.74	0.00	0.34	0.47	0.81	0.00	0.65	0.48	0.74	0.00

%CS = percent of variance that is cross-sectional (R^2 from regression on plant dummies)
%TS = percent of variance that is time-series (R^2 from regression on year dummies)

Variable Definitions

BOD	=	Biological oxygen demand i at time t (in tons/capacity)
TSS	=	Total suspended solids i at time t (in tons/capacity)
SO_2	=	Sulfur dioxide emissions i at time t (in tons/capacity)
$PM_{2.5}$	=	Particulate matter of 2.5 millimeters or less in diameter at plant i at time t (in tons/capacity)
TOXIC	=	TRI chemical releases at plant i at time t (in tons/capacity)
OUTPUT	=	Total value of shipments from plant i at time t
DIRTY TECH	=	dummy = 1 for paper mills with pulping facilities, oil refineries using catalytic cracking and for steel mills with blast furnaces
OLD	=	A dummy variable = 1 if a plant was open prior to 1972
LABOR	=	Production worker hours worked at plant i at time t
CAPITAL	=	Real gross book value of capital at plant i at time t
MATERIALS	=	Real value of materials used at plant i at time t
MULTIUNIT	=	A dummy variable = 1 if the plant is part of a multi-plant firm
FIRMSIC	=	A dummy variable = 1 if the firm's primary activity is the same as the plant's
FIRMEMP	=	Employment the firm that owns plant i at time t
FIRMPROF	=	Firm profit rate (net earnings/capital stock) at plant i at time t
FIRMPLANTS	=	Number of plants the firm owns in the same industry at plant i at time t
WATERACT	=	The predicted number of water actions at plant i at time t-2
WATERINSP	=	The predicted number of water inspections at plant i at time t-2
AIRACT	=	The predicted number of air actions at plant i at time t-2
AIRINSP	=	The predicted number of air inspections at plant i at time t-2
WATER PAOC	=	Water pollution abatement operating costs/plant capacity at plant i at time t-2
AIR PAOC	=	Air pollution abatement operating costs/plant capacity at plant i at time t-2
PAOC	=	Total pollution abatement operating costs/plant capacity at plant i at time t-2
GREEN VOTE	=	A state's pro-environmental Congressional voting score (League of Conservation Voters)
NONATTAIN	=	A dummy variable for plant i at time t = 1 if plant i is located in an area that is not in compliance with National Air Quality Standards for both sulfur dioxide and fine particulates at time t

Table 2
TECHNICAL EFFICIENCY – OIL

(dependent variable = log(OUTPUT)

MODEL	2A	2B	2C	3D
	Determinants of Production Frontier			
Log(LABOR)	0.1500***	0.1628***	0.1616***	0.1588***
	(0.0147)	(0.0130)	(0.0132)	(0.0130)
Log(CAPITAL)	0.0096	0.0110*	0.0067	0.0073
	(0.0091)	(0.0066)	(0.0060)	(0.0062)
Log(MATERIALS)	0.8234***	0.8186***	0.8278***	0.8283***
	(0.0231)	(0.0117)	(0.0111)	(0.0117)
	Determinants of Inefficiency			
MULTIUNIT	--	--	--	--
FIRMSIC	-0.0856*	-0.0733*	-0.0981***	-0.1199***
	(0.0513)	(0.0380)	(0.0320)	(0.0315)
FIRMEMP	0.0093	0.0090	0.0144	0.0151
	(0.0164)	(0.0172)	(0.0139)	(0.0147)
FIMPROF	0.0060	0.0002	-0.0017	-0.0024
	(0.0095)	(0.0040)	(0.0040)	(0.0031)
FIRMPLANTS	-0.0124	-0.0044	-0.0058	-0.0061*
	(0.0062)**	(0.0040)	(0.0036)	(0.0034)
OLD	0.1219	0.1569***	0.1160***	0.1391***
	(0.0436)**	(0.0312)	(0.0255)	(0.0260)
DIRTYTECH		-0.0490	0.0172	0.0218
		(0.0335)	(0.0272)	(0.0274)
PAOC		0.0009	0.0004	0.0004
		(0.0016)	(0.0017)	(0.0016)
GREEN VOTE			-0.0025***	-0.0029***
			(0.0007)	(0.0007)
NONATTAIN			-0.0728***	-0.0817***
			(0.0213)	(0.0254)
AIRINSP				0.0230
				(0.0169)
WATERINSP				0.0211**
				(0.0090)
AIRACTS				-0.0118**
				(0.0058)
WATERACTS				-0.0054
				(0.0044)
GAMMA	0.0324	0.6068	0.5621*	0.5432***
	(0.1659)	(0.0388)***	(0.0421)	(0.0434)
LR TEST	39.40***	92.86***	120.92***	127.16***
LogL	263.02	289.76	303.79	306.90
MEAN EFF	0.9477	0.8139	0.7410	0.7357
OBS	1058	1058	1058	1058

Notes: (Standard Errors). -- = significant negative at 5% level (coefficient value not disclosable)
All regressions include constant and year dummies
*** = significant at the 1% level or better
** = significant at the 5% level or better
* = significant at the 10% level or better

Table 3
TECHNICAL EFFICIENCY – PAPER
(dependent variable = log(OUTPUT)

MODEL	3A	3B	3C	3D
	Determinants of Production Frontier			
Log(LABOR)	0.2877***	0.2837***	0.2869***	0.2854***
	(0.0101)	(0.0103)	(0.0101)	(0.0103)
Log(CAPITAL)	-0.0081***	-0.0074***	-0.0077***	-0.0071***
	(0.0025)	(0.0025)	(0.0025)	(0.0024)
Log(MATERIALS)	0.7182***	0.7116***	0.7084***	0.7073***
	(0.0079)	(0.0082)	(0.0080)	(0.0081)
	Determinants of Inefficiency			
MULTIUNIT	0.0608**	0.0955**	0.0904***	0.1001**
	(0.0312)	(0.0415)	(0.0321)	(0.0363)
FIRMSIC	-0.1383***	-0.1791***	-0.1328***	-0.1392***
	(0.0162)	(0.0272)	(0.0170)	(0.0207)
FIRMEMP	-0.0133*	-0.0157*	-0.0152**	-0.0168**
	(0.0081)	(0.0092)	(0.0075)	(0.0077)
FIMPROF	0.0001	0.0006	0.0002	0.0003
	(0.0002)	(0.0007)	(0.0004)	(0.0004)
FIRMPLANTS	0.0009	0.0004	0.0011**	0.0011*
	(0.0006)	(0.0007)	(0.0006)	(0.0006)
OLD	0.1240***	0.1719***	0.1135***	0.1274***
	(0.0140)	(0.0288)	(0.0165)	(0.0226)
DIRTYTECH		-0.0685***	-0.0178	-0.0172
		(0.0184)	(0.0136)	(0.0181)
PAOC		0.0110	0.0072	0.0080
		(0.0117)	(0.0114)	(0.0111)
GREEN VOTE			0.0030***	0.0032***
			(0.0004)	(0.0005)
NONATTAIN			-0.0026	-0.0078
			(0.0129)	(0.0136)
AIRINSP				0.0163
				(0.0130)
WATERINSP				0.0134**
				(0.0067)
AIRACTS				-0.0065
				(0.0044)
WATERACTS				-0.0038
				(0.0043)
GAMMA	0.358***	0.283***	0.337***	0.297***
	(0.0573)	(0.0722)	(0.0564)	(0.0534)
LR TEST	241.52***	248.32***	335.02***	338.25***
LogL	214.08	217.49	260.84	262.45
MEAN EFF	0.6101	0.8419	0.6893	0.7919
OBS	3115	3115	3115	3115

See notes in Table 2

Table 4
TECHNICAL EFFICIENCY – STEEL

(dependent variable = log(OUTPUT))

MODEL	4A	4B	4C	4D
	Determinants of Production Frontier			
Log(LABOR)	0.4086***	0.4543***	0.4740***	0.4909***
	(0.0213)	(0.0236)	(0.0214)	(0.0250)
Log(CAPITAL)	0.0533***	0.0547***	0.0579***	0.0671***
	(0.0107)	(0.0116)	(0.0105)	(0.0124)
Log(MATERIALS)	0.5192***	0.4799***	0.4518***	0.4613***
	(0.0201)	(0.0230)	(0.0211)	(0.0220)
	Determinants of Inefficiency			
MULTIUNIT	0.1091*	0.1542**	0.1414**	0.1301**
	(0.0640)	(0.0666)	(0.0616)	(0.0478)
FIRMSIC	0.1753**	0.0794	0.0097	0.0212
	(0.0632)	(0.0631)	(0.0721)	(0.0477)
FIRMEMP	-0.0702***	-0.0837***	-0.0900***	-0.0566***
	(0.0196)	(0.0181)	(0.0195)	(0.0114)
FIMPROF	-0.0090***	-0.0079*	-0.0070**	-0.0060***
	(0.0029)	(0.0048)	(0.0027)	(0.0020)
FIRMPLANTS	-0.0115**	-0.0193***	-0.0159**	-0.0107***
	(0.0046)	(0.0061)	(0.0059)	(0.0031)
OLD	0.1059**	0.0796**	0.1494***	0.0307
	(0.0410)	(0.0340)	(0.0483)	(0.0243)
DIRTYTECH		-0.0457*	-0.0982**	-0.0137
		(0.0265)	(0.0443)	(0.0269)
PAOC		9.8535***	10.1471***	7.8296***
		(1.2426)	(1.1129)	(0.7981)
GREEN VOTE			0.0016	0.0001
			(0.0010)	(0.0009)
NONATTAIN			0.0437	0.0284
			(0.0345)	(0.0275)
AIRINSP				0.0455**
				(0.0188)
WATERINSP				0.0195**
				(0.0083)
AIRACTS				-0.0055
				(0.0051)
WATERACTS				-0.0044
				(0.0077)
GAMMA	0.1256	0.0878***	0.0487**	0.00002
	(0.0985)	(0.0258)	(0.0186)	(0.0004)
LR TEST	90.87***	188.38***	200.95***	194.03***
LogL	-106.12	-57.37	-51.08	-54.54
MEAN EFF	0.7699	0.8341	0.8365	0.8904
OBS	823	823	823	823

See notes in Table 2

TABLE 5
SUR MODELS - OIL

DEP VAR	SO2	PM25	AINEFF	BOD	TSS	WINEFF	TRI	TINEFF
DIRTY TECH	0.6795***	0.1129***	0.0763	0.0974	0.0657	0.0107	0.0699**	0.0565**
	(0.1406)	(0.0305)	(0.0536)	(0.0707)	(0.0477)	(0.0413)	(0.0304)	(0.0277)
OLD	0.0849	0.0703**	0.1149**	-0.0267	-0.0911*	0.0371	0.0407	0.0702***
	(0.1374)	(0.0298)	(0.0508)	(0.0767)	(0.0518)	(0.0437)	(0.0303)	(0.0262)
PLANTEMP	-0.1344**	-0.0309**	-0.0527**	-0.0386	-0.0163	-0.0041	0.0267*	-0.0129
	(0.0676)	(0.0146)	(0.0255)	(0.0372)	(0.0251)	(0.0209)	(0.0150)	(0.0132)
MU LTIUNIT	+	-	-	+	+		+	-
FIRMSIC	-0.1684	-0.0451	-0.1037	0.0372	0.0872	-0.1509***	-0.0479	-0.2140***
	(0.1961)	(0.0425)	(0.0721)	(0.0961)	(0.0649)	(0.0557)	(0.0409)	(0.0352)
FIRMEMP	-0.0566	-0.0003	0.0719***	-0.0031	-0.0018	0.0253	0.0033	0.0038
	(0.0675)	(0.0146)	(0.0248)	(0.0355)	(0.0240)	(0.0200)	(0.0155)	(0.0133)
FIRMPROF	0.0026	-0.0037	-0.0127	-0.0025	-0.0018	0.0014	-0.0053	0.0068**
	(0.0243)	(0.0053)	(0.0089)	(0.0101)	(0.0068)	(0.0057)	(0.0039)	(0.0033)
FIRMPLANTS	0.0009	-0.0017	-0.0041	0.0015	0.0023	-0.0040	0.0052	0.0006
	(0.0154)	(0.0033)	(0.0057)	(0.0074)	(0.0050)	(0.0041)	(0.0034)	(0.0029)
PAOC			7.0297***			0.0012	0.0004	0.0009
			(2.4846)			(0.0022)	(0.0026)	(0.0022)
AIRPAOC	12.1105	3.1087						
	(10.5952)	(2.2976)						
WATERPAOC				25.8456**	45.0628***			
				(10.5033)	(7.0880)			
GREENVOTE	-0.0032	0.0006	-0.0031**	-0.0002	0.0003	-0.0016	-0.0044***	-0.0015**
	(0.0033)	(0.0007)	(0.0014)	(0.0016)	(0.0011)	(0.0010)	(0.0007)	(0.0007)
NONATTAIN	-0.0384	-0.2973**	0.0420			0.0266		0.0164
	(0.1212)	(0.1210)	(0.1214)			(0.0349)		(0.0241)
AIRACTS	-0.0113	-0.0182***	-0.0167			0.0031		-0.0097*
	(0.0282)	(0.0061)	(0.0111)			(0.0082)		(0.0057)
AIRINSP	0.2031**	0.0556***	0.0301			0.0106		0.0056
	(0.0849)	(0.0184)	(0.0317)			(0.0232)		(0.0163)
WATERACTS			0.0009	-0.0045	-0.0065	0.0195***		0.0091**
			(0.0085)	(0.0111)	(0.0075)	(0.0066)		(0.0043)
WATERINSP			0.0125	0.0046	0.0082	0.0056		0.0302***
			(0.0155)	(0.0175)	(0.0118)	(0.0147)		(0.0088)
OBS	246	246	246	377	377	377	876	876
R2	0.1947	0.1561	0.1156	0.0499	0.1396	0.1676	0.1069	0.0989

SUR Residual Correlations

	SO_2	$PM_{2.5}$	BOD	TSS	TOX
		EMIT*INEFF			
EMIT*INEFF	0.0820	0.0269	0.0372	0.0505	0.1638*
		EMIT*EMIT			
SO_2	1.0	0.4549***	-0.0477	-0.1532	0.1392**
$PM_{2.5}$	0.4549***	1.0	-0.0832	-0.1009	0.1423*
BOD	-0.0477	-0.0832	1.0	0.1573*	0.1232*
TSS	-0.1532	-0.1009	0.1573**	1.0	0.2142***
TOX	0.1392**	0.1423*	0.1232*	0.2142***	1.0

See notes in Table 2

AINEFF, WINEFF, TINEFF = production inefficiency, based on first-stage stochastic frontier production function.

MULTIUNIT = where coefficients not disclosable, signs reported, doubled sign = significant at 5% level

TABLE 6
SUR MODELS - PAPER

DEP VAR	SO2	PM25	AINEFF	BOD	TSS	WINEFF	TRI	TINEFF
DIRTY TECH	0.1728	0.3313***	-0.0265	0.4683***	0.8441***	-0.0265**	0.6371***	-0.0017
	(0.1499)	(0.0631)	(0.0183)	(0.0639)	(0.0711)	(0.0113)	(0.0310)	(0.0074)
OLD	-0.0435	-0.0815	0.0404***	-0.1591***	-0.1492	0.0543***	-0.0223	0.0461***
	(0.1282)	(0.0539)	(0.0148)	(0.0553)	(0.0615)*	(0.0085)	(0.0300)	(0.0061)
PLANTEMP	0.1209*	0.0109	0.0190**	0.0195	0.0676*	-0.0025	0.1106***	0.0098***
	(0.0732)	(0.0308)	(0.0085)	(0.0342)	(0.0380)	(0.0049)	(0.0177)	(0.0034)
MU LTIUNIT	0.0983	0.0340	0.0503	+	+	++	-0.0193	0.0186
	(0.2809)	(0.1181)	(0.0324)				(0.0820)	(0.0160)
FIRMSIC	0.3625**	-0.0198	-0.0544***	-0.2033***	-0.0792	-0.0229**	-0.0965***	-0.0462***
	(0.1509)	(0.0635)	(0.0176)	(0.0671)	(0.0747)	(0.0100)	(0.0364)	(0.0071)
FIRMEMP	-0.0930	0.0344	-0.0127	-0.1838***	-0.2385***	0.0019	0.0357	-0.0028
	(0.0748)	(0.0314)	(0.0086)	(0.0376)	(0.0419)	(0.0056)	(0.0183)	(0.0036)
FIRMPROF	0.0128	-0.0025	-0.0031***	-0.0056	-0.0045	-0.0016**	-0.0003	0.0001
	(0.0099)	(0.0042)	(0.0011)	(0.0043)	(0.0048)	(0.0006)	(0.0004)	(0.0001)
FIRMPLANTS	0.0002	0.0003	0.0008	0.0265***	0.0283***	0.0000	0.0042***	0.0005*
	(0.0058)	(0.0025)	(0.0007)	(0.0030)	(0.0033)	(0.0004)	(0.0013)	(0.0003)
PAOC			0.0194			0.7359***	0.0154	0.0095
			(0.0117)			(0.1297)	(0.0375)	(0.0073)
AIRPAOC	12.2216	10.1138***						
	(7.6693)	(3.2232)						
WATERPAOC				19.2050***	19.9380***			
				(2.6536)	(2.9530)			
GREENVOTE	0.0038	-0.0078***	0.0003	-0.0102***	-0.0142***	0.0008***	-0.0096***	0.0011***
	(0.0032)	(0.0014)	(0.0004)	(0.0014)	(0.0016)	(0.0002)	(0.0007)	(0.0002)
NONATTAIN	-0.2973**	-0.0540	0.0062			-0.0012		0.0080
	(0.1210)	(0.0509)	(0.0140)			(0.0090)		(0.0062)
AIRACTS	-0.0232	-0.0282**	-0.0096**			-0.0061***		-0.0033**
	(0.0267)	(0.0112)	(0.0040)			(0.0023)		(0.0016)
AIRINSP	0.4638***	0.1107**	0.0259**			0.0029		0.0087
	(0.1053)	(0.0443)	(0.0123)			(0.0075)		(0.0052)
WATERACTS			-0.0099***	0.0201*	0.0012	-0.0001		-0.0020
			(0.0038)	(0.0122)	(0.0136)	(0.0018)		(0.0014)
WATERINSP			0.0175***	-0.0055	-0.0375*	0.0116***		0.0056**
			(0.0056)	(0.0174)	(0.0194)	(0.0033)		(0.0023)
OBS	459	459	459	1174	1174	1174	2435	2435
R2	0.1170	0.2886	0.1337	0.2817	0.3514	0.1386	0.3673	0.0923

SUR Residual Correlations

EMIT*INEFF

	SO_2	$PM_{2.5}$	BOD	TSS	TOX
EMIT*INEFF	-0.0022	-0.0354	-0.0350	-0.0493	-0.0115

EMIT*EMIT

	SO_2	$PM_{2.5}$	BOD	TSS	TOX
SO_2	1.0	0.3367***	-0.0898	-0.0746	0.1390*
$PM_{2.5}$	0.3367***	1.0	0.1729**	0.1603**	0.2646***
BOD	-0.0898	0.1729**	1.0	0.7272***	0.1958**
TSS	-0.0746	0.1603**	0.7272***	1.0	0.2150***
TOX	0.1390*	0.2646***	0.1958**	0.2150***	1.0

See notes in Table 2
AINEFF, WINEFF, TINEFF = production inefficiency, based on first-stage stochastic frontier production function.
MULTIUNIT = where coefficients not disclosable, signs reported, doubled sign = significant at 5% level

TABLE 7
SUR MODELS - STEEL

DEP VAR	SO2	PM25	AINEFF	BOD	TSS	WINEFF	TRI	TINEFF
DIRTY TECH	0.2579**	0.1231	-0.0540	0.1231***	0.4736***	-0.0660	-0.1101**	0.0329
	(0.1398)	(0.0830)	(0.0988)	(0.0291)	(0.0977)	(0.0765)	(0.0458)	(0.0530)
OLD	0.0747	0.0223	0.2689***	0.0360	-0.0341	0.0093	0.1048**	0.1075**
	(0.1399)	(0.0831)	(0.0994)	(0.0321)	(0.1076)	(0.0779)	(0.0446)	(0.0461)
PLANTEMP	0.1849***	0.0032	-0.1280***	-0.0878***	0.2340***	-0.0736*	0.1107***	-0.0582***
	(0.0609)	(0.0362)	(0.0422)	(0.0186)	(0.0624)	(0.0419)	(0.0209)	(0.0207)
MU LTIUNIT	+	-	+	--	--	++	++	++
FIRMSIC	0.1212	0.0547	0.0871	-0.2193***	-0.1430	0.5652***	0.0197	0.0659
	(0.1854)	(0.1102)	(0.1267)	(0.0602)	(0.2019)	(0.1398)	(0.0755)	(0.0725)
FIRMEMP	0.0202	-0.0372	-0.1132***	-0.0076	-0.0576	-0.0174	-0.0238	-0.0726***
	(0.0537)	(0.0319)	(0.0366)	(0.0153)	(0.0515)	(0.0365)	(0.0220)	(0.0215)
FIRMPROF	0.0085	0.0089	-0.0149**	-0.0021	-0.0077	-0.0109**	0.0043	-0.0094***
	(0.0106)	(0.0063)	(0.0071)	(0.0023)	(0.0079)	(0.0056)	(0.0034)	(0.0032)
FIRMPLANTS	0.0308**	0.0177**	-0.0252**	0.0066	0.0499***	-0.0304***	-0.0029	-0.0099*
	(0.0144)	(0.0086)	(0.0097)	(0.0039)	(0.0132)	(0.0086)	(0.0057)	(0.0055)
PAOC			3.7090			3.1317	2.6999*	6.2729***
			(2.7645)			(4.4606)	(1.4382)	(1.3997)
AIRPAOC	28.8934***	8.0615*						
	(7.9444)	(4.7214)						
WATERPAOC				14.8649***	-28.6067**			
				(3.9573)	(13.2943)			
GREENVOTE	0.0005	0.0011	-0.0013	-0.0004	0.0029	-0.0007	-0.0002	0.0010
	(0.0030)	(0.0018)	(0.0027)	(0.0008)	(0.0028)	(0.0022)	(0.0011)	(0.0014)
NONATTAIN	0.0420	-0.0021	-0.1029			0.0723		0.0419
	(0.1214)	(0.0722)	(0.0820)			(0.0600)		(0.0414)
AIRACTS	-0.0311	-0.0146	0.0110			0.0201*		-0.0014
	(0.0223)	(0.0133)	(0.0171)			(0.0120)		(0.0088)
AIRINSP	0.0877	0.1195***	0.0814*			-0.0203		0.0244
	(0.0676)	(0.0402)	(0.0483)			(0.0406)		(0.0263)
WATERACTS			-0.0213	-0.0372***	0.0147	0.0296		0.0126
			(0.0225)	(0.0087)	(0.0290)	(0.0220)		(0.0111)
WATERINSP			0.0250	0.0339***	0.0179	0.0243		0.0249*
			(0.0278)	(0.0079)	(0.0266)	(0.0234)		(0.0137)
OBS	164	164	164	255	255	255	690	690
R2	0.3708	0.2031	0.2964	0.3598	0.2786	0.2859	0.1020	0.1669

SUR Residual Correlations

	SO_2	$PM_{2.5}$	BOD	TSS	TOX
			EMIT*INEFF		
EMIT*INEFF	-0.0349	0.0009	0.2383*	0.2454*	0.0641*
			EMIT*EMIT		
SO_2	1.0	0.4084***	-0.0557	0.0858	-0.0629
$PM_{2.5}$	0.4084***	1.0	0.4417***	0.3618***	-0.0301
BOD	-0.0557	0.4417***	1.0	0.4107***	0.0307
TSS	0.0858	0.3618***	0.4107***	1.0	-0.1133*
TOX	-0.0629	-0.0301	0.0307	-0.1133*	1.0

See notes in Table 2
AINEFF, WINEFF, TINEFF = production inefficiency, based on first-stage stochastic frontier production function.
MULTIUNIT = where coefficients not disclosable, signs reported, doubled sign = significant at 5% level.

5B. "What Determines the Opportunity Cost of Pollution Abatement? A Production Function Approach"

I. Introduction

Prior to the establishment of the Environmental Protection Agency (EPA) in the early 1970s, and the passage of the Clean Air Act (CAA) and Clean Water Act (CWA), environmental regulation was done primarily by state and local agencies with very little enforcement. However, during the nearly 35 years since the passage of the CAA and CWA the federal government has taken the lead role in regulation, imposing more stringent regulations with correspondingly stricter enforcement, driven by a concern that unregulated production processes cause too much environmental damage, imposing too many external costs on society in terms of air and water pollution. The benefits from environmental regulation are substantial, but there are concerns that environmental regulations, both through direct pollution abatement costs and the opportunity costs associated with lost output, reduce the productivity/efficiency of U.S. manufacturing establishments, thereby reducing their international competitiveness.

The predicted negative impact of environmental regulation on productivity has been widely examined over the past 25 years. Denison (1979) used estimates of abatement costs to calculate productivity effects of environmental regulation and found only a small impact on productivity because compliance costs are a relatively small share of total costs. Econometric studies with industry-level data like Gray (1986,1987), Barbera and McConnell (1986), and Shadbegian (1996) tend to find significant negative impacts of regulation on productivity, although the effects are not always very large. Research using establishment-level data tend to find even larger (more negative) effects of regulation on productivity: Gollop and Roberts (1983) for electric utilities, Joshi et. al. (2001) for steel mills, Gray and Shadbegian (2003), Boyd and McClelland (1999), and Fare, Grosskopf, Lovell, and Pasurka (1989) for pulp and paper mills and Gray and Shadbegian (2002) for plants in the steel, oil, and paper industries.[24]

We investigate the impact of environmental regulation and technology on the opportunity cost of pollution abatement, measured as the reduction in output associated with pollution abatement activities, using confidential plant-level U.S. Census Bureau data on 68 paper mills from 1974-1990. We extend an approach from Prywes (1984) to examine the connection between regulation and the opportunity cost of pollution abatement by using detailed data on pollution abatement expenditures which allows us to disaggregate inputs (capital, labor, and materials) into their abatement and production components. We then examine whether or not the stringency of environmental regulation, measured by the number of EPA regulatory actions directed at the plant in a given year, is related to this plant-level measure of the opportunity cost of pollution abatement. This analysis will look separately at the air pollution and water pollution sides of regulatory activity and abatement expenditures. We also examine whether or not the age of the plant and technology in place at the plant – whether or not the plant has a pulping facility – is related to this plant-level measure of the opportunity cost of pollution abatement. We find that EPA regulatory actions (air and water) have no significant impact on opportunity costs, however

[24] Berman and Bui (2001) find little effect of abatement costs on the productivity of oil refineries, which is at least somewhat consistent with Gray and Shadbegian (2002) who find that abatement costs had the smallest impact on productivity for oil refineries.

plants with pulping facilities do have significantly higher opportunity costs of pollution abatement.

Section II describes the environmental concerns of the pulp and papermaking process and how the industry is affected by regulation. In section III we present the production function model we use to estimate the opportunity cost of environmental regulation. Section IV describes the data used in the analyses and econometric issues. In Section V we present the results, with concluding remarks in Section VI.

II. Environmental Regulation and Productivity in the Pulp and Paper Industry

The pulp and paper industry is a major source of air and water pollution. On the water pollution side, it is the largest industrial process water user in the U.S. and (before the increased regulatory requirements of the 1970s) a major source of chemical discharges into rivers - some early paper mills were built over rivers so that any process spills could be easily flushed away through drains in the floor. On the air pollution side, many paper mills have large boilers to generate power and steam for the plant and to consume wood scraps, while some also have recovery boilers to recycle process chemicals (in the kraft pulping technique). The focus of regulatory attention was on conventional air and water pollutants during the time period we examine here (1974-1990). More recently the EPA has paid considerable attention to toxic releases of dioxin and related chemicals from kraft paper mills using chlorine bleaching techniques, and new regulations (the "cluster rule") took effect in 2002 to limit these toxic releases [see Gray and Shadbegian (2007) for a discussion of the effectiveness of those regulations].

The paper-making process can be broken into two major stages, pulping and paper-making. In the pulping stage, wood fibers are separated out from various sources including raw wood, wood chips, or recycled paper, using a variety of chemical and mechanical methods. These fibers, which in many cases are bleached to increase their whiteness, are mixed with water to form a slurry. In the second (paper-making) stage, this slurry (more than 90% water at the beginning) is placed on a fast-moving wire mesh which then passes through a succession of dryers to eliminate the water and create a continuous sheet of paper.

The pulping stage generates most of the pollution, along with most of the technology differences across plants, when the plant begins the process with raw wood. The wood fibers have to be separated from the lignin that binds them together, which can be done with chemical reactions, mechanical pressure, or various combinations of heat, pressure, and chemicals. Different pulping methods give rise to different pollution concerns: traditional sulfite chemical pulping leaves various chemicals in the wastewater, while mechanical pulping requires considerable energy, usually supplied by a power boiler that generates air pollution. Some plants begin their paper-making using recycled cardboard or paper, so that no real pulping process is required (add water and stir to separate the paper fibers), while other non-pulping plants use pulp produced and sold by other mills. Some air emissions can arise from power boilers needed to create steam for the dryers and some water discharges can arise from residual fibers remaining in the water as the paper is dried, but on the whole non-pulping plants generate much less pollution than pulping plants. Therefore, we focus on whether or not a plant includes a pulping process as the key technology difference across plants.

During the past 35 years the pulp and paper industry has significantly decreased its water and air pollution. On the water pollution side, nearly all plants which discharge wastewater to rivers and streams have installed secondary treatment facilities to abate traditional forms of water pollutants, although some smaller plants (particularly non-pulping ones) may discharge their wastewater through a municipal treatment plant and not require on-site treatment. On the air pollution side, many plants with power boilers have installed electrostatic precipitators to abate particulate emissions and flue gas desulfurization units (scrubbers) to abate sulfur dioxide emissions. In addition to these 'end-of-pipe' controls, plants have become much more efficient at managing the material flow through the plants, resulting in the recovery and reuse of fibers from the wastewater and exhaust gases from the pulping and bleaching stages being captured and treated. The recapture of fiber from the wastewater can even provide a net economic benefit to the plant, in addition to abating water discharges.

These pollution abatement activities can be quite costly for the plants. The most obvious expenses are the capital investments associated with end-of-pipe control equipment, but operating that equipment requires electricity and labor. Meeting regulatory requirements for paperwork to document compliance activities and managing those activities requires additional labor. Making changes to one part of the production process to meet environmental goals can also disrupt other parts, imposing additional costs. For example, installing oxygen delignification, which reduces the need for chlorine bleaching, could increase the flow of waste material to a recovery boiler by 3 percent. Because the capacity of the recovery boiler was designed to match the capacity of the rest of the process, the plant would either be forced to invest tens of millions of dollars for a new recovery boiler or accept a permanent 3 percent reduction in overall production.

The costliness of abatement expenditures differs substantially across plants. In general, older plants, built before environmental regulations came into place, have greater difficulty in achieving a certain level of compliance. For example, reducing air pollution from escaping process gasses might require capturing and incinerating those gases in a boiler, made much more difficult if the plant was originally designed with buildings spaced far apart. This disadvantage for older plants may be partially or completely counterbalanced by the tendency for regulators to incorporate 'grandfather' clauses which exempt existing plants from the most stringent regulations. For example, air pollution regulations impose more stringent New Source Performance Standards on new or substantially renovated plants. Several researchers have examined the likelihood that such regulations will have perverse effects on total emissions, discouraging investment in new capital, both in electric power generation (Nelson and Tietenberg (1993)) and automobiles (Gruenspecht (1982)). In addition to differences in abatement costs across plants due to age, specific details of the production technology in place at a plant will influence abatement costs. The strongest influence is expected to be whether or not the plant includes a pulping process, with pulping plants expected to have much higher costs.

Plants may also face different regulatory stringency, depending on their location. Air pollution regulations are more stringent in areas where pollution levels exceed federal National Ambient Air Quality Standards (NAAQS). Water pollution discharge limits differ across plants, depending on the size of the receiving stream and downstream uses of the water. In addition, much of the regulatory process is carried out by state environmental agencies, doing most of the inspections and undertaking most of the enforcement actions designed to induce plants to comply with regulations. In many cases, state regulators are also responsible for drawing up permits that spell out the requirements for pollution control activities at the plant. This provides some flexibility for state agencies to differ in the effective stringency of environmental regulations imposed on plants in the state. In our analysis we use the intensity of enforcement activity directed towards a plant as an indicator of the regulatory stringency faced by the plant.

III. Theoretical and Empirical Models

The paper most closely related to this paper is Prywes (1984), which examines the impact of regulation (environmental and OSHA) on labor productivity in the U.S. Chemical industry. Prywes (1984) does this by estimating a production function – with 28 4-digit Standard Industrial Classification (SIC) industries within the chemical industry from 1971-76 – in which he disaggregates the industry's capital stock into one part used to produce industry output and another part used to comply with regulations, based on data on the share of new investment going to produce industry output or to regulatory activities.[25] He then estimates the effect of regulation on labor productivity (LPROD) via a two-step process. First, he uses the predicted value of output to estimate LPROD with non-abatement capital:

(1) $F(KP, L, E, M) / L,$

where F(•) is a traditional production function, KP is the capital stock assigned to output production, L is labor, E is energy, and M the material inputs – this is a measure of LPROD under regulation (with some capital used for pollution abatement). He then used the estimated coefficients from the production function in (1), to calculate predicted values of output, assuming that the capital stock assigned to regulatory activities was available for output production:

(2) $F(KP+KA, L, E, M) / L,$

where KA is the abatement capital stock (used to comply with OSHA and EPA regulations). Prywes refers to this as "unregulated" LPROD, because firms are not using any capital to comply with regulations. The difference between unregulated LPROD and regulated LPROD represents the opportunity cost of regulatory activities. Prywes found that capital invested to comply with regulations, as opposed to producing traditional output, reduced labor productivity by 2.3% by 1976.

We calculate the opportunity cost of environmental regulations in the pulp and paper industry, using a similar "assigned" input model, by augmenting the approach by Prywes (1984). Unlike Prywes, who had to rely on industry-level data, we have plant-level data, which allows us to take advantage of variation in production and abatement activity within and between plants to identify the opportunity cost of environmental regulation. In particular, we have plant-level measures of production (Y), total capital (K), total labor (L), and total materials, including energy (M), and pollution abatement expenditures capital, labor, and materials from the U.S. Census Bureau for 68 pulp and paper mills from 1974-1990. Our data on pollution abatement expenditures allows us to disaggregate all our inputs, not just capital, into production inputs (KP, LP, and MP) and abatement inputs (KA, LA, and MA).[26] Following Prywes, we then estimate a

---

[25] Färe, Grosskopf, and Pasurka (2008) refer to this as the "assigned input" model because it assumes we can identify which inputs are assigned to traditional output production and which inputs are assigned to regulation activities.

[26] Pollution abatement obviously leads to the production of a cleaner, healthier environment, so it is not that we mean to imply that abatement inputs are unproductive, but simply that they are not used to

production function using only production inputs

(3) F(KP, LP, MP)

to get the predicted level of output based on a world with regulation (Y_R) . We then use the estimated coefficients from this production function along with total inputs (production plus abatement) to estimate output in a world without regulation (Y_{UR}), assuming that all abatement inputs would be used instead to produce industry output.

(4) F[(KP+KA), (LP+LA), (MP+MA)]

This model assumes that pollution abatement inputs completely "crowd out" production inputs.[27] Thus, the reduction in traditional output production associated with the reallocation of inputs away from producing traditional output to pollution abatement activities represents the opportunity cost of pollution abatement activities and we calculate it as

(5) Opportunity Cost = $(Y_{UR} - Y_R)/Y$,

where:
Y_{UR} = predicted output in a world without regulation
Y_R = predicted output in a world with regulation
Y = actual output

Following Prywes (1984) we estimate a nested CES production function.[28] The mathematical form of the nested CES production function is

(6) $Y_{KL} = [\delta_0 * KP^{-\rho 0} + (1-\delta_0) * LP^{-\rho 0}]^{-1/\rho 0}$

(7) $Y = A * [\delta_1 * (Y_{KL})^{-\rho 1} + (1-\delta_1) * MP^{-\rho 1}] * e^{Year(t)}$

substituting (6) into (7) yields

(8) $Y = A * \{ \delta_1 * [\delta_0 * KP^{-\rho 0} + (1-\delta_0) * LP^{-\rho 0}]^{\rho 1/\rho 0} + (1-\delta_1) * MP^{-\rho 1}\}^{-1/\rho 1} * e^{Year(t)}$

Y_{KL} is the intermediate input produced by KP and LP and the ρ's are the parameters that determine the elasticities of substitution between the inputs and Year(t) is a set of year dummy variables. As a robustness check we also estimate a Cobb-Douglas production function, which is a limiting case of the CES production function when the elasticity of substitution is constrained to equal 1, of the following form:

(9) $Y = A * (KP)^{\alpha KP} * (LP)^{\alpha LP} * (MP)^{\alpha MP} * e^U$

---

produce 'traditional' output – in our case paper.

[27] Gray and Shadbegian (1998) provide evidence that investment in pollution abatement equipment "crowds out" production investment nearly one-to-one.

[28] The nested CES production function was developed by Sato (1967).

After obtaining the opportunity cost of capital based on the estimated coefficients from the CES and Cobb-Douglas production functions, we test whether or not the stringency of environmental regulation, measured by the number of EPA regulatory actions directed at the plant in a given year, raises the opportunity cost of pollution abatement. According to the above analysis we would expect plants that incorporate some pulping process starting with raw wood will have to allocate more inputs to pollution abatement, thereby causing more disruption to their production process, and therefore have higher opportunity costs of pollution abatement than plants with only the paper-making part of the process.[29] Thus, we will also control for technology using a PULP dummy variable. Our analysis will also look separately at the air pollution and water pollution sides of regulatory activity (Air_Actions and Water_Actions) and the opportunity cost of abatement expenditures.

(10) Opportunity $\text{Cost}_i = \Sigma(\text{YUR}_{it} - \text{YR}_{it})/ \Sigma Y_{it} = G(\text{PULP},\text{REGULATION})$

where REGULATION is a measure of regulatory stringency.

IV. Data and Econometric Issues

The research for this paper was conducted at the U.S. Census Bureau's Boston Research Data Center, using confidential Census databases developed by the Census Bureau's Center for Economic Studies. The two Census data sources we use are the Longitudinal Research Database (LRD), which contains information on individual manufacturing plants from the Census of Manufactures and Annual Survey of Manufacturers[30] over time and the Pollution Abatement Costs and Expenditures (PACE) survey, which contains annual plant-level pollution abatement operating cost data from 1974 to 1994.[31,32] From the LRD we selected those pulp and paper mills (from NAICS 322110 and 322120) with continuous LRD and PACE data from 1972-1990 and with adequate data to construct a capital stock measure, dropping a few plants with implausible values for key variables, resulting in a final sample which contains 68 pulp and paper mills (1156 plant-year observations). From the LRD we use the value of shipments adjusted for inventory changes and deflated by the industry price of shipments (using the appropriate industry deflator from Bartelsman and Gray [1996]) to measure a plant's output. We use three inputs: labor, capital, and materials (which includes energy). Labor is the number of worker hours, which is equal to production worker hours plus non-production worker hours.[33] The dollar expenditures on materials are converted into real terms by dividing them by an industry-specific price index. We construct a measure of each plant's real capital stock based on a standard perpetual-inventory method, applied to the Census data on new investment in the plant.

---

[29] We also expect older plants to have more difficulty meeting a given standard, given they were not designed with pollution abatement in mind, and hence need to use more inputs for pollution abatement, leading to higher opportunity costs of pollution abatement, but grandfathering could reduce or eliminate this difference. Also plants undergoing a substantial renovation might be more productive, but might also face greater regulatory stringency.
[30] For a more detailed description of the LRD data see McGuckin and Pascoe (1988).
[31] For a more detailed description of the PACE data see Streitwieser (1996) and Ross et al (2004).
[32] No survey was done in 1987 for budget reasons, and we interpolate that year's data.
[33] The LRD does not contain information on non-production worker hours so we assume each non-production worker works 2000 hours per year.

We combine this production data with data from the PACE survey. The PACE survey samples approximately 20,000 plants per year, focusing on large plants in heavily polluting manufacturing industries. The plants are asked about both new capital expenditures and total annual operating costs related to pollution abatement activities, which are disaggregated into labor, materials, and depreciation. To convert labor and materials into real terms we divide each of them by their respective industry-specific price index. We also use the data on pollution abatement depreciation and new capital expenditures (appropriately deflated) to calculate a real pollution abatement capital stock using a perpetual inventory method.

Our regulatory measures come from two EPA databases: Compliance Data System (CDS) and Permit Compliance System (PCS). The CDS and PCS provide annual measures of air and water regulatory enforcement activity, respectively, directed towards each plant. To measure air pollution enforcement, we use AIR_ACTIONS, the log of the total number of air regulatory actions (this includes both inspection type 'actions' including inspections, emissions monitoring, and stack tests, as well as, non-inspection-type 'actions' including notices of violation, penalties, and phone calls) directed towards the plant during the year. Similarly, we measure the amount of water regulation directed at a plant as WATER_ACTIONS, the log of the total number of water regulatory actions, as well as, non-inspection-type 'actions.' Note the CDS data starts in late 1970's and the PCS data begins during the mid-1980s.

Several econometric issues arise for the estimation of the parameters of any production function. First, it is possible that omitted variables, such as managerial abilities or access to well-trained workers, influences a plant's production. To the extent that these omitted variables are correlated with other included variables, our estimates could be biased – and the process of profit-maximizing is likely to generate such correlations. For example, firms with well-trained/experienced management might choose to increase the scale of their operations, creating a strong correlation between the use of inputs and the resulting output. However, excellent managerial ability does not necessarily lead to an overstatement of impacts: if, as found for steel mills in Deily and Gray (1991), regulators avoid stringent regulation at plants that are on the verge of closing, more stringent regulation would be directed towards more successful plants, decreasing the estimated impact of regulatory stringency on plant performance.

Our sample consists of a balanced panel of plants with complete Census data. This eliminates plants that either enter or exit the industry during our sample period (1974-1990). Ollie and Pakes (1996) demonstrate that estimates from an *artificially* balanced panel may be biased, since a firm's decision to invest in a plant or to close it down is based in part on the plant's underlying productivity. The extent of the selectivity bias depends on the degree of entry and exit in the industry. Olley and Pakes find substantial biases in the telecommunications equipment industry, which has lots of entry and exit. However, the pulp and paper industry has little entry and exit, thus the use of a balanced panel should be less problematic here than in the telecommunications equipment industry.

V. Results

Table 1 lists the definitions of the variables used in the analysis, along with their means and standard deviations. Roughly half our plants incorporate a pulping technology and on average each plant is faced with a total of 37 air and 13 water actions between 1974 and 1990 – recall we have approximately 12 years of air pollution regulatory data and about 6 years of water pollution regulatory data, so it is not too surprising that the average plant faces nearly 3 times as much air enforcement as water enforcement activity.

Table 2 presents the estimated coefficients for both the log-linear CES (8) and Cobb-Douglas (9) production function models using only production inputs. Both the CES and Cobb-Douglas production functions exhibit approximate constant returns to scale: estimated returns to scale are 1.00 and 0.96 respectively. As expected, capital, labor, and materials always have a significant positive impact on output. The CES and Cobb-Douglas production functions input coefficients are very similar in magnitude, although the estimated labor coefficient is a bit larger for the CES model and the estimated capital coefficient is somewhat larger for the Cobb-Douglas model. These simple models explain nearly all of the variation in output across plants and over time, with R-squared values of roughly 90%.

Using the estimated coefficients from the CES and Cobb-Douglas models, along with total inputs (production + abatement) we calculate the opportunity cost of pollution abatement according to equation (10). Both the CES and Cobb-Douglas models yield rather similar and quite substantial opportunity costs – roughly 10% of output per year assuming a CES production technology and roughly 12% if we assume a Cobb-Douglas production technology.

To assess the impact of EPA regulations on the opportunity cost of pollution abatement we estimate several versions the following equation, using the calculated opportunity cost from both the CES and Cobb-Douglas production functions:

(11) Opportunity Cost = f(Z_ACTIONS, PULP, PULP* Z_ACTIONS)

where Z = Air and Water.

As often happens with plant-level data, much of the variation in our key variables is cross-sectional, and PULP is fixed over time (making it impossible to estimate its coefficient through a fixed-effect model), therefore we estimate equation (11) by OLS with a cross-section of aggregate opportunity cost and EPA regulatory actions over our entire time period (1974-1990).

Tables 3 and 4 present the results of these models using the opportunity cost from the CES model. In table 3, we see that PULP has the expected significant positive impact on the opportunity cost of pollution abatement. In particular, the opportunity cost at pulp mills is just over 5 percentage points (just over 50%) higher than at paper mills. On the other hand, neither air or water enforcement activity has any significant impact on opportunity costs.

In table 4 we allow the relationship between opportunity costs and EPA enforcement to differ by our technology measure (PULP). As we noted about there are many more environmental concerns at pulp mills, therefore we may expect EPA enforcement activity to have a bigger impact on the opportunity cost at pulp mills. However, the results in table 4 suggest that there is no significant bigger impact of EPA enforcement activity on opportunity cost at pulp mills. In fact, if anything EPA enforcement activity appears to have a smaller impact on opportunity cost at pulp mills.[34,35]

---

[34] See appendix tables 3A and 4A for Cobb-Douglas results – qualitatively there are no differences from the CES results.

[35] To check the robustness of our results we also estimated models for three different time periods: 1) 1974-1984; 2) 1979-1990; and 3) 1985-1990. There are no qualitative differences with the results presented here – all results are available from the authors.

VI. Concluding Remarks

In this paper we investigated the impact of environmental regulation and technology on the opportunity cost of pollution abatement in a production function framework – we estimate both a CES and a Cobb-Douglas production function. First, we find that both the CES and Cobb-Douglas models yield sizeable opportunity costs – roughly 10% of output per year assuming a CES production technology and roughly 12% if we assume a Cobb-Douglas production technology. In a second stage analysis (using the predicted opportunity cost from the estimated production functions) we find that the use of pulping technology at a plant significantly increases the opportunity cost of pollution abatement by just over 5 percentage points (just over 50%) compared with paper mills. However, we did not find any significant impact on the stringency of either air or water enforcement activity.

We are currently planning to improve and extend our analysis in several ways. First, previous research has shown that pollution abatement costs are hard to measure and probably underestimate the actual cost of pollution abatement [see Boyd and McClelland (1999), Becker and Henderson (2001), Joshi et al (2001),Gray and Shadbegian (2002,2003), Shadbegian and Gray (2005)], while other research has shown that most accurately reported abatement data are capital expenditures. Therefore, to test the robustness of our estimates of opportunity costs from our first stage analysis we will follow Prywes (1984) in only adjusting the capital input for abatement costs (we will not adjust labor and materials).

Second, in our second stage analysis we plan to incorporate several other (most likely better) measures of the stringency of environmental regulation faced by the plant: 1) on the air side, we will include a dummy variable indicating if the plant is located in a county that is in non-attainment status with respect to federal NAAQS; 2) on the water side, we will include a numeric rating from EPA's Majors Rating Database indicating the degree to which the plant is a significant source of water pollution and a dummy variable indicating if the plant discharges into a river that is a source of public drinking water, giving any water pollution from that plant the potential for public health effects; and 3) we will include the support for environmental legislation by that state's Congressional delegation as a measure of political support for and/or a measure of the state-level regulatory climate for environmental regulation.

Third, the so-called 'Porter' hypothesis [Porter (1991) and Porter and van der Linde (1995)] predicts that plants which are 'progressive' with respect to pollution abatement – those seeking to redesign their production process rather than simply using end-of-line abatement methods – may be more efficient at pollution abatement. Therefore, we plan to estimate a set of analyses allowing for differences between plants whose abatement capital investments are predominantly in "change-in-production-process" abatement techniques rather than in "end-of-line" abatement techniques.

References

Barbera, A.J., McConnell, V.D., 1986. Effects of pollution control on industry productivity: a factor demand approach. Journal of Industrial Economics 35, 161-72.

Bartelsman, E.J., Gray, W.B., 1996. The NBER manufacturing productivity database. NBER Technical Working Paper 205.

Becker, R. A., 2001. Air pollution abatement costs under the Clean Air Act: evidence from the PACE Survey. Center for Economic Studies Working Paper 01-12.

Becker, R. A., Henderson, J.V., 2001. Costs of air quality regulation. In: Carraro, C., Metcalf, G.e. (Editors), Behavioral and Distributional Effects of Environmental Policy. National Bureau of Economic Research and The University of Chicago Press, Chicago, IL..

Berman, E., Bui, L.T., 2001. Environmental regulation and productivity: evidence from oil refineries. Review of Economics and Statistics 83, 498–510.

Boyd, G. A., McClelland, J.D., 1999. The impact of environmental constraints on productivity improvement in integrated paper plants. Journal of Environmental Economics and Management 38, 121–142.

Deily, M. E., Gray, W. B., 1991. Enforcement of pollution regulations in a declining industry. Journal of Environmental Economics and Management 21, 260-274.

Denison, E.P., 1979. Accounting for Slower Economic Growth: The U.S. in the 1970s, The Brookings Institution, Washington DC.

Färe, R., Grosskopf, S., and C., Pasurka, C., 2008.Pollution Abatement and Productivity Growth: Evidence from Germany, Japan, the Netherlands, and the United States

Färe, R., Grosskopf, S., Lovell, C., Pasurka, C., 1989. Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach," Review of Economics and Statistics 71, 90-98.

Gallaher, M., Morgan, C., Shadbegian, R.J., 2008. Redesign of the 2005 Pollution Abatement Costs and Expenditure Survey U. S. E.P.A. National Center for Environmental Economics Working Paper no. 2008-01.

Gollop, F.M., Roberts, M. J., 1983. Environmental regulations and productivity growth: the case of fossil-fueled electric power generation. Journal of Political Economy 91, 654-74.

Gray, W.B., 1986. Productivity Versus OSHA and EPA Regulations, UMI Research Press, Ann Arbor, MI.

Gray, W.B., 1987. The cost of regulation: OSHA, EPA and the productivity slowdown. American Economic Review 77, 998-1006.

Gray, W.B., Shadbegian, R.J. Regulatory Regime Changes Under Federalism: Do States Matter More? Presented at Brandies University (November 2007), Yale University (November 2007), University of New Hampshire (December 2007) and Harvard University's Kennedy School of Government (May 2007).

Gray, W.B., Shadbegian, R.J., 2003. Plant vintage, technology, and environmental regulation. Journal of Environmental Economics and Management 46, 384-402.

Gray, W.B., Shadbegian, R.J., 2002. Pollution abatement costs, regulation, and plant-level productivity. In: Gray, W.B. (Editor), The Economic Costs and Consequences of Environmental Regulation. Ashgate Publications, Aldershot, UK.

Gray, W.B., Shadbegian, R.J., 1998. Environmental regulation, investment timing, and technology choice. Journal of Industrial Economics, 46, 235-56.

Gruenspecht, H.K., 1982. Differentiated regulation: the case of auto emissions standards. American Economic Review 72, 328-331.

Joshi, S., Krishnan, R., Lave, L., 2001. Estimating the hidden costs of environmental regulation. Accounting Review 76, 171-198.

McGuckin, R.H., Pascoe, G.A., 1988. The Longitudinal Research Database: status and research possibilities. Survey of Current Business 68.

Nelson, R.H., Tietenberg, T., 1993. Differential environmental regulation: effects on electric utility capital turnover and emissions. Review of Economics and Statistics 75, 368-373.

Olley, G.S., A. Pakes, A., 1996. The dynamics of productivity in the telecommunications equipment industry. Econometrica 64, 1263-1297.

Porter, M.E., 1991. America's green strategy. Scientific American 168.

Porter, M.E., van der Linde, C.,1995. Towards a new conception of the environment-competitiveness relationship. Journal Economic Perspectives 9, 97-118.

Ross, M.T., Gallaher, M.P., Murray, B.C., Throneburg, W.W., Levinson, A. July 2004. “PACE Survey: Background, Applications, and Data Quality Issues.” Research Triangle Park, NC: RTI International. Available at <http://yosemite.epa.gov/ee/epa/eed.nsf/ffb05b5f4a2cf40985256d2d00740681/cf0ffb9e37c9a7eb85256edd004d3282/$FILE/2004-09.pdf>.

Sato, Kazuo, 1967. A Two-level constant-elasticity-of-substitution production function. Review of Economic Studies 34, 201-218.

Shadbegian, R.J., 1996. How costly is environmental regulation? evidence from U.S. manufacturing. In: Hickey, K., Kantarelis, D. (Editors), Our Natural Environment: Concepts & Solutions, Proceedings of the 2nd International Interdisciplinary Conference on the Environment.

Shadbegian, R.J., Gray, W.B., 2005. Pollution abatement expenditures and plant-level productivity: a production function approach. Ecological Economics 54, 196-208.

Streitwieser, M., 1996. Evaluation and use of the Pollution Abatement Cost and Expenditure survey micro data. Center For Economic Studies Working Paper no. 96-1.

U.S. Bureau of the Census, “Pollution Abatement Costs and Expenditures,” U.S. Govt. Printing Office, Washington, DC, various issues.

Table 1 – Summary Statistics

Variable	Obs.	Mean	Std. Dev.
First Stage Variables			
Log(OUTPUT)	1156	10.49	0.615
Total Inputs			
Log(CAPITAL)	1156	10.63	0.909
Log(LABOR)	1156	7.03	0.641
Log(MATERIALS)	1156	10.21	0.568
Production Inputs			
Log(CAPITAL)	1156	10.46	0.896
Log(LABOR)	1156	6.97	0.648
Log(MATERIALS)	1156	10.09	0.560
Second Stage Variables			
PULP	68	0.56	0.500
AIR ACTIONS	68	37.35	29.428
WATER ACTIONS	68	13.15	31.423
OPPORTUNITY COST – CES	68	9.50%	4.124
OPPORTUNITY COST – CD	68	11.54%	4.235

OUTPUT = Total value of shipments from plant i at time t
CAPITAL = Real capital stock at plant i at time t
LABOR = Worker hours worked at plant i at time t
MATERIALS = Real value of materials used at plant i at time t
PULP = A dummy variable = 1 if the plant employs a pulping technology
AIR ACTIONS = The number of air actions directed at plant i from 1974-1990
WATER ACTIONS = The number of water actions directed at plant i from 1974-1990
OPPORTUNITY COST (CES) = Percentage of lost output due to pollution abatement technology (from the CES production function)
OPPORTUNITY COST (CD) = Percentage of lost output due to pollution abatement technology (from the Cobb-Douglas production function)

Table 2
Production Function Models (N=1156)

CES Production Function

Dependent Variable = log(OUTPUT)

	Coeff.	Std.Error
Log(CAPITAL)	0.188	(0.0120)
Log(LABOR)	0.251	(0.0160)
Log(MATERIALS)	0.561	(0.0194)

$R^2 \approx 0.90$

Cobb-Douglas Production Function

Dependent Variable = log(OUTPUT)

	Coeff.	Std.Error
Log(CAPITAL)	0.181	(0.0092)
Log(LABOR)	0.201	(0.0122)
Log(MATERIALS)	0.588	(0.0182)

$R^2 = 0.92$

The Cobb-Douglas production function also includes a set of year dummy variables that are not presented here.

Table 3
Basic Technology and Regulatory Models (n=68)
(Dep.Var.= CES Opportunity Cost)

CONSTANT	6.611	9.043	9.482	6.901	6.526	6.828
	(0.591)	(0.815)	(0.547)	(0.720)	(0.625)	(0.736)
PULP	5.162			5.304	5.182	5.346
	(0.791)			(0.819)	(0.797)	(0.827)
AIR ACTIONS		0.012		-0.010		-0.011
		(0.017)		(0.014)		(0.014)
WATER ACTIONS			0.001		0.006	0.007
			(0.016)		(0.013)	(0.013)
R^2	0.392	0.008	0.000	0.397	0.394	0.400

(standard errors)

Table 4
Extended Technology and Regulatory Models (n=68)
(Dep.Var.= CES Opportunity Cost)

CONSTANT	5.869	6.518	5.873
	(0.993)	(0.643)	(1.013)
PULP	6.864	5.203	6.815
	(1.321)	(0.877)	(1.376)
AIR ACTIONS	0.025		0.025
	(0.027)		(0.030)
AIR ACTIONS*	-0.047		-0.047
PULP	(0.032)		(0.034)
WATER ACTIONS		0.006	0.001
		(0.015)	(0.017)
WATER ACTIONS*		-0.002	0.003
PULP		(0.028)	(0.028)
R^2	0.417	0.394	0.417

(standard errors)

APPENDIX

Table 3A
Basic Technology and Regulatory Models(n=68)
(Dep.Var.= Cobb-Douglas Opportunity Cost)

CONSTANT	8.843	11.226	11.509	9.204	8.739	9.113
	(0.640)	(0.839)	(0.561)	(0.778)	(0.676)	(0.795)
PULP	4.831			5.007	4.855	5.059
	(0.856)			(0.885)	(0.862)	(0.893)
AIR ACTIONS		0.008		-0.012		-0.014
		(0.018)		(0.015)		(0.015)
WATER ACTIONS			0.003		0.007	0.009
			(0.017)		(0.014)	(0.014)
R^2	0.326	0.004	0.000	0.332	0.328	0.337

Table 4A
Extended Technology and Regulatory Models (n=68)
(Dep.Var.= Cobb-Douglas Opportunity Cost)

CONSTANT	8.155	8.733	8.170
	(1.075)	(0.695)	(1.097)
PULP	6.591	4.871	6.513
	(1.431)	(0.948)	(1.489)
AIR ACTIONS	0.023		0.022
	(0.030)		(0.033)
AIR ACTIONS*	-0.048		-0.046
PULP	(0.034)		(0.037)
WATER ACTIONS		0.007	0.003
		(0.017)	(0.018)
WATER ACTIONS*		-0.001	0.002
PULP		(0.030)	(0.031)
R^2	0.352	0.328	0.353

5C. "Do Firms Shift Production across States to Avoid Environmental Regulation?"

1. Introduction

Environmental regulation in the U.S. has a decidedly federal nature, with state regulatory agencies responsible for much of the enforcement activity, along with some setting of standards. Different states, facing different benefits and costs from environmental regulation, might be expected to choose different levels of stringency, imposing different abatement costs. In turn, firms might respond to differences in costs by shifting their operations, opening or expanding plants in less stringent states, and closing or reducing their operations in stricter states.

We examine the impact of regulatory stringency on firms' allocation of their production across different states, measured by the share of a firm's total production occurring in each state. This is (to our knowledge) the first examination of this topic. Existing studies of regulatory impact using plant-level data have tended to focus on discrete decisions: plant openings and closings. Bartik [2], McConnell and Schwab [21], and Levinson [19] found relatively small or insignificant impacts, but more recent studies have found larger impacts. For example, Becker and Henderson [4] found large reductions in the number of new plants opening in counties with stricter regulation, as did List, et. al. [20]. Furthermore, Gray [12] found lower birth rates of new plants in states with stricter regulation, and Deily and Gray [8] found that steel mills facing more stringent regulatory enforcement were more likely to close. Finally, Greenstone [16], a paper closer in spirit to our paper, finds significant reductions in economic activity of polluting plants in higher-stringency counties, but that paper does not consider the allocation of production within a firm, and it concentrates on a single regulatory measure (county attainment status) for conventional air pollutants, while we consider several state-level measures of stringency, reflecting a wider range of pollutants.

In addition to being novel, examining shifts in production shares is quantitatively important. In our data, changes in production at existing plants account for two-thirds of the aggregate changes in firms' production shares over time, while plant openings and closings account for only about one-sixth each. It is not obvious whether differences in environmental regulation should affect production shares more than they affect plant openings and closings. On the one hand, shifting production among existing plants may be easier than opening or closing plants, making such shifts <u>more</u> sensitive to differences in regulation. On the other hand, many regulations, such as new source performance review, tend to be stricter for new plants and exempt existing ones due to grandfathering, possibly making existing plants <u>less</u> affected by differences in regulation than new plants.

We use eight years of plant-level Census data (1967-2002) for pulp and paper mills from the Census Bureau's Longitudinal Research Database. The pulp and paper industry was chosen for this study because it is a major source of air and water pollution, includes many plants owned by a wide range of firms, has substantial interstate shipments, and its investment and productivity was found to be affected significantly by environmental regulation in past research (Gray and Shadbegian [13], [14], [15]). The data set includes firm identifiers, allowing us to calculate the share that each state represents in a firm's shipments. We also use information on each firm's compliance status from EPA regulatory databases to see whether more compliant firms are more or less sensitive to differences in state regulatory stringency. We control for other state characteristics that could influence production allocation, such as input factor prices and quality, industry concentration, and the demand for paper.

Using seven different measures of state regulatory stringency, we find a significant relationship between regulatory stringency and production allocation. States with stricter regulations have smaller production shares, even after controlling for a variety of other state characteristics. This impact is concentrated in firms with low levels of compliance with environmental regulations. Firms with high compliance rates show little or no impact of regulatory stringency on production allocation. These results are consistent with a model where differences across firms in compliance rates are driven primarily by differences in compliance <u>costs</u> (e.g. economies of scale in compliance), rather than by differences in the <u>benefits</u> of compliance (e.g. maintaining the firm's reputation). Briefly, if firms choose low compliance rates because they see few benefits from complying, they would have no need to avoid high-stringency states. If, instead, low-compliance firms would like to comply, but do not because it is too costly, they would avoid high-stringency states - which is what we observe.

Section 2 presents the theoretical and econometric models we use in analyzing the firm's decision to allocate its production across states, and relates this decision to the firm-level compliance decision. Section 3 describes the data. Section 4 presents the results, followed by our conclusions and some thoughts for future research in Section 5.

2. Model

Within the U.S. federal system of environmental regulation, state regulatory agencies play a major role: they perform most of the inspections and other enforcement actions for both air and water pollution, and in most cases they are responsible for writing the permits that limit the air and water pollution coming from individual facilities. State agencies follow guidelines developed by Federal EPA, and operate under federal oversight, but have considerable latitude in their activities. In some cases (particularly regarding toxics), state laws impose additional legal requirements on facilities. Thus, despite the common framework of federal legislation, and oversight by EPA, there can be substantial variation in regulatory stringency and degree of enforcement across states.

State regulatory stringency may influence firms' decisions along many dimensions. The usual assumption is that production costs are higher in stricter states where firms can be required to meet tougher emissions standards, install higher-capacity (more expensive) pollution control equipment, incur higher operating costs, and perform more frequent maintenance.[36] In addition to higher production costs, more stringent states may have more complex permit procedures, requiring firms to undertake lengthy negotiations whenever they wish to change their production process, and perhaps imposing uncertainty about whether the changes will be permitted at all. Since these permits are commonly required when opening a new plant, there could also be a direct impact of regulatory stringency on the expenses or time required to open a new plant.[37]

---

[36] Becker [3] demonstrates the connection between regulatory stringency and pollution abatement costs. Other studies have measured regulation-induced increases in costs as decreases in productivity. Färe et al [9], Gray [11], and Barbera and McConnell [1] use industry-level data. In plant-level work, Gollop and Roberts [10] study electric utilities, while Berman and Bui [5], Boyd and McClelland [6], and Gray and Shadbegian [14, 15] examine manufacturing plants.

[37] The importance of permit uncertainty in the paper industry is discussed in Gray and Shadbegian [13]. We have no direct measures of permit difficulties, but conversations with industry people suggest that states which are stricter on our regulatory stringency measures are likely to have more delays and uncertainty in their permitting process.

In addition to the overall impact of regulatory stringency on firms' decisions, we are also interested in heterogeneity across firms in their decisions. For example, we observe variations in regulatory compliance across firms, with larger firms serving national markets having better environmental performance (being more often in compliance with regulations) than smaller firms serving local markets. Why might such differences occur?

Differences in compliance between large and small firms could arise from differences in their costs of dealing with the complexity of environmental regulations. Larger firms can afford a corporate environmental staff supporting many plants. Smaller firms, relying on plant-level personnel with many other responsibilities, cannot keep up with frequent regulatory changes.[38] Larger firms may also have the political clout to intervene in the standards-setting process, making compliance easier.[39] These economies of scale in compliance should give larger firms an advantage, especially in states with stringent regulations (and more complex bureaucratic procedures to enforce those regulations), allowing them to choose higher compliance rates.

Differences across firms in compliance could also arise from differences in their benefits of compliance, attributable to the importance of reputation, both in terms of reputation with regulatory agencies and with customers. Failure to comply with regulations may result in lost sales, if customers value a 'green' image for the products they consume. Regulators may punish violators with stricter future enforcement at all plants owned by the firm (see Harrington [18]). In both cases, the importance of reputation relies on non-compliant behavior being highly visible, and on there being a large number of future interactions where the punishment can take place. Smaller firms have fewer other plants or future sales to be punished, and their violations are likely to be less newsworthy. Therefore smaller firms should face smaller benefits from compliance, leading them to choose lower levels of compliance effort.

Now consider the optimizing decision of a profit-maximizing firm choosing its production level Q_S in each of a number of different states, as shown in Equation 1 below.

$$(1) \quad \max_{Q_S,\, A_S} \ \Pi = R(Q_S) - C(Q_S) - \alpha_c * PAC(A_S) * Q_S - \alpha_b * P_S * (1 - A_S) * Q_S$$

$R(Q_S)$ and $C(Q_S)$ refer to the revenue function (net of transportation costs to consumers, possibly located in other states) and production cost function in state s. We assume that over the relevant range of output the revenue and cost functions have the usual shape – diminishing marginal revenue $\left(d^2R(Q_s)/dQ_s^2 < 0\right)$ and increasing marginal costs $\left(d^2C(Q_s)/dQ_s^2 < 0\right)$. We also assume that production of Q causes pollution and the firm is faced with a choice about how much of its pollution to abate, A_S ($0 <= A_S <= 1$), with resulting abatement costs $PAC(A_S)$. We

[38] These differences may be growing smaller over time (though we do not test for that here). Down-sizing and cost-cutting pressures at large corporations have reduced the size of corporate staffs, and there has been greater use of outside consultants specializing in environmental issues, providing smaller firms with access to some scale economies. These trends have been more pronounced in recent years, so should be less important for the period being studied here.

[39] Environmental officers at large corporations commonly serve on state environmental advisory boards, where they are in a position to influence the development of new regulations.

further assume increasing marginal abatement costs ($d^2PAC_S / dA_S^2 > 0$). On the other hand, not abating pollution can also be costly, as the firm faces expected penalties P_S from state regulators, where P_S depends on both inspection frequency and the level of penalties for violations. Note that both abatement costs and penalties are measured proportional to output. The model allows for heterogeneity across firms in both costs of abatement α_c (e.g. economies of scale in abatement) and benefits from abatement α_b (e.g. "penalties" from customer backlash if the firm is found in violation).

A profit-maximizing firm chooses both the optimal level of output (Q_S^*) and the optimal level of abatement (A_S^*) in each state. The first-order condition for choosing Q_S^* is shown in Equation 2, where the usual equality between marginal revenue and marginal cost (R'=C') is complicated by an additional wedge, based on a combination of the cost of pollution abatement and the penalties from non-abatement. The first-order condition for choosing As* is shown in Equation 3, where the firm sets its marginal abatement cost equal to its expected penalties from not abating pollution, adjusted by the firm-specific factors α_c and α_b.

(2) $R'(Q_S^*) = C'(Q_S^*) + \alpha_c * PAC(A_S^*) + \alpha_b * P_S^* * (1 - A_S^*)$

(3) $PAC'(A_S^*) = (\alpha_b / \alpha_c) * P_S$

With constant or declining marginal costs of production and no transportation costs, a profit-maximizing firm should produce all its output in the lowest-cost state, taking into account pollution-related cost differences. Since we are analyzing data for firms that produced output in at least four different states, they must have either increasing marginal production costs or some sort of transportation costs, in order to have an interior solution to Equation 2 in multiple states. Still, firms will tend to produce less in those states with higher regulatory stringency: all else equal, higher P_S in a state encourages a greater abatement effort (A_S), and these two effects combine to create a larger wedge between marginal revenue and marginal cost. In the extreme, firms may choose to produce nothing in states with sufficiently high regulatory stringency.

We are also interested in differences across firms in their sensitivity to state regulatory stringency, dQ_S^*/dP_S. These differences could arise from differences in the firm's α_c or α_b. We do not observe α_c and α_b, but we do observe the firm's level of regulatory compliance, which we take as an indicator of its average abatement decisions. Suppose that differences in compliance across firms are driven primarily by differences in their cost factors α_c. High-compliance firms would be those with lower α_c and a smaller wedge, and thus would be <u>less</u> sensitive to regulatory stringency. If, instead, differences across firms in compliance are driven primarily by differences in their benefit factors α_b, high-compliance firms would be those with higher α_b and a larger wedge, and thus would be <u>more</u> sensitive to regulatory stringency.

We can see this more simply by considering the extreme cases, where α_c=0 or α_b=0. If α_c=0, then it is costless for the firm to abate, so it sets A_S^*=1 and the wedge disappears. In this case, differences in P_S have no effect on high-compliance firms. On the other hand, if α_b=0, then the firm sees no benefit from abatement, so it sets A_S^*=0. Again the wedge disappears, but now it is low-compliance firms that are unaffected by differences in P_S. In our empirical work, we interact the firm's overall compliance rate with a measure of state regulatory stringency to test which effect is the more important source of firm heterogeneity. Based on the argument above, a positive coefficient on the interaction term indicates that differences in the costs of pollution abatement are the more important source of firm heterogeneity: higher firm compliance reduces the negative impact of state stringency on production within the state. A negative coefficient indicates that differences in benefits are more important.

We use a conditional logit model for the analysis, examining the probability that a firm allocates a given unit of production to a given state, given the characteristics of that state and all the other available states to choose from:

$$(4) \quad \text{Prob(firm i chooses state s)} = \frac{\exp(\beta * Z_s + \delta * P_s + \gamma * A_i * P_s)}{\prod_j \exp(\beta * Z_j + \delta * P_j + \gamma * A_i * P_j)}.$$

State characteristics Z_S include the cost of labor and other inputs, along with factors that might influence marginal revenue, such as industry concentration and an index of paper demand within the state. Following this model focuses our attention on the differences in regulation (and other explanatory variables) across states at a given time. A general increase in regulatory stringency across all states could leave the ratio in equation (4) unchanged, in which case it would be predicted not to influence the firm's allocation decision – every unit of production has to be allocated somewhere, and it is the differences in P and Z across states which matter in the conditional logit model.

Firm characteristics cannot directly enter the model, since they would cancel out in the numerator and denominator of (4), but we interact our measures of regulatory stringency with the firm's compliance rate, to see whether low-compliance firms respond more or less to regulatory differences. We use the fraction of all of the firm's plants that are in compliance, based on all plant-year observations with compliance data, so each firm has one compliance rate, fixed over time. This is intended to capture differences across firms in their long-term compliance tendencies.[40] We consider two types of interactions, one using the continuous measure of compliance and the other using a spline in compliance to see how responsiveness changes as compliance rates change.

The model does not allow us to differentiate shifts in production across existing plants from shifts due to plant openings and plant closings. We might expect shifting production

---

[40] Comments on an earlier specification raised concerns about possible endogeneity of compliance. This seems less relevant in our current conditional logit specification; but we did try instrumenting for the firm's compliance rate, predicting plant-level compliance based on plant age and output, state regulatory enforcement, and state and year dummies, and then averaging it across all plants in the firm, with essentially identical results (available from the authors).

among existing plants to be easier than opening new plants, since new plants are generally subject to more stringent regulations. However, air pollution regulations requiring stricter rules for new plants (New Source Performance Standards) can also require existing plants to be treated as new if they substantially expand their production process. This could make production shifts among existing plants more costly. In any event, our estimated effects are best thought of as averages across the different categories of changing production shares, weighted by their relative sizes.

To implement our model using a standard conditional logit routine, we treat each firm as making 100 decisions in each time period, allocating 100 'percentage points' of its production across the available states. The estimation routine interprets this as generating a huge sample size for the analysis, with correspondingly small standard errors and large t-statistics – but the impact is predictable, so we can adjust for it.[41] The key is to decide what the "true" sample size is, from which the appropriate adjustment factor can be calculated and applied. In our analyses we use the actual number of firm-state-year observations with positive production. This should be a conservative measure of sample size (and hence produce conservative standard errors), since it excludes any states where the firm is not currently producing.

3. Data

Our basic plant-level data on production comes from the Longitudinal Research Database (LRD) maintained at the Center for Economic Studies of the U.S. Census Bureau (see McGuckin and Pascoe [22] for a detailed description). We use information from the Census of Manufactures, done every five years since 1967 on all manufacturing plants in the country (around 300,000 plants in each census). For this paper, we concentrate on pulp and paper mills, which we have studied extensively, including an analysis of the impact of pollution abatement costs on productivity (Gray and Shadbegian [14],[15] and Shadbegian and Gray [23]). The plant-level data includes a firm identifier, with which we link together all the paper mills owned by the same firm in each Census year from 1967-2002.

We add up the total value of shipments from each plant owned by the firm and calculate the share of a firm's production arising in each state, which forms the dependent variable (SHTVS) for our analysis.[42] In order to focus on those firms which are in a position to allocate production across states, we limit our sample to those firms which produced in at least four different states at some point. This would give us a 'balanced' panel, if all firms were in business throughout the period. A few of our firms are out of existence at some point (corresponding to the birth or death of the entire firm). We drop those firm-year observations since their production shares cannot be defined in that year, but keep them in the sample for the other years.

In what ways do firms shift production in our data? Changes in production shares at continuing plants accounted for 68 percent of all share changes, while plant openings accounted

---

[41] For example, doubling the sample size (allocating 200 rather than 100 shares of production) doubles the log-likelihood and reduces all standard errors by the square root of 2, but has no effect on the estimated coefficients.

[42] We could calculate plant-level production shares, but our explanatory variables are state-specific, so we use state-level shares instead.

for 17 percent and closings for 15 percent. Thus changes in production shares at existing plants are about four times as important as plant openings or closings in terms of moving production activity across plants in different states.

Does it make sense to treat the market as being served by plants in many different states? The 1993 Commodity Flow Survey reports the distance traveled by shipments for particular industries. Based on these data, paper shipments traveled an average of 238 miles, with 26 percent of shipments traveling further than 500 miles.[43] This indicates a somewhat national market for paper, with opportunities to shift production across states, but not a market in which firms are concentrating all their production in one or a few states.

As noted earlier, firms' decisions about whether or not to comply with regulations may provide some information about their sensitivity to regulatory costs. We use plant-level air pollution compliance data for 1979-1989 taken from the EPA's Compliance Data System, where compliance is defined as not being 'in violation' for any pollutant at any point during the year. All of the available plant-years of compliance data were linked together by firm, and the 'firm compliance average' was calculated as the fraction of all observations in compliance.[44] We use a single compliance measure for each firm (not a time-varying one) because the compliance data is not consistently available before the 1980s. Using a single compliance measure is appropriate as long as differences in compliance primarily reflect long-run differences between firms, rather than transitory fluctuations.

Aside from the firm compliance variable, all of the explanatory variables in our model are state-specific. These range from state-level regulatory variables to input cost and other factors expected to influence the production decision. In earlier plant-location analyses (Gray [12]) the issue of endogeneity of these explanatory variables arose, and was addressed in part by lagging the explanatory variables by five years. Thus 1977 explanatory variables are assumed to influence the birth rate of new plants between 1977 and 1982. We use a similar procedure here, so that 1977 explanatory variables are used to explain production shares in 1982.

We use a total of seven measures of state-level regulatory stringency, taken from a variety of sources. One problem with our regulatory measures is that most are not available before the 1980s, and many have no time-series variation available at all. Our principle index of regulatory stringency does have some time-series variation and covers the entire period: support for environmental legislation in Congress. The League of Conservation Voters calculates a scorecard for each member of Congress on environmental issues, with data available back to the early 1970s, which we extended back to the 1960s. We use the average score for the state's House of Representative members (GREENVOTE) in our analysis.[45]

---

[43] Calculations done by the author, using the publicly available 1993 Commodity Flow Survey on CD-ROM. The details of this analysis (aggregating data for specific state-industry cells on the average shipment distance and the frequency distribution of shipments for different categories of distances) are available from the author. The averaging is done based on each shipment's value.

[44] We originally compiled the CDS information for our productivity analyses, so the compliance variable is only available for firms which had at least one plant in our productivity sample.

[45] The earliest year available in the League of Conservation Voters data is 1970. We calculated comparable measures for the 1960s, using congressional voting data on environment-related legislation in the 1960s. Of course the environmental bills being considered in the 1960s were fewer and less costly than those in later years, but the votes should reflect similar differences in state preferences for regulation.

The Census Bureau's Pollution Abatement Costs and Expenditures (PACE) survey reports the dollars spent for pollution abatement by manufacturing firms, giving totals for all industries in each state and for all plants nationwide in each industry. We divide annual pollution abatement operating costs by total manufacturing shipments to measure pollution abatement intensity (for each state and each industry). We then calculate the predicted abatement intensity for each state, multiplying each industry's abatement intensity by its share in total state employment (from the Census of Manufactures). The residual abatement intensity (actual minus predicted), is used in the regressions (PAOCADJ). The PACE survey was only carried out between 1973 and 1994, so we extrapolate our starting (and ending) values to fill in the missing years. This is equivalent to assuming that the relative rankings of the states were unchanged during the missing period, since the conditional logit analysis focuses exclusively on within-year comparisons of state stringency.

The Green Index publication (Hall and Kerr [17]) contains one-time rankings of all the states on a large number of environmental-related variables. A measure of regulatory stringency is the 'Green Policies' (ENVPOLICY) index, designed to measure the stringency of state environmental regulations based on a set of 77 specific indicators, such as the presence of state laws on specific topics such as recycling. A measure of environmental problems in each state is the 'Green Conditions' (DIRTY) index, which indicates the state's combined ranking on over 100 measures of the quality of the state's environment, including air and water pollution information.[46] CONVMEMB (taken from the same source) is the number of members of three conservation groups (Sierra Club, Greenpeace, and National Wildlife Federation) per 1000 in the state population, indicating support for environmental issues among the state's electorate. REGSPEND is the dollars per capita spent on the state's programs for environmental and natural resources in 1988 (Council of State Governments [7]).

A direct measure of enforcement activity for air pollution regulation is taken from the EPA's Compliance Data System. This database reports all air pollution inspections, identifying the affected plant by industry and location. The total number of inspections of manufacturing plants between 1984 and 1987, divided by the number of manufacturing plants in 1982, was calculated for each state (AIRINSP). Greater enforcement activity is expected to put more pressure on plants in the state to come into compliance with air pollution regulations, raising costs and reducing profitability. In Deily and Gray [8] a similar measure of enforcement was found to increase the probability that a steel plant would close.

One final regulatory variable (NONATTAIN) measures the state's attainment status for key air pollutants. We select a single pollutant that is particularly relevant for the paper industry (particulates), and calculate the fraction of the counties in the state that are not in attainment.[47] Other researchers (e.g. Becker and Henderson [4], Greenstone [16]) have concentrated exclusively on this measure of stringency, and carried out all their analyses at the county level. Since we are considering several other regulatory measures, all of which are defined at the state level, as are most of our control variables, we chose to aggregate attainment status to the state level to match the rest of our data. A high value of NONATTAIN should be associated with

[46] In the original rankings, low scores reflected stricter regulation and a cleaner environment. We multiplied ENVPOLICY by -1 to improve comparability (higher value = greater stringency).
[47] We would like to thank Randy Becker for providing this attainment data.

more stringent regulation, as states are required to impose more restrictions on plant expansion or new plant construction in non-attainment areas.

We also create additional variables measuring the characteristics of the paper industry in each state. DEMAND is a state-specific demand index for paper in the state. We use data on employment for each one-digit industry in the state, and combine it with data from the 1982 input-output tables on how much paper each one-digit industry consumes (per employee). To capture ‘final demand’ for paper by consumers, we use the state's total income and calculated final demand per dollar of total state income. Adding up the industry and consumer demand for paper gives an indicator of total demand in the state. It only captures shifts in within-state demand; to the extent that the market is national or regional in scope, this local demand index may be less important.

HERF is the Herfindahl index for paper mills in the state, measuring how concentrated the production of paper is in the state. We identify all plants in the industry in each Census year, add up their individual shipments, and calculate a share of each plant in the total shipments. Finally, we square each plant's share and sum them. A number close to one indicates highly concentrated production, while numbers near zero indicate little concentration. To the extent that a more concentrated industry has more market power, it could raise price in response to stricter regulations, so may be less sensitive to regulatory pressures. Of course, an ideal measure of such concentration would be firm-level, rather than plant-level, and might include plants in nearby states that supplied the same market.

CLOUT is paper industry shipments from plants in the state, divided by the total gross state product. A large industry might be expected to have more political power, and thus to be able to gain exemptions from regulatory pressures. On the other hand, a large industry is likely to be a larger contributor to the total pollution problem in the state, and may be a more visible target for stricter regulatory pressures. CLOUT should get a positive coefficient, reflecting whatever characteristics make the state a desirable location.

In addition to the regulatory variables and the variables measuring the characteristics of the paper industry, a number of other variables are used to control for differences across states that might influence production allocation. These variables were used in earlier work focusing on plant location, Gray [12], and were designed to capture a wide range of the other factors affecting the location decision. The earlier work found them to be generally significant as a group, although only a subset would be individually significant in any given regression. Factor price measures include ENERGYPRI (dollars per million BTU, from the Energy Information Administration), LANDPRICE (value per acre of agricultural land and buildings, from the City and County Databook), and WAGE (average hourly wage in manufacturing, taken from the Statistical Abstract). All dollar values are converted to real 1982 values using the GDP deflator. Labor market indicators include UNION (percent of non-agricultural workforce unionized, from Bureau of Labor Statistics), UNEMP (civilian unemployment rate), and INCOME (income per capita). Labor quality is measured by the fraction of the over-25 population with college degrees (COLLEDUC). Tax differences are measured by state and local taxes, divided by gross state product (TAXGSP). ELECDEM is the percentage of votes for Democratic candidates in the U.S. House of Representatives for the state. Population density (POPDEN) controls for differences in the size of the local product market and possibly also for ‘agglomeration effects’ (the tendency to locate where existing businesses are already located). AREA provides a physical measure of the extent of the available market in the state.

4. Results

Table 1 presents the means and standard deviations for each variable used in the analysis. We have about 40 firms in our sample and up to 7 years of data for each firm, resulting in a sample size of 3574 firm-state observations with non-zero production. In our data, the average paper firm is operating in about 15 states, resulting in an average of about 6-7 percent of the firm's production occurring in each state (or alternatively a probability of about 6-7 percent that a given unit of the firm's production occurs in a given state). We should note that the firm sizes are somewhat skewed, so that a "typical" firm might be operating in 8-10 states. Most firms have relatively high compliance rates, averaging around 70 percent of their plants in compliance.

Table 2 presents the basic models, using the conditional logit model described earlier. The model explains 10-15 percent of the variation in production allocation across our firm-state observations, once state characteristics or state dummies are included in the model. Consider model 3, which includes state characteristics but not state dummies. The DEMAND index, as expected, shows that higher state demand for the industry's product is associated with greater production in the state; CLOUT is also positive. ENERGYPRI and WAGE have the expected significant negative impact on production shares: states with higher energy prices and a higher wages are allocated lower production shares. COLLEDUC has the expected positive effect on production shares, though it is only marginally significant. On the other hand, several variables have unexpected effects, and some of them are significant in model 3, such as LANDPRICE, TAXGSP, and ELECDEM. Not surprisingly, including state dummy variables in model 4 raises the overall explanatory power of the model, but reduces the significance of most of the state characteristics. In fact, DIRTY and AREA drop out of the model when the state dummies are included, since they are purely cross-sectional variables.

The main focus of this study is on state regulatory stringency, as measured by GREENVOTE, and its interaction with firm compliance rates. The GREENVOTE variable is consistently negative and significant, while the interaction between compliance and stringency (COMP*GREENVOTE) is consistently positive and significant. This indicates that firms with low compliance rates tend to avoid states with stricter regulation, but that the effect is smaller for firms with higher compliance rates. In fact, at a high enough compliance rate, the marginal effect of more stringency is positive. The 'crossover' compliance rate varies from 56-74 percent in the models with state dummies to 97 percent in the models with state characteristics, but not state dummies. The average compliance rate in our sample, 70 percent, is near the crossover point of 74, so the marginal impact of stringency on a typical firm's production allocation is likely to be small. Still, the results indicate that low-compliance firms are significantly more likely to avoid high-stringency states, which is consistent with compliance decisions being driven by differences in compliance <u>costs</u> across firms (economies of scale in compliance), rather than differences in <u>benefits</u> (maintaining firm reputation).

In Table 3 we examine the interaction between the regulatory measures and the firm's compliance rate using a less constrained approach, creating dummies for firms with compliance rates exceeding 70 percent and 85 percent, which correspond very roughly to the median and upper quartile of the firm compliance rate distribution.[48] For those models that incorporate state characteristics, we find that the impact of regulatory stringency on production allocation, as measured by GREENVOTE, is negative and significant for those firms with less-than-average

[48] Due to Census confidentiality restrictions, we cannot report the exact values that correspond to a single observation in the dataset, such as the median value.

compliance rates (below 70 percent). For firms with intermediate compliance rates (between 70 and 85 percent), the impact of regulatory stringency is smaller, but still negative, while those firms with very high compliance rates (over 85 percent) tend to show a positive impact of regulatory stringency of production allocation.

Table 4 examines six other measures of state regulatory stringency, along with their interactions with firm compliance. Because these measures (except PAOCADJ and NONATTAIN) have no within-state variation, we cannot include state fixed-effects in these models. We do include the full set of state-specific control variables, which have similar coefficients (not shown here) to those found in Table 2 (model 3). In the upper panel, most of the other stringency measures give results similar to GREENVOTE, with a negative coefficient on the regulatory variable and a positive interaction with firm compliance (only ENVPOL has the unexpected positive sign on the regulatory variable). Those measures for which both terms are significant (PAOCADJ, NONPM, and CONVMEMB) have cross-over points for their compliance rates roughly similar to those found for GREENVOTE, ranging from 54 percent for PAOCADJ to 97 percent for CONVMEMB.

The results in the lower panel of Table 4 show the interactions of these 6 regulatory measures with dummies indicating firm compliance rates greater than 70 or 85 percent. The impacts here are less consistent than those for GREENVOTE in Table 3, but for those regulatory measures with consistently significant effects in the upper panel (PAOCADJ, NONATTAIN, and CONVMEMB), we see that firms with below-average compliance seem to be more sensitive to regulation than high-compliance firms. Also, the highest-compliance firms have consistently positive effects relative to the lowest-compliance ones – allocating relatively more production to those states with more stringent regulation.

How large are these effects of state stringency on firm production? The marginal effects for Model 3 in Table 2 are GREENVOTE= -0.129 and COMP*GREENVOTE= +0.133. Thus a firm that is never in compliance would allocate 2.5 percentage points less production to a state with a one standard deviation (19.683) higher GREENVOTE value. For a firm that is producing in 10 states, this shift in production would amount to one-quarter of its average state production share. On the other hand, a firm that is always in compliance would allocate 0.1 percentage points more production to the same high-stringency state. In Table 3, the marginal effects are GREENVOTE= -0.070, COMP70*GREENVOTE= +0.015, and COMP85*GREENVOTE= +0.053. Going from low to high compliance categories, a one standard deviation difference in GREENVOTE would lead a firm to reduce production by 1.4, 1.1, and 0.04 percentage points, respectively. The other stringency measures from Table 4 show considerably smaller marginal effects, with the largest impact coming for NONATTAIN, where a one standard deviation higher stringency rate corresponds to 0.8 percentage points less production for a non-compliant firm.

5. Conclusions

We examine the decision faced by a firm trying to allocate its production across plants in several states, based in part on the regulatory stringency in those states. We are able to measure these decisions between 1967 and 2002, at five year intervals, using the Census Bureau's Longitudinal Research Database. We focus on paper firms, which face relatively stringent environmental regulation, have many firms with operations in multiple states, and have shown significant impacts of regulation in earlier studies.

We find a significant relationship between our regulatory variables and production allocation within the paper industry. States with stricter regulations have smaller production shares, even after controlling for a variety of other state characteristics. Interacting firm compliance and state stringency, we find that the impact of stringency is concentrated on low-compliance firms. In fact, firms with high compliance rates appear to be slightly more likely to produce in more stringent states. The crossover points (where state stringency has no impact on production location), occur between 50 and 80 percent compliance rates, relatively close to the actual compliance rates of about 70 percent in our data. Our model predicts that a state with one standard deviation higher stringency (as measured by pro-environmental voting) would get a production share that is 2.5 percentage points lower for a firm that is never in compliance, but is 0.1 percentage points higher for a firm that is always in compliance. This represents a substantial shift in state-level production shares for a typical firm producing in 10 states.

Our result that high-compliance firms are less likely to avoid more stringent states is consistent in our theoretical model with compliance decisions being driven by differences in compliance costs across firms (economies of scale in compliance), rather than differences in benefits (maintaining firm reputation). If firms are choosing low compliance rates because they do not see any benefits from complying, they would not need to avoid high-stringency states (since they are not planning to comply anyway). If the low-compliance firms are trying to comply, but failing due to high compliance costs, they would want to avoid high-stringency states – and this is the case that we find support for in our empirical results.

We anticipate further work in this area, looking in more detail at changes in allocation over time and developing a model of a firm's compliance behavior in order to better understand how regulation affects production allocation decisions.

REFERENCES

1. A. J. Barbera and V. D. McConnell, Effects of Pollution Control on Industry Productivity: A Factor Demand Approach, *J. Industrial Econom.*, **35**, 161-172 (1986).

2. T. J. Bartik, The Effects of Environmental Regulation on Business Location in the United States, *Growth Change*, **19**, 22-44 (1988).

3. R. A. Becker, Air Pollution Abatement Costs under the Clean Air Act: Evidence from the PACE Survey, *J. Environ. Econom. Management*, **50**, 144-169 (2005).

4. R. A. Becker and J. V. Henderson, Effects of Air Quality Regulation on Polluting Industries, *J. Pol. Econom.*, **108**, 379-421 (2000).

5. E. Berman and L. T. Bui, Environmental Regulation and Productivity: Evidence from Oil Refineries, *Rev. Econom. and Stat.*, **83**, 498-510 (2001).

6. G. A. Boyd and J. D. McClelland, The Impact of Environmental Constraints on Productivity Improvement in Integrated Paper Plants, *J. Environ. Econom. Management*, **38**, 121-142 (1999).

7. Council of State Governments, "Resource Guide to State Environmental Management", Lexington, KY (1991).

8. M. E. Deily and W. B. Gray, Enforcement of Pollution Regulations in a Declining Industry, *J. Environ. Econom. Management*, **21**, 260-274 (1991).

9. R. Färe, S. Grosskopf, C. Lovell, and C. Pasurka, Multilateral Productivity Comparisons When Some Outputs are Undesirable: A Nonparametric Approach, *Rev. Econom. Statist.*, **71**, 90-98 (1989).

10. F. M. Gollop and M. J. Roberts, Environmental Regulations and Productivity Growth: The Case of Fossil-fueled Electric Power Generation, *J. Political Econom.*, **91**, 654-674 (1983).

11. W. B. Gray, The Cost of Regulation: OSHA, EPA, and the Productivity Slowdown, *Amer. Econom. Rev.*, **77**, 998-1006 (1987).

12. W.B. Gray , Manufacturing Plant Location: Does State Pollution Regulation Matter? National Bureau of Economic Research, Working Paper 5880 (1997).

REFERENCES (cont.)

13. W. B. Gray and R. J. Shadbegian, Environmental Regulation, Investment Timing, and Technology Choice, *J. Ind. Econom.*, **46**, 235-256 (1998).

14. W. B. Gray and R. J. Shadbegian, Pollution Abatement Costs, Regulation, and Plant-Level Productivity, in "The Economic Costs and Consequences of Environmental Regulation" (W. Gray, Ed.), Ashgate Publications, Burlington, VT (2002).

15. W. B. Gray and R. J. Shadbegian, Plant Vintage, Technology, and Environmental Regulation, *J. Environ. Econom. Management*, **46**, 384-402 (2003).

16. M. Greenstone, The Impacts of Environmental Regulations on Industrial Activity: Evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufactures, *J. Political Econom.*, **100**, 1175-1219 (2002).

17. B. Hall and M.L. Kerr. "Green Index: A State-by-State Guide to the Nation's Environmental Health". Island Press, Washington, DC (1991).

18. W. Harrington, Enforcement Leverage when Penalties are Restricted, J. Public Econom., 37, 29-53 (1988).

19. A. Levinson, Environmental Regulations and Manufacturer's Location Choices: Evidence from the Census of Manufactures, *J. Public Econom.*, **62**, 5-30 (1996).

20. J. A. List, D.L. Millimet, P.G. Fredricksson and W.W. McHone, Effects of Environmental Regulations on Manufacturing Plant Births: Evidence from a Propensity Score Matching Estimator, *Rev. Econom. Statist.*, **85**, 944-952 (2003).

21. V. D. McConnell and R. M. Schwab, The Impact of Environmental Regulation on Industry Location Decisions: The Motor Vehicle Industry, *Land Econom.*, **66**, 67-81 (1990).

22. R. H. McGuckin and G. A. Pascoe, The Longitudinal Research Database: Status and Research Possibilities, *Survey Current Business*, **68**, 30-37 (1988).

23. R. J. Shadbegian and W. B. Gray, Pollution Abatement Expenditures and Plant-Level Productivity: A Production Function Approach, *Ecological Econom.*, **54**, 196-208 (2005).

TABLE 1
Descriptive Statistics
(3574 obs)

Variable	Mean (Std. Dev.)
Dependent Variable	
SHTVS	6.355 (14.004)
shipments from firm's plants in state, divided by total firm shipments (*100)	
Firm characteristics	
COMP	0.707 (0.197)
firm compliance (% firm's plants in compliance with air pollution regulations, 1979-1989)	
State regulatory stringency	
GREENVOTE	46.136 (19.683)
pro-environment Congressional voting (League of Conservation Voters)	
PAOCADJ	0.364 (1.253)
pollution abatement costs in state (adjusted for industry mix)	
ENVPOLICY	-1.982 (0.660)
Green Policies index from Hall and Kerr [17]; bigger negative=less strict	
AIRINSP	0.048 (0.061)
state air pollution inspection rate (inspections/plants), 1979-1989	
NONATTAIN	9.146 (10.620)
percent of state's counties in non-attainment for particulate concentrations	
CONVMEMB	8.366 (3.321)
membership in 3 conservation groups, late 1980s, per 1000 population	
REGSPEND	24.599 (13.504)
state government environmental spending per capita, 1988	
Industry characteristics within state	
DEMAND	2.765 (0.592)
demand index for paper in state, based on industry mix	
HERF	0.305 (0.260)
herfindahl index for paper industry in state, based on plant-level shipments	
CLOUT	0.172 (0.353)
paper industry shipments/Gross State Product	

TABLE 1 (cont.)
State Control Variables

WAGE	7.464	(2.601)
1982$ average manufacturing wage		
ENERGYPRI	0.287	(0.280)
1982$ per million BTU (*1000)		
LANDPRICE	0.797	(0.807)
1982$ (1000) value per acre		
UNION	22.604	(10.218)
non-farm unionization rate		
UNEMP	5.855	(2.428)
civilian unemployment rate		
COLLEDUC	13.643	(5.865)
percent college graduates in population		
TAXGSP	8.248	(1.443)
total state and local taxes, as percent of gross state product		
ELECDEM	0.465	(0.184)
fraction voting for Democratic Congressional candidates		
INCOME	8.935	(6.616)
1982$ (1000) Income per capita		
POPDEN	0.195	(0.229)
(1000) population per square mile		
AREA	0.059	(0.049)
land area in million square miles		
DIRTY	4.658	(0.621)
Green Conditions index from Hall and Kerr [17]		

TABLE 2
Basic Production Share (SHTVS) Models
N=3574

Model:	1	2	3	4
GREENVOTE	−0.564[c]	−1.498[a]	−2.734[a]	−2.274[a]
	(−1.88)	(−3.92)	(−7.97)	(−5.55)
COMP* GREENVOTE	2.198[a]	2.698[a]	2.823[a]	3.087[a]
	(4.82)	(5.40)	(5.75)	(6.03)
DEMAND			0.805[a]	0.712[a]
			(16.44)	(3.86)
HERF			−2.858[a]	−1.140[a]
			(−18.33)	(−3.81)
CLOUT			0.199[a]	−0.210
			(3.64)	(−1.25)
WAGE			−0.089[a]	−0.071
			(−2.82)	(−1.16)
ENERGY			−2.311[a]	−0.940[b]
			(−8.54)	(−2.28)
LANDPRICE			0.109[b]	0.073
			(1.96)	(0.90)
UNION			0.006	−0.001
			(1.63)	(−0.11)
UNEMP			−0.021	−0.030
			(−1.37)	(−1.39)
COLLEDUC			0.029[c]	−0.038
			(1.87)	(−1.38)
TAXGSP			0.189[a]	0.147[a]
			(8.28)	(3.52)
ELECDEM			2.328[a]	0.080
			(10.62)	(0.29)
INCOME			0.015	0.007
			(0.86)	(0.23)

Table 2 (cont)

POPDEN			-0.873[a]	-0.135
			(-4.96)	(-0.07)
AREA			3.179[a]	
			(5.56)	
DIRTY			0.093	
			(1.64)	
STATE DUMMIES	NO	YES	NO	YES
Log-L	-92440	-79281	-84598	-78909
Pseudo R^2	0.005	0.147	0.089	0.151

Notes:

(T-statistics) adjusted for the “true’ sample size
a = significant at the 1% level or better
b = significant at the 5% level or better
c = significant at the 10% level or better

TABLE 3
Production Share (SHTVS) Models
Using Spline on Firm Compliance
N=3574 (t-statistics)

Model :	1	2	3	4
GREENVOTE	0.427[a]	-0.308	-1.480[a]	-0.918[a]
	(3.03)	(-1.21)	(-7.53)	(-3.26)
COMP70 *GREENVOTE	0.196	0.301	0.329	0.405
	(0.85)	(1.22)	(1.33)	(1.59)
COMP85 *GREENVOTE	0.956[a]	1.127[a]	1.131[a]	1.193[a]
	(4.42)	(4.82)	(4.82)	(4.92)
STATE CHARS	NO	NO	YES	YES
STATE DUMMMIES	NO	YES	NO	YES
Log-L	-92388	-79216	-84541	-78850
Pseudo R^2	0.006	0.147	0.090	0.151

NOTES:
These model numbers correspond to those in Table 2, including all of the state-level control variables in models 3 and 4.

(T-statistics) adjusted for the "true' sample size
a = significant at the 1% level or better
b = significant at the 5% level or better
c = significant at the 10% level or better

TABLE 4
Production Share (SHTVS) Models Using
Alternative Regulatory Measures
N=3574 (t-statistics)

	PAOCADJ	ENVPOL	AIRINSP	NONATTAIN	CONVMEMB	REGSPEND
RegVar	−0.141[b]	0.176[c]	−13.334[a]	−2.459[a]	−0.099[a]	−1.165
	(−2.52)	(1.79)	(−6.86)	(−8.24)	(−4.37)	(−0.22)
Comp*Reg	0.262[a]	0.092	3.720	3.235[a]	0.102[a]	15.965[b]
	(3.73)	(0.84)	(1.53)	(8.89)	(4.15)	(2.48)
Log-L	−84807	−84846	−82552	−84557	−84845	−84790
Pseudo R^2	0.087	0.087	0.111	0.090	0.087	0.087

	PAOCADJ	ENVPOL	AIRINSP	NONATTAIN	CONVMEMB	REGSPEND
RegVar	−0.018	0.244[a]	−12.493[a]	−0.671[a]	−0.044[a]	5.438[b]
	(−0.73)	(3.87)	(−13.09)	(−4.32)	(−2.90)	(1.96)
Comp70*Reg	0.130[a]	−0.109[c]	3.570[a]	0.353[b]	−0.005	4.469
	(3.91)	(−1.92)	(3.13)	(2.05)	(−0.39)	(1.38)
Comp85*Reg	−0.035	0.217[a]	−1.573	1.180[a]	0.067[a]	7.050[b]
	(−1.11)	(3.98)	(−1.45)	(6.92)	(5.76)	(2.28)
Log-L	−84798	−84774	−82517	−84506	−84716	−84750
Pseudo R^2	0.087	0.087	0.112	0.090	0.088	0.088

NOTES:
All regressions include all of the state-level control variables from model 3 in Table 2 (not state dummies, since most of the regulatory variables examined here are cross-sectional in nature).
(T-statistics) adjusted for the "true' sample size
a = significant at the 1% level or better
b = significant at the 5% level or better
c = significant at the 10% level or better

5D. "The Environmental Performance of Polluting Plants: A Spatial Analysis"

1. INTRODUCTION

This paper examines the determinants of environmental performance at a sample of U.S. manufacturing plants, concentrating especially on spatial factors. Differences in environmental performance across plants could be driven by differences in plant-specific characteristics (age, size, production technology), firm-specific characteristics (size, profitability, corporate culture), or external pressures (regulatory stringency, enforcement intensity, or lobbying pressures from neighborhood environmental groups). Environmental performance could be spatially correlated, with nearby plants having similar performance, if it is driven by location-specific external pressures: plants in the same state facing the same regulatory agency or plants in the same neighborhood facing the same environmental group. Spatial correlation could also result from endogenous interactions in plant behavior, such as "demonstration effects", where one plant's high compliance rate pressures neighboring plants to raise their own compliance rates.

Spatial correlation can be important in its own right, if it results in the concentration of poor performance among sets of nearby plants, creating local "hot spots". If hot spots are sufficiently damaging, social welfare might be improved by negative spatial correlations, where poor performers are balanced out by good performers in the same neighborhood. A less optimistic view of regulatory policy would point to concerns about environmental justice, with plants in less politically connected neighborhoods receiving less regulatory attention, resulting in local concentrations of poor environmental performance.

Spatial correlation could also bias the results of studies that fail to control for the spatial effects. For example, industry agglomeration could generate a "selection effect", whereby plants that cluster together for production-side reasons also tend to have similar environmental performance. These local similarities in performance could be mistakenly identified as the "treatment effect" of a location-specific factor such as regulatory stringency. Spatial econometric analyses can avoid such biases by testing for correlations in the explanatory variables and by controlling for the impact of neighboring plants' behavior.

There exists a substantial body of research examining the determinants of environmental performance, as measured by air pollution emissions and compliance. Compliance status is examined by Gray and Deily (1996), Gray and Shadbegian (2005), and Nadeau (1997), while emissions have been studied by researchers including Kahn (1999), Shadbegian and Gray (2003), and Gray and Shadbegian (2004).[49] This research most often focuses on *specific* deterrence, which is the direct impact of enforcement activity, i.e. the impact of an inspection on future compliance at the plant being inspected. In contrast, fewer studies have examined *general* deterrence, which occurs when an inspection affects compliance at other plants, by raising those plants' expectations of the amount of enforcement they will face in the future.

Spatial factors play a role in many of the variables used in these studies, although none have used spatial econometric models. The measures of regulatory enforcement are inherently spatial: differences across plants in regulatory activity depend on differences in enforcement stringency across regulatory agencies and nearby plants tend to face the same regulator.

[49] Studies on water pollution include Magat and Viscusi (1990), Laplante and Rilstone (1996), Helland (1998), Shimshack (2003), Sigman (2002, 2004) and Gray and Shadbegian (2004).

Jurisdictional boundaries provide another potentially important spatial factor connected with regulation, if regulators pay less attention to plants near the border, whose pollution primarily affects people in the next jurisdiction. The importance of these border effects is examined by Kahn (1999), Sigman (2002, 2004) and Helland (2003). Finally, the political clout of the population surrounding the plant may influence regulatory activity; measures of political activity and population demographics have been examined by Hamilton (1993, 1995), Arora and Cason (1999) and Gray and Shadbegian (2004).

Our analysis incorporates spatially-based information in three new ways. First, in addition to the usual demographic and political information about those living near the plant, we construct a measure of regulatory activity at nearby plants that distinguishes between plants in the same state and plants in different states, allowing us to test for general deterrence effects and to test whether those deterrence effects end at jurisdictional borders. Second, we test for spatial correlations in the explanatory variables, in the performance measures, and in the residuals from non-spatial models. Comparing the magnitudes of these correlations allows us to see whether spatial correlations in plant characteristics (possibly driven by industry agglomeration effects) contribute to correlations in environmental performance. Finally, we use spatial econometric techniques to allow explicitly for correlations with the performance of nearby plants, to see whether (and how much) omitted spatial effects bias the results of non-spatial models.

Our results indicate a significant role for spatial factors in environmental performance, without seriously biasing the effects of other factors. Compliance status is positively correlated at nearby plants in the same state, but this correlation does not carry across state borders. The residuals from a compliance model show weaker spatial correlations, so spatial correlations in explanatory variables can explain a sizable part (but not all) of the correlation in compliance across nearby plants. In spatial econometric models we find that spatially-lagged compliance terms are small and usually not significant, confirming that the explanatory variables capture most of the spatial effects. Our analyses of air pollution emissions, for both conventional and toxic pollutants, show no evidence of spatial correlations – in fact few variables in our model show significant impacts on air pollutant emissions, perhaps due to the smaller sample sizes involved or due to the heterogeneity of the plants included in our sample (in order to obtain sufficient numbers of nearby plants for the spatial econometric analysis, we include all manufacturing plants, not just those from a single industry as most prior research has done).

Much of the explanatory power of the compliance models comes from plant-specific characteristics, with larger, older, and more pollution-abatement-intensive plants having lower compliance rates. Local demographic characteristics matter – having more elderly or minority residents nearby is associated with greater compliance – but political activity has little impact. We find the expected effects of regulatory enforcement (although not always significant): more inspections at the plant, at nearby plants, and at all other plants in the state, are associated with greater compliance. The latter two results demonstrate the importance of general deterrence effects. Inspections at nearby plants in other states do not seem to increase compliance, showing a significantly different effect from inspections at nearby plants in the same state, and reinforcing the message that jurisdictional borders matter.

Section 2 presents a model of spatial correlations in environmental performance. Section 3 describes the data used in the analysis, including possible spatial characteristics of the regulatory variables. Section 4 discusses issues relating to spatial econometrics that are important for estimating our models. Section 5 presents the results, and Section 6 concludes.

2. SPATIAL CORRELATIONS IN ENVIRONMENTAL PERFORMANCE

As Manski (2000) observes, it can be difficult to distinguish among three reasons for correlations in outcomes within a group: endogenous interactions, contextual interactions, and correlated effects. In our case, these three reasons correspond to a plant's environmental performance being influenced by the actual performance of nearby plants, being influenced by other (exogenous) characteristics of nearby plants, and only appearing to be influenced by nearby plants' performance – the latter case arising if neighboring plants share similar unmeasured characteristics influencing their performance, leading to similarities in performance across neighboring plants without a direct causal link. All three cases could result in positive spatial correlations in performance, and the spatial econometric techniques we use in this research help focus our attention on the different ways in which neighboring plants are related.

To better understand the reasons for such spatial correlations, we begin with a basic model of environmental performance. Consider an individual manufacturing plant[50] seeking to maximize profits while facing benefits and costs associated with a given level of environmental performance (EP). We abstract from the production side of the plant's decision, represented in Equation (1) by a base level of profits Π_0, and focus on the relative magnitudes of the compliance costs associated with achieving a particular level of EP and the penalty from regulatory agencies predicted for a plant with that level of EP

$$(1) \qquad \Pi(EP,Xcc,Xpen) = \Pi_0 - CompCost(EP,Xcc) - Penalty(EP,Xpen)$$

with $\partial CompCost/\partial EP>0$ and $\partial Penalty/\partial EP<0$. A profit-maximizing plant will balance the marginal costs of improved performance with the marginal benefits – recognizing that the benefits of increased EP come in the form of lower penalties

$$(2) \qquad \partial CompCost/\partial EP = -\partial Penalty/\partial EP$$

Xcc (and Xpen) in Equation (1) are characteristics of the plant or the plant's environment that increase the marginal costs (or marginal penalties) associated with any given level of EP, so $\partial^2 CompCost/\partial EP\partial Xcc>0$ and $\partial^2 Penalty/\partial EP\partial Xpen<0$. Xcc variables include plant characteristics that affect the costs of achieving a given level of EP (its size, age, production technology, managerial ability, etc); Xpen variables include the expected level of environmental regulatory activity faced by the plant (raising the likelihood that a poorly performing plant will be caught), and the stringency of that regulation (raising the dollar penalty that will be imposed if the plant is caught). Not all Xpen variables need to be tied to characteristics of the regulatory agency; the demographics and politics of the surrounding population may also matter. Plants surrounded by politically active and environmentally concerned neighbors could face a higher Xpen due to those neighbors' ability to intervene in the environmental permitting process to punish plants with low EP.

Figure 1 shows the impact of changes in Xcc and Xpen on the optimal level of performance, EP^*, working through Equation (2). If cost-related factors increase from X^0_{CC}

[50] We speak of profit-maximizing plants, rather than firms, since all of our analysis is done at the plant level.

to X_{CC}^{1} then EP* decreases from EP_0^* to EP_1^*. On the other hand, if benefit-related factors increase from X_{PEN}^{0} to X_{PEN}^{2} then EP* increases from EP_0^* to EP_2^*. Note that a single factor could affect both Xcc and Xpen. For example, if regulations are grandfathered, older plants may face less strict regulations (Xpen decreases), but may also find it more costly to achieve a given level of performance (Xcc increases), with both effects tending to reduce EP* at older plants.[51]

In this model, spatial correlation could arise for a variety of reasons. First, the factors that drive environmental performance could themselves be spatially correlated. These correlations arise automatically in the construction of many of our explanatory variables: plants in the same neighborhood are necessarily surrounded by the same demographic factors; nearby plants are usually regulated by the same agency. Spatial correlation in other explanatory variables may be more subtle, with plant characteristics such as age and size exhibiting spatial correlation when similar plants tend to cluster together due to agglomeration effects as found in Henderson (1999). Some unmeasured factors that influence performance may also have a spatial component, such as an especially active neighborhood environmental group, which could drive similarities in the residual (unexplained) performance at neighboring plants.

Spatial effects could also occur in regulatory pressures. Some states might have more aggressive regulatory agencies, doing more inspections and imposing more penalties throughout the state (Gray and Deily (1996)). At a more local level, the locations of regulatory offices may influence regulatory intensity if facilities near the office are more frequently inspected. Spatially defined enforcement variables may help us test broader regulatory issues, such as decomposing the impact of inspections into general and specific deterrence. We would expect that plants would be more attentive to inspections at nearby plants (rather than distant ones) when forming predictions about the local stringency of enforcement. This can be tested by comparing the impacts of local- and state-level enforcement activity. The fact that most regulatory activity is done by state regulatory agencies also provides a spatially-defined consistency check: inspections at nearby plants in other states should be irrelevant.

Finally, a purely spatial component of the model can arise if the environmental performance at one plant is directly related to the performance at nearby plants. For example, one plant with especially good performance could have a demonstration effect (showing that good performance is possible), putting more pressure on neighboring plants to perform well. Regulators might also have preferences related to the spatial pattern of environmental performance, though the sign of this effect is unclear – a desire to avoid hot spots would lead to negative spatial correlations while a desire to push all polluters away from politically active areas towards less favored areas could lead to positive correlations (the latter effect being at the heart of the literature on environmental justice).

3. DATA DESCRIPTION

Our analysis uses cross-sectional data on environmental performance in 1997 for 521 manufacturing plants, located within 50 miles of the centers of three US cities. These cities are

---

[51] Note that this is based on measuring EP in terms of emissions performance. If we measure EP in terms of regulatory compliance, the less stringent regulations due to grandfathering could make older plants more likely to be in compliance than younger ones, even if the older plants' emissions performance is worse.

all near state borders, providing us with many adjacent plants, some in different states, allowing us to test for differences in regulatory impacts and spatial correlations across jurisdictional boundaries. The cities (and states) involved are St. Louis (Missouri and Illinois), Cincinnati (Ohio, Kentucky, and Indiana), and Charlotte (North and South Carolina). We gathered data for all plants located within 50 miles of any of the cities from EPA databases. Plant location information (latitude and longitude) came from EPA's Envirofacts database, taken from the Permit Compliance System and the Toxic Release Inventory modules. The final sample of 521 plants came from a merger of plant-level Census microdata and EPA data that required plants to have both Census and EPA data, including air pollution compliance information for 1997. We use two subsamples of the 521 plants for further analyses: 299 of these plants have data on releases of toxic air pollutants, while 102 of these plants have air pollution emissions data for conventional pollutants, particulates and sulfur dioxide.[52]

Our research was carried out at the Census Bureau's Boston Research Data Center, using confidential plant-level 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 (for a more detailed description of the LRD data, see McGuckin and Pascoe (1988)). From the LRD we extracted information for 1997, originally collected in the 1997 Census of Manufactures. We use the plant's total value of shipments (TVS) as a direct measure of the plant's size, deflated and in log form (SIZE), as well as to scale many of the other variables in this study including the emissions-based dependent variables. Our control for plant age (AGE) is the plant's age in 1997 (1997 – year of birth).[53] We control for the plant's efficiency using labor productivity (LPROD) measured as real output per employee. Finally a dummy variable (SINGLE) identifies plants which are owned by single-plant firms (firms which own no other manufacturing plants).

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 data include annual plant-level pollution abatement operating cost data from 1979 to 1994. Since the survey was not carried out in 1997, we use the plant's abatement operating costs from 1991-1994, and divide this by the plant's shipments in those years to get a measure of the pollution abatement expenditure intensity at the plant, PAOC, as a percentage of total costs.[54]

Our regulatory measures come from EPA databases. From the Integrated Data for Enforcement Analysis (IDEA) database we obtain a quarterly history of the plant's air pollution compliance status. Our compliance measure, COMPLY is a dummy variable, indicating whether the plant was in compliance throughout the year (if a plant was out of compliance in any quarter, COMPLY was set to zero).[55] To measure air pollution enforcement activity, we used

[52] The scope of the sample we created for this project was limited by the considerable effort required to gather, merge, and clean the multiple EPA and Census datasets needed for the analysis.
[53] We would like to thank John Haltiwanger for providing the plant age information, which was calculated based on Census data.
[54] We imputed PAOC based on published 4-digit industry data for those plants which were not in the PACE survey.
[55] There are several different codes for compliance status in the EPA data, but only one or two of the non-compliance codes are at all frequent, so it was not practical to construct a multinomial

information from the Envirofacts database to construct INSPECT, the total number of 'inspection-type' actions (e.g. inspections, emissions monitoring, stack tests) directed towards this plant during the 1993-1995 period. We created INSPNB by summing INSPECT over all manufacturing plants within 10 miles, and INSPNBOUT as the part of INSPNB contributed by plants located in other states. For a state-level measure of overall regulatory activity, STACT, we calculated the average number of regulatory actions in 1997 per plant in the entire state.

We obtain data on air pollution emissions from EPA's 1996 Emissions Inventory database (the closest available year to 1997, since the Inventory is done on a three-year cycle). The Emissions Inventory database provides information on the tons of emissions per year for criteria air pollutants, of which we consider particulates under 2.5 microns (PM25) and sulfur dioxide (SO2).[56] These variables have been scaled by the plant's total value of shipments in 1997, so they represent pollution intensity (tons of pollution per million dollars of shipments). The EPA's 1997 Toxic Release Inventory (TRI) provides information on releases of toxic pollutants into the air (AIRTOX) for all manufacturing facilities with sufficiently large use and/or emissions of toxic substances, which we also express in intensity terms.

We use demographic information at the block group level from the 1990 Census of Population (as compiled by Geolytics, Inc, in their CensusCD data) to measure the characteristics of the population near each plant (taking all block groups with centroids within 10 miles of the plant as the relevant population). The health of some people, such as the old and the very young, is more sensitive to air pollution, which should lead a "socially optimizing" regulator to put more pressure on nearby plants to improve their environmental performance. We measure these groups by ELDERS, the fraction of the population 65 or older, and KIDS, the fraction of the population under 6. For "Environmental Justice" reasons we might expect plants located in poor and minority neighborhoods to face less pressure to improve environmental performance.[57] We measure this with POOR, the fraction of the population living below the poverty line, and MINORITY, the fraction of the population that is nonwhite.

We use information at the county level to characterize the political climate surrounding the plant. TURNOUT is the fraction of registered voters in the county who voted in the 1992 Presidential election. DEMOCRAT is the fraction of voters in the county voting for the Democratic Presidential candidate in 1992. ENVSPEND is the percentage of the budgets of all local governments within the county that is spent on environmental amenities such as parks and recreation. All three of these variables are expected to raise a plant's environmental performance, since they are associated with politically active, liberal, and pro-environmental populations being around the plant.

Finally, we calculate whether a plant is within 10 miles of a state border, represented with a dummy variable BORDER. Regulators might feel less political pressure to strictly regulate a plant when some of the negative impact from its pollution is affecting residents of another state.

---

measure of compliance. We follow EPA's categorization of which codes refer to non-compliance.

[56] We also analyzed emissions of nitrogen oxides, finding results similar to those for sulfur dioxide.

[57] According to the Office of Environmental Justice at EPA, environmental justice exists when "no group of people, including racial, ethnic, or socioeconomic group, … bear[s] a disproportionate share of the negative environmental consequences resulting from industrial, municipal, and commercial operations."

Previous research by Gray and Shadbegian (2004) finds evidence of a border effect – plants located near state borders emit more air pollution.

4. SPATIAL ECONOMETRIC METHODS

Based on the earlier discussion (and Figure 1), we expect a plant's environmental performance to depend on a set of factors that shift the plant's marginal compliance cost and expected penalty

(3) $$EP_i^* = \alpha + \beta^* Xcc_j + \delta^* Xpen_i + e_i$$

The coefficients on the Xcc variables are expected to be negative, while those on the Xpen variables should be positive, noting the earlier caveat that some factors (e.g. plant age) could shift both curves.

As described in Anselin (1988), spatial econometrics incorporates information about the spatial orientation of data points into traditional economic models. Spatial dependence can arise in a model in two ways: spatial dependence of the error terms and structural spatial dependencies of the dependent variable (these two types are sometimes called spatial error models and spatial lag models, respectively). The former effect can occur when spatially correlated explanatory variables are omitted from the model. If these omitted variables are unrelated to the variables included in the model, OLS will yield unbiased yet inefficient estimates, since it ignores the correlation of the error terms. We can correct for spatial error effects by modifying the error term from Equation (3)

(4) $$e_i = \rho^* W^* e_i + u_i$$

W in Equation (4) is a weighting matrix that puts more weight on nearby observations, possibly also limited to similar observations (in our case, plants in the same state and/or industry). W^*e_i is therefore a spatially lagged error term, ρ is the autoregressive coefficient, and we assume $u \sim N(0, \sigma^2)$.

Structural spatial dependencies arise when the environmental performance of the plant is directly dependent on the performance of nearby plants, based on the behavior of plants or regulators as described above (demonstration effects for plants, hot spots or environmental justice effects for regulators). We can account for structural spatial dependencies by augmenting Equation (3) as follows

(5) $$EP_i^* = \alpha + \rho^* W^* EP_i^* + \beta^* Xcc_i + \delta^* Xpen_i + e_i$$

Here $W^*EP_i^*$ is a spatially lagged dependent variable, ρ is the autoregressive coefficient, and we assume $e \sim N(0, \sigma^2)$. Note that structural spatial dependencies cause more problems than do spatially dependent errors: omitting the spatially lagged dependent variable can lead OLS to produce biased estimates and invalid statistical tests, through an omitted variable bias.

We begin our modeling by estimating non-spatial models, along the lines of Equation (3), to provide a baseline set of results for comparison with our spatial models. We then test for spatial correlation in the explanatory variables. Next we test for spatial correlation in the environmental performance variables and the residuals from the non-spatial models to see whether omitted factors might be driving spatial effects in performance, or whether the spatial effects are primarily due to structural spatial dependencies. Based on these results we decide whether to estimate a model with spatially correlated errors, as in Equation (4), or with structural spatial dependencies, as in Equation (5). Finally, we compare our spatial results with the results from the non-spatial models, to see how much they affect the estimated coefficients. We use the spatial econometrics library in the Econometrics Toolbox for MATLAB, as described in Lesage (1999) to perform all of our spatial econometric analyses.[58]

5. RESULTS

Table 1 presents summary statistics for the variables used in our analysis. Note that we actually have three samples of data, depending on the dependent variable in the analysis: 102 plants for emissions of conventional air pollutants, 299 plants for releases of toxic air pollutants, and all 521 plants for compliance with air pollution regulations. The explanatory variables are presented only for the full sample, but means for the subsamples with emissions data[59] differ little from those calculated for the full sample – plants with emissions data are somewhat less likely to be in compliance with air regulations and have a history of receiving slightly more air inspections, although neither sample of plants is getting many inspections, with only 48% of the plants in the full sample receiving any air inspections in the 1993-1995 period.

We begin our analysis by examining the determinants of environmental performance without using spatial econometrics, as in Equation (3). Table 2 presents the determinants of compliance, using a probit model due to the binary nature of the compliance variable. Most of the significant results are for plant characteristics. Plants that are larger, plants in dirty industries, plants with higher pollution abatement spending, and plants owned by single-plant firms are all significantly less likely to be in compliance.[60] The effects of plant age and productivity are not significant, though age has the expected sign (younger plants are more often in compliance). The demographics of the surrounding population show some of the expected effects, yet these effects are mostly insignificant: plants in neighborhoods with more elderly people or more young children have better performance, while plants in poor neighborhoods (and non-minority neighborhoods) have worse performance. These demographic results are similar to those in Gray and Shadbegian (2004), which also found minority effects contrary to those anticipated by environmental justice concerns. The political variables are also insignificant, although their signs are consistent across the models: plants located in counties which spend more on environmental activities, counties with higher voter turnout, and (surprisingly) counties with more Republican voting or near state borders, have higher compliance rates.

Model 2b contains two measures of regulatory activity, INSPECT and STACT. Both measures have the expected positive impact on compliance, indicating the presence of both specific (INSPECT) and general (STACT) deterrence effects, but neither is significant. Measures of general deterrence with more precise spatial definition, INSPNB and INSPNBOUT, are included in Model 2c, with the expected signs (and borderline significance). Inspections at

---

[58] The toolbox is available at http://www.spatial-econometrics.com.

[59] Complete results available from authors.

[60] The numerical coefficients for SINGLE could not be disclosed for confidentiality reasons. SINGLE is not included in our later analyses of emissions and toxic releases because those analyses contain very few single-plant firms.

nearby plants help increase compliance, but only if those plants are in the same state. We discuss these regulatory effects in more detail later, in the context of our spatial econometric models.

Table 3 presents the results for emissions of air pollutants, both toxic (AIRTOX) and conventional (PM25, SO2). As it happens, we do not find any evidence that air pollution enforcement reduces emissions – the only significant effect of regulatory activity is higher releases when nearby plants have been getting air pollution inspections (an unexpected result). The only explanatory variable with consistently strong effects is plant size, where larger plants show smaller emissions – but since emissions are calculated relative to plant size, and only plants with relatively large emissions are included in the EPA data, the SIZE coefficients can hardly be treated as evidence for economies of scale in controlling emissions.

We now turn to spatially explicit analysis of the data. In Table 4 we examine the degree of spatial correlation in our data, using Moran's I test and three spatial weighting matrices. The first weighting matrix (INV) weights data from all the other plants near the same city by the inverse of the distance to those plants. The second weighting matrix (INV_ST) allows us to test for the importance of borders by using the same inverse distance weights but applying a zero weight to plants located a different state. We also examine a third measure (INV_ST_SIC) which further restricts the weights to plants in both the same state and the same 2-digit SIC industry (limited to the compliance models, where the sample size is sufficiently large).

Panel A shows the spatial correlations for our dependent variables, the measures of environmental performance. The only one that shows strong structural dependencies is compliance. A plant's compliance status tends to be positively correlated with the compliance status of nearby plants. The weighting matrix matters for this comparison – the spatial effects are much larger when we restrict our attention to plants in the same state (INV_ST), but are small and insignificant when we include plants in neighboring states. Restricting the weight matrix to only plants in the same industry and state (INV_ST_SIC) further increases the magnitude of the spatial correlation for compliance. Neither toxic nor conventional pollutant emissions show any significant evidence of spatial correlation; sulfur dioxide emissions show a (surprisingly) negative spatial correlation, but this is small and not significant.

Panel B shows the spatial correlations for the explanatory variables, all of which except INSPECT show positive spatial correlations.[61] Note that using a different spatial weighting matrix makes little difference in the estimated spatial correlation for any of the explanatory variables. On the whole, these results support the existence of agglomeration effects. Nearby plants tend to be similar plants, and this would be expected to generate spatial relationships in the environmental performance measures (though we only find such effects for compliance).

Panel C of Table 4 shows the spatial correlations for the residuals from the non-spatial models estimated earlier. Given the results in Panel A, it is not surprising that the residuals from the models of air pollutant emissions show uniformly insignificant spatial correlation. On the other hand, the compliance residuals continue to show positive spatial effects for those weighting matrices (INV_ST and INV_ST_SIC) where the earlier spatial effects were found. However, these residuals show smaller spatial correlations than the original compliance measures. These reductions are larger for model 2c, which accounts for local general deterrence with INSPNB and INSPNBOUT, than for model 2b, which uses the state-level measure of general deterrence,

[61] We do not calculate spatial correlations for the demographic (neighborhood-based) or political (county-based) variables, since they are spatially correlated by construction.

STACT. This suggests that part of the spatial correlation in COMPLY is being driven by spatially correlated explanatory variables – using the INV_ST weighting matrix, 35% of the spatial effects for compliance are explained by model 2b and an additional 18% (for a total of 53%) are explained by model 2c.[62]

Having found evidence of spatial correlations, at least for compliance, we now move to spatial econometric techniques that can explicitly control for these spatial effects. We are interested in the significance of the spatial terms, as well as any impact that their inclusion has on the estimated coefficients for other explanatory variables. As noted earlier, we could control for spatial correlation in the error terms (Equation 4) or for structural spatial dependencies (Equation 5). To choose between these methods, we return to the results in Table 4, comparing the magnitudes of the spatial correlation in the original environmental performance variables and the spatial correlation in the residuals from the non-spatial models. The correlations for the original compliance measure are substantially larger than those for the residuals, indicating that the structural spatial dependencies model is more appropriate (see Anselin and Rey (1991)). Thus we choose to estimate Equation (5), including a spatially lagged dependent variable in the model.

Table 5 shows the results for our spatial models of compliance, using three variations on the spatial weighting matrix. We find a small positive impact of RHO, the spatially lagged compliance of nearby plants, significant in models (5a and 5b) using the broader spatial weights (INV and INV_ST) and the less precise measure of general deterrence (STACT), but insignificant and occasionally negative in the other models. This is consistent with the results of Table 4, where the observed variables from a non-spatial model explained much of the spatial correlation in compliance.

Applying spatial econometric techniques does not greatly affect the coefficients on the other variables in the model, as can be seen by comparing coefficients in Table 5 to those in Table 2. The significance levels on other explanatory variables in the spatial model are similar to, or even a bit larger than, those found in the non-spatial model. This is most noticeable for the regulatory enforcement measures. The specific deterrence effect (INSPECT) is at least borderline significant in all models. The INSPNB and INSPNBOUT measures of general deterrence both gain significance with the INV_ST_SIC weight matrix. Some of the plant characteristics also gain in significance. On the whole, including the spatially lagged dependent variable in the analysis strengthens rather than weakens the importance of the other explanatory variables in the model.

Consider the regulatory variables in more detail, focusing on model 5f, which includes the most spatially-detailed regulatory measures. First, which is more important, specific deterrence (INSPECT) or general deterrence (INSPNB)? The INSPECT coefficient is roughly ten times larger than that of INSPNB (0.183 vs. 0.015), but the mean of INSPECT is only one-fortieth that of INSPNB (0.48 vs 18.96). This suggests that the overall effect of regulation through general deterrence (mean*coefficient of INSPNB) could be at least as important as its effect through specific deterrence.

Turning to the importance of jurisdictional boundaries for regulatory analyses, the negative sign on INSPNBOUT shows that inspections on plants in neighboring states are not as effective at improving compliance. In fact, the negative coefficient on INSPNBOUT is larger in magnitude than the positive one on INSPNB, so increased inspections at plants in neighboring

[62] Model 2b = (.057-.037)/.057 = 35%; Model 2c = (.057-.027)/.057 = 53%. For INV_ST_SIC the reductions are somewhat smaller: 27% and 41%, respectively.

states would be predicted to reduce a plant's compliance, although this effect is not statistically significant. One possible explanation is that state regulators, concerned about other trouble spots in their own state, do not bother putting much effort into areas near 'clean' borders (where neighboring regulators are pressuring the plants on their side of the border to reduce pollution) – a sort of cross-border substitution of regulatory intensity.

We carry out similar analyses for the toxic release and air emissions measures in Table 6. The RHO term shows insignificant effects for spatially lagged performance, consistent with the spatial correlation results in Table 4. As we found earlier for the non-spatial models in Table 3, the other explanatory variables are generally insignificant, and we see a similar pattern of signs between the spatial and non-spatial models of emissions.

6. CONCLUSIONS

We incorporate a variety of spatial components in our models of plant-specific environmental performance (measured by air pollution compliance, conventional air emissions and toxic releases). We create explanatory variables based on the plant's location, test for spatial correlation in environmental performance and the explanatory variables, and examine whether spatial patterns in the explanatory variables can explain spatial patterns in the dependent variables (performance). We then explicitly model the spatial component of environmental performance using a structural spatial dependencies model, incorporating spatially lagged dependent variables. Finally, we compare the results of spatial and non-spatial models to see how including spatial effects influences the estimated impact of different explanatory variables.

A large amount of the explanatory power of the compliance models comes from plant-specific characteristics, with larger, older, more pollution-abatement-intensive plants, and those in single-plant firms, having lower compliance levels. Some local demographic characteristics matter – having more elderly or minority residents nearby is associated with somewhat greater compliance rates – but political measures show little impact on compliance. The effects of inspection activity tend to have the expected signs, but are not always significant. Having more inspections at the plant, at nearby plants and at plants in the same state is associated with greater compliance. The comparison of coefficients and means for the measures of general and specific deterrence effects suggests that general deterrence is at least as important as specific deterrence. Inspections at nearby plants in other states do not seem to increase compliance, confirming the importance of recognizing borders when modeling the impact of regulatory activity on compliance.

Our spatial analysis indicates significant positive spatial correlations in compliance: plants located near each other tend to have similar compliance rates. In addition, this effect does not cross state borders – only plants in the same state behave similarly - reinforcing the importance of jurisdictional boundaries in a federal regulatory system where most of the enforcement activity is done by state regulators. The explanatory variables in our models also show positive spatial correlations: nearby plants are similar in terms of size, productivity, age, and abatement expenditures, and these effects do carry across state borders. Spatial patterns in explanatory variables appear to explain a sizable fraction of the spatial patterns in compliance, as the residuals from some compliance models show less than half the spatial correlation of the original compliance measures. Models which explicitly incorporate spatially-lagged compliance status in the estimation find rather small effects, but their inclusion raises the significance level of some of the other spatially-explicit explanatory variables in the models, including measures of regulatory activity.

Our findings of significant spatial effects for compliance status do not carry over to our other measures of environmental performance – emissions of conventional and toxic air pollutants. In fact, few variables we tested had significant impacts on either toxic releases or conventional air emissions. This may be partially due to the smaller samples of plants with toxic release or conventional air emissions data. It may also be due to the heterogeneity of the plants included in the analysis. Unlike most prior research, we include plants from all manufacturing industries in our analysis, rather than focusing on a specific industry. This was necessary to get enough plants close enough together to do spatial analyses, but the different processes determining pollution intensities for plants in different industries may make it problematic to estimate a single equation covering all plants. Compliance effects may be less industry-specific, and hence easier to estimate. Being a binary variable, compliance does not exhibit as great a variation in range across industries, which may also help the estimation.

Thus, our overall results indicate a significant, but limited, role for explicitly including spatial factors when modeling environmental performance. Our future research plans include a wider testing of alternative specifications of the spatial effects, to see how robust our conclusions are to different spatial weighting matrices and different sets of explanatory variables. We also hope to expand the analysis to include panel data on both air and water pollution performance, as well as expanding the dataset to include plants near additional cities. This will help us provide a richer picture of the spatial correlations in compliance across plants, and may increase our ability to explain what causes those correlations.

REFERENCES

Anselin, Luc. 1988. Spatial Econometrics: Methods and Models, Dordrecht: Kluwer Academic Publishers.

Anselin, Luc, and Sergio J. Rey. 1991. "Properties of Tests of Spatial Dependence in Linear Regression Models," *Geographical Analysis*, 23, 112-131.

Arora, Seema, and Timothy N. Cason. 1999. "Do Community Characteristics Influence Environmental Outcomes? Evidence from the Toxic Release Inventory," *Southern Economic Journal*, 65, 691-716.

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

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

Gray, Wayne B., and Ronald J. Shadbegian. 2004. "Optimal Pollution Abatement – Whose Benefits Matter and How Much?," *Journal of Environmental Economics and Management*, 47, 510-534.

Gray, Wayne B., and Ronald J. Shadbegian. 2005. "When and Why Do Plants Comply? Paper Mills in the 1980s," *Law and Policy*, 27, 238-261.

Hamilton, James. 1993. "Politics and Social Costs: Estimating the Impact of Collective Action on Hazardous Waste Facilities," *Rand Journal of Economics*, 24, 101-125.

Hamilton, James. 1995. "Testing for Environmental Racism: Prejudice, Profits, Political Power?" *Journal of Policy Analysis and Management*, 14, 107-132.

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

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

Helland, Eric A. 2003. "Pollution Incidence and Political Jurisdiction: Evidence from the TRI," *Journal of Environmental Economics and Management*, 46, 403-424.

Henderson, J. Vernon. 1999. "Marshall's Economies," Working Paper No. 7358, National Bureau of Economic Research.

Kahn, Matthew E. 1999. "The Silver Lining of Rust Belt Manufacturing Decline," *Journal of Urban Economics*, 46, 360-376.

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

LeSage, James P. 1999. Spatial Econometrics, available at http://www.spatial-econometrics.com.

LeSage, James P. 2000. "Bayesian Estimation of Limited Dependent Variable Spatial Autoregressive Models," *Geographical Analysis*, 32, 19-35.

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

Manski, Charles F. 2000. "Economic Analysis of Social Interactions", *The Journal of Economic Perspectives*, 14:115-136

McGuckin, Robert H., and George A. Pascoe. 1988. "The Longitudinal Research Database: Status and Research Possibilities," *Survey of Current Business*, 68, 30-37.

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

Scholz, John T. and Wayne B. Gray. 1990. "OSHA Enforcement and Workplace Injuries: A Behavioral Approach to Risk Assessment," *Journal of Risk and Uncertainty*, 3, 283-305.

Shadbegian, Ronald J. and Wayne B. Gray. 2003. "What Determines the Environmental Performance of Paper Mills? The Roles of Abatement Spending, Regulation, and Efficiency," Topics in Economic Analysis & Policy, 3, http://www.bepress.com/bejeap/topics/vol3/iss1/art15.

Shimshack, Jay P. and Michael B. Ward. 2005. "Regulator reputation, enforcement, and environmental compliance" *Journal of Environmental Economics and Management*, 50, 519-540.

Sigman, Hilary 2002. "International Spillovers and Water Quality in Rivers: Do Countries Free Ride?," *American Economic Review*, 92, 1152-1159.

Sigman, Hilary. 2004. "Transboundary Spillovers and Decentralization of Environmental Policies," *Journal of Environmental Economics and Management*, 50, 82-101.

TABLE 1: Descriptive Statistics (calculated for 521 observations in the compliance sample, except as noted)

Variable	mean (s.d)	mean (s.d.)	mean (s.d.)	Description
Dependent Variables				
COMPLY	0.891 (0.312)			Dummy variable=1 if a plant is in compliance with air regulations in 1997
AIRTOXTVS	1.238 (4.990)			(N=299) TRI air emissions/shipments (tons/$000,000) in 1997
PM25TVS	0.360 (0.718)			(N=102) Particulates emissions under 2.5 microns/shipments (tons/$000,000) in 1996
SO2TVS	3.613 (17.933)			(N=102) Sulfur dioxide emissions/shipments (tons/$000,000) in 1996
Inspection Activity				
INSPECT	0.484 (0.742)			Number of plant inspections (1993-1995)
STACT	0.575 (0.222)			Average number of regulatory actions per plant in state (1997)
INSPNB	18.960 (18.056)			Total number of 1993-1995 inspections at all manufacturing plants within 10 miles
INSPNBOUT	2.019 (6.637)			Total number of 1993-1995 inspections at all manufacturing plants located within 10 miles of the plant, but located in a neighboring state
Plant Characteristics				
SIZE	10.223 (1.520)			Log of real shipments in 1997
AGE	40.545 (18.536)			Age of the plant = 1997- year plant was opened
LPROD	0.297 (0.386)			Log of real shipments/employment in 1997
PAOC	0.874 (1.388)			Pollution abatement operating costs/shipments (1991-1994 average)
DIRTYSIC	0.361 (0.481)			Dummy variable =1 if a plant is in SIC 26, 28, 29, 33, or 34
Demographic Variables				
POOR	10.894 (3.941)			Percentage of population within 10 miles living below the poverty line in 1990
ELDERS	11.882 (2.115)			Percentage of population within 10 miles 65 or older in 1990
MINORITY	18.622 (11.832)			Percentage of population within 10 miles nonwhite in 1990
KIDS	8.629 (0.730)			Percentage of population within 10 miles under the age of 6 in 1990
BORDER	0.390 (0.488)			Dummy variable = 1 if a plant is within 10 miles of a state border
ENVSPEND	1.947 (2.766)			Share of county local government spending on environmental amenities in 1992
DEMOCRAT	0.401 (0.107)			Fraction in the county voting for the Democratic candidate in 1992
TURNOUT	0.549 (0.069)			Fraction of registered voters in county voting in 1992 Presidential election

TABLE 2: Non-Spatial Models of Compliance (t-statistics in parentheses)

	2a	2b	2c
DEPVAR	COMPLY	COMPLY	COMPLY
INSPECT		0.153	0.174
		(1.31)	(1.47)
INSPNB			0.013
			(1.65)
INSPNBOUT			-0.023
			(-1.49)
STACT		0.517	
		(0.82)	
LPROD	-0.014	0.009	-0.009
	(-0.06)	(0.04)	(-0.04)
AGE	-0.005	-0.005	-0.006
	(-1.13)	(-1.14)	(-1.38)
SIZE	-0.196	-0.203	-0.199
	(-2.85)	(-2.87)	(-2.81)
SINGLE	--	--	--
DIRTYSIC	-0.437	-0.414	-0.447
	(-2.37)	(-2.20)	(-2.39)
PAOC	-0.129	-0.130	-0.123
	(-2.49)	(-2.47)	(-2.26)
POOR	-0.043	-0.025	-0.023
	(-1.16)	(-0.61)	(-0.61)
MINORITY	0.019	0.015	0.015
	(1.83)	(1.27)	(1.31)
ELDERS	0.113	0.118	0.113
	(1.82)	(1.88)	(1.82)
KIDS	0.052	0.104	0.112
	(0.37)	(0.68)	(0.78)
BORDER	0.067	0.066	0.047
	(0.33)	(0.33)	(0.23)
ENVSPEND	0.069	0.068	0.048
	(0.88)	(0.86)	(0.68)
DEMOCRAT	-0.569	-0.602	-1.628
	(-0.49)	(-0.51)	(-1.26)
TURNOUT	1.088	1.922	1.487
	(0.78)	(1.16)	(1.01)
R-SQUARED	0.130	0.138	0.146
LOG-L	-156.47	-155.12	-153.69

Note: Estimates are based upon observations of 521 plants in 1997, using a probit analysis. Exact coefficients for SINGLE cannot be reported, due to Census disclosure rules; the table shows the sign and (when doubled) statistical significance at the 5% level.

TABLE 3: Non-Spatial Models of Air Emissions (t-statistics in parentheses)

DEPVAR	3a AIRTOX	3b AIRTOX	3c PM25	3d PM25	3e SO2	3f SO2
INSPECT	0.128	0.098	0.096	0.082	5.772	5.897
	(0.36)	(0.28)	(0.96)	(0.80)	(2.26)	(2.28)
INSPNB		0.061		-0.001		0.082
		(2.40)		(-0.10)		(0.32)
INSPNBOUT		-0.015		0.004		-0.149
		(-0.32)		(0.26)		(-0.36)
STACT	-1.274		-0.983		0.450	
	(-0.55)		(-1.24)		(0.02)	
AGE	0.010	0.006	0.011	0.011	0.060	0.057
	(0.70)	(0.39)	(2.84)	(2.86)	(0.64)	(0.58)
LPROD	1.010	1.000	0.021	0.073	1.031	1.084
	(1.29)	(1.28)	(0.09)	(0.33)	(0.18)	(0.19)
SIZE	-1.235	-1.181	-0.092	-0.099	-3.943	-3.924
	(-5.06)	(-4.88)	(-1.34)	(-1.43)	(-2.28)	(-2.26)
DIRTYSIC	-1.225	-1.213	-0.117	-0.048	-0.925	-0.956
	(-1.87)	(-1.88)	(-0.56)	(-0.24)	(-0.17)	(-0.18)
PAOC	-0.170	-0.129	0.016	0.016	-0.661	-0.670
	(-0.83)	(-0.63)	(0.17)	(0.17)	(-0.28)	(-0.28)
POOR	-0.086	0.002	-0.032	-0.026	0.203	0.210
	(-0.58)	(0.01)	(-0.79)	(-0.64)	(0.20)	(0.20)
MINORITY	0.044	-0.001	0.011	0.008	0.011	0.033
	(1.11)	(-0.04)	(1.11)	(0.71)	(0.04)	(0.12)
ELDERS	0.101	0.061	-0.007	-0.007	1.009	1.129
	(0.47)	(0.29)	(-0.11)	(-0.101)	(0.60)	(0.66)
KIDS	-0.235	0.058	-0.023	0.052	1.532	2.015
	(-0.42)	(0.11)	(-0.11)	(0.25)	(0.29)	(0.38)
BORDER	1.105	0.807	-0.245	-0.169	-1.331	-1.123
	(1.46)	(1.06)	(-1.08)	(-0.74)	(-0.23)	(-0.19)
ENVSPEND	-0.094	-0.119	-0.016	-0.001	-0.255	-0.288
	(-1.00)	(-1.26)	(-0.60)	(-0.04)	(-0.37)	(-0.45)
DEMOCRAT	-5.067	-8.926	0.455	1.908	2.681	3.889
	(-1.29)	(-2.11)	(0.25)	(1.29)	(0.06)	(0.10)
TURNOUT	4.800	5.624	-2.005	-1.225	-15.699	-10.381
	(0.86)	(1.25)	(-1.01)	(-0.61)	(-0.31)	(-0.20)
R-sq	0.156	0.158	0.218	0.204	0.187	0.189

Note: Estimates are based upon observations of 299 plants in 1997 for AIRTOX and 102 plants in 1996 for PM25 and SO2, using an ordinary least squares (OLS) analysis.

TABLE 4: Moran's I Tests for Spatial Correlations (p-values in parentheses)

A: Dependent Variables

VARIABLE	#OBS	WEIGHT=INV	INV_ST	INV_ST_SIC
COMPLY	521	0.015 (0.109)	0.057 (0.000)	0.079 (0.013)
AIRTOX	299	0.005 (0.363)	0.011 (0.335)	
PM25	102	0.003 (0.380)	0.006 (0.375)	
SO2	102	-0.017 (0.394)	-0.017 (0.395)	

B: Explanatory Variables

VARIABLE	#OBS	WEIGHT=INV	INV_ST	INV_ST_SIC
INSPECT	521	0.007 (0.280)	0.009 (0.288)	0.012 (0.361)
LPROD	521	0.047 (0.000)	0.057 (0.000)	0.186 (0.000)
AGE	521	0.115 (0.000)	0.127 (0.000)	0.134 (0.000)
PAOC	521	0.045 (0.000)	0.045 (0.001)	0.152 (0.000)
SIZE	521	0.053 (0.000)	0.059 (0.000)	0.299 (0.000)

C: Residuals from Non-Spatial Models

VARIABLE(Model)	#OBS	WEIGHT=INV	INV_ST	INV_ST_SIC
COMPLY (2b)	521	-0.003 (0.395)	0.037 (0.009)	0.058 (0.063)
COMPLY (2c)	521	-0.004 (0.392)	0.027 (0.047)	0.047 (0.114)
AIRTOX (3b)	299	-0.010 (0.360)	-0.001 (0.230)	
PM25 (3d)	102	-0.028 (0.287)	-0.033 (0.311)	
SO2 (3f)	102	-0.035 (0.333)	-0.037 (0.335)	

Notes: The calculations of the Moran's I test are done using three different spatial weighting matrices: INV = (1/distance), INV_ST = (1/distance) restricted to plants in the same state, and INV_ST_SIC = (1/distance) restricted to plants in the same state and in the same 2-digit SIC Industry. The model numbers for residuals in panel C refer to the models estimated in tables 2 and 3.

TABLE 5: Spatially-Lagged Models of Compliance (p-values in parentheses)

	5a	5b	5c	5d	5e	5f
DEPVAR	COMPLY	COMPLY	COMPLY	COMPLY	COMPLY	COMPLY
WEIGHT	INV	INV	INV_ST	INV_ST	INV_ST_SIC	INV_ST_SIC
RHO	0.010	0.008	0.015	0.009	-0.012	-0.019
	(0.092)	(0.192)	(0.033)	(0.157)	(0.303)	(0.182)
INSPECT	0.178	0.195	0.189	0.190	0.172	0.183
	(0.065)	(0.039)	(0.051)	(0.052)	(0.077)	(0.068)
INSPNB		0.007		0.005		0.015
		(0.168)		(0.301)		(0.022)
INSPNBOUT		-0.021		-0.014		-0.024
		(0.078)		(0.175)		(0.082)
STACT	0.170		-0.118		0.480	
	(0.398)		(0.422)		(0.246)	
LPROD	-0.001	0.032	0.030	0.015	0.021	0.033
	(0.496)	(0.441)	(0.470)	(0.500)	(0.458)	(0.467)
AGE	-0.005	-0.006	-0.005	-0.006	-0.005	-0.007
	(0.131)	(0.093)	(0.124)	(0.094)	(0.125)	(0.070)
SIZE	-0.205	-0.210	-0.212	-0.199	-0.224	-0.218
	(0.000)	(0.002)	(0.002)	(0.003)	(0.000)	(0.005)
SINGLE	--	--	--	--	--	--
DIRTYSIC	-0.451	-0.431	-0.473	-0.442	-0.448	-0.470
	(0.007)	(0.004)	(0.011)	(0.006)	(0.012)	(0.005)
PAOC	-0.135	-0.131	-0.131	-0.119	-0.133	-0.130
	(0.003)	(0.012)	(0.003)	(0.020)	(0.009)	(0.013)
POOR	-0.020	-0.012	-0.020	-0.009	-0.024	-0.022
	(0.286)	(0.370)	(0.307)	(0.386)	(0.288)	(0.278)
MINORITY	0.012	0.014	0.013	0.012	0.013	0.015
	(0.135)	(0.107)	(0.119)	(0.152)	(0.133)	(0.085)
ELDERS	0.111	0.118	0.109	0.114	0.120	0.120
	(0.040)	(0.040)	(0.027)	(0.025)	(0.039)	(0.042)
KIDS	0.104	0.132	0.096	0.141	0.098	0.115
	(0.252)	(0.172)	(0.257)	(0.141)	(0.248)	(0.216)
BORDER	0.087	0.064	0.061	0.052	0.084	0.064
	(0.358)	(0.379)	(0.384)	(0.399)	(0.356)	(0.379)
ENVSPEND	0.078	0.065	0.062	0.082	0.135	0.075
	(0.106)	(0.113)	(0.114)	(0.087)	(0.064)	(0.131)
DEMOCRAT	-1.291	-1.760	-1.167	-1.538	-0.675	-1.901
	(0.135)	(0.081)	(0.165)	(0.089)	(0.304)	(0.074)
TURNOUT	1.888	1.672	1.676	1.556	1.680	1.346
	(0.119)	(0.122)	(0.157)	(0.140)	(0.191)	(0.169)

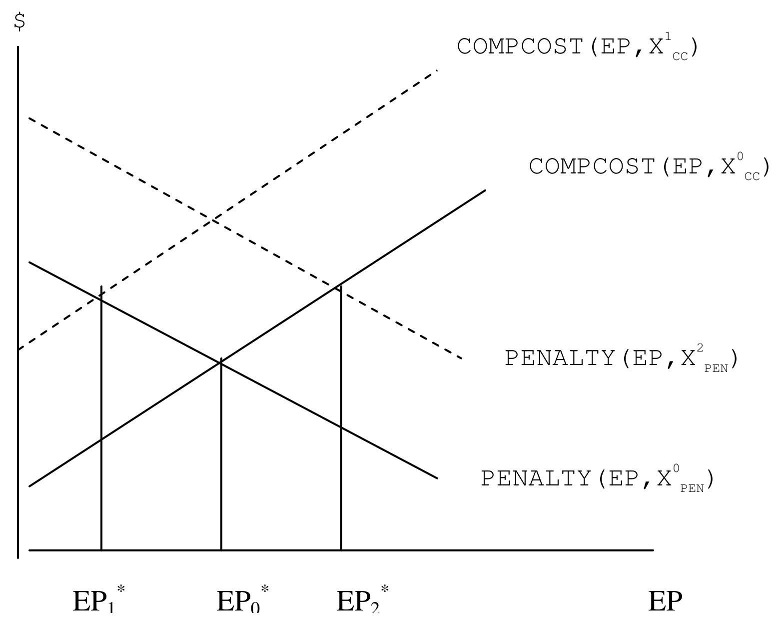
Note: These estimates are based upon observations of 521 plants in 1997, using a Bayesian spatial probit analysis, as described in LeSage (2000). RHO is the estimated autoregressive coefficient, as in Equation (5). The analyses are done using three different spatial weighting matrices: INV = (1/distance), INV_ST = (1/distance) restricted to plants in the same state, and INV_ST_SIC = (1/distance) restricted to plants in the same state and the same 2-digit SIC industry. Exact coefficients for SINGLE cannot be reported, due to Census disclosure rules; the table shows the sign and (when doubled) statistical significance at the 5% level.

TABLE 6: Spatially-Lagged Models of Air Emissions (t-statistics in parentheses)

	6a	6b	6c	6d	6e	6f
DEPVAR	AIRTOX	AIRTOX	PM25	PM25	SO2	SO2
WEIGHT	INV	INV_ST	INV	INV_ST	INV	INV_ST
RHO	-0.026	-0.029	-0.029	-0.032	-0.033	-0.035
	(-1.509)	(-1.674)	(-0.646)	(-0.714)	(-0.693)	(-0.735)
INSPECT	0.210	0.219	0.081	0.081	5.896	5.899
	(0.306)	(0.320)	(0.879)	(0.882)	(2.551)	(2.553)
INSPNB	0.149	0.156	0.000	0.000	0.081	0.083
	(2.853)	(2.934)	(0.013)	(0.041)	(0.352)	(0.358)
INSPNBOUT	-0.030	-0.050	0.003	0.003	-0.143	-0.144
	(-0.325)	(-0.544)	(0.223)	(0.204)	(-0.383)	(-0.387)
LPROD	2.139	2.113	0.073	0.072	1.013	0.995
	(1.428)	(1.411)	(0.365)	(0.360)	(0.200)	(0.197)
AGE	0.013	0.014	0.011	0.011	0.057	0.057
	(0.463)	(0.473)	(3.192)	(3.191)	(0.659)	(0.660)
SIZE	-2.346	-2.352	-0.099	-0.099	-3.921	-3.920
	(-5.035)	(-5.053)	(-1.609)	(-1.611)	(-2.525)	(-2.525)
DIRTYSIC	-2.521	-2.522	-0.043	-0.043	-0.854	-0.853
	(-2.032)	(-2.034)	(-0.236)	(-0.234)	(-0.184)	(-0.184)
PAOC	-0.269	-0.274	0.014	0.014	-0.707	-0.707
	(-0.682)	(-0.693)	(0.169)	(0.168)	(-0.330)	(-0.330)
POOR	-0.047	-0.045	-0.031	-0.031	0.165	0.164
	(-0.181)	(-0.174)	(-0.831)	(-0.838)	(0.177)	(0.176)
MINORITY	-0.010	-0.014	0.009	0.009	0.039	0.039
	(-0.133)	(-0.191)	(0.876)	(0.880)	(0.153)	(0.154)
ELDERS	0.128	0.134	-0.003	-0.002	1.229	1.240
	(0.315)	(0.328)	(-0.047)	(-0.034)	(0.800)	(0.807)
KIDS	0.032	0.054	0.051	0.050	2.083	2.087
	(0.032)	(0.055)	(0.270)	(0.268)	(0.440)	(0.440)
BORDER	1.523	1.462	-0.161	-0.161	-1.100	-1.100
	(1.039)	(0.998)	(-0.782)	(-0.780)	(-0.213)	(-0.213)
ENVSPEND	-0.239	-0.239	-0.002	-0.002	-0.296	-0.300
	(-1.318)	(-1.320)	(-0.072)	(-0.074)	(-0.514)	(-0.520)
DEMOCRAT	-16.890	-16.772	1.954	1.948	3.434	3.255
	(-2.063)	(-2.049)	(1.473)	(1.469)	(0.102)	(0.097)
TURNOUT	10.075	10.177	-1.115	-1.056	-11.021	-10.565
	(1.158)	(1.171)	(-0.617)	(-0.582)	(-0.243)	(-0.233)
_RSQUARE	0.177	0.179	0.203	0.203	0.188	0.188
_LOGL	-969.75	-978.31	-63.276	-63.268	-392.48	-392.40

Note: Estimates are based upon observations of 299 plants in 1997 for toxic air pollutants (AIRTOX, models 6a and 6b), and 102 plants in 19965 for conventional air pollutants (SO2 and PM25), using a spatially lagged regression analysis. RHO is the estimated autoregressive coefficient, as in Equation (5). Two different spatial weighting matrices are considered: INV = (1/distance) and INV_ST = (1/distance) restricted to plants in the same state.

FIGURE 1: Impact of Shifts in Xcc, Xpen on Optimal Performance EP*



Increase in marginal COMPCOST ($X^{0}_{CC} < X^{1}_{CC}$)
lowers EP* ($EP_0^* > EP_1^*$)
Increase in marginal PENALTY ($X^{0}_{PEN} < X^{2}_{PEN}$)
raises EP* ($EP_2^* > EP_0^*$)

5E. “Regulatory Regime Changes Under Federalism: Do States Matter More?”

1. INTRODUCTION

After the passage of the 1970 Clean Air Act Amendments and 1972 Clean Water Act Amendments the United States has been able to achieve substantial improvements in both air and water quality due in large part to increasing stringency of regulation, which has caused continuous declines in emissions from industrial sources. In the United States environmental policymaking is conducted via a federalist system with the federal U. S. Environmental Protection Agency (EPA) setting the stringency of regulation and states’ implementing and enforcing the regulations. The ability of states to implement and enforce regulations provides them with a considerable amount of discretion (e.g. setting water permit discharge levels, number of plant inspections).

State discretion potentially has both pros and cons. First, this discretion allows each state to develop their own methods of regulating, thereby providing opportunities to develop more innovative policies, which can lead to more net benefits from regulation. However, there is potential for such discretion to be abused. For example, states may free ride on their neighbors by allowing plants located near state borders (border plants) to emit more pollution than non-border plants – Sigman (2005), Helland and Whitford (2003), and Gray and Shadbegian (2004) all find evidence of this behavior.[63] Finally, states may choose to be less rigorous in terms of enforcing regulations in an effort to attract new businesses to the state, resulting in a so-called “race to the bottom.”[64,65]

We would expect states to differ in their ability and/or desire to implement and enforce EPA regulations. Therefore, it is not clear whether making national regulations stricter in such a federal setting will increase or reduce differences across states in effective regulatory stringency. Stricter national rules may “raise the bar” and force less stringent states to make greater changes. On the other hand, since much of regulatory activity is done at the state level, stricter regulations at the national level may strengthen the bargaining power of regulators in more stringent states, enabling them to increase their stringency more than other states.

In 1998 the EPA promulgated the first integrated, multi-media regulation – known as the “cluster rule” (CR). The goal of the CR was to reduce the pulp and paper industry’s toxic releases into the air and water. By promulgating both air and water regulations at the same time EPA made it possible for pulp and paper mills to select the best combination of pollution prevention and control technologies, with the hope of reducing the regulatory burden.

We test the impact of the air and water regulations in the CR, using data from 1996-2005 for 150 pulp and paper mills, including information on both toxic and conventional pollutants. We include a wide range of control variables shown in previous research to affect plant environmental performance, including plant- and firm-level characteristics and regulatory

[63] In particular, Sigman finds that states allow plants to emit greater amounts of water pollution when that pollution crosses state borders via interstate rivers. Helland and Whitford, using annual (1987-1996) county-level TRI data, find that facilities located in counties on state borders (border counties) emit significantly more air and water toxics than facilities located in non-border counties. Gray and Shadbegian (2004) find that pulp and paper mills whose pollution impacts the population of neighboring states emit more pollution.

[64] See Sigman (2003) for more information on the discretionary powers of the states.

[65] There is a large literature examining the “race to the bottom”; see Oates (2001).

activity. We find significant reductions in total toxics and air toxics around the time that the CR was implemented, though not for water toxics. However, plants identified as facing stricter CR rules do not generally show larger reductions in toxics. We find no evidence for large reductions in conventional pollutants around the CR implementation date, but do observe significant positive correlations in residuals across the different pollutants, suggesting the presence of unmeasured factors that may improve (or worsen) a plant's performance across the board.

Finally, we find some evidence that the differences across states in regulatory stringency may have been lessened by EPA's adoption of the CR. Plants located in states with more political support for stringent regulation have lower toxic releases on average throughout the period, but they have a smaller decline in toxic releases over time, as shown by our 5-year-change analysis. This suggests that some of the reductions required by the CR had already been implemented in high-stringency states, so the CR had a greater impact on plants in lower-stringency states.

Section 2 provides background information on pollution from the pulp and paper industry and a brief history of the Cluster Rule. Section 3 reviews the relevant literature, while section 4 presents a model of the determinants of environmental performance. Section 5 discusses the data and empirical methodology. Section 6 presents the results, followed by concluding comments in section 7.

2. REGULATING THE PULP AND PAPER INDUSTRY

During the past 35 years environmental regulation on the U.S. manufacturing sector has become increasingly tougher in terms of both stringency, and enforcement and monitoring. Prior to the creation of the federal Environmental Protection Agency (EPA) in the early 1970's environmental rules were predominantly enacted at the state level, and were not rigorously enforced. Since the early 1970's the federal government has been the principal player in developing stricter regulations and promoting a greater emphasis on enforcement, much of which is still performed by state regulatory agencies under varying degrees of federal supervision.

The evolving stringency of environmental regulation has imposed large costs on traditional 'smokestack' industries, like the pulp and paper industry, which is one of the most highly regulated industries due to the large volumes of both air and water pollution it generates. Although these regulatory efforts have proven costly to the pulp and paper industry they have also been successful in reducing the emissions of conventional air and water pollutants with the advent of secondary wastewater treatment, electrostatic precipitators, and scrubbers. Furthermore, some mills have gone beyond these end-of-pipe control technologies, and have redesigned their production process, *e.g.* more closely monitoring material flows to further reduce emissions. In general these modifications have been much easier to achieve at newer plants, which were, at least to a certain extent, designed with pollution controls in mind – some old pulp mills were intentionally constructed over rivers, so that any spills or leaks could run through holes in the floor for 'easy disposal.' These rigidities can be partially or completely offset by the propensity for most regulations to incorporate grandfather clauses exempting existing plants from the most stringent requirements – for example, until more recent standards limited their NOx emissions, most small old boilers were exempt from air pollution regulations.

The entire pulp and paper industry faces significant levels of environmental regulation. However, plants within the industry face differential impacts from regulation, depending in part on their technology (pulp and integrated mills vs. non-integrated mills[66]), age, location, and the level of regulatory effort directed at the plant. Previous studies, including Gray and Shadbegian (2003), have shown that the most important determinant of the regulatory impact on a plant is whether or not the plant contains a pulping facility, since the pulping process (separating the fibers need to make paper from raw wood) is much more pollution intensive than the paper-making process.[67] Different pulping processes result in different types of pollution: mechanical pulping uses more energy, generating air pollution from a power boiler, while chemical pulping could generate water pollution from spent chemicals, some of them potentially toxic. In addition, if a white paper product is desired the pulp must be bleached. The Kraft chemical pulping process was originally considered to be relatively low-polluting in terms of conventional air and water pollution. Unfortunately, when combined with elemental chlorine bleaching, it can create chloroform, furan, and trace amounts of dioxin, raising concerns over toxic releases that contributed, at least indirectly, to the development of the Cluster Rule.

An incident in Times Beach, Missouri (located near St. Louis) helped raise concerns about toxic pollutants in general, and dioxin in particular. On December 5th, 1982 the Meramec River flooded Times Beach, contaminating nearly everything in the town with dioxin that had been deposited by dust spraying in the early 1970's. The Center for Disease Control concluded that the town was uninhabitable and in 1983 the US EPA bought Times Beach and relocated its residents, reinforcing in the public mind the dangers of dioxin.

In the aftermath of the Times Beach incident two influential environmental groups, the Environmental Defense Fund and the National Wildlife Federation, sued the EPA for not adequately protecting the U.S. public from the risks of dioxin. As part of a 1988 settlement with the environmental groups the EPA agreed to study the health risks of dioxin and to set regulations to reduce dioxin emissions. Ten years later, EPA implemented regulations that included dioxin reductions, as part of the Cluster Rule.

The Cluster Rule

In 1998 the EPA promulgated the first integrated, multi-media regulation – known as the "cluster rule" (CR) – to protect human health by reducing the pulp and paper industry's toxic releases into the air and water. The Cluster Rule was scheduled to take effect (for the most part) three years later, in April 2001. By promulgating both air and water regulations at the same time EPA allowed pulp and paper mills to consider multiple regulatory requirements at one time, hoping to reduce the aggregate regulatory burden on the mills. The more stringent (technology based) air regulations in the CR call for substantial reductions in hazardous air pollutants (reduce by 59%), sulfur (47%), volatile organic compounds (49%) and particulate matter (37%). The more stringent (technology based) water regulations in the CR call for a 96% reduction in dioxin and furan, and a 99% reduction in chloroform. EPA estimates that approximately 490 pulp and paper mills are subject to the new CR air regulations. Furthermore, any pulp and paper mill that has the potential to emit ten tons per year of any particular hazardous air pollutant (HAP) or an aggregate of 25 tons per year of all HAPs is subject to the even more stringent maximum

---

[66] Integrated mills produce their own pulp and non-integrated mills purchase pulp or use recycled wastepaper.

[67] The two main environmental concerns during paper-making stage are air pollution if the mill has its own power plant and the residual water pollution generated during the drying process.

achievable control technology (MACT) standards for HAPs, under the National Emission Standards for Hazardous Air Pollutants (NESHAP). EPA estimated that 155 of the 490 affected pulp and paper mills would be subject to the new MACT standards. Finally, pulp and paper mills that chemically pulp wood (96 of the 155) are also required to meet a new set of effluent standards, defined as best available technology economically achievable (BAT) standards. These effluent standards are to take effect when the plant's water pollution discharge permit is renewed, which spreads the effective date out over several years (since many water permits last for five years). Thus we have a set of regulations affecting multiple pollution media, with different sets of plants facing different stringency on the different media, with some of the stringency changes occurring at different times for different plants. This allows us multiple dimensions along which to test the impact of the Cluster Rule.

3. LITERATURE REVIEW

Much of the empirical research on the impact of environmental regulation has focused on the effect of reported pollution abatement costs on productivity.[68] However, there is a growing literature, including studies by Magat and Viscusi (1990), Gray and Deily (1996), Laplante and Rilstone (1996), Nadeau (1997), Shadbegian and Gray (2003,2006), Earnhart (2004a,2004b), Schimshack and Ward (2005), and Gray and Shadbegian (2005,2007), which examines the environmental performance of polluting plants with respect to conventional air and water pollutants. Some studies have focused on the effectiveness of enforcement activities (mainly carried out by the states) in terms of raising compliance rates or lowering emissions. Gray and Deily (1996) and Gray and Shadbegian (2005) find that plants that face greater levels of air enforcement activity by regulators have higher compliance rates, while Nadeau (1997) finds these plants spend less time in non-compliance. In terms of the impact of water regulations, Magat and Viscusi (1990) and Laplante and Rilstone (1996) find that greater levels of water pollution enforcement activity result in lower water discharges. Furthermore, Shimshack and Ward (2005) find that one additional fine in a state for violating a water standard leads to roughly a two-thirds reduction in the statewide violation rate in the following year, suggesting that the regulator's enhanced reputation has a general deterrence effect leading to increased environmental performance at other plants in the state as well as at the fined plant. Earnhart (2004a) analyzes the impact of EPA regulations on the level of environmental performance of municipal wastewater treatment facilities in Kansas finding that the *threat* of federal inspections and enforcement action and the *threat* of state enforcement action significantly increase environmental performance. In a second study, Earnhart (2004b) finds that both income of a community and its political activism tend to significantly reduce discharge rates of municipal wastewater treatment plants in Kansas.

Shadbegian and Gray (2003) perform a more detailed examination of the environmental performance of 68 pulp and paper mills, finding that air emissions are significantly lower at plants: which have a larger air pollution abatement capital stock; which face more stringent local regulation; and which have higher production efficiency. Furthermore, they find a negative residual correlation between emissions and efficiency, providing evidence that plants which are more efficient in production are also more efficient in pollution abatement.

[68] Research on the productivity effects of environmental regulation include Denison (1979), Gollop and Roberts (1983), Barbera and McConnell (1986), Gray (1986, 1987), Boyd and McClelland (1999), Berman and Bui (2001), Gray and Shadbegian (2002, 2003), and Shadbegian and Gray (2005,2006).

Shadbegian and Gray (2006) examined the impact of regulatory stringency on plants in the pulp and paper, steel, and oil industries and find that plants facing more local regulatory stringency had better (air and water) environmental performance. Finally, Gray and Shadbegian (2007) examine spatial factors affecting environmental performance of polluting plants, measured by air emissions and regulatory compliance. They find that increased regulatory activity has significant effects for compliance, but for not emissions. In particular, they find that increased regulatory activity has the expected effect of increasing compliance with air regulations, both at the inspected plant and at neighboring plants, but only for plants operating in the same state, indicating the importance of jurisdictional boundaries.

In addition to the large literature that now exists on the impact of regulation on the environmental performance of polluting plants with respect to conventional pollutants there is a growing literature which examines the impact of different EPA programs and community characteristics on toxic emissions. For example, Khanna and Damon (1999) find evidence that participation in EPA's voluntary 33/50 Program (a program under which facilities volunteered to decrease a certain specified set of their toxic releases by 33% by 1992 and 50% by 1995 relative to their 1988 levels) led to a significant decline in these toxic releases over the period 1991-93. On the other hand, Bui (2005) examines whether or not TRI induced public disclosure contributed to the decline in reported toxic releases by oil refineries. Bui finds some evidence that the public disclosure provisions of TRI may very well have caused some reductions in reported TRI releases. However she also finds evidence that reductions in toxic releases are a byproduct of more traditional command and control regulation of emissions of *non*-toxic pollutants.

In two additional studies which belong to the so-called environmental justice (EJ) literature, Arora and Cason (1999) and Wolverton (2002) examine the impact of community characteristics on toxic emissions. Arora and Cason, analyzing 1993 TRI emissions, find evidence race is significantly positively related to TRI releases, but only in non-urban areas of the south. Wolverton (2002) finds larger TRI reductions in minority neighborhoods than in non-minority neighborhoods in Texas, precisely the opposite of the assertions of many earlier entries in the EJ literature.

4. DETERMINANTS OF ENVIRONMENTAL PERFORMANCE

An individual manufacturing plant faces costs and benefits from complying with environmental regulation, depending on characteristics of the plant, the firm which owns the plant, and the regulatory stringency it faces. Given these constraints, the firm operating the plant maximizes 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, emissions reductions), taking into account the expected reactions of the firms to that enforcement.

There are substantial differences in pollution problems across different manufacturing plants. Difficulties in compliance might be related to a plant's production technology at the plant (e.g. pulp mills versus plants which buy pulp) or the plant's age or size. Differences in compliance behavior might also be related to the plant's productivity (proxying for economic performance and management ability). The impact of most of these plant characteristics on environmental performance could go either way: older plants might find it harder to comply with new stricter standards, but could be grandfathered; larger plants might enjoy economies of scale in pollution abatement compliance, but could also have more places that something could go wrong.

The expected direct benefit the plant receives from compliance is the avoidance of penalties. Therefore a plant's decision to comply depends on both the magnitude of the penalty and the probability of being caught in noncompliance; the latter depends on the amount of enforcement activity faced by the plant.

Environmental performance may also depend on characteristics of the firm which owns the plant, such as its financial condition. Pollution abatement can involve sizable capital expenditures, which may be more easily raised by more profitable firms. 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 one of the highly regulated industries, 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 see some effect of firm size. In sum, a plant's compliance status depends on plant characteristics and firm characteristics, and the level and efficacy of enforcement activity directed towards it.

Based on the above discussion, we estimate a model of plant environmental performance:

$$Z_{pkt} = f_k(CLUSTER_{pkt}, STATE_{jt}, CLUSTER_{pkt}*STATE_{jt}, X_{pt}, X_{ft}, YEAR_t, u_{pkt})$$

Here Z_{pkt} measures the environmental performance of plant p at time t along dimension k, including emissions of different air and water pollutants, possibly conventional as well as toxic (note that in this context, higher values of Z would represent poorer performance, so we'd expect negative coefficients on terms that improve performance). $CLUSTER_{pkt}$ is a measure of the stringency of the Cluster Rule related regulations faced by different plants at different times, which is expected to raise environmental performance (in its simplest form, CLUSTER could be a time dummy, turned on in 2001). $STATE_{jt}$ is an index of how rigorously a state is expected to enforce environmental regulations, which is also expected to raise environmental performance. The CLUSTER*STATE interaction term allows us to test whether stricter state regulatory agencies have been differentially affected by the Cluster Rule. This effect could go either way. Plants in states with preferences for strong environmental regulation might have already implemented some of the Cluster Rule requirements, and would therefore show less of an impact from the Cluster Rule on their performance, and a positive coefficient on the interaction. Alternatively, if stricter states are always looking for ways to increase regulatory stringency, the requirements of the Cluster Rule might provide those states with further regulatory tools, allowing them to become even stricter and resulting in a negative coefficient on the interaction. The model also includes characteristics of the plant (X_p) and firm (X_f), year dummies ($YEAR_t$) to allow for changes in environmental performance or its definition over time, and other unmeasured factors (u_{pkt}).

We supplement our basic analyses of the impact of the Cluster Rule on various measures of emissions, with a seemingly unrelated regression (SUR) model. This allows us to test for correlations between the unexplained variation in different environmental performance measures, particularly for correlations across pollution media: air and water pollutants, and toxic and conventional pollutants. We would generally expect to find positive correlations across pollutants, as unobserved factors (such as management ability or local regulatory pressures) lead a plant to do better (or worse) than expected on a wide range of pollutants, but it's possible that some plants are able to substitute one type of pollution abatement for another when redesigning their production process.

5. DATA AND EMPIRICAL METHODOLOGY

This study examines the impact of the Cluster Rule on pollution emissions for a wide range of pollutants, as well as testing whether the gap in environmental performance across plants regulated in different states has been shrinking or growing as a result of the Cluster Rule. We control for a number of other factors shown in previous research to affect plant environmental performance, including plant- and firm-level characteristics. We also include a number of other control variables designed to capture characteristics of the location of the mill that could influence the level of regulatory activity it faces.

In past studies we developed a comprehensive database of U.S. pulp and paper mills to study the impact of environmental regulation on plant-level productivity and investment. This database includes published plant-level data from the Lockwood Directory and other industry sources to identify each plant's production capacity (both pulp capacity and paper capacity), age, production technology, and corporate ownership. We add financial data taken from Compustat, identifying firm profitability and firm size.

Our pulp and paper mill data is merged with annual plant-level information on quantities of pollution for both air and water pollution and for conventional and toxic pollutants. The EPA’s Toxic Release Inventory (TRI) database provides annual information on the amount and type of releases of a wide range of hazardous substances. Given that the Cluster Rule focuses on reducing toxics, we defined our sample of plants in large part as those appearing in 10 consecutive years of TRI data, from 1996 to 2005, providing us with 5 years before and 5 years after the Cluster Rule implementation in 2001. This requirement (and a few restrictions for availability of other key variables) results in a sample of 150 plants. We aggregate the TRI data to create four measures of toxic pollution: total on-site releases (including air, water, underground injection, and other land releases), air releases, water releases, and releases of chloroform.[69]

Our measures of conventional air and water pollutants come from other EPA databases. The EPA’s Envirofacts and Integrated Data for Enforcement Analysis databases provide information on water pollution discharges for Biochemical Oxygen Demand (BOD) and Total Suspended Solids (TSS), covering the period from 1996 to 2002. Air pollution emissions data for particulates (PM10), volatile organic compounds (VOCs), and sulfur dioxide (SO_2) come from the National Emissions Inventory for 1996-1999 and 2002. There is not perfect overlap between the set of plants we obtained from the TRI and these databases, so our measures of conventional pollutants are only available for a subsample of the data.

Testing for an impact of the Cluster Rule requires us to identify which plants are affected by which parts of the rule, and at what time. All of the plants in our analysis are covered by the most general part of the Cluster Rule, which calls for reductions in releases of air toxics, beginning in April 2001. EPA also published a list identifying the 155 plants with sufficiently large emissions of hazardous air pollutants to qualify for the MACT standards, and a list identifying the 96 of those plants that would face the BAT water standards. We linked those lists

---

[69] Of the different chemicals targeted by the Cluster Rule, only chloroform has been recorded in the TRI for a sufficiently long time to be included in our analysis (dioxin and related compounds were not added to the TRI until 2000, by which time many plants had already achieved their reductions).

to the 150 plants in our database, identifying 105 MACT plants and 65 BAT plants. Because the stricter water regulations for a given BAT plant become effective when that plant renews its water discharge permit, we use water permit date information from the Envirofacts database to assign an effective date for each BAT plant (EFFECTIVE BAT). The requirements for MACT plants come into place in 2001, so the indicator for that regulation (EFFECTIVE MACT) is turned on in 2001.

We also need a measure of regulatory stringency at the state level, to test whether the Cluster Rule has tended to increase or decrease the differences in stringency across states. For this we rely on an index of the political support for environmental regulation within a state, based on the pro-environment voting of its Congressional delegation (GREEN VOTE). These data are collected and reported by the League of Conservation Voters. They provide considerable explanatory variation both across states and over time, and we have used this variable extensively in earlier research.

6. RESULTS

Table 1 presents descriptive statistics for our data. The average plant in our sample reports nearly a million pounds of toxic releases annually, of which the majority are air toxics. As noted earlier, most of the dioxin-related substances were not included in the TRI until 2000, so we focus on releases of chloroform as an indicator of activity that might generate dioxin.[70] Releases of chloroform are relatively rare, with only about one-fifth of the sample reporting any chloroform releases; this number shrank rapidly during the years between 1996 and 2005.

The 5-year-change versions of the dependent variables identify the growth (or decline) of toxic releases and other pollutants over a five-year period, designed to identify trends in pollution across the time when the cluster rule was implemented. Total toxic releases at the average plant declined by about 30 percent over five years, with air toxic releases declining by a somewhat larger amount and water toxic releases increasing. There was also a huge decrease in releases of chloroform, which was one of the targets of the Cluster Rule, as we observed earlier. In terms of conventional pollutants, we saw declines of about 20 percent for water pollutants, with larger declines for sulfur dioxide and increases for particulates and VOCs.

Our initial analysis of the toxic release data is presented in Table 2. Most of the variables in the model show significant effects and generally have the expected signs, although this is less often true for chloroform releases, which also has the lowest R-squared. A one standard deviation change in our measure of state-level political support for regulatory stringency, GREEN VOTE, is associated with a 20 percent decline in toxic releases, and about twice as large a decline in chloroform. Plant characteristics are significant, as expected, with larger pulping plants and kraft mills having more toxic releases. On the firm side, more profitable firms show generally lower releases, although larger firms do not have lower releases, as we might have expected if larger firms provide more compliance assistance to individual plants. Plants located within 50 miles of a state border have higher air and total releases, while plants located in a non-attainment county (with respect to ambient particulates) have lower releases. Plants located in

70 Chlorinated toxic pollutants including dioxins, chloroform, and furans are byproducts of the elemental chlorine bleaching process, being created when elemental chlorine and hypochlorite react with the lignin in wood.

poor neighborhoods tend to have more releases, while those in highly-educated neighborhoods have fewer releases.

Our focus in Table 2 is on the pattern of the year dummies, to see whether toxic releases in the years after the cluster rule is implemented appear significantly different (and lower) from toxic releases in the years before implementation. Of all the toxic measures, the air toxic model comes the closest to this pattern; the results for the total toxic model are similar, not surprising since air toxics are the largest component of total toxics in our sample. We observe a large drop in releases in 2001 relative to 2000, with relatively little variation on either side of the implementation point. What variation there is fits a relatively quick adjustment period - a bit of a downturn starting in 2000 and continuing into 2002. A statistical test for coefficient equality shows essentially no difference for the coefficients within each period, and a noticeably larger difference across the periods (marginally significant for total emissions). By contrast, the chloroform releases show a substantial downward trend from the start of the pre-cluster period, with a leveling-out (at much lower levels) in the post-cluster period. We find significant differences within the pre-cluster period and between the periods, but not within the post-cluster period. This is consistent with paper manufacturers taking steps during the 1990s to phase out their use of chlorine bleaching, even before the cluster rule took effect.

Table 3 presents the results of an analysis with a more nuanced model of the impacts of the cluster rule on toxic releases (we omit a discussion of the coefficients on the control variables, which are similar to those seen in Table 2). Although we anticipate a general increase in regulatory stringency around the implementation date, different plants face different degrees of stringency, and there is some variation in the timing. Along the stringency dimension, we have some plants facing MACT air standards and/or BAT water standards, while others do not. Along the timing dimension, the more stringent water standards were to be implemented when a plant renewed its water discharge permits. Identifying the impacts of these regulatory differences is complicated, because the regulatory stringency depends on the level of releases from the plant, with the more stringent MACT rules applying to plants emitting relatively large amounts of toxics. We therefore include dummy variables indicating a plant's eligibility for the MACT or BAT rules in all the years of the data analysis, along with dummy variables (EFFECTIVE-MACT and EFFECTIVE-BAT) indicating when that part of the cluster rules became effective for that plant.

The pattern of year dummies is similar to that found in Table 2. Since we are controlling separately for the MACT and BAT standards, this indicates that other plants in the paper industry, not affected by MACT or BAT also made considerable reductions in air, chloroform, and total releases over this time period. As expected, the MACT and BAT dummies are significantly positive in the air and water toxic equations, reflecting the targeting of those additional requirements towards the largest sources within the industry. The measures of the impact of additional regulatory stringency, EFFECTIVE MACT and EFFECTIVE BAT, show weaker results. The EFFECTIVE MACT measure actually shows an increase in toxics following the implementation date. The EFFECTIVE BAT measure does show a decrease of about 30 percent in water toxics, but this is not significant.

An alternative approach to measuring the impact of the implementation is shown in Table 4, where we move to an analysis of 5-year-changes in toxic releases. Here we calculate the change in log releases over a five-year period, hopefully smoothing out some of the year-to-year fluctuations in releases and concentrating on medium-run changes that reflect improvements in plant operating procedures or investments in pollution abatement activity. The analysis includes five observations per plant for the 2001-2005 releases, each measured relative to the releases from five years earlier, 1996-2000. The intercept terms reflect the declines over the period in all the releases (except water releases). Again, we see an unexpected positive sign for plants covered by the MACT air regulation, suggesting that they are reducing their air toxic releases by less than other, non-MACT plants. The BAT water regulations are associated with a greater reduction in water toxics than that achieved by plants facing less stringent regulation.

Another coefficient of interest in Table 4 is GREEN VOTE, reflecting differences in the amount of toxic reductions achieved by plants in states with different political support for stringent regulations. This coefficient is positive in all models, and significant for air and total toxics. The coefficient found on GREEN VOTE for air toxics here (+0.012) is comparable in magnitude to that found in Table 1 (-0.015). Taken together, these results suggest that plants located in states with more political support for strict environmental regulations achieved lower levels of toxic releases in the years before the cluster rule was implemented, but that plants located in other, less stringent states, have tended to catch up, at least in part, after the cluster rule was implemented.

In Tables 5 and 6 we turn our attention to discharges of conventional air and water pollutants, considering three air pollutants (PM10, SO2, and VOC) and two water pollutants (BOD and TSS). While conventional pollutants are not directly addressed by the cluster rule, EPA had suggested that the steps taken under the cluster rule to reduce air toxic releases could also lead to some reductions in other air pollutants, most notably particulates and VOCs. We defined our dataset based on having complete toxic release data, not complete air and water pollution data, so the analyses here are being done on subsamples of our plants. We have 144 plants with a total of 599 plant-years of air pollution data and 107 plants with 749 plant-years of water pollution data; the water pollution data came with complete 1996-2002 data for each plant, while the air pollution data came in two sets, one for 1996-1999 and the other for 2002, with incomplete overlaps between them, so that we can calculate long changes in the air pollution measures for only 104 plants.

The various control variables in Table 5 show impacts that are broadly similar to those found earlier for toxic releases. Both air and water pollution levels are significantly lower in states with more support for regulatory stringency, as measured by GREEN VOTE: a one standard deviation higher GREEN VOTE value is associated with 20-50 percent lower levels of emissions. Plant characteristics are again significant, with larger pulp mills showing higher pollution levels. Firm characteristics are less significant, and the plant location and demographics variables for water pollution are more consistent with those found for toxics, with plants near state borders and in poor or less well-educated neighborhoods having higher pollution levels.

Turning to the impact of the cluster rule, in Table 5 we apply an analysis similar to that used in Table 3, although our ability to measure any effects is hampered by limited data in the post-cluster period - a single year (2002) for air pollution and only two years (2001-2002) for water pollution. In addition to year dummies, we also include the detailed measures of which plants were affected by different regulatory stringencies under the cluster rule and at different times. Unlike the results we found for toxic releases, there are no significantly negative year dummies for any of the air or water pollutants. In fact, the water pollutants seem to be decreasing over the years while the air pollutants are staying the same or increasing, the opposite of what we found for toxics.

Looking at the more detailed measures, MACT and BAT plants have higher emissions of conventional pollutants to go with their higher emissions of toxic pollutants. This relationship is strongest for particulates and VOCs in MACT plants, which provides indirect support for EPA's suggestion of where to look for a toxic-conventional link. In fact, we have some direct evidence of an effect in this area with the negative coefficients on EFFECTIVE MACT, although these effects are not significant. For water pollutants, the corresponding coefficients are positive, though again not significant.

These indications of a connection between the cluster rule and reductions in conventional pollutants do not carry over to the analysis of long differences in air and water pollution presented in Table 6. Here all of the detailed regulatory stringency measures have positive coefficients. Few of the other coefficients are significant, although the reduction in air pollutants seems to be smaller at plants in states that have more political support for regulation, again suggesting that further reductions may be more difficult to achieve in those states.

Finally, we examine the relationship between different pollutants at the same plant, both in terms of levels and changes over time. Table 7 shows the results of a seemingly unrelated regression analysis focusing on the toxic release data for air, water, and chloroform. We see a significant set of correlations across the residuals from the different equations. This suggests the presence of unmeasured factors influencing the different pollutants in the same direction, perhaps including the quality of plant management or local pressures from regulators and plant neighbors. When we turn to the changes in air, water, and chloroform releases over a five-year period, we continue to find a significant positive correlation between unexplained changes in air and water releases (and a significant overall correlation among the residuals), but changes in chloroform releases are no longer strongly related to air and water changes.

Because our data for conventional air and water pollutants is only available for a subsample of our plants, we chose to maintain our sample size by estimating each model independently of the others, calculating the residual, and then looking for correlations across the residuals for different pollutants at the same plant. Table 8 shows the correlations for the levels of toxic and conventional pollutants. We find consistently positive, and generally significant, correlations across all the pollutants. The results for the changes, in Table 9, are somewhat weaker, but still show positive relationships in most cases. This suggests that plants with greater than expected reductions in one pollutant also have unexpected reductions in other pollutants.

7. CONCLUDING REMARKS

In this paper we examine the impact of the Cluster Rule on the environmental performance of plants in the pulp and paper industry. This was EPA's first integrated, multi-media regulation, announced in 1997, promulgated in 1999, and effective in 2001 (with some variation in effective date, as described above). Using a sample of 150 pulp and paper mills, we test for changes in emissions of toxic pollutants. We find significant reductions in total toxics and air toxics around the time that the CR was implemented, though not for water toxics. These reductions in air and total toxics are highly concentrated around the time of implementation, with little evidence of anticipation or delay in responding to the implementation date. By contrast, the very large reduction in chloroform releases begins well before the CR effective date, indicating some anticipation of the new rules, possibly triggered by non-regulatory factors affecting the industry, such as pressure from customers and environmental organizations to reduce dioxin.

When we examine the plant's CR status in more detail, plants identified as facing stricter CR rules, on either the air (MACT) or water (BAT) side, do not show consistently greater reductions in those toxic releases. We find no evidence for large reductions in conventional pollutants around the CR implementation date, but do observe significant positive correlations in residuals across the different pollutants, suggesting the presence of unmeasured factors that may improve (or worsen) a plant's environmental performance across the board.

Finally, we find some evidence that the differences across states in regulatory stringency may have been lessened by EPA's adoption of the CR. Plants located in states with more political support for stringent regulation have lower toxic releases on average throughout the period, but they have a smaller decline in toxic releases over time, as shown by our 5-year-change analysis. This suggests that some of the reductions required by the CR had already been implemented in high-stringency states, so the CR had a greater impact on plants in lower-stringency states.

These results should be recognized as preliminary, based in part on the limitations of the datasets being used here. We intend to expand the years of data on conventional air and water pollutants incorporated in the analysis, to get a stronger test for reductions in those pollutants after the CR was implemented. We also intend to test alternative measures of state regulatory stringency, to get a better handle on how a regulatory structure under federalism responds to changes in centrally-mandated stringency as new regulations are introduced. Finally, an innovative provision in the CR is the ability of plants to opt into the Voluntary Advanced Technology Incentives Program (VATIP), agreeing to further reductions (beyond those required by the CR) in the future, but extending their effective compliance date beyond April 15th, 2001. We have not yet located a list of plants that joined the VATIP (despite several contacts with EPA), but hope to add this information to the analysis, so we can get a more precise estimate of the effective date of the CR for all affected plants.

REFERENCES

Arora S. and Cason, T.N.(1999.)Do Community Characteristics Influence Environmental Outcomes? Evidence from the Toxic Release Inventory. Southern Economic Journal, 65,691-716.

Barbera, A.J., McConnell, V.D., 1986. Effects of pollution control on industry productivity: a factor demand approach. Journal of Industrial Economics 35, 161-72.

Berman, E., Bui, L.T., 2001. Environmental regulation and productivity: evidence from oil refineries. Review of Economics and Statistics 83, 498–510.

Boyd, G. A., McClelland, J.D., 1999. The impact of environmental constraints on productivity improvement in integrated paper plants. Journal of Environmental Economics and Management 38, 121–142.

Bui, L. T. M., 2005. Public Disclosure of Private Information as a Tool for Regulating Environmental Emissions: Firm-Level Responses by Petroleum Refineriesto the Toxics Release Inventory. Center for Economic Studies Working Paper 05-13.

Denison, E.P., 1979. Accounting for Slower Economic Growth: The U.S. in the 1970s, The Brookings Institution, Washington DC.

Earnhart, D., 2004a. Regulatory factors shaping environmental performance at publicly-owned treatment plants. Journal of Environmental Economics and Management 48, 655–681.

Earnhart, D., 2004b. The effects of community characteristics on polluter compliance levels. Land Economics 80, 408–432.

Gollop, F.M., Roberts, M. J., 1983. Environmental regulations and productivity growth: the case of fossil-fueled electric power generation. Journal of Political Economy 91, 654-74.

Gray, W.B., 1986. Productivity Versus OSHA and EPA Regulations, UMI Research Press, Ann Arbor, MI.

Gray, W.B., 1987. The cost of regulation: OSHA, EPA and the productivity slowdown. American Economic Review 77, 998-1006.

Gray, W.B., Shadbegian, R.J., 2002. Pollution abatement costs, regulation, and plant-level productivity. In: Gray, W.B. (Editor), The Economic Costs and Consequences of Environmental Regulation. Ashgate Publications, Aldershot, UK.

Gray, W.B. and M.E. Deily. 1996. Compliance and Enforcement: Air Pollution Regulation in the U.S. Steel Industry. Journal of Environmental Economics and Management, 31, 96-111.

Gray, W.B., Shadbegian, R.J., 2003. Plant vintage, technology, and environmental regulation. Journal of Environmental Economics and Management, 46, 384-402.

Gray, W.B. and R.J. Shadbegian. 2005. When and Why do Plants Comply? Paper Mills in the 1980s. Law and Policy, 27, 238-261.

Gray, W.B. and R.J. Shadbegian. 2007. The Environmental Performance of Polluting Plants: A Spatial Analysis. Journal of Regional Science, 47, 63-84.

Helland, E.A. and Whitford, A.B. 2003. Pollution Incidence and Political Jurisdiction: Evidence from the TRI. Journal of Environmental Economics and Management, 46, 403-424.

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

Khanna, M.and Damon, L.A. (1999). EPA's Voluntary 33/50 Program: Impact on Toxic Releases and Economic Performance of Firms. Journal of Environmental Economics and Management 37, 1-25.

Lockwood-Post Pulp and Paper Directory, Miller-Freeman Publishing Company, various issues.

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

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

Oates, W.E. 2001. A Reconsideration of Environmental Federalism. Resources for the Future Discussion Paper 01-54.

Shimshack, Jay P. and Michael B. Ward. 2005. Regulator reputation, enforcement, and environmental compliance. Journal of Environmental Economics and Management, 50, 519-540.

Shadbegian, R.J. and W.B. Gray. 2003. What Determines the Environmental Performance of Paper Mills? The Roles of Abatement Spending, Regulation, and Efficiency. Topics in Economic Analysis & Policy 3, http://www.bepress.com/bejeap/topics/vol3/iss1/art15

Shadbegian, R.J. and W.B. Gray. 2005. Pollution Abatement Expenditures and Plant-Level Productivity: A Production Function Approach. Ecological Economics, 54, 196-208.

Shadbegian, R.J. and W.B. Gray. 2006. Assessing Multi-Dimensional Performance: Environmental and Economic Outcomes. Journal of Productivity Analysis, 26, 213-234.

Sigman, H., 2003. Letting states do the dirty work: State responsibility for environmental regulation. National Tax Journal, 56, pp. 107-122.

Sigman, H. 2002. 2005. Transboundary Spillovers and Decentralization of Environmental Policies. Journal of Environmental Economics and Management, 50, 82-101.

U.S. Environmental Protection Agency. 1985. Soil Screening Survey at Four Midwestern Sites. EPA 905/4-85-005. Environmental Services Division, Eastern District Office, Region V, U.S. Environmental Protection Agency, Westlake, OH.

Wolverton, A. (2002). The Demographic Distribution of Pollution: Does neighborhood Composition Affect Plant Pollution Behavior? U.S. Environmental Protection Agency, National Center for Environmental Economics mimeo.

TABLE 1

DESCRIPTIVE STATISTICS
(N=1500 unless otherwise noted)

VARIABLE	MEAN (STD DEV)	{log mean,std}	5-YEAR-CHANGE
DEPENDENT VARIABLES			
TOTAL AIR EMISSIONS[a] Total toxic air emissions (in pounds)	761863.4 (851008.4)	{12.35,2.57}	{-0.379,1.6}
TOTAL WATER EMISSIONS[a] Total toxic air emissions (in pounds)	57229.2 (149833.0)	{8.15,4.06}	{0.383,2.5}
CHLOROFORM[a] Total Chloroform emissions (in pounds)	67861.8 (69465.7)	{2.26,4.39}	{-2.648,4.7}
TOTAL TRI EMISSIONS[a] Total toxic emissions (in pounds)	914882.9 (984479.9)	{12.71,2.12}	{-0.287,1.3}
PM10 (N=599)[a] Tons of particulate emissions per year	488.3 (625.8)	{5.20,1.85}	{0.147,1.2}
SO_2 (N=599)[a] Tons of sulfur dioxide emissions per year	2409.7 (3905.8)	{6.49,2.24}	{-0.321,1.8}
VOCS (N=599)[a] Tons of volatile organic compound emissions per year	686.8 (879.6)	{5.66,1.60}	{0.366,1.7}
BOD (N=749)[a] Biological oxygen demand discharged	4784.8 (5007.7)	{7.86,1.31}	{-0.193,0.8}
TSS (N=749)[a] Total suspended solids discharged	7308.1 (8813.6)	{8.22,1.36}	{-0.191,1.0}
EXPLANATORY VARIABLES			
MACT Dummy variable =1 for plants which must install maximum available control technology to abate toxic air emissions	0.7 (0.5)		
EFFECTIVE-MACT Dummy variable =1 for MACT plants after 2000	0.35 (0.5)		
BAT Dummy variable =1 for plants which must install best available technology to abate toxic water releases	0.43 (0.5)		
EFFECTIVE-BAT Dummy variable =1 for BAT plants with timing based on date of plant’s water permit	0.25 (0.4)		

TABLE I (cont)

GREEN VOTE State pro-environment Congressional voting (League of Conservation Voters)	43.12 (22.05)	
KRAFT Dummy variable =1 for plants which use the kraft pulping process	0.59 (0.49)	
PULP CAPACITY[a] Plant capacity - tons of pulp per day	761.4 (724.4)	(4.92,3.04)
PAPER CAPACITY[a] Plant capacity - tons of paper per day	831.9 (724.6)	(5.40,2.71)
OLD PLANT Dummy variable =1 for plants opened before 1960	0.63 (0.48)	
RETURN ON ASSETS Firm's rate of return on assets (Compustat)	0.81 (2.61)	
EMPLOYMENT Firm's number of employees in 1000's (Compustat)	20.74 (31.97)	
BORDER PLANT Dummy =1 for plants located within 50 miles of a state border	0.27 (0.44)	
POOR Fraction of the population within 50 miles of the plant living below the poverty line	0.16 (0.06)	
COLLEGE Fraction of the population within 50 miles of the plant who graduated from college	0.16 (0.04)	
NONTSP Dummy variable =1 for plants located in non-attainment area for TSP	0.23 (0.42)	

a = measured in logs in the regressions; in some analyses measured in 5-year-changes

TABLE 2
BASIC TRI MODELS (N=1500)

DEPVAR	TOTAL AIR EMISSIONS	TOTAL WATER EMISSIONS	CHLOROFORM EMISSIONS	TOTAL TRI EMISSIONS
CONSTANT	11.107	3.872	6.320	11.281
	(22.66)	(4.79)	(6.61)	(29.49)
GREEN VOTE	-0.015	-0.009	-0.024	-0.010
	(-4.80)	(-1.71)	(-3.87)	(-4.12)
PLANT CHARACTERISTICS				
KRAFT	1.136	0.574	0.057	0.957
	(6.84)	(2.09)	(0.18)	(7.39)
PULP CAPACITY	0.226	0.503	0.203	0.229
	(8.25)	(11.08)	(3.79)	(10.71)
PAPER CAPACITY	0.069	-0.269	-0.357	0.007
	(2.97)	(-7.03)	(-7.91)	(0.37)
OLD PLANT	0.130	-0.333	0.854	-0.128
	(1.09)	(-1.70)	(3.68)	(-1.38)
FIRM CHARACTERISTICS				
RETURN ON ASSETS	-0.031	-0.10	0.10	-0.042
	(-1.39)	(-2.69)	(2.28)	(-2.42)
EMPLOYMENT	0.151	0.271	-0.704	0.128
	(2.20)	(2.39)	(-5.26)	(2.39)
PLANT LOCATION AND DEMOGRAPHICS				
BORDER STATE	0.569	0.194	-0.103	0.420
	(4.68)	(0.96)	(-0.44)	(4.43)
POOR	1.677	13.267	2.732	2.550
	(1.24)	(6.02)	(1.04)	(2.42)
COLLEGE	-4.916	3.222	4.484	-2.267
	(-3.56)	(1.41)	(1.66)	(-2.10)
NONTSP	-0.340		1.753	-0.498
	(-2.54)		(6.72)	(-4.78)
PRE-CLUSTER RULE				
y1997	-0.035	0.412	-0.190	0.109
	(-0.15)	(1.06)	(-0.41)	(0.59)
y1998	-0.060	0.803	-0.340	0.084
	(-0.25)	(2.06)	(-0.74)	(0.46)
y1999	-0.067	0.775	-0.698	0.048
	(-0.28)	(1.99)	(-1.52)	(0.26)
y2000	-0.20	0.630	-1.419	-0.027
	(-0.85)	(1.61)	(-3.09)	(-0.15)

TABLE 2 (cont.)

POST-CLUSTER RULE

y2001	-0.424	0.722	-2.578	-0.240
	(-1.78)	(1.83)	(-5.53)	(-1.29)
y2002	-0.464	0.815	-2.835	-0.275
	(-1.96)	(2.08)	(-6.13)	(-1.49)
y2003	-0.502	0.996	-2.982	-0.303
	(-2.12)	(2.54)	(-6.46)	(-1.64)
y2004	-0.419	1.103	-3.139	-0.223
	(-1.77)	(2.82)	(-6.80)	(-1.21)
y2005	-0.488	1.015	-3.287	-0.280
	(-2.06)	(2.59)	(-7.12)	(-1.52)
R^2	0.387	0.327	0.203	0.452
F-TEST I	0.21	1.43	2.95	0.19
F-TEST II	0.05	0.33	0.72	0.06
F-TEST III	0.12	1.35	16.89	1.65

NOTES:
(t-statistics in parentheses)
All models include a dummy variable MISSFIRM=1 for firms with missing Compustat data.
F-TEST I tests for the equality of y1996-y2000
F-TEST II tests for the equality of y2001-y2005
F-TEST III tests for the equality of y1996-y2005

TABLE 3
EXENDED TRI MODELS (N=1500)

DEPVAR	TOTAL AIR EMISSIONS	TOTAL WATER EMISSIONS	CHLOROFORM EMISSIONS	TOTAL TRI EMISSIONS
CONSTANT	10.194 (21.15)	3.305 (4.08)	5.198 (5.53)	10.536 (28.16)
MACT	1.585 (8.71)		-0.632 (-1.61)	1.334 (8.56)
EFFECTIVE MACT	0.365 (1.68)		-0.596 (-1.27)	0.350 (1.87)
BAT		1.192 (4.41)	3.823 (11.30)	-0.016 (-0.12)
EFFECTIVE BAT		-0.327 (-1.02)	-3.390 (-8.42)	-0.097 (-0.60)
GREEN VOTE	-0.009 (-2.83)	-0.008 (-1.47)	-0.024 (-4.08)	-0.005 (-1.97)
PLANT CHARACTERISTICS				
KRAFT	0.754 (4.67)	0.50 (1.83)	0.221 (0.70)	0.640 (5.11)
PULP CAPACITY	0.109 (3.89)	0.429 (9.07)	0.118 (2.14)	0.134 (6.09)
PAPER CAPACITY	0.087 (3.95)	-0.234 (-6.04)	-0.310 (-7.07)	0.020 (1.12)
OLD PLANT	0.001 (0.01)	-0.391 (-2.00)	0.805 (3.63)	-0.235 (-2.66)
FIRM CHARACTERISTICS				
RETURN ON ASSETS	-0.049 (-2.29)	-0.104 (-2.84)	0.091 (2.18)	-0.058 (-3.48)
EMPLOYMENT	0.079 (1.20)	0.260 (2.31)	-0.721 (-5.63)	0.066 (1.29)
PLANT LOCATION AND DEMOGRAPHICS				
BORDER PLANT	0.812 (6.91)	0.340 (1.69)	0.016 (0.07)	0.616 (6.74)
POOR	3.262 (2.52)	14.109 (6.44)	2.817 (1.12)	3.832 (3.81)
COLLEGE	-3.826 (-2.90)	3.614 (1.59)	4.543 (1.77)	-1.369 (-1.34)
NONTSP	-0.239 (-1.87)		1.536 (6.15)	-0.410 (-4.13)

TABLE 3 (cont.)

PRE-CLUSTER RULE				
y1997	-0.076	0.403	-0.199	0.074
	(-0.34)	(1.04)	(-0.46)	(0.43)
y1998	-0.144	0.776	-0.201	0.020
	(-0.64)	(2.00)	(-0.46)	(0.12)
y1999	-0.122	0.765	-0.422	0.013
	(-0.54)	(1.97)	(-0.96)	(0.07)
y2000	-0.260	0.650	-0.825	-0.058
	(-1.16)	(1.66)	(-1.86)	(-0.33)
POST-CLUSTER RULE				
y2001	-0.774	0.798	-0.922	-0.526
	(-2.82)	(1.94)	(-1.73)	(-2.47)
y2002	-0.798	0.910	-1.017	-0.543
	(-2.93)	(2.21)	(-1.91)	(-2.57)
y2003	-0.831	1.092	-1.162	-0.567
	(-3.05)	(2.65)	(-2.19)	(-2.68)
y2004	-0.752	1.198	-1.319	-0.490
	(-2.76)	(2.91)	(-2.48)	(-2.32)
y2005	-0.818	1.110	-1.467	-0.544
	(-3.00)	(2.70)	(-2.76)	(-2.57)
R^2	0.443	0.339	0.28	0.509

NOTES: see Table 2

TABLE 4
TRI MODELS IN 5-YEAR-CHANGE FORM (N=750)

DEPVAR	TOTAL AIR EMISSIONS	TOTAL WATER EMISSIONS	CHLOROFORM EMISSIONS	TOTAL TRI EMISSIONS
CONSTANT	-1.933	0.760	-2.367	-1.693
	(-3.71)	(0.94)	(-1.70)	(-3.91)
EFFECTIVE MACT	0.376		1.086	0.213
	(2.29)		(2.24)	(1.42)
EFFECTIVE BAT		-0.353	-4.510	-0.040
		(-1.74)	(-11.94)	(-0.34)
GREEN VOTE	0.012	0.001	0.011	0.010
	(3.81)	(0.14)	(1.33)	(3.84)
PLANT CHARACTERISTICS				
KRAFT	-0.249	-0.429	0.082	-0.168
	(-1.37)	(-1.52)	(0.17)	(-1.11)
PULP CAPACITY	0.034	-0.057	-0.216	0.056
	(1.10)	(-1.17)	(-2.54)	(2.13)
PAPER CAPACITY	-0.054	0.038	0.207	-0.059
	(-2.16)	(0.96)	(3.06)	(-2.80)
OLD PLANT	0.375	0.213	-0.551	0.213
	(2.94)	(1.07)	(-1.62)	(2.01)
FIRM CHARACTERISTICS				
RETURN ON ASSETS	-0.121	-0.111	0.176	-0.104
	(-4.03)	(-2.35)	(2.19)	(-4.17)
EMPLOYMENT	0.090	-0.257	0.313	0.083
	(1.24)	(-2.24)	(1.61)	(1.37)
PLANT LOCATION AND DEMOGRAPHICS				
BORDER PLANT	0.420	0.424	0.522	0.291
	(3.21)	(2.06)	(1.49)	(2.66)
POOR	5.467	6.288	-8.029	4.856
	(3.83)	(2.85)	(-2.10)	(4.09)
COLLEGE	-2.799	1.033	2.795	-0.871
	(-1.88)	(0.44)	(0.70)	(-0.70)
NONTSP	-0.664		-1.509	-0.578
	(-4.67)		(-3.95)	(-4.86)
POST-CLUSTER RULE				
y2002	0.083	-0.387	0.339	-0.106
	(0.47)	(-1.39)	(0.72)	(-0.72)
y2003	0.130	-0.314	0.506	-0.059
	(0.73)	(-1.12)	(1.06)	(-0.40)

TABLE 4 (cont)

y2004	0.189	-0.114	0.616	0.053
	(1.07)	(-0.40)	(1.30)	(0.36)
y2005	0.256	-0.113	1.286	0.064
	(1.44)	(-0.40)	(2.71)	(0.43)
R^2	0.126	0.059	0.275	0.134

NOTES: see Table 2;
5-YEAR-CHANGE calculated as $\log(Y_t) - \log(Y_{t-5})$,
so only post-CR years 2001-2005 are included in the regression.

TABLE 5
CONVENTIONAL AIR/WATER POLLUTION EMISSION MODELS

DEPVAR	PM10	SO_2	VOCS	BOD	TSS
CONSTANT	4.383 (7.34)	8.059 (10.52)	5.395 (9.45)	8.069 (23.24)	8.192 (21.88)
MACT	0.775 (3.91)	0.202 (0.79)	0.656 (3.46)		
EFFECTIVE MACT	-0.481 (-1.45)	0.132 (0.31)	-0.520 (-1.64)		
BAT				0.176 (1.77)	0.228 (2.12)
EFFECTIVE BAT				0.139 (1.03)	0.098 (0.67)
GREEN VOTE	-0.018 (-4.30)	-0.023 (-4.28)	-0.020 (-5.04)	-0.016 (-6.63)	-0.011 (-4.31)
PLANT CHARACTERISTICS					
KRAFT	0.415 (2.24)	0.582 (2.45)	0.499 (2.82)	-0.246 (-2.19)	-0.254 (-2.09)
PULP CAPACITY	0.211 (6.16)	0.30 (6.80)	0.065 (1.98)	0.204 (10.71)	0.227 (11.08)
PAPER CAPACITY	-0.071 (-2.52)	0.006 (0.16)	0.016 (0.59)	-0.099 (-6.05)	-0.110 (-6.27)
OLD PLANT	0.114 (0.81)	0.540 (3.00)	-0.032 (-0.24)	0.076 (0.91)	-0.038 (-0.42)
FIRM CHARACTERISTICS					
RETURN ON ASSETS	-0.001 (-0.04)	0.050 (1.71)	0.006 (0.28)	0.007 (0.45)	0.008 (0.44)
EMPLOYMENT	0.097 (1.17)	0.192 (1.80)	0.031 (0.39)	0.148 (2.90)	0.125 (2.28)
PLANT LOCATION AND DEMOGRAPHICS					
BORDER PLANT	0.145 (0.98)	-0.050 (-0.26)	0.151 (1.07)	0.233 (2.65)	0.336 (3.55)
POOR	-0.957 (-0.62)	-12.629 (-6.41)	-1.318 (-0.90)	1.478 (1.62)	1.540 (1.56)
COLLEGE	-0.903 (-0.56)	-10.445 (-5.01)	-0.780 (-0.50)	-4.011 (-3.92)	-3.419 (-3.10)
NONTSP	-0.503 (-3.07)	-0.113 (-0.54)	0.169 (1.08)		

TABLE 5 (cont.)

PRE-CLUSTER RULE					
y1997	0.036	0.10	0.072	0.066	-0.003
	(0.19)	(0.40)	(0.39)	(0.48)	(-0.02)
y1998	0.078	0.108	0.093	0.055	-0.017
	(0.40)	(0.43)	(0.50)	(0.40)	(-0.11)
y1999	0.058	0.029	0.062	-0.003	-0.067
	(0.30)	(0.11)	(0.33)	(-0.02)	(-0.45)
y2000				-0.054	-0.129
				(-0.38)	(-0.85)
POST-CLUSTER RULE					
y2001				-0.103	-0.125
				(-0.69)	(-0.77)
y2002	0.527	-0.189	0.791	-0.148	-0.205
	(1.70)	(-0.47)	(2.67)	(-0.98)	(-1.26)
R^2	0.39	0.319	0.259	0.425	0.384
OBS	599	599	599	749	749

NOTES: see Table 2

TABLE 6
CONVENTIONAL AIR/WATER POLLUTION EMISSION MODELS
IN 5-YEAR-CHANGE FORM

DEPVAR	**PM10**	**SO_2**	**VOCS**	**BOD**	**TSS**
CONSTANT	-1.384	-2.742	-1.398	-1.170	-1.436
	(-0.95)	(-1.56)	(-0.81)	(-2.33)	(-2.36)
EFFECTIVE	0.051	1.332	0.056		
MACT	(0.11)	(2.40)	(0.10)		
EFFECTIVE				0.161	0.208
BAT				(1.29)	(1.38)
GREEN VOTE	0.010	0.031	0.020	-0.001	-0.002
	(1.07)	(2.76)	(1.83)	(-0.43)	(-0.40)
PLANT CHARACTERISTICS					
KRAFT	-0.032	0.338	-0.109	-0.191	0.077
	(-0.07)	(0.64)	(-0.21)	(-1.10)	(0.36)
PULP	-0.154	-0.176	-0.047	0.032	-0.003
CAPACITY	(-1.90)	(-1.80)	(-0.49)	(1.11)	(-0.08)
PAPER	0.116	0.128	0.033	0.006	0.033
CAPACITY	(1.69)	(1.54)	(0.40)	(0.26)	(1.12)
OLD PLANT	-0.236	-0.159	0.279	0.032	-0.10
	(-0.71)	(-0.40)	(0.70)	(0.25)	(-0.66)
FIRM CHARACTERISTICS					
RETURN ON	-0.092	-0.091	0.029	0.013	0.040
ASSETS	(-1.04)	(-0.85)	(0.27)	(0.39)	(0.96)
EMPLOYMENT	0.074	-0.138	-0.039	0.190	0.212
	(0.38)	(-0.58)	(-0.17)	(2.49)	(2.28)
PLANT LOCATION AND DEMOGRAPHICS					
BORDER	0.713	0.262	-0.253	0.093	0.287
PLANT	(1.94)	(0.59)	(-0.58)	(0.71)	(1.80)
POOR	4.713	6.817	6.809	0.743	0.096
	(1.31)	(1.57)	(1.59)	(0.54)	(0.06)
COLLEGE	2.569	-1.198	0.497	0.867	1.948
	(0.63)	(-0.24)	(0.10)	(0.56)	(1.04)
NONTSP	0.321	-0.597	0.148		
	(0.81)	(-1.24)	(0.31)		
y2002				-0.034	-0.043
				(-0.30)	(-0.31)
R^2	0.139	0.186	0.079	0.083	0.093
OBS	104	104	104	214	214

NOTES: see Table 2, 4

TABLE 7
SEEMINGLY UNRELATED REGRESSION MODELS: TRI
(CORRELATIONS OF RESIDUALS)

PANEL A: LEVELS

	AIR	WATER
WATER	0.1592	
CHLOROFORM	0.1480	0.0492

Breusch-Pagan test of independence: chi2(3) = 74.526, Pr = 0.0000

PANEL B: 5-YEAR-CHANGE FORM

Correlation matrix of residuals:

	AIR	WATER
WATER	0.2246	
CHLOROFORM	0.0075	-0.0263

Breusch-Pagan test of independence: chi2(3) = 38.404, Pr = 0.0000

TABLE 8
CORRELATIONS OF RESIDUALS: LEVELS

	TRI AIR	TRI WATER	CHLOROFORM	PM10	SO_2	VOCS	BOD
TRI WATER	0.1592*						
CHLOROFORM	0.1480*	0.0492					
PM10	0.3378*	0.1277*	0.0199				
SO_2	0.0821*	0.1441*	0.0053	0.4055*			
VOCS	0.3086*	0.0490	0.0956*	0.3128*	0.1520*		
BOD	0.2825*	0.2192*	0.1043*	0.2633*	0.0893	0.2381*	
TSS	0.2533*	0.2293*	0.0010	0.2938*	0.1143*	0.1425*	0.8872*

* = significant at the 5% level or better

TABLE 9
CORRELATIONS OF RESIDUALS: 5-YEAR-CHANGE FORM

	TRI AIR	TRI WATER	CHLOROFORM	PM10	SO_2	VOCS	BOD
TRI WATER	0.2246*						
CHLOROFORM	0.0075	-0.0263					
PM10	0.1352	0.3606*	0.0449				
SO_2	0.2757*	0.3913*	-0.1650	0.3235*			
VOCS	0.1858	0.2020*	0.1389	0.4416*	0.4632*		
BOD	-0.0135	0.0557	0.2396*	0.3231*	0.0244	0.1472	
TSS	-0.0222	0.0016	0.2231*	0.1639	0.0080	-0.0143	0.8785*

* = significant at the 5% level or better

5F. "Spatial Patterns in Regulatory Enforcement: Local Tests of Environmental Justice"

1. INTRODUCTION

Our chapter examines the allocation of environmental regulatory activity, testing a key potential explanation for "Environmental Justice" concerns .[71] In the United States environmental policymaking is carried out under a federalist system. The U. S. Environmental Protection Agency (EPA) sets national air and water quality standards for particular pollutants (e.g. $PM_{2.5}$[72]), while state regulatory agencies have the primary responsibility to implement and enforce those regulations. The power of the states to implement and enforce regulations affords them with a substantial amount of discretion (e.g. setting a plant's permitted level of air and water pollution emissions, or allocating inspections across different facilities). We might expect regulators to direct more enforcement activity at plants located in areas that receive greater benefits (or face lower costs) from pollution abatement. Regulators could also respond to political pressure, directing more activity at plants in rich, white neighborhoods and less activity at plants in poor, minority neighborhoods, which could result in poorer environmental conditions in less privileged areas, creating a potential for "Environmental Injustice". Of course, this implicitly assumes that the affected neighborhoods prefer to receive more regulatory activity; if regulatory actions result in plant closings or job losses, the community might prefer less regulatory activity.

We perform our analysis on a sample of 1616 manufacturing plants located near four large U.S. cities: Los Angeles, Boston, Columbus, and Houston. We use plant-level information from the Census Bureau's confidential establishment-level Longitudinal Research Database (LRD). The LRD includes annual information on individual manufacturing plants, including total value of shipments, labor productivity, capital stock, fuels, and age of the plant; we use data for 2002, originally collected in the 2002 Census of Manufactures.

We measure the regulatory stringency being directed towards a particular plant in terms of the numbers of air pollution inspections and enforcement actions directed at that plant from 2000-2002, using data taken from EPA's Integrated Data for Enforcement Analysis database. We find evidence, as expected, that plant characteristics significantly affect the amount of regulatory activity directed at a plant. In particular, we find that bigger plants and plants with higher fuel consumption face significantly more regulatory activity, as do plants in single-plant firms (firms which own a single manufacturing facility).

We find that nearby political activity significantly affects the amount of regulatory activity directed at a plant. Plants surrounded by politically active populations (measured by voter turnout) and more liberal populations (measured by the percentage voting for the Democratic candidate for President) receive more regulatory attention. These results are broadly consistent with the results of prior research. For example, Hamilton (1995) finds that the capacity expansion decisions of commercial hazardous waste facilities are negatively correlated with political activity. Viscusi and Hamilton (1999) find that Superfund sites located in more pro-environmental areas and with greater political activity have more stringent environmental

---

[71] According to the Office of Environmental Justice at EPA, environmental justice exists when "no group of people, including racial, ethnic, or socioeconomic group, … bear[s] a disproportionate share of the negative environmental consequences resulting from industrial, municipal, and commercial operations."
[72] $PM_{2.5}$ refers to fine particles – 2.5 micrometers in diameter and smaller – which are unhealthy to breathe and have been associated with premature mortality and other serious health effects.

clean up targets for cancer risk, while Sigman (2001) finds EPA processes Superfund sites faster in communities with more political activity. Both of these results show that community activism is an important factor affecting EPA's bureaucratic priorities. In this current volume, Jenkins and Maguire find that more politically active states set higher hazardous waste taxes, providing a greater deterrent to waste disposal. However Wolverton, both in the current volume and in earlier work (Wolverton 2009), finds that the location of polluting plants in two large cities in Texas is not significantly influenced by the level of community political activity.

The focus of our analysis is how the demographic characteristics of the nearby populations influence the amount of regulatory activity faced by our plants. We examine two sets of demographic variables: one representing groups expected to have relatively high sensitivity to air pollution (children and elders), and the other representing disadvantaged groups (poor and minorities). We find some of the expected relationships, but relatively little statistical significance. In terms of the more sensitive groups, we find that plants with more elders nearby do face more inspections (though not more enforcement), but this effect is only significant when we exclude the other control variables from our model. Plants with more children nearby show less clear patterns, although they also tend to be more positive in models without other control variables. These findings are consistent with those of Gray and Shadbegian (2004) for a similar analysis of U.S. pulp and paper mills.

In terms of our "Environmental Justice" analysis, we also find relatively little statistical evidence that regulatory activity is less intense in plants near disadvantaged demographic groups. Plants located in minority neighborhoods, as expected, are inspected less often and face fewer enforcement actions, but both these effects are insignificant in models with a full set of controls, and plants located in poor neighborhoods tend to face (unexpectedly) more regulatory activity.[73] Some models (without a full set of control variables) found significantly fewer inspections at plants near minority populations. Most of our results are consistent with previous research by Hamilton (1995), Been and Gupta (1997), Arora and Cason (1999), Gray and Shadbegian (2004), and Wolverton (2009; <and in this volume>) which all find in various ways that minorities and the poor are not systematically exposed to more pollution. However, our results are inconsistent with some other existing studies that find some evidence raising possible environmental justice concerns. Sigman (2001) finds that EPA processes Superfund sites more quickly in communities with higher median income. Jenkins, Maguire, and Morgan (2004) find that communities with relatively more minorities receive lower 'host' fees for the siting of landfills, while richer communities receive higher 'host' fees. Finally, in the current volume, Jenkins and Maguire find (in their preferred specification) that states with larger minority populations living near waste sites set lower hazardous waste taxes, raising the likelihood of greater waste disposal, thereby raising possible environmental justice concerns in the way hazardous waste is taxed.

The remainder of the paper is organized as follows. Section 2 outlines a simple model of pollution abatement in a federalist system. In section 3 we present a description of our data and our empirical methodology. Section 4 contains our results and finally we present some concluding remarks and possible extensions in section 5.

[73] Gray and Shadbegian (2004) also found little significant evidence of diminished regulatory activity near poor and minority populations.

2. MODEL OF POLLUTION ABATEMENT REGULATION UNDER FEDERALISM

Why do profit-maximizing plants allocate resources to pollution abatement? If pollution were a pure externality, only negatively impacting people who live downwind or downstream of the emitting source, we would not expect to observe any profit-maximizing plant allocating any resources to pollution abatement. Thus, there must be some "external" pressure on the firm to provide an incentive for pollution abatement. Many sources of such external pressure exist. Some of these are market-based, such as consumer demand for products produced with "green/clean" technologies, which allows firms doing more pollution abatement to charge higher prices. The threat of civil law suits or the possibility of Coasian bargaining could provide additional incentives. If the firm's managers have a taste for 'good citizenship' (and the flexibility to spend the firm's funds on pollution abatement), that could also "internalize" the externality, from the perspective of the firm's decision-making. However, we believe that the main incentive for reducing pollution emissions in the U.S. is governmental regulatory activity, especially for the air pollutants we examine in this paper.[74] Therefore it is important to understand the determinants of the amount of regulatory pressure faced by a plant. A large part of that regulatory pressure comes from regular inspections to identify non-compliance, and from enforcement actions designed to force changes at non-compliant plants, and the allocation of those inspections and enforcement actions are the focus of our analysis.

As noted above, the United States conducts environmental policymaking under a federal system, in which the US EPA sets national standards and each individual state has its own environmental regulatory agency which is responsible for implementing and enforcing regulations to meet those standards. The responsibility of the states to implement and enforce regulations affords them considerable flexibility to direct varying degrees of regulatory pressure on polluting plants, in spite of the fact that their activities are monitored by the federal EPA. In fact, state regulators have the responsibility and authority to write the State Implementation Plans which identify permitted air emissions at individual facilities, in order to meet ambient air quality requirements. In addition, the vast majority of air pollution inspections and enforcement actions are performed by state, not federal, regulators. This importance of state-level decisions makes it more likely that local political pressures could influence regulatory activity (as compared to a centralized system where all the important decisions were being made in Washington D.C., far from local political influence).

Optimal regulations would maximize social welfare by setting the marginal benefit from pollution abatement equal to the marginal cost of abatement. In equation (1) below, optimal abatement values, A_i^*, differ for each plant, based on factors which impact the marginal benefits and marginal costs of abatement. The marginal benefits of pollution abatement differ across plants mainly due to the number (and characteristics) of the people who live near the plant who are being exposed to the pollution. On the other hand, the marginal costs of abatement differ across plants based mainly on their production technology, size, and age. Making the standard assumption that the marginal cost of pollution abatement increases with abatement intensity (or at least intersects the marginal benefits curve from below), plants with higher marginal benefits

[74] The compliance-enforcement literature contains numerous studies which show the effectiveness of EPA enforcement, including Magat and Viscusi (1990), Gray and Deily (1996), LaPlance and Rilstone (1996), Nadeau (1997), Helland (1998), and Gray and Shadbegian (2005,2007).

(or lower marginal costs) should do more abatement. If A* is the optimal abatement level, we have $d A_i^*$ /dPLANT$_i$<0 for PLANT characteristics that increase marginal costs, and $d A_i^*$ /dPEOPLE$_i$>0 for PEOPLE characteristics that increase marginal benefits.

(1) $MC(PLANT_i, A_i^*) = MB(PEOPLE_i, A_i^*)$

Our study focuses on the differences across plants in the marginal benefits of pollution abatement (MB_i), while also controlling for plant characteristics affecting marginal abatement costs (e.g. size, fuel use etc). We model the marginal benefit function as aggregating up the individual marginal benefits from pollution reductions for all people living around a plant, as shown in equation (2) below. The locations of the people are indexed by x and y. The marginal benefits MB_i from pollution abatement at a given plant depend largely on the number of people in the area (measured by ρ_{xy}, the population density at a given point[75]) and the emissions that they are exposed to (E_{xy}). We measure differences in people's health susceptibility to pollution exposure by S_{xy}.[76] Finally, we allow for the possibility that the benefits accruing to different population groups are given different weights, through the use of the α_{xy} term.

(2) $$MB_i = \iint_{xy} \alpha_{xy} S_{xy} E_{xy} \rho_{xy} dx dy$$

Note that differences in α_{xy} across groups of people (e.g. by race or socioeconomic status) could be associated with "Environmental Justice concerns", since people with lower α_{xy} are likely to be exposed to higher pollution levels (cleaning up the pollution affecting those groups would receive a "lower benefit" in the MB=MC calculation, resulting in less cleanup). Where could these differences in α_{xy} come from? This depends in large part on how the marginal benefits are assumed to be affecting the firm's decision about how much pollution to abate. If pollution abatement comes from the firm's managers deciding to "do good" for the community, they may be more sympathetic to neighborhoods whose demographic composition is similar to their own. If it comes from threats of legal action or Coasian bargaining, homogenous neighborhoods with powerful community connections may get greater weight. Note that all these examples assume that the affected neighborhoods receive the benefits from pollution abatement, but not the costs (so more abatement is better for them). If abatement pressures are expected to result in plant closings or job losses, the community might in some circumstances prefer to have less pollution abatement.

The possibility that we focus on here is that state regulators are choosing their regulatory stringency (especially the frequency of inspections and enforcement actions) in order to maximize net political support for their regulatory activities (Stigler (1971), Peltzman (1976), Deily and Gray(1991)). This suggests that socio-economic groups with less political clout (e.g.

---

[75] Our only direct measure of the overall benefits from pollution abatement at a particular plant is population density. This implicitly assumes equal exposures Exy for everyone included in equation 2, although we do test different-sized neighborhoods around the plants, which could allow for some diminution of impact with distance.

[76] Our interpretation focuses on health benefits from pollution abatement, but if people differ in the utility they assign to pollution reductions, those differences could also translate into different values of S_{xy}

poor or minorities) would be given less weight (assigned a smaller value of α_{xy}) in the agency's calculations. On the other hand, politically active people, especially those who strongly favor environmental issues, may apply extra pressure on regulators to increase the regulatory stringency applied to nearby plants, effectively giving those people a larger value of $\alpha_{xy.}$, with more regulatory activity and more pollution abatement

3. DATA AND EMPIRICAL METHODOLOGY

Our analysis uses cross-sectional data on environmental regulatory activity in 2000-2002 for 1616 manufacturing plants, located near four large cities: Los Angeles, Boston, Columbus, and Houston. We included four cities in four different states to allow us to test whether the allocation process differs between cities in higher- and lower-regulation states.[77] Those tests (results available upon request) have not shown any systematic differences in the allocation process across the four individual cities, so they are not presented here. We gathered data for all plants located within 50 miles of any of the cities from EPA databases. Plant location information (latitude and longitude) came from EPA's Facility Registry System database. The final sample of 1616 plants came from a merger of plant-level Census data and EPA data that required each plant to be present in both the Census and EPA datasets.[78]

Our regulatory enforcement data come from the EPA's Envirofacts and Integrated Data for Enforcement Analysis databases. These datasets allow us to differentiate between two different types of regulatory pressures faced by each plant – enforcement actions (ENFORCE) and 'inspection-type' actions (INSPECT) – directed at the plant between 2000 and 2002. Enforcement actions include notices of violation, penalties, and follow-up phone calls, while 'inspection-type' actions include onsite inspections, emissions monitoring, stack tests. Based on discussions with regulators, the number of enforcement actions is more likely to be associated with problems at the plant, while the number of inspections is more connected with the size of the plant.

Harrington (1988) illustrates that in a repeated game, a regulator could increase the expected long-run penalty for non-compliance considerably by establishing two classes of regulated plants - good and bad. The good plants are assumed to cooperate with regulators and are inspected only rarely. The bad plants are assumed to be uncooperative with regulators and face much greater inspection and enforcement activity. To control for this effect we include a lagged measure of past violations of environmental standards (VIOL_97), indicating whether the plant was out of compliance at any point in 1997[79].

We estimate four different versions of equation (3) below for the dependent variables measuring regulatory stringency. We measure stringency as the number of inspections (INSP) and enforcement actions (ENFORCE) a plant receives over the 2000-2002 period (using three

[77] According to Hall and Kerr's (1991) 'Green Policies' index, designed to measure the stringency of state environmental regulations, Los Angeles and Boston are in higher regulation states than Columbus and Houston (scores of 0.8, 1.4, 2.0, and 2.7 respectively, where a lower score reflects stricter regulation).

[78] The scope of the sample we created for this project (i.e. analyzing only four cities) was limited by the considerable effort required to gather, merge, and clean the multiple EPA and Census datasets needed for the analysis.

[79] It would be interesting to know whether these violations related to paperwork violations or actual emissions violations, but unfortunately this information is not provided in the air pollution compliance data used here.

years of data to provide more variation in the dependent variables). Since both INSP and ENFORCE are often zero and are otherwise relatively small integers, we estimate the equations using a Poisson model (actually, we use a Negative Binomial model, to allow for the observed over-dispersion of the data, relative to the simpler Poisson model).[80, 81] Each dependent variable Y_{it} is a function of PLANT and PEOPLE characteristics, as well as STATE and COUNTY variables and CITY dummy variables:

(3) $Y_{it} = F(PLANT_{it}, PEOPLE_{it}, STATE_{it}, COUNTY_{it}, CITY_i)$

where Y_{it} is one of the two dependent variables in our analysis: Air Pollution Inspections and Enforcement.

Prior to discussing the expected impacts of our neighborhood level socio-economic and demographic variables we first detail the plant-, state-, and county-level control variables included in each model. Our plant level control variables include plant size, capital stock, fuel use, productivity, plant age, and corporate structure from the Census Bureau's confidential plant-level Longitudinal Research Database (LRD). The LRD includes annual information on individual manufacturing plants, including total value of shipments, labor productivity, capital stock, fuels, and age of the plant. These data are collected in the Census of Manufactures and Annual Survey of Manufacturers (for a more detailed description of the LRD data, see McGuckin and Pascoe (1988)).[82] From the LRD we extract information for 2002, originally collected in the 2002 Census of Manufactures. We use the plant's total value of shipments in log form (SIZE) and capital stock in log form (CAPITAL) to measure the size of the plant. To control for fuel use, which should be positively correlated with air emissions, we use the log of the cost of purchased fuels. Our control for plant age (AGE) is based on the first year the plant appears in the LRD.[83] We control for the plant's efficiency using labor productivity (LPROD) measured as real output per employee. Finally, we include a dummy variable (SINGLE), which identifies plants which are part of single-plant firms (firms which own no other manufacturing plants) to control for corporate structure. If single plants have less political clout then we would expect to find them receiving more attention from regulators - they might also be more apt to have paperwork violations, as compared to larger firms which could take advantage of economies of scale in providing regulatory compliance support from their corporate headquarters.

We use voting information at the county level to characterize the political climate

---

[80] The Poisson regression model is appropriate in cases when the dependent variable is a count (e.g. number of inspections and enforcement actions). The Poisson distribution assumes that the dependent variable's mean is equal to its variance, but in many cases count data exhibit over-dispersion (a variance greater than its mean). In these cases a model that allows for over-dispersion, such as the Negative Binomial model used here, is more appropriate (and our Negative Binomial results show significant over-dispersion in our data).

[81] We also estimate each model with OLS, to test the robustness of the coefficient results.

[82] The establishment-level data in the LRD are collected and protected under Title 13 of the U.S. Code. Restricted access to these data can be arranged through the U.S. Census Bureau's Center for Economic Studies (CES). See http://www.ces.census.gov/ for details.

[83] We would like to thank John Haltiwanger for providing us with our plant's age and capital stock, which were calculated based on establishment level Census data.

surrounding the plant[84]. The use of voter activity to overcome externalities is discussed in Olson (1965). A positive influence on α_{xy} is expected to come from voter activity, measured using county voter turnout in the 2000 presidential election (TURNOUT). We also include DEMOCRAT, the fraction of voters in the county voting for the Democratic Presidential candidate in 2000, as an indication of voter support for more active regulatory interventions[85]. Both of these variables are expected to result in more regulatory activity at a plant, since they are associated with having more politically active, liberal people living near the plant[86].

Now consider the variables which are at the heart of our analyses, those related to environmental justice concerns that plants might be treated differently based on the racial, ethnic, or socioeconomic composition of the surrounding population. In our analyses the "potentially less valued" (low α_{xy}) populations are poor and minorities. Our measure of POOR is the percentage of the nearby population living below the poverty line; our measure of MINORITY is the percentage of the nearby population which is not non-Hispanic whites. Environmental justice concerns could be raised if plants near POOR and MINORITY populations face less regulatory activity. We measure the overall population being affected by pollution from the plant (ρ_{xy}) with POPDEN, the population density around the plant, which is expected to be associated with increased regulatory activity. Possible differences in health sensitivity by age group (S_{xy} in equation 2) are represented by CHILDREN (the percentage of the nearby population under the age of 6) and ELDERS (the percentage of the nearby population over the age of 65). Since both groups are expected to be more sensitive to pollution, both CHILDREN and ELDERS should be positively related to regulatory activity.

We create the above mentioned socio-economic and demographic variables from detailed geographic area (Census block groups) data on population characteristics from the 2000 U.S. Census of Population, as compiled in the Census-CD datasets prepared by Geolytics, Inc. We do not know, a priori, the 'optimal' (or even most appropriate) size of a neighborhood to examine the effects of benefits and our socio-economic and demographic variables on regulatory activity. Therefore we take advantage of our ability to 'construct' neighborhoods of different sizes to see how far the benefit and political effects extend. In particular, we 'construct' four different-sized neighborhoods: one consisting of the closest block group, and three additional neighborhoods based on "circles" around the plant - all block groups that fall within R miles of the plant, where R = 1, 5 and 10. Distances are calculated between each plant and the centroid of each block group to determine which block groups fall within R mile(s) of the plant, and the block group values for each population characteristic are aggregated to get the overall value for each plant. As it happens, we did not find perfectly consistent results across different neighborhood sizes (some demographic variables had stronger effects when measured in smaller neighborhoods, others were stronger when measured in larger neighborhoods). We report here the results for 1- and 10-mile circles around the plant (other results are available from the authors upon request).

[84] Unfortunately, voting data at finer levels of geographic detail (e.g. precinct-level data) cannot be used, because they are not collected in similar ways across these four states.

[85] We tried using League of Conservation Voters data on pro-environmental voting in Congress, which did get the expected positive coefficient but was consistently insignificant, perhaps because of limited geographic variability, being measured at the Congressional district level (results available upon request).

[86] Politically active Republicans might be expected to push for less regulatory activity on ideological grounds. The political clout of Democrats might be expected to depend on the party affiliation of the state's Governor, but during our sample period only California had a Democratic governor, so we had no variation to test that hypothesis.

We also considered alternative demographic measures, based on the heterogeneity of the population surrounding the plant, presuming that a more heterogeneous population will have a more difficult time mobilizing for political action. Researchers have considered the impact of ethnic or linguistic fragmentation as it affects economic growth in developing countries (e.g. Easterly and Levine (1997)), or the impact of racial or educational heterogeneity on community activity (e.g. Vigdor (2004) and Videras (2007)). For our analysis we constructed two homogeneity indices, each calculated as the sum of squared shares of subgroups within the population. The education homogeneity index (HOM_ED), is based on the shares of college graduates, high school graduates, and high school dropouts near the plant. The racial homogeneity index (HOM_RACE) is based on the shares of African Americans, Asians, Native Americans, Hispanics, and non-Hispanic whites near the plant (with the latter group also including "all other" racial groups).

4. RESULTS

Table 1 contains the means and standard deviations, along with variable descriptions, of all variables used in this study. In our data the average plant receives roughly twice as many air inspections as enforcement actions per year – though the inspection distribution is skewed, with more than half our plants not receiving an inspection in 2000-2002. Turning now to our key demographic variables, which allow us to test for environmental justice concerns, we see that in terms of segments of the population which may be more sensitive to pollution emissions (CHILDREN and ELDERS), less than 10% of our population is under the age of 6 and roughly 12% is over the age of 65. In terms of our variables which measure segments of the population which have less 'political clout' (POOR and MINORITY), about 14% of our population has income below the poverty line and just over 25% of our population are minorities. There is much more variation across plants for the POOR and MINORITY variables than for the CHILDREN and ELDERS variables.

In Table 2 we present the results of the basic model for air pollution regulatory activity.[87] Our basic model works quite well, explaining roughly 20% of the variation across plants in inspection and enforcement activity. The key control variables have the expected sign in nearly all cases. We find that larger plants, which typically generate more pollution, face more inspections and enforcement activity. Plants which use more fuels, again expected to emit more air pollution, face significantly more regulatory activity. Plants which are owned by single-plant firms (firms which own no other manufacturing plants) also face significantly more regulatory activity. Finally, plants with past violations (VIOL_97) face greater regulatory activity, though this effect is only significant in the OLS models. The other control variables (capital intensity, labor productivity, and plant age) have less consistent and generally insignificant effects.

We add three additional variables to our basic model in Table 3 – POPDEN, TURNOUT, and DEMOCRAT. In general, the key plant-level control variables continue to have the same effect as found in the basic model in Table 2. POPDEN, our proxy for the marginal benefits from pollution abatement, has an unexpectedly negative effect on the amount of regulatory activity faced by a plant, but is only significant in the OLS model for inspections.[88] This implies

[87] All the results presented below include city fixed effects – we get qualitatively similar results when we drop the fixed effects (results available from the authors).

[88] Gray and Shadbegian (2004) find similarly odd results, using much more sophisticated measures of the marginal benefit of pollution abatement. We also tried including measures of plant density (the number of

that regulators are not directing additional regulatory pressure, in the form of more inspections or more enforcement actions, towards potentially high benefit plants. On the other hand, our political variables, TURNOUT and DEMOCRAT, have the expected positive signs and are generally significant. This provides evidence that regulators respond to pressure from the surrounding population, with more politically active and more liberal populations encouraging more regulatory activity.

In Table 4A we add demographic/socio-economic variables to our full model.[89] CHILDREN and ELDERS are two demographic groups which are expected to receive greater health benefits from pollution abatement than the rest of the population. Focusing on the results of the Negative Binomial models, we see that plants which are near more sensitive population groups (CHILDREN and ELDERS) face more inspections, as expected. However, this effect is never significant. On the other hand, ELDERS and CHILDREN show some unexpectedly negative (yet generally insignificant) effects on enforcement activity, as well as some differences between the OLS and Negative Binomial results. On the whole, we do not find convincing evidence that regulators put more pressure, in the form of inspections and enforcement activity, on plants located in areas with more sensitive populations. This is a surprise, but it may be the case that our measures of regulatory pressure (simple counts of inspection and enforcement actions) are not really capturing the amount of pressure these plants face. High-benefit plants may face other kinds of pressures (e.g. community action, permit stringency, etc.) that we cannot observe. If regulators, with limited time to perform regulatory enforcement, know that a plant is facing these other pressures, then they might not feel the need to allocate more inspections and enforcement actions to those plants.

Now we turn to the impact of POOR and MINORITY (our potentially disadvantaged populations) on regulatory activity, the focus of our "Environmental Justice" analysis. As happened with CHILDREN and ELDERS, we find little evidence that regulators treat poor or minority populations differently than other populations in their allocation of regulatory activity. MINORITY has the expected negative effect on regulatory activity, but this effect is insignificant, while the POOR coefficient has an unexpectedly positive effect on regulatory activity, although this effect is also generally insignificant.

One possible concern with the results in Table 4A is that we are estimating the full model, and that some of our control variables may be capturing the mechanisms by which the demographic variables might influence regulatory activity. For example, poor and minority neighborhoods have lower voter turnout, so the significant TURNOUT effect in the model might leave little to be explained by POOR and MINORITY[90]. We tested several variations of our models, including different combinations of the demographic variables, or excluding some control variables (such as lagged violations and political activism). The remaining panels of Table 4 consider progressively simpler models. Table 4B includes our four key demographic variables and city dummies, but no other control variables. Table 4C includes only one demographic variable at a time along with city dummies. Finally, Table 4D presents simple

---

other plants in out data within a given radius of the plant), to test whether areas with many plants received fewer inspections per plant (possibly explaining the negative POPDEN results), but plant density was generally insignificant, and its inclusion in the model didn't affect the POPDEN coefficient's sign (results available on request).

[89] We only provide the newly estimated coefficients in Table 4A, but in general the other variables have the same qualitative effects shown in Tables 2 and 3.

[90] In our dataset the correlations of POOR and MINORITY with TURNOUT are about -0.7.

correlations between each of the demographic variables and the regulatory activity measures. It's worth noting that dropping the other control variables results in considerably less explanatory power (lower R^2) in these analyses, as compared to those in Table 4A.

There is a tendency, most noticeable in Table 4B, for the coefficients on the demographic variables to become more consistent in sign, and occasionally become significant, when the other control variables are dropped from the model. ELDERS and CHILDREN are more consistently positive than in the full model, and are both significant in the 10-mile-circle Negative Binomial inspection model. POOR is consistently positive (but insignificant), while MINORITY remains negative and is significant for the Negative Binomial inspection equations. In Table 4C, where the demographic variables enter separately, the coefficients on ELDERS and CHILDREN are less consistently positive, but we now see significantly negative (negative binomial) results for POOR and MINORITY, with fewer inspections at plants in POOR and MINORITY neighborhoods. The importance of controlling for differences across cities can be seen by comparing Table 4C and Table 4D - only about half (9 of 16) of the correlations in 4D (without city controls) have the same sign as the regression coefficients in 4C (with city controls), and this discrepancy holds for all 4 of the demographic variables.

In Table 5, we consider the possibility that the homogeneity of the surrounding population might influence their ability to mobilize support for greater regulatory activity. We test homogeneity in educational attainment as well as in racial composition. We should find positive coefficients, if (as expected) more homogeneous neighborhoods are able to exert more effective pressure on regulators. We find the expected results for educational homogeneity, where we find positive effects that are usually significant, but not for racial homogeneity, where the coefficients are negative (and generally insignificant).

Given these initial results, we concentrate our attention on educational homogeneity in the remainder of Table 5 (we carried out similar analyses for racial homogeneity, without finding much of significance). We first consider a decomposition of the educational homogeneity index into its three components, the squared shares of the three educational subcategories. These components usually show positive effects on regulatory activity, consistent with the HOM_ED coefficients; the dropout share is more often negative than the others, but the differences between the components are not generally significant. We then test whether homogeneity matters differently for different populations by interacting HOM_ED with other variables: TURNOUT, POOR, and MINORITY. None of the interactions are significant, but we do find negative coefficients on POOR and MINORITY, suggesting that the advantages of homogeneity are less effective in poor or minority neighborhoods.

5. CONCLUDING REMARKS

In this paper we use a plant-level data set consisting of 1616 U.S. manufacturing plants in four large U.S. cities – Los Angeles, Boston, Columbus, and Houston – to test whether or not regulators treat different segments of the population differently when allocating regulatory activity. A key potential explanation for "Environmental Justice" concerns is that regulators might direct more regulatory activity at plants in rich, white neighborhoods and less in poor, minority neighborhoods, resulting in poorer environmental conditions in less privileged areas. We focus on differences across plants in the benefit side of the MB=MC equation, but our use of confidential Census plant-level data allows us to control for a variety of plant characteristics (size, age, productivity, capital intensity, and energy intensity) which could affect marginal abatement costs.

Our basic model for air pollution regulatory activity works quite well, explaining roughly 20% of the variation in inspection and enforcement activity, and our key control variables generally have the expected sign. One exception to this is the population density near the plant, which should increase the benefits of pollution reductions, but seems to have a negative effect on regulatory enforcement (though significant in only one model).

Examining the characteristics of the nearby population, we find that, as expected, plants in areas with more politically active (TURNOUT) and more liberal (DEMOCRAT) populations face significantly more regulatory pressure. On the demographic characteristics, the results are much weaker. We expect CHILDREN and ELDERS to be more sensitive to pollution emissions, but their coefficients are not always positive, and rarely significant.

Our measures of disadvantaged populations also show limited effects. We expect plants with more POOR and MINORITIES nearby to face less regulatory pressure. We find the expected sign for MINORITY, but these impacts are insignificant, while we find (unexpected) positive signs for POOR. Thus, we find relatively little statistical evidence that regulators are less active at plants near poor or minority populations. When other control variables are excluded from the model, the negative MINORITY effect is significant for inspections (but the POOR effect remains surprisingly positive).

We also test for the impact of population homogeneity near the plant, using measures of educational attainment and racial diversity. We find the expected impact for diversity in educational attainment (more homogeneous neighborhoods seem to have greater political clout, in terms of receiving more regulatory attention), but no impact of racial diversity on regulatory activity. Interactions of educational diversity with other demographic variables are generally insignificant.

The generally insignificant results for POOR and MINORITY do not necessarily rule out the presence of 'Environmental Justice' concerns in the allocation of regulatory activity across plants. Differences in regulatory pressure may arise through other avenues than the simple numeric count of inspections or enforcement actions. A politically well-connected population could intervene in permit renewals, organize community action against the plant, or encourage regulators to pursue qualitatively different avenues (e.g. the use of criminal penalties for violations) that we cannot observe in our data. Still, we might have expected to see some evidence of demographically-related differences in the intensity of regulatory activity if 'Environmental Justice' concerns had large effects.

We hope to extend this project in a number of directions in future work, including generating better measures of the marginal benefits of pollution cleanup at different plants (based on physical models of pollution flows), disaggregating our socio-economic and demographic variables into the eastern and western half of the circles drawn around each plant, and conducting a spatial econometric analysis of the regulatory attention paid to neighboring plants. Additional insights could be gained from a panel data analysis, relating changes in regulatory activity over time to changes in demographic patterns (this would also help address concerns about the potential endogeneity of the demographic variables, relative to spatial differences in pollution).

REFERENCES

S. Arora, T. N.Cason, "Do community characteristics influence environmental outcomes? Evidence from the Toxic Release Inventory," *Southern Economic Journal* **65,** 691-716 (1999).

R.A. Becker, “Pollution Abatement Expenditure by U.S. Manufacturing Plants: Do Community Characteristics Matter?” *Contributions to Economic Analysis and Policy* **3** (2004).

V. Been, F. Gupta, “Coming to a Nuisance or Going to a Barrios? A Longitudinal Analysis of Environmental Justice Claims,” *Ecology Law Quarterly* **24**, 1-56 (1997).

M. E. Deily, W. B. Gray, Enforcement of pollution regulations in a declining industry, *J. Environ. Econom. Management* **21**, 260-274 (1991).

Easterly, W. and, Levine, R. "Africa's Growth Tragedy: Policies and Ethnic Divisions." *Quarterly Journal of Economics*, 112 (1997): 1203-125.

W.B. Gray, M. E. Deily “Compliance and Enforcement: Air Pollution Regulation in the U.S. Steel Industry,” *Journal of Environmental Economics and Management* 31 (1996): 96-111.

W. B. Gray, R. J. Shadbegian, “Optimal Pollution Abatement – Whose Benefits Matter and How Much,” *Journal of Environmental Economics and Management* **47**, 510-534 (2004).

W. B. Gray, R. J. Shadbegian, “When and Why do Plants Comply? Paper Mills in the 1980s,” *Law and Policy* **27**, 238-261 (2005).

B. Hall, M.L. Kerr. Green Index: A State-by-State Guide to the Nation's Environmental Health. Island Press, Washington, DC (1991).

J. Hamilton, “Testing for Environmental Racism: Prejudice, Profits, Political Power?,” *Journal of Policy Analysis and Management* **14**, 107-132 (1995).

W. Harrington, “Enforcement Leverage when Penalties are Restricted,” *Journal of Public Economics* **37**, 29-53 (1988).

E. Helland, “The Enforcement of Pollution Control Laws: Inspections, Violations, and Self-Reporting,” *Review of Economics and Statistics* 80 (1998): 141-153.

B. Laplante, Benoit, P. Rilstone (1996) “Environmental Inspections and Emissions of the Pulp and Paper Industry in Quebec,” *Journal of Environmental Economics and Management* 31(1996): 19-36.

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

R.H. McGuckin, G. A. Pascoe, “The Longitudinal Research Database: Status and Research Possibilities,” *Survey of Current Business* (1988).

L.W. Nadeau “EPA Effectiveness at Reducing the Duration of Plant-Level Noncompliance,” *Journal of Environmental Economics and Management* 34 (1998): 54-78.

R. Jenkins, K. Maguire, C. Morgan, “Host Community Compensation and Municipal Solid Waste Landfills,” *Land Economics* **80**, 513-528 (2004).

R. Jenkins and K. Maguire (2009), “State Hazardous and Solid Waste Taxes: Understanding Their Variability” NCEE WP ….

O. Mancur. “The Logic of Collective Action”, Harvard University Press, Cambridge, MA, 1965.

S. Peltzman, “Toward a More General Theory of Regulation” *Journal of Law and Economics* **19**, 211-240 (1976).

R.J. Shadbegian, W.B. Gray “What Determines the Environmental Performance of Paper Mills? The Roles of Abatement Spending, Regulation, and Efficiency,” *Topics in Economic Analysis & Policy* 3 (2003): http://www.bepress.com/bejeap/topics/vol3/iss1/art15

R.J. Shadbegian, W.B. Gray “Assessing Multi-Dimensional Performance: Environmental and Economic Outcomes,” *Journal of Productivity Analysis* 26, 213-234 (2006).

H. Sigman, “The Pace of Progress at Superfund Sites: Policy Goals and Interest Group Influence,” *Journal of Law and Economics* **44**, 315-344 (2001).

G. J. Stigler. “The Theory of Economic Regulation” *Bell Journal of Economics and Management Science* **2**, 3-21 (1971).

A. Videras, “The Effects of Diversity on Revealed Preferences for Environmental Goods,” July 2007.

J. Vigdor, “Community Composition and Collective Action: Analyzing Initial Mail Response to the 2000 Census,” *Review of Economics and Statistics*, February 2004, 86(1): 303-312.

W. K. Viscusi, J.T. Hamilton, “Are Risk Regulators Rational? Evidence from Hazardous Waste Cleanup Decisions,” *American Economic Review* **89**, 1010-1027 (1999).

A. Wolverton, “The Demographic Distribution of Pollution: Does neighborhood Composition Affect Plant Pollution Behavior?,” U.S. Environmental Protection Agency, National Center for Environmental Economics mimeo (2002).

A. Wolverton, “Effects of Socio-Economic and Input-Related Factors on Polluting Plants’ Location Decisions,” *The B.E. Journal of Economic Analysis & Policy*: Vol. 9 : Iss. 1 (Advances), Article 14 (2009).

A. Wolverton, “The Role of Demographic and Cost-Related Factors in Determining Where Plants Locate – A Tale of Two Texas Cities” (2009) NCEE WP …

TABLE 1

SUMMARY STATISTICS
(N=1616)

VARIABLE (N)	MEAN (STD DEV)	
Dependent Variables		
AIR INSP Number of air pollution inspections	0.503 (1.875)	
AIR ENFORCE Number of air pollution enforcement actions	0.267 (1.054)	
Plant-level Control Variables		
SIZE Log of total value of shipments	9.482 (1.780)	
LPROD Log of labor productivity	5.617 (1.025)	
CAPITAL Log of the capital stock	8.191 (2.474)	
FUELS Log of the cost of purchased fuels	3.908 (2.401)	
SINGLE Dummy variable =1 if this plant is a single plant firm	0.418 (0.493)	
AGE Log of the age of the plant	3.022 (0.545)	
VIOL_97 Dummy variable = 1 if the plant was out of compliance with air regulations in 1997	< 0.05	
Demographic Variables		
	1-Mile Circle	**10-Mile Circle**
POPDEN Log of population density	7.742 (1.593)	7.538 (1.165)
CHILDREN Percentage of the population under 6 years old	8.839 (2.449)	8.717 (1.271)
ELDERS Percentage of the population 65 years old and over	11.297 (4.571)	11.165 (2.532)
POOR Percentage of the population living below the poverty line	13.675 (9.587)	12.296 (5.439)

Table 1 (cont)

MINORITY	26.471 (23.021)	6.518 (18.134)
Percentage of the population who are minorities (Hispanic and/or non-white)		
HOM_RACE	0.676 (0.215)	0.599 (0.209)
Homogeneity index = sum of squared shares of racial groups in population (African Americans, Asians, Native Americans, Hispanics, and non-Hispanic whites)		
HOM_ED	0.503 (0.054)	0.464 (0.045)
Homogeneity index = sum of squared shares of educational groups in population (college graduates, high-school graduates, high-school dropouts)		

Political Variables

TURNOUT	49.820 (8.460)
Percentage of the population over 18 voting in the 2000 presidential election	
DEMOCRAT	54.757 (9.917)
Percentage of the population over 18 voting Democrat in the 2000 presidential election	

TABLE 2
Basic Inspection and Enforcement Models

MODEL	OLS	N.B.	OLS	N.B.
DEP. VAR.	INSP	INSP	ENFORCE	ENFORCE
CONSTANT	-2.537	-3.489	-1.598	-6.166
	(0.428)	(0.506)	(0.237)	(0.838)
BOSTON	0.266	0.106	0.307	1.651
	(0.167)	(0.175)	(0.092)	(0.536)
HOUSTON	1.553	1.089	1.120	3.237
	(0.193)	(0.183)	(0.107)	(0.534)
LOS ANGELES	-0.012	-1.239	0.386	2.059
	(0.174)	(0.220)	(0.096)	(0.534)
SIZE	0.099	0.139	0.044	0.127
	(0.042)	(0.053)	(0.023)	(0.079)
LPROD	0.126	-0.046	0.099	0.052
	(0.055)	(0.065)	(0.030)	(0.093)
CAPITAL	0.003	-0.025	0.012	0.020
	(0.024)	(0.027)	(0.013)	(0.041)
FUELS	0.168	0.233	0.095	0.239
	(0.024)	(0.030)	(0.013)	(0.042)
SINGLE	0.333	0.270	0.203	0.421
	(0.102)	(0.130)	(0.057)	(0.187)
AGE	0.071	0.120	-0.029	-0.204
	(0.083)	(0.107)	(0.046)	(0.138)
VIOL_97	0.960	0.227	0.638	0.335
	(0.257)	(0.216)	(0.143)	(0.335)
R^2	0.206	0.173	0.225	0.175

(Standard Errors)
A pseudo R^2 statistic is reported for the Negative Binomial Model.

TABLE 3
Expanded Basic Inspection and Enforcement Models

MODEL	OLS	N.B.	OLS	N.B.
DEP. VAR.	INSP	INSP	ENFORCE	ENFORCE
CONSTANT	-3.596	-4.554	-2.708	-10.624
	(0.969)	(1.130)	(0.539)	(1.760)
BOSTON	0.126	-0.029	0.107	0.809
	(0.234)	(0.289)	(0.130)	(0.612)
HOUSTON	1.820	1.330	1.290	3.871
	(0.231)	(0.233)	(0.128)	(0.588)
LOS ANGELES	0.268	-1.000	0.453	2.207
	(0.207)	(0.266)	(0.115)	(0.582)
SIZE	0.102	0.140	0.045	0.125
	(0.042)	(0.052)	(0.023)	(0.078)
LPROD	0.118	-0.061	0.097	0.040
	(0.055)	(0.066)	(0.030)	(0.093)
CAPITAL	0.002	-0.024	0.013	0.024
	(0.024)	(0.027)	(0.013)	(0.041)
FUELS	0.165	0.232	0.094	0.238
	(0.024)	(0.031)	(0.014)	(0.042)
SINGLE	0.354	0.278	0.209	0.436
	(0.102)	(0.129)	(0.057)	(0.188)
AGE	0.078	0.120	-0.032	-0.214
	(0.083)	(0.107)	(0.046)	(0.137)
VIOL_97	0.868	0.148	0.605	0.330
	(0.258)	(0.219)	(0.143)	(0.327)
TURNOUT	0.024	0.022	0.015	0.056
	(0.011)	(0.013)	(0.006)	(0.021)
DEMOCRAT	0.007	0.006	0.009	0.035
	(0.008)	(0.011)	(0.004)	(0.014)
POPDEN	-0.071	-0.040	-0.007	0.014
	(0.033)	(0.031)	(0.018)	(0.043)
R^2	0.211	0.175	0.229	0.180

(Standard Errors)
A pseudo R^2 statistic is reported for the Negative Binomial Model.

TABLE 4A
Inspection and Enforcement Models with Demographics

MODEL	OLS	N.B.	OLS	N.B.	OLS	N.B.	OLS	N.B.
DEP. VAR.	INSP	INSP	INSP	INSP	ENFORCE	ENFORCE	ENFORCE	ENFORCE
DISTANCE	1-MILE	1-MILE	10-MILES	10-MILES	1-MILE	1-MILE	10-MILES	10-MILES
POOR	1.689	1.167	2.938	1.720	0.758	0.533	1.854	4.519
	(0.639)	(0.745)	(2.100)	(2.757)	(0.356)	(1.012)	(1.169)	(3.751)
MINORITY	-0.394	-0.699	-1.875	-1.398	-0.258	-0.445	-0.424	-0.367
	(0.344)	(0.407)	(1.134)	(1.328)	(0.192)	(0.565)	(0.632)	(1.896)
ELDERS	0.957	0.855	2.858	3.206	0.505	-0.140	0.280	-11.245
	(1.188)	(1.301)	(4.151)	(4.935)	(0.661)	(1.932)	(2.312)	(7.893)
CHILDREN	-4.794	1.913	-7.569	8.405	1.429	8.040	-2.668	-4.468
	(2.166)	(2.292)	(7.618)	(8.846)	(1.206)	(3.273)	(4.243)	(13.538)
R^2	0.217	0.176	0.218	0.182	0.232	0.185	0.233	0.184

(Standard Errors)
A pseudo R^2 statistic is reported for the Negative Binomial Model.
All models in this table contain all the variables contained in Table 3.

TABLE 4B
Inspection and Enforcement Models with Only Demographics – (Four Variables Together)

MODEL	OLS	N.B.	OLS	N.B.	OLS	N.B.	OLS	N.B.
DEP. VAR.	INSP	INSP	INSP	INSP	ENFORCE	ENFORCE	ENFORCE	ENFORCE
DISTANCE	1-MILE	1-MILE	10-MILES	10-MILES	1-MILE	1-MILE	10-MILES	10-MILES
POOR	0.847	1.037	0.399	0.570	0.399	0.651	0.456	0.872
	(0.634)	(0.829)	(1.934)	(2.581)	(0.355)	(1.108)	(1.084)	(3.574)
MINORITY	-0.768	-1.035	-1.612	-2.706	-0.367	-0.763	-0.355	-0.664
	(0.343)	(0.452)	(0.816)	(1.028)	(0.192)	(0.611)	(0.457)	(1.472)
ELDERS	0.399	0.849	7.838	11.584	0.159	0.464	3.225	9.422
	(1.245)	(1.473)	(4.141)	(5.035)	(0.698)	(2.136)	(2.322)	(7.598)
CHILDREN	-4.891	-1.009	7.647	20.597	1.254	5.968	6.624	27.734
	(2.232)	(2.443)	(7.389)	(9.780)	(1.251)	(3.366)	(4.143)	(14.431)
R^2	0.120	0.116	0.21	0.122	0.126	0.106	0.126	0.106

(Standard Errors)
A pseudo R^2 statistic is reported for the Negative Binomial Model.
All models in this table contain city dummy variables.

TABLE 4C
Inspection and Enforcement Models with Only Demographics (One Variable per Model)

MODEL	OLS	N.B.	OLS	N.B.	OLS	N.B.	OLS	N.B.
DEP. VAR.	INSP	INSP	INSP	INSP	ENFORCE	ENFORCE	ENFORCE	ENFORCE
DISTANCE	1-MILE	1-MILE	10-MILES	10-MILES	1-MILE	1-MILE	10-MILES	10-MILES
POOR	-0.352	-0.313	-1.971	-3.334	0.089	0.268	0.018	0.881
	(0.502)	(0.619)	(1.136)	(1.566)	(0.281)	(0.827)	(0.635)	(1.911)
MINORITY	-0.642	-0.703	-1.549	-2.620	-0.209	-0.256	-0.228	0.061
	(0.278)	(0.333)	(0.488)	(0.645)	(0.156)	(0.462)	(0.273)	(0.816)
ELDERS	1.593	1.239	6.289	5.480	-0.061	-0.998	1.522	0.165
	(1.146)	(1.388)	(3.038)	(3.303)	(0.641)	(1.971)	(1.700)	(5.081)
CHILDREN	-5.275	-2.262	-1.645	4.070	1.085	4.962	2.838	14.125
	(2.000)	(2.231)	(5.813)	(6.790)	(1.120)	(2.949)	(3.249)	(9.745)

(Standard Errors)
A pseudo R^2 statistic is reported for the Negative Binomial Model.
Each coefficient comes from a separate regression, as inspections and enforcement are regressed on one demographic variable at a time (all models also contain city dummy variables)

TABLE 4D
Inspection and Enforcement Correlations with Demographics(N=1616)

	INSP	ENFORCE
DISTANCE = 1-MILE		
ELDERS	0.010	-0.076
CHILDREN	-0.051	0.067
POOR	0.019	0.078
MINORITY	-0.025	0.067
DISTANCE = 10-MILES		
ELDERS	-0.069	-0.163
CHILDREN	0.065	0.160
POOR	0.030	0.127
MINORITY	-0.016	0.104

TABLE 5
Inspection and Enforcement Models Including Homogeneity Measures (N=1616)

MODEL	OLS	N.B.	OLS	N.B.	OLS	N.B.	OLS	N.B.
DEP. VAR.	INSP	INSP	INSP	INSP	ENFORCE	ENFORCE	ENFORCE	ENFORCE
DISTANCE	1-MILE	1-MILE	10-MILES	10-MILES	1-MILE	1-MILE	10-MILES	10-MILES
Race								
HOM_RACE	-0.414	-0.283	-1.952	-1.070	-0.135	-0.224	-1.090	-1.165
	(0.305)	(0.367)	(0.803)	(0.990)	(0.170)	(0.472)	(0.447)	(1.418)
Education								
HOM_ED	2.784	2.241	6.172	2.991	1.810	2.705	2.725	-0.637
	(0.896)	(0.959)	(1.630)	(1.748)	(0.499)	(1.387)	(0.909)	(2.433)
Education Homogeneity Decomposition								
$DROPOUT^2$	5.007	3.081	-9.978	-10.648	0.705	1.524	-5.429	-17.371
	(2.540)	(2.844)	(7.553)	(8.814)	(1.413)	(3.997)	(4.214)	(13.406)
$HSGRAD^2$	3.214	2.304	5.289	1.403	1.762	2.164	2.197	-3.904
	(0.982)	(1.053)	(1.821)	(1.982)	(0.546)	(1.566)	(1.016)	(2.961)
$COLLEGE^2$	3.889	2.354	4.016	-1.320	1.713	1.133	1.406	-9.798
	(1.385)	(1.492)	(2.749)	(3.129)	(0.770)	(2.455)	(1.534)	(5.352)
Education Interactions (separate runs)								
Hom_Ed	2.186	2.921	0.770	5.425	1.230	5.467	0.269	7.510
	(1.514)	(1.552)	(3.332)	(3.652)	(0.842)	(2.295)	(1.859)	(6.059)
Hom_Ed*	4.479	-5.257	39.210	-17.647	4.339	-19.505	17.822	-53.338
POOR	(9.136)	(9.404)	(21.098)	(23.264)	(5.080)	(12.796)	(11.774)	(36.465)
Hom_Ed	4.185	3.021	3.923	4.948	1.872	3.194	1.686	2.418
	(1.264)	(1.286)	(2.518)	(2.751)	(0.703)	(2.003)	(1.405)	(4.938)
Hom_Ed*	-5.981	-4.169	7.682	-6.996	-0.268	-2.038	3.549	-8.821
MINORITY	(3.804)	(4.518)	(6.557)	(7.592)	(2.117)	(5.971)	(3.658)	(12.451)
Hom_Ed	6.687	-1.391	2.669	-9.987	7.087	7.820	2.865	-4.542
	(4.832)	(5.317)	(6.525)	(7.289)	(2.685)	(7.998)	(3.640)	(11.668)
Hom_Ed*	-0.081	0.075	0.076	0.279	-0.109	-0.112	-0.003	0.089
TURNOUT	(0.098)	(0.109)	(0.136)	(0.152)	(0.055)	(0.173)	(0.076)	(0.259)

(Standard Errors)
All models in this table include all the variables contained in Table 4.

5G. "Benefits and Costs from Sulfur Dioxide Trading: A Distributional Analysis"

I. Introduction

Prior to the passage of Title IV of the 1990 Clean Air Act Amendments (CAAA), there had been a lively debate involving Congress, the U.S. Environmental Protection Agency (EPA), and academics, about the need for reducing sulfur dioxide (SO_2) emissions due to the problem of acid rain. In addition to domestic pressure, Canada was putting political pressure on the United States to decrease acid rain. Just after the passage of the CAAA the United States and Canada signed the Canada-United States Air Quality Agreement, aimed at controlling transboundary acid rain. How damaging is acid rain? The National Acid Rain Precipitation Assessment Program found that acid rain causes minor damage to crops and modest damage to aquatic life in acidified lakes and streams. Burtraw et al. (1997) estimate the expected environmental benefits from recreational activities, residential visibility, and morbidity to be about $13 per capita in 1990.

On the other hand, SO_2 also combines in the atmosphere with ammonia to form sulfates – fine particulates ($PM_{2.5}$) – which have been shown in several studies to contribute significantly to pre-mature mortality. Thus, even if acid rain has only a marginal environmental impact, reductions in SO_2 emissions have additional (and potentially much larger) health benefits, through reduced pre-mature mortality. EPA (2003) estimates that the human health benefits of the Acid Rain Program will be roughly $50 billion annually, due to decreased mortality, fewer hospital admissions and fewer emergency room visits, by the year 2010.

Coal from fossil-fuel fired electric utilities accounts for most of SO_2 emissions in the United States. Title IV of the 1990 CAAA set an annual 9 million ton cap on SO_2 emissions from all fossil fuel fired electric utilities. This cap, which is to be fully achieved by 2010, requires the affected electric utilities to reduce their aggregate SO_2 emissions by 10 million tons below their 1980 levels. Along with requiring substantial SO_2 reductions Title IV also abandoned the command-and-control approach to the regulation of utilities, where utilities were required to meet individual emission standards set by regulators, in favor of a more flexible, cost-efficient tradable permit approach. This more flexible approach made the substantial SO_2 reduction politically feasible and is widely believed to have led to tremendous cost savings relative to the command-and-control approach. Keohane (2003) estimated that the system of allowance trading resulted in cost savings between $150 million and $270 million annually, compared to a uniform emissions-rate standard.

Title IV allows permits to be bought and sold freely anywhere in the continental United States.[91] Allowing permits to be bought and sold freely may inadvertently create a divergence between the people who are paying for the SO_2 reductions and those that are benefiting from the

* The authors wish to thank Douglas Latimer, currently with EPA Region 8, for providing us with the Source-Receptor Matrix Model and for insightful conversations about how to use the model. We are grateful to seminar participants at Harvard and the 2004 AERE Summer Workshop for helpful comments and to Denny Ellerman and Nathaniel Keohane for providing us with cost data. The opinions and conclusions expressed are those of the authors and not the United States Environmental Protection Agency.

[91] The only time a plant would be prevented from buying allowances to emit more SO_2 would be if that plant was located in a county which was in violation of the National Ambient Air Quality Standard (NAAQS) for SO_2, which were set at levels to prevent local adverse health outcomes. However, this has rarely posed a problem for permit trading since the Title IV cap requires a significantly greater reduction of aggregate SO_2 emissions than what is required to meet the NAAQS for SO_2.

reductions. Morgan and Shadbegian (2003) find that the SO_2 trading program may have inadvertently resulted in some environmental injustices – mainly higher levels of emissions in disproportionately poor and minority areas.[92]

In this chapter we extend the work of Morgan and Shadbegian by examining the spatial distribution of the costs and benefits associated with air quality improvements that occurred during the first year under Title IV of the CAAA. The air quality improvements are measured relative to the level of emissions under the former command-and-control regime, which allowed a greater level of emissions. We examine the spatial distribution of the costs and benefits both in terms of the states and regions being affected and the socio-economic composition of the affected population.

The vast majority of dollar-valued benefits from air pollution abatement arise from the impact of airborne particulates ($PM_{2.5}$) on premature mortality. A 1995 EPA study reports that of the estimated $22.2 trillion worth of benefits derived from the Clean Air Act of 1970, reductions in particulate-related mortality contributed more than $20 trillion. We use a spatially-detailed air pollution dispersion model (the Source-Receptor Matrix) to evaluate the impact of SO_2 emission reductions from each plant on county-level concentrations of particulates during Phase I of Title IV. Using existing evidence on the connection between particulate exposures and mortality, we translate the reductions in secondary particulate concentrations in each county in the United States into the dollar benefits from reductions in premature mortality.

Who pays for the improvements in air quality? One possible answer is "nobody," if efficiency improvements resulting from the new emissions trading system (e.g., more flexible production switching, less uncertainty about regulatory requirements) outweigh the additional abatement costs on a plant-by-plant basis. A more likely scenario is that some plants face higher costs of abatement, which are passed along to their customers. If some plants increase their emissions and buy additional allowances, the population affected by the worsening air quality will be "paying" some of the costs of the greater air quality improvements near other plants that reduced their emissions in order to sell the allowances.

Arrow et al. (1996) argue that along with a cost-benefit analysis measuring the aggregate net benefits from a regulation, a good analysis will also examine the distributional consequences. In this chapter we compare the overall net health benefits that were achieved under Title IV along with the spatial distribution of those net benefits to test whether there were unforeseen consequences of the regulatory change in terms of adverse impacts on particular regions or socio-economic groups. The findings will indicate whether these distributional impacts are of only second-order importance compared to the overall net benefits, or whether they are sufficiently large for policy-makers to take them into account when considering future market-oriented regulatory reforms.

Using data for the 148 dirtiest coal-fired utilities we find, as expected, that the aggregate benefits in 1995 caused by reductions in SO_2 emissions under Title IV greatly exceed their costs: we estimate benefits of $56 billion (a bit larger than EPA's estimates of total benefits of $50 billion by 2010) and costs of only $558 million. Therefore, the net benefits from the SO_2 reduction are roughly $55 billion or $100 in benefits for every $1 in abatement costs. The net benefits are positive in every EPA region, but are highly concentrated. We find that nearly 90%

[92] According to the Office of Environmental Justice at EPA, environmental justice exists when "no group of people, including racial, ethnic, or socioeconomic group, … bear[s] a disproportionate share of the negative environmental consequences resulting from industrial, municipal, and commercial operations."

of the benefits and costs of the overall reductions under Title IV are concentrated in four regions – the northeast, north central, mid-Atlantic, and southeast. In terms of the socio-economic distribution of net benefits, we find that minority groups (African-Americans and Hispanics) receive a greater share of the benefits than of the costs. The poor are the only group raising any environmental justice concerns, receiving a slightly higher share of the costs than of the benefits. However this assumes the poor purchase as much electricity as the rich, but most likely they purchase less.

The rest of the chapter is organized as follows. In section II we present background information on Title IV of the CAAA of 1990. Section III contains a brief survey of the literature on studies examining various aspects of the Title IV trading program and various aspects of environmental justice. Section IV describes the methodology we use to estimate both the health benefits and the costs of SO_2 abatement under Title IV and section V describes our sample of plants. In section VI we discuss our findings and we end with some concluding remarks in Section VII.

II. Title IV: Background Information

Title IV of the CAAA completely changed the way coal-fired utilities were regulated in the United States Prior to Title IV utilities were regulated by a command-and-control regime that targeted the sulfur content of the coal used at each individual plant. Title IV established a cap-and-trade program that set a cap on total SO_2 emissions, distributed allowances among generating units equal to that cap, and allowed plants to freely trade these allowances among their own units, to sell them to other plants, or to bank them for future use. The only requirement faced by a plant under the trading program is that it must have enough allowances at the end of the year to cover each ton of SO_2 emitted that year. Thus, the allowance trading program instituted by Title IV provides much greater flexibility to achieve any given emission standard because utilities which face high marginal abatement cost may purchase SO_2 permits from utilities which face lower marginal abatement costs.

The goal of Title IV was to reduce aggregate SO_2 emission levels to approximately 9 million tons by 2010, roughly half of the 1980 level. The reduction was to be achieved in two phases. Phase I (1995-1999) targeted the dirtiest 110 power plants (with 263 generating units). These generating units, called the Table A units, were required to reduce their emissions to 7.2 million tons per year starting in 1995, 6.9 million tons per year in 1996, and then 5.8 million tons per year from 1997-1999. The Table A units emitted 8.7 million tons of SO_2 in 1990 and only emitted 4.5 million tons in 1995 (roughly 50% less). The number of allowances a unit received was based on its average 1985-1987 heat input times an average emission rate of 2.5 lbs of SO_2 per million BTUs of heat input. Each allowance gave a unit the right to emit one ton of SO_2, and the unit could only emit an amount of SO_2 equal to the number of allowances held.[93]

Phase II, which began in the year 2000, brought the smaller generators – generators that have an output capacity of 25 megawatts or greater – under the cap-and-trade system.[94] In addition to imposing constraints on the smaller and cleaner units, the Table A units were required to make additional reductions in their SO_2 emissions – reducing their overall emissions by

[93] Generating units face a fine of $2000 for each ton of SO_2 emitted for which they do not have an allowance.

[94] Some of these smaller generators 'opted' into Phase I, under the "substitution" and "compensation" provisions, and are included in this analysis.

another 3.4 million tons, down to 2.4 million tons by 2010. Annual allowance allocations to each unit were based on an average emission rate of 1.2 lbs of SO_2 per million BTUs of heat input, a much stricter standard than the 2.5 lbs during Phase I.

In 1995 SO_2 emissions dropped dramatically. Phase I units emitted a total of only 4.9 million tons, a reduction of 4.6 million tons – 3.2 million tons more than was required.[95] In fact, SO_2 emissions started to decrease right after the passage of Title IV, even before the trading system was in place. Several explanations have been offered for the pre-1995 reduction. Plants may have complied early in order to pass on to consumers the additional cost of low-sulfur coal or the cost of installing scrubbers. Some states amended their State Implementation Plans (SIPs) requiring utilities to reduce their emissions before the first year of Phase I. The most likely explanation is that railroad deregulation made it cheaper to transport low-sulfur coal to Midwest electric power plants, the geographic area that experienced the most reductions in SO_2 emissions between 1985 and 1993 (Ellerman and Montero, 1998).

Another important feature of the SO_2 allowance market is that allowances that are not used in one year may be banked and used in any subsequent year. That is, a plant may reduce emissions below its annual allocation and deposit the extra allowances in an emissions bank. These *banked* allowances are perfect substitutes for future year allowances, and may be used or sold. Banking during Phase I could help plants adapt to the more stringent limits imposed under Phase II by smoothing the required reductions over time. This explanation is borne out by experience: plants banked over 11.5 million allowances during Phase I (1995-1999), then used 1.2 million of these banked allowances in the first year of Phase II (2000), followed by 1.08 million allowances in 2001 and another 650,000 million allowances in 2002. This suggests that the extra abatement during Phase I was intentional (rather than being an unexpected result of lower than expected prices for low-sulfur coal).

III. Literature Review

A. SO_2 Trading Program

Long before the advent of emissions trading, Gollop and Roberts (1985) estimated that a cost-effective allocation of pollution abatement across electrical utilities would result in a nearly 50% reduction in pollution abatement costs, suggesting potentially large savings from emissions trading. Since the passage of the 1990 CAAA, many papers, including Joskow et al. (1998), Schmalensee et al. (1998), Carlson et al. (2000), Keohane (2003), and Shadbegian and Morgan (2003) have examined various aspects of the actual SO_2 allowance trading program including its cost savings, environmental effectiveness, spatial patterns of abatement, pollution control innovations, and the efficiency of the banking of permits. The potential success of any pollution permit-trading program depends on the efficiency of the market of the tradable permits. Joskow et al. (1998) assess the efficiency of the market for SO_2 permits by comparing the price of permits auctioned by EPA between 1993 and 1997 with private market indices. Joskow et al. (1998) find that by the end of 1994 these prices were virtually identical and thereby conclude that the private market for tradable permits was relatively efficient. Schmalensee et al. (1998) also conclude that the private market for tradable permits was relatively efficient by noting the growth in the level of the trading volume in the market: 1.6 million, 4.9 million, and 5.1 million allowances were traded in 1995, 1996, and 1997, respectively.

[95] Phase I units include all 263 Table A units plus 111 units that 'opted' into Phase I – see Section V Sample Coverage for details.

Keohane (2003) estimates that using a system of tradable allowances resulted in annual cost savings between $150 million and $270 million compared to a uniform emissions-rate standard. However, Carlson et al. (2000) conclude that the large decrease in abatement costs during the beginning of Title IV relative to the original estimates resulted more from a technological change that reduced the cost to switch to low sulfur coal and the decrease in the price of low sulfur coal rather than the ability to trade permits per se. Shadbegian and Morgan (2003) examine the impact of the stringency of SO_2 regulations on the productivity of electric utilities. They find that regulatory stringency had a significantly negative effect on productivity prior to Title IV, but that during Title IV regulatory stringency had only small insignificant negative impact on productivity.

B. Distribution of Pollution

During the past decade there has been an increasing number of studies that examine various aspects of environmental justice – polluting plants' location decisions, expansion decisions of hazardous waste facilities, fees paid to communities to *host* facilities, plant emissions, and regulator decisions – in a formal multiple regression framework. Previous anecdotal evidence (see GAO, 1983 and United Church of Christ, 1987) suggests that firms tend to locate their polluting plants in areas with a greater percentage of poor people and minorities. However, Been and Gupta (1997) examining the location decisions of commercial hazardous waste treatment storage and disposal facilities (TSDFs) find mixed evidence of environmental injustice. In particular, they find no statistical evidence that TSDFs were more likely to be sited in neighborhoods that were disproportionately African American at the time of siting and that poor neighborhoods are actually negatively correlated with TSDF sitings, but they do find evidence that TSDFs were more likely to be sited in disproportionately Hispanic areas. Wolverton (2002a), examining the location decisions of toxic waste emitting plants in Texas, shows that if one considers the socioeconomic characteristics of the community at the time the plant is sited, that contrary to the anecdotal evidence, race does not matter and poor communities actually attract disproportionately *fewer* polluting plants – a finding similar to Been and Gupta (1997).

Hamilton (1993, 1995) examines whether exposure to environmental risk is related to socioeconomic characteristics of a neighborhood and political activism. Specifically, Hamilton examines the relationship between the net capacity expansion decisions of commercial hazardous waste facilities and race, income, education, and voter turnout (level of political activity). Hamilton finds that the decision to expand net capacity is not significantly related to any of the socioeconomic variables, but is significantly negatively correlated with voter turnout. On the other hand, Jenkins et al. (2004) show that counties with greater percentages of minority residents receive lower *host fees* for the siting of landfills, while richer counties receive higher host fees, results consistent with the idea of environmental injustice.

Three additional studies examine the relationship between pollution emissions and the socioeconomic characteristics of communities to assess the validity of the claim of environmental injustice: Arora and Cason (1999), Wolverton (2002b), and Gray and Shadbegian (2004). Arora and Cason (1999) examine 1993 Toxic Release Inventory (TRI) emissions for the entire United States finding evidence of racial injustice only in non-urban areas of the south. Wolverton (2002b) examines the relationship between TRI releases and socioeconomic characteristics of communities in Texas and finds that plants tend to reduce TRI releases *more* in minority neighborhoods than in non-minority neighborhoods, exactly the opposite of the claim of environmental racism. Gray and Shadbegian (2004) examine the relationship between SO_2, PM_{10}, BOD, and TSS emissions of pulp and paper mills and socioeconomic variables finding mixed results.[96] For all four pollutants Gray and Shadbegian find that plants with a greater percentage of poor nearby emit more pollution, a result consistent with environmental injustice, but that plants with more minorities nearby actually emit *less* pollution, a result inconsistent with environmental injustice.

Finally Becker (2003), using establishment-level data on manufacturing plants from the U.S. Census Bureau's Pollution Abatement Costs and Expenditures (PACE) survey, examines the relationship between air pollution abatement expenditures and community demographics. Becker (2003) finds that, after controlling for a number of plant-level characteristics and levels of federal, state, and local regulation, communities with higher homeownership rates and higher per capita income enjoy greater pollution abatement activity from their nearby plants.

IV. The Benefits and Costs of Cleaner Air

A. Benefits from Cleaner Air

We identify the benefits of reducing SO_2 emissions (SO2BEN) from a given source with the change in mortality risk from exposure to ambient particulate concentrations caused by those SO_2 emissions. These health benefits are measured using a simplified linear damage function, based on estimated parameters from the appropriate literature:

SO2BEN = SO2DIFF*AIR_QUAL_TC * HEALTH_CHG * POP * VSL.

AIR_QUAL_TC is the transfer coefficient – the change in air quality (ambient particulates) per unit change in SO_2 emissions (SO2DIFF). HEALTH_CHG is the change in mortality risk to the affected population due to the changes in air quality. POP is the size of the affected population, and VSL is the dollar value placed on reducing pre-mature mortality.

We measure the changes in air quality at any given location using the Source-Receptor (S-R) Matrix Model, as described in Latimer (1996) and Abt (2000). The S-R Matrix model was originally calculated using the Climatological Regional Dispersion Model (CRDM). The model incorporates data on pollution emissions from 5,905 distinct sources in the United States, along with additional sources from Mexico and Canada.[97] The S-R Matrix relates emissions of specific pollutants from each source to the resulting ambient concentrations of each pollutant in every county in the United States. Specifically, the S-R Matrix provides a set of transfer coefficients which yield county-by-county changes in annual average pollutant concentrations for each one ton change in emissions of a particular pollutant from a particular source. The S-R Matrix transfer coefficients are a function of many factors including wet and dry deposition of gases and particles, chemical conversion of SO_2 and nitrogen oxide (NO_X) into secondary particulates, effective stack height, and several atmospheric variables (wind speed, wind direction, stability,

[96] BOD (biological oxygen demand) and TSS (total suspended solids) are two commonly used measures of water pollution.

[97] Emissions sources in the United States combine ground-level sources, county-level sources and individual sources. Ground-level sources were estimated for each of the 3,080 contiguous counties, while elevated sources were grouped according to effective stack height. Point sources with an effective stack height greater than 500 meters were modeled as individual sources of emissions. All the sources in the same county that had an effective stack height less than 250 meters were grouped together into a single county-level source, as were those with effective stack heights between 250 meters and 500 meters. In total there were 5,905 U.S. sources modeled in the S-R matrix (ground-level sources were also aggregated at the county level).

and mixing heights). We use the impact of SO_2 emissions on ambient concentration of $PM_{2.5}$ in each county to measure AIR_QUAL_TC.

Our measure of HEALTH_CHG concentrates on the long-term mortality effects of particulate matter ($PM_{2.5}$) – an assumption consistent with past studies (Rowe et al. 1995; Levy et al. 1999). Since our study focuses on the benefits of reduced SO_2 emissions we concentrate on the health benefits from lower concentrations of secondary particulates that result from SO_2 emissions. We use the findings from the American Cancer Society study, the most comprehensive analysis of long-term mortality effects from air pollution to date (Pope et al. 2002). They find approximately 4% higher mortality rates in people exposed to a 10 $\mu g/m^3$ increase in $PM_{2.5}$ concentrations (95% confidence interval: 1%, 8%). We assume that the point estimate is applicable to the secondary particulates formed from SO_2 (Pope et al. 202 found similar numbers for sulfate particles in their study).[98]

Our estimate of the exposed population, POP, is based on county-level data from the 1990 Census of Population. This data identifies the total number of people living in each county (and hence the number affected by the average ambient pollution concentrations in that county). In addition, it provides information on the socio-economic characteristics of each county's population (e.g., income, age, race), which helps us examine issues of environmental justice.

Finally, to place a dollar value on pre-mature mortality, we use a recent EPA (1997) benefit-cost analysis that estimated the value of a statistical life (VSL). The EPA study pooled contingent valuation and wage-risk studies to produce a central estimate of $5.4 million (in 1995 dollars) per life saved. Note that our calculations assign constant values of the VSL and HEALTH_CHG terms for the entire population. Each exposed person faces the same average dollar harm from exposures to particulates, allowing for neither differences in sensitivities for different populations nor differences in valuation.[99] Note also that the very large estimates we obtain for the benefits of reducing SO_2 emissions could be interpreted as a combination of these two factors: one could get smaller benefits by assuming either smaller health effects or a lower VSL.

B. Costs of Cleaner Air

There are three options (or combinations of options) available to plants to comply with Title IV: installing a scrubber, switching to low sulfur coal, or buying allowances. Our measure of SO_2 abatement cost (COST) is based on the method each plant actually used to comply with Title IV. Based on Ellerman et al. (1997) we have the total cost of abatement for each of the 374 Phase I units (plant-boiler observations) affected by Title IV. In 1995, the average cost per ton of *switching* and *scrubbing* is $153 and $265 respectively, while the average cost of a permit is $128.50.[100]

We assume that all of the additional costs of abatement are passed along to the utility's customers, and further assume that all customers live within the state where the utility is

---

[98] Chay and Greenstone (2003a, 2003b) examine the effect of particulate exposures on infant mortality, and obtain impacts of a similar magnitude, measured in terms of increased mortality rates.
[99] Our data would readily permit the calculation to differ in sensitivity and valuation for different subpopulations – if one could generate a consensus on how to quantify such differences, a politically charged issue that we avoid here.
[100] We would like to thank Denny Ellerman for providing us with these data.

located.[101] We use the 1990 Census of Population to allocate each plant's abatement costs equally to all people living within that state, with the different socio-economic groups receiving benefits and costs proportional to their share in the overall population.

V. Sample Coverage

Phase I of Title IV regulated the emissions of 263 generating units (the Table A generating units) owned by 110 plants. An additional 38 "substitution and compensation" plants (111 generating units) "opted into" Phase I, bringing the final total to 374 generating units. Our sample consists of all 148 plants and their 374 generating units. The geographic distribution of these plants – heavily concentrated in the Midwest – is shown in Figure 1.

In Table 1 we present information on SO_2 emissions and the allocation of SO_2 allowances obtained from the EPA's Allowance Tracking System (ATS).[102] The 148 plants in our sample emitted a total of 9.5 million tons of SO_2 during 1990, the year Title IV was passed. By 1995, our 148 plants had reduced their SO_2 emissions by 4.6 million tons from their 1990 levels, cutting them almost in half, although Title IV had only required them to reduce emissions by 15%, to 8.1 million tons.

VI. Distribution of Benefit and Costs

In Table 2 we present the health benefits and abatement costs associated with the actual 1995 SO_2 emissions reductions: counterfactual SO_2 emissions minus actual emissions. The counterfactual emissions in 1995 are those we would have observed in the absence of the 1990 CAAA and are the same as those presented in Ellerman et al. (1997). As expected, the aggregate benefits in 1995 resulting from reductions in SO_2 emissions from the 1995 counterfactual levels far outweigh their costs: we estimate benefits of nearly $56 billion and costs of only $558 million. An alternative assumption on abatement costs, that the actual cost of a ton of abatement is equal to the permit price ($128.5 in 1995), results in total abatement costs of only $496 million. In either case these increased abatement costs are dwarfed by the increased benefits from the SO_2 reduction, which are roughly 100 times as large.

The net benefits are positive in every region, however they are highly concentrated across regions. Not surprisingly, given the concentration of the plants in the Midwest and the pattern of airflow from west to east, the benefits that result from the large reductions in emissions are highly concentrated geographically in the east. Table 3A contains the distribution of benefits and costs across the 10 different EPA regions. As shown in Figure 2, the overwhelming majority of the net benefits (89%) are concentrated in four regions (2, 3, 4, and 5). In addition, three of these regions (3, 4, and 5) pay a very large percentage of the overall costs (90%). Regions 4, 5, and 7 all pay a higher percentage of the costs than they receive in terms of health benefits. Region 5 (the North Central states) is the biggest relative loser, paying 45% of the costs while only receiving 26% of the benefits. On the other hand, Regions 1 (New England) and 2 (NY and NJ) are the biggest relative winners, only paying 0.2% and 1.2% of the costs while receiving 6% and 17% of the benefits, respectively.

In Table 3B we compare the net benefits per capita in each region and this leads to a somewhat different ranking of relative winners and losers than we observed with the shares of benefits and costs. Regions 1-5 each derive more than $249 per capita net benefits. Region 3

[101] If we had data on cross-state electricity sales, we could adjust our cost calculations to reflect this.
[102] We would like to thank Denny Ellerman for providing us with this data.

(the mid-Atlantic states) receives the highest level of net benefits, $502 per capita, followed by Regions 2, 1, 5 and 4. Interestingly Region 5, which was the biggest relative loser in terms of shares of benefits versus shares of costs, does reasonably well in terms of net benefits (nearly $300 per capita), due to the relatively large population in Region 5 (and because benefits are much larger than costs in absolute magnitude).

To examine whether or not there are any environmental justice concerns surrounding the SO_2 trading program we consider the distribution of benefits and costs received by different demographic groups. To do this, we used the demographic composition of every county in the United States, assuming that everyone in the county was equally affected by changes in pollution and by changes in electricity prices, to calculate the fraction of national benefits and national costs received by each group. Table 4A shows the per capita benefits, costs, and net benefits for the total population and for five different demographic groups: African-Americans, Hispanics, poor (the population living below the poverty line), kids (the population under the age of 6), and elders (the population over the age of 65). Table 4B then shows the ratio of benefits to costs for the different groups. The results show that both the Hispanic and African-American communities received a much larger share of the benefits than the costs, although this arises for different reasons. The African-American community pays costs similar to the overall population yet receives 20% higher benefits, while the Hispanic community receives roughly half the amount of the average per capita benefits, but pays only 30% of the average costs. Kids and elders received roughly the same share of benefits and costs as the overall population. On the other hand, the poor received slightly less of the benefits than of the costs from SO_2 reductions, which could raise some environmental justice concerns if the poor purchase as much electricity as the rich.

To further examine the distribution of benefits and costs along demographic lines, we calculated them separately for each plant in our sample, asking whether that plant's changes in emissions led to a disproportionately large increase in costs (relative to benefits) for any of these groups. For each group we then calculated the fraction of plants that had disproportionately large costs relative to benefits. These numbers are presented in Table 5. A number greater than 50% indicates that changes in emissions had negative effects more often than positive ones on that demographic group. Since these calculations are not weighted by plant size, they need not give the same results as those in Table 4. The results are, on the whole, reasonably similar to those in Table 4, although we do not see the poor being disadvantaged here (only kids show a disproportionately negative effect). As in Table 4, the African-American and Hispanic communities do quite well – only 25% and 10% of the plants have a negative effect on these communities respectively. Therefore we conclude that there are no significant environmental justice concerns raised by Title IV, except, as noted above, the poor received slightly less of the benefits than of the costs from SO_2 reductions.

VII. Concluding Remarks

In this chapter we analyze plant-level information on fossil fuel fired electric utilities to examine the distribution of costs and health benefits associated with the air quality improvement achieved by Title IV of the 1990 CAAA. We examine the distribution of benefits and costs both in terms of the regions being affected and the socio-economic composition of the affected population.

Our results suggest that, as expected, the aggregate health benefits in 1995 caused by reductions in SO_2 emissions under Title IV greatly exceeded their costs. We estimate benefits of $56 billion and costs of only $558 million leading to $55 billion dollars of net benefits from the

SO_2 reductions. The net benefits are positive in every region of the country, but are highly concentrated across regions. In particular, nearly 90% of the benefits and costs are concentrated in Regions 2-5 representing the northeast, north central, mid-Atlantic, and southeast. Maryland, Ohio, Pennsylvania, Washington DC, and West Virginia are the biggest winners in terms of per capita net benefits – all have per capita net benefits of $500 or above. Six other states have net benefits greater than $350 per capita: Delaware, Indiana, Kentucky, New Jersey, Tennessee, and Virginia.

In terms of the socio-economic distribution of net benefits, we find very little if any evidence for environmental justice concerns. The African-American and Hispanic communities receive a substantially greater share of the benefits associated with SO_2 abatement under Title IV than they do of the costs (higher benefits for the African-American community, lower costs for the Hispanic community). The poor do have a slightly higher share of costs than benefits (assuming they purchase the same amount of electricity as the rich), the only (weak) evidence supporting any environmental justice concerns.

REFERENCES

Abt Associates, "The Particulate-Related Health Benefits of Reducing Power Plant Emissions," prepared for Clean Air Task Force (October 2000).

K. Arrow, M.L. Cropper, G.C. Eads, R.W. Hahn, L.B. Lave, R.G. Noll, P.R. Portney, M. Russell, R. Schmalensee, V.K. Smith, and R.N. Stavins, "Is There a Role for Benefit-Cost Analysis in Environmental, Health, and Safety Regulation?" *Science*, 272:221-222 (12 April 1996).

Becker, R. A., "Pollution Abatement Expenditure by U.S. Manufacturing Plants: Do Community Characteristics Matter?" *Center for Economic Studies Working Paper* no. 03-18, (2003).

V. Been, "Locally Undesirable Land Uses in Minority Neighborhoods: Disproportionate Siting or Market Dynamics," *The Yale Law Journal* **103**, 1383-1421 (1994).

V. Been and F. Gupta, "Coming to a Nuisance or Going to a Barrios? A Longitudinal Analysis of Environmental Justice Claims," *Ecology Law Quarterly* **24**, 1-56 (1997).

Burtraw, D., A. Krupnick, E. Mansur, D. Austin, and D. Farrell, "The Costs and Benefits of Reducing Acid Rain", Resources for the Future Discussion Paper 97-31-REV, Washington, D.C.: Resources for the Future (1997).

C.P. Carlson, D. Burtraw, M. Cropper, and K. Palmer, "SO_2 Control by Electric Utilities: What are the Gains from Trade?," *Journal of Political Economy* **108**, 1292-1326 (2000).

K. Chay and M. Greenstone, "The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession," Quarterly Journal of Economics, 1121-1167 (2003a).

____________, "Air Quality, Infant Mortality, and the Clean Air Act of 1970," NBER Working Paper 10053 (2003b).

A. D. Ellerman, R. Schmalensee, P. Joskow, J. Montero, and E. Bailey, <u>Emissions Trading Under the U.S. Acid Rain Program: Evaluation of Compliance Costs and Allowance Market Performance.</u>, MIT Center for Energy and Environmental Policy Research, 1997.

A. D. Ellerman, and J. Montero, "The Declining Trend in Sulfur Dioxide Emissions: Implications for Allowance Prices," *Journal of Environmental Economics and Management*, **36**, 26-45 (1998).

J. Evans, S.K. Wolff, K. Phonboon, J. Levy, K. Smith, "Exposure Efficiency: An Idea Whose Time Has Come?" Paper for the Scientific Group on Methodologies for the Safety Evaluation of Chemicals (SGOMSEC 14), November 1999.

F. M. Gollop, and M.J. Roberts, "Cost Minimizing Regulation of Sulfur Emissions: Regional Gains in Electric Power," *Review of Economics and Statistics*, 81-90 (1985).

W. B. Gray and R. J. Shadbegian, "Optimal Pollution Abatement – Whose Benefits Matter and How Much," *Journal of Environmental Economics and Management* 47, 510-534 (2004).

Government Accounting Office, Siting of Hazardous Waste Landfills and Their Correlation with Racial and Economic Status of Surrounding Communities, GAO, Washington DC (1983).

J. Hamilton, Politics and Social Costs: Estimating the Impact of Collective Action on Hazardous Waste Facilities, *Rand Journal of Economics* **24**, 101-125 (1993).

J. Hamilton, "Testing for Environmental Racism: Prejudice, Profits, Political Power?," *Journal of Policy Analysis and Management* **14**, 107-132 (1995).

E. Helland and A. B. Whiford, "Pollution Incidence and Political Jurisdiction: Evidence from the TRI," presented at the American Economic Association Meetings (January 2001) and the Western Economic Association Meetings (July 2001).

R. Jenkins, K. Maguire and C. Morgan, "Host Community Compensation and Municipal Solid Waste Landfills," *Land Economics* (forthcoming 2004).

P.L. Joskow, R. Schmalensee, and E. Bailey, "The Market for Sulfur Dioxide Emissions," *The American Economic Review* **88**, 669-685 (1998).

N. Keohane, "What Did the Market Buy? Cost Savings Under the U.S. Tradable Permits Market Program for Sulfur Dioxide", Yale Center for Environmental Law and Policy Working Paper ES #33 (2003).

D. A. Latimer, "Particulate Matter Source-Receptor Relationships Between All Point and Area Sources in the United States and PSD Class I Area Receptors," prepared for EPA, OAQPS (September 1996).

J. I. Levy**,** J.K. Hammitt, Y.Yanagisawa, J.D. Spengler, "Development of a New Damage Function Model for Power Plants: Methodology and Applications," *Environmental Science and Technology* **33**: 4364-4372 (1999).

C. Morgan and R. Shadbegian "Environmental Justice and Emission Trading: Evidence from the Electric Utility Industry," Presented at Resources for the Future (February 2003), EPA's National Center of Environmental Economics Seminar Series (March 2003) and Clark University (April 2003).

C. A. Pope III, R. T. Burnett, M. J. Thun, E. E. Calle, D. Krewski, K. Ito, G. D. Thurston, "Lung Cancer, Cardiopulmonary Mortality, and Long-term Exposure to Fine Particulate Air Pollution," *Journal of the American Medical Association*, 287, 1132-1141 (2002).

R.D. Rowe, C.M. Lang, L.G. Chestnut, D.A. Latimer, D.A. Rae, S.M. Bernow, D.E. White. The New York Electricity Externality Study Volume I: Introduction and Methods. Empire State Electric Energy Research Corporation: New York, 1995.

R. Schmalensee, P.L. Joskow, A.D. Ellerman, J.P. Montero, E.M. Bailey, "An Interim Evaluation of Sulfur Dioxide Emissions Trading," *Journal of Economic Perspectives* **12**, 53-68 (1998).

R. Shadbegian, W. Gray, and J. Levy, "Spatial Efficiency of Pollution Abatement Expenditures," presented at the Western Economic Association Meetings (June 1999), NBER Environmental Economic Meetings (April 2000), International Atlantic Economic Association Meetings (October 2000), and U.S. E.P.A. National Center for Environmental Economics (October 2000).

R. Shadbegian and C. Morgan, "Environmental Regulation in the Electric Utility Industry: Are There Productivity Gains From Emissions Trading?" Presented at the International Atlantic Economic Association Meetings (October 2002) and the Western Economic Association Meetings (July 2003).

H. Sigman, "The Pace of Progress at Superfund Sites: Policy Goals and Interest Group Influence," *Journal of Law and Economics*, **44**, 315-344 (2001).

United Church of Christ, Toxic Waste and Race in the United States, UCC: Commission for Racial Justice (1987).

U.S. Environmental Protection Agency, "The Benefits and Costs of the Clean Air Act, 1970 to 1990," October, 1997.

U. S. Environmental Protection Agency, EPA Acid Rain Program 2001 Progress Report, http://www.epa.gov/airmarkets/cmprpt/arp01/2001report.pdf, November 2002.

U. S. Environmental Protection Agency, Effects of Acid Rain: Human Health, http://www.epa.gov/airmarkets/acidrain/effects/health.html, November 2003.

W. K. Viscusi and J.T. Hamilton, "Are Risk Regulators Rational? Evidence from Hazardous Waste Cleanup Decisions," *American Economic Review* **89**, 1010-1027 (1999).

A. Wolverton, "Does Race Matter? An Examination of a Polluting Plant's Location Decision," U.S. Environmental Protection Agency, National Center for Environmental Economics mimeo (2002a).

A. Wolverton, "The Demographic Distribution of Pollution: Does neighborhood Composition Affect Plant Pollution Behavior?," U.S. Environmental Protection Agency, National Center for Environmental Economics mimeo (2002b).

Table 1 – Phase I Units

	Phase I Units*
SO_2 Emissions in 1990 (tons)	9,468,183
SO_2 Emissions in 1995 (tons)	4,902,778
Allowances in 1995	8,076,472
Boilers	374
Plants	148

* = Includes all Phase I units – the 110 Table A plants (263 units) plus the 38 "Substitution and Compensation" plants (111 units)

Table 2 – Benefits and Costs

Benefits	$55.94 billion
Costs	$0.56 billion
Net Benefits	$55.38 billion

Table 3A – Percentage Distribution of Benefits and Costs Across Regions

Region	STATES	BENEFIT	COST
1	CT,MA,ME,NH,RI,VT	6.21%	0.19%
2	NJ,NY	16.84%	1.24%
3	DC,DE,MD,PA,VA,WV	23.69%	15.36%
4	AL,FL,GA,KY,MS,NC,SC, TN	22.05%	30.33%
5	IL,IN,MI,MN,OH,WI	26.19%	44.74%
6	AR,LA,NM,OK,TX	2.82%	0.00%
7	IA,KS,MO,NE	2.07%	8.14%
8	CO,MT,ND,SD,UT,WY	0.11%	0.00%
9	AZ,CA,NV	0.02%	0.00%
10	ID,OR,WA	0.00%	0.00%

Table 3B – Average Dollar Per Capita Distribution of Benefits and Costs Across Regions

Region	AVERAGE BENEFIT	AVERAGE COST	AVERAGE NET BEN
1	256.2	0.1	256.1
2	354.7	0.2	354.4
3	505.5	3.3	502.2
4	252.7	3.5	249.2
5	303.7	5.2	298.5
6	51.3	0	51.3
7	93.2	3.7	89.5
8	7.5	0	7.5
9	0.3	0	0.3
10	0.3	0	0.3

Table 4A -- Benefits and Costs Across Different Populations (average per capita $1995)

DEMOGRAPHIC GROUP	BENEFITS	COSTS	NET BENEFITS
TOTAL	213.1	2.1	211.0
AFRICAN-AMERICANS	253.6	2.1	251.5
HISPANICS	102.0	0.6	101.4
POOR	202.8	2.2	200.6
KIDS	204.9	2.0	202.9
ELDERLY	220.8	2.2	218.6

Table 4B -- Benefit/Cost Ratio Across Different Populations

DEMOGRAPHIC GROUP	Benefits/Costs
TOTAL	100
AFRICAN-AMERICANS	121
HISPANICS	180
POOR	93
KIDS	100
ELDERLY	99

Table 5 – Distribution of Benefits and Costs Across Different Populations (% of Plants with Cost Share>Benefit Share)

DEMOGRAPHIC GROUP	Cost Share>Benefit Share
AFRICAN-AMERICAN	25%
HISPANIC	10%
POOR	48%
KIDS (6 and under)	52%
ELDERLY (65 and older)	43%

Figure 1
Distribution of Plants in Database
(148 Plants; scale=1995 SO_2 emissions in tons)

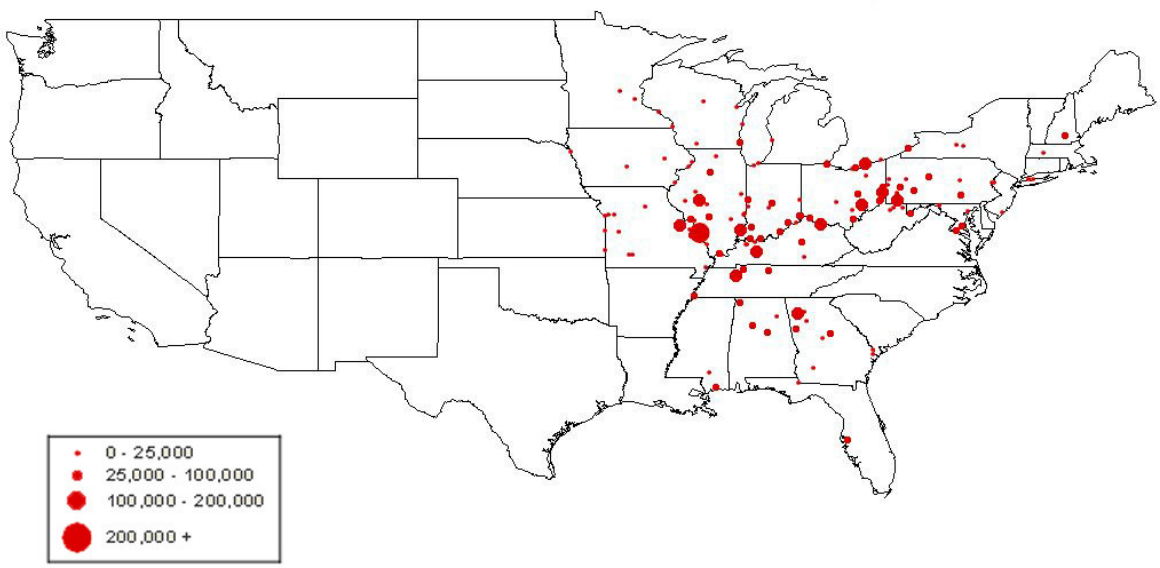
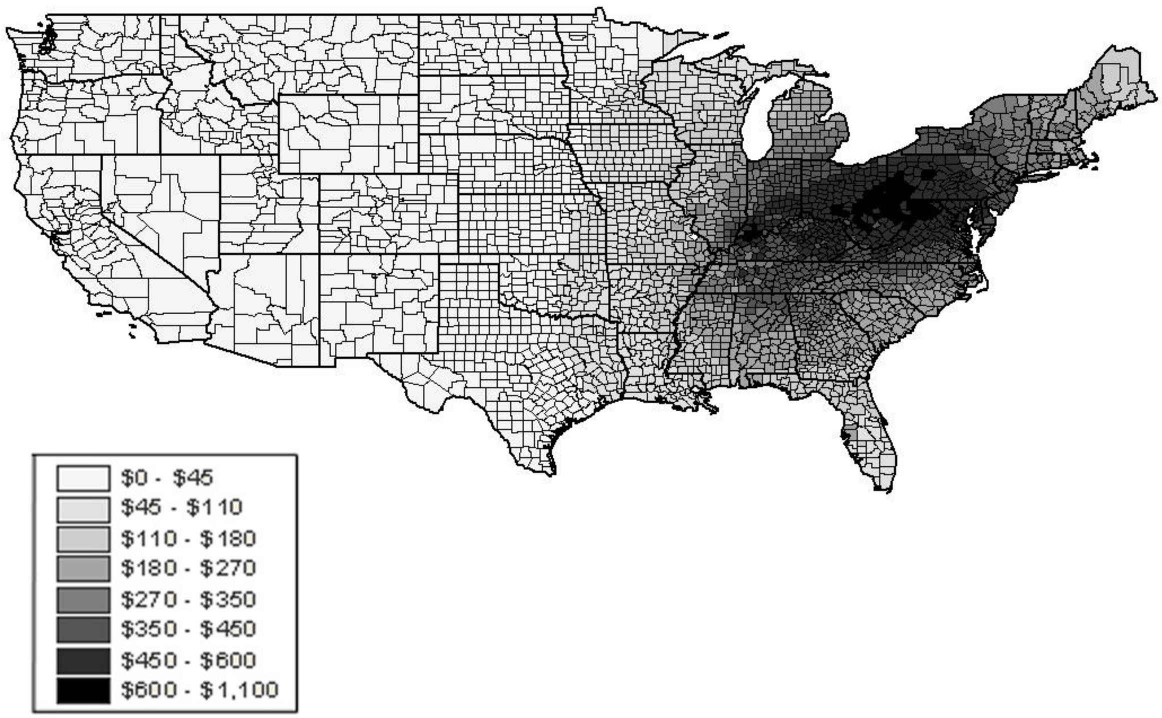


Figure 2
Geographic Distribution of Net Benefits



5H. "A Spatial Analysis of the Consequences of the SO2 Trading Program"

I. Introduction

During the late 1980's, prior to the passage of Title IV of the 1990 Clean Air Act Amendments (CAAA), there had been a spirited debate involving Congress, the Environmental Protection Agency (EPA), and academics, about the importance of reducing sulfur dioxide (SO_2) emissions due to the problem of acid rain. Acid rain occurs when SO_2, released as a gas from coal when it is burned at high temperatures, reacts with water in the atmosphere to form sulfurous acid and sulfuric acid and then returns to earth in the form of raindrops and dry particles. Some of the acid rain caused by SO_2 emissions from coal-fired utilities in the upper Midwest falls in Canada. Thus, in addition to domestic pressure to reduce SO_2 emissions, Canada was also putting political pressure on the U.S. to decrease its SO_2 emissions. Soon after the passage of the CAAA the U.S. and Canada formally agreed to control transboundary acid rain by signing the Canada-United States Air Quality Agreement.

The ecological damage from acid rain, while important, is relatively minor when compared to decreases in premature mortality from SO_2 reduction. For example, Burtraw et al (1997) estimate the expected environmental benefits from recreational activities, residential visibility, and morbidity from the Acid Rain Program to be only $13 per capita in 1990. On the other hand, in 2002 the EPA estimated that, by 2010, human health benefits from the Acid Rain Program will be approximately $50 billion annually (due to many fewer cases of premature mortality, fewer hospital admissions and fewer emergency room visits). These human health benefits mainly arise from lower ambient levels of secondary particles (PM_{10} and $PM_{2.5}$) – which have been linked in numerous studies to premature mortality – which form when SO_2 combines with ammonia in the atmosphere.

Most of the SO_2 emissions in the United States come from coal fired electric utilities. Title IV of the 1990 CAAA establishes an annual emissions cap of 9 million tons of SO_2 emissions from all fossil-fuel fired electric utilities over 25 megawatts, to be fully implemented by 2010. This annual cap requires the affected electric utilities to reduce their total SO_2 emissions by 10 million tons below their 1980 levels. Title IV also significantly changed the manner in which coal-fired utilities were regulated from command-and-control emission standards to a more flexible, cost-efficient system of allowance trading. The more flexible allowance trading approach made the considerable SO_2 reductions politically feasible and is generally thought to have led to large cost savings relative to the previous command-and-control approach. For example, Keohane (2003) estimated that the allowance trading system resulted in annual cost savings between $150 million and $270 million relative to a uniform emissions-rate standard. Furthermore, the tremendous flexibility of the allowance trading program provides the market with the proper incentives to produce an efficient allocation of SO_2 reductions, if SO_2 emissions have the same marginal benefit everywhere across the United States. However, our estimates of the health benefits resulting from SO_2 reductions indicate substantial heterogeneity across plants in the marginal benefit per ton of SO_2 reduced. Therefore, since Title IV allows one-to-one allowance trading, we should not expect the resulting allocation of emission reductions to maximize the net benefits from SO_2 reductions.

In this paper we extend the work of Shadbegian, Gray, and Morgan (2006) by examining two different scenarios of SO_2 reductions leading to significant air quality improvements. In one scenario, we measure these improvements relative to the level of emissions under the former command-and-control regime, which allowed a greater level of emissions. In another scenario, we measure the improvements relative to a counterfactual distribution of emissions based on requiring emissions reductions similar in magnitude to those actually achieved under Title IV, but imposed on plants through a reduction in the allowable emissions rate for all plants, without the possibility of trading.

The overwhelming majority of the dollar-valued benefits from air quality improvements come from the impact of airborne fine particulate matter ($PM_{2.5}$ and PM_{10}) on premature mortality. In 1997 the EPA estimated that $20 trillion dollars of the estimated $22.2 trillion dollars worth of benefits derived from the Clean Air Act of 1970 (between 1970 and 1990) resulted from reductions in particulate-related premature mortality. In this paper, we use a spatially-detailed air pollution receptor model (the Source-Receptor Matrix) to model the impact that SO_2 emissions have on $PM_{2.5}$ concentration levels in each county in the United States during 1995, the first year of Title IV. We then use information from the epidemiology literature on the correlation between exposure to $PM_{2.5}$ and mortality to translate the reductions in secondary $PM_{2.5}$ concentrations in each county in the U.S. into the dollar benefits from reductions in premature mortality.

Are the substantial air quality improvements due to lower SO_2 emissions costless? The answer could be yes if increases in efficiency resulting from the new allowance trading system (e.g. more flexibility in complying with regulations, less uncertainty about future regulatory requirements) more than offset the extra abatement costs on a plant-by-plant basis. However, a more likely outcome is that some plants will still face higher abatement costs, which will be passed along to their customers. Furthermore, if some plants buy SO_2 allowances to increase their emissions (or at least not to lower them by as much as they otherwise would have), the population impacted by the worsening air quality (or at least the relatively less clean air) will be 'paying' some of the costs of the greater air quality improvements near other plants that reduced their emissions in order to sell SO_2 allowances. In addition to comparing the costs and benefits that arise from lower SO_2 emissions under Title IV, we simulate the impact of requiring a comparable reduction in overall SO_2 emissions under the old command-and-control regime, assuming that a uniform emission standard is in place at all plants.

Using data for the 148 dirtiest coal-fired utilities we find, as expected, that the aggregate benefits in 1995 from lower SO_2 emissions under Title IV greatly exceed their costs: we estimate benefits of $56 billion (a bit larger than EPA's estimates of total benefits of $50 billion by 2010) and costs of only $558 million. Therefore, the net benefits from the SO_2 reduction are roughly $55 billion or $100 in benefits for every $1 in abatement costs. Comparing the consequences of requiring similar overall emissions reductions using command-and-control regulation, we find that trading results in significantly lower costs ($94 million or 16.8% lower). However, shifts in the spatial distribution of emissions tend to lower aggregate benefits from SO_2 reductions, since allowance buyers have emissions with higher marginal benefits (damage) than allowance sellers. This result suggests the possibility of limiting trades between plants, either by defining trading zones that would allow only trades between plants in the same zone, or by developing some sort of 'exchange rate' for allowance trades, based on the relative marginal benefits of the two plants involved. We explore the possibility of trading zones, but find that considerable heterogeneity in marginal benefits within regions limits the potential gains from such systems.

The rest of the paper is organized as follows. In section II we present background information on Title IV of the CAAA of 1990. Section III contains a brief survey of the literature on studies examining various aspects of the Title IV trading program. Section IV describes the methodology we use to estimate both the health benefits and the costs of SO_2 abatement under Title IV and Section V describes our sample of plants. In Section VI we discuss our findings and we end with some concluding remarks in Section VII.

II. Title IV: Background Information

Title IV of the 1990 CAAA significantly changed the manner in which coal-fired utilities were regulated in the U.S. Before Title IV utilities were regulated by command-and-control emission standards, where utilities were required to meet individual emission standards set by regulators. Title IV established a more flexible, cost-efficient cap-and-trade program that set a cap on total SO_2 emissions, allocated allowances among generating units equal to that cap, and allowed plants to freely trade these allowances among their own units, to sell them to other plants, or to bank them for future use.[103] The only requirement imposed on a plant under the allowance trading program is that, at the end of the year, it must have one allowance for each ton of SO_2 emitted that year. Thus, the allowance trading program created by Title IV provides more flexibility to comply with any given emission standard, because utilities which have high marginal abatement cost may purchase SO_2 allowances from utilities which have lower marginal abatement costs.

The overall goal of Title IV was to decrease total SO_2 emissions to roughly 9 million tons by 2010, approximately half of the 1980 level. The reduction was to be accomplished in two phases. Phase I, which occurred from 1995-1999 targeted the dirtiest 110 power plants with 263 generating units. These generating units, referred to as the Table A units, were required to lower their aggregate emissions to 7.2 million tons per year in 1995, 6.9 million tons in 1996, and then 5.8 million tons from 1997-1999. In 1990, together the Table A units emitted 8.7 million tons of SO_2, but they only emitted 4.5 million tons in 1995 (nearly 50% less). During Phase I the initial number of allowances a generating unit was allocated was determined by multiplying its average 1985-1987 heat input by an average emission rate of 2.5 lbs of SO_2 per million BTUs of heat input.[104] Each SO_2 allowance gave a generating unit the right to emit one ton of SO_2, and at the end of the year the generating unit could only emit an amount of SO_2 equal to the number of allowances it held.[105]

Phase II, which began in 2000, expanded the cap-and-trade program to include any fossil-fueled fired generating units with an output capacity of 25 megawatts or greater.[106] In addition to including most of the smaller and cleaner units, Phase II also required the Table A units to make further reductions in their SO_2 emissions – reducing their aggregate SO_2 emissions by an

[103] The only time a plant is denied the right to buy allowances is when that plant is located in a county which is in violation of the National Ambient Air Quality Standard (NAAQS) for SO_2, which is set at a level to prevent local adverse health outcomes. However, this has not proved to be a major hindrance in the SO_2 allowance market since the Title IV cap requires a considerably larger reduction of aggregate SO_2 emissions than what is required to meet the NAAQS for SO_2.

[104] Note allowances are allocated to individual generating units and not to plants.

[105] Generating units face a fine of $2000 for each ton of SO_2 emitted for which they do not have an allowance.

[106] Some of these smaller generating units (111) joined Phase I, under the “substitution” and “compensation” provisions of the CAAA, and are included in this analysis.

additional 3.4 million tons, down to 2.4 million tons by 2010. During Phase II basic annual allowance allocations to each generating unit are based on an average emission rate of 1.2 lbs of SO_2 per million BTUs of heat input, a much more stringent standard than the emission rate of 2.5 lbs during Phase I.

Two additional provisions of Title IV – 'substitution' and 'compensation' – allow other generating units not required to make reductions during Phase I to voluntarily come under Title IV along with the Table A units. The substitution provision allows Table A units to contract for emission reductions at non-Table A units instead, thereby reducing the cost of SO_2 reduction. On the other hand, the compensation provision prevents Table A units from meeting their emission reductions by simply reducing generation. In other words, if a Table A unit significantly reduces its generation below its baseline levels then it must bring one or more non-Table A units under Phase I regulation to compensate. The increased generation at the non-Table A units must offset the reduction at the Table A unit.

The total number of allowances available to participating units in 1995 was 8.7 million. The initial allocation of allowances issued to the Table A units was approximately 5.55 million. The number each unit received was based on their historical coal use and emission rates. The 'compensating' and 'substitution' units were granted a total of 1.33 allowances. Additional allowances were also issued through allowance auctions (175,000 in 1995) and through other bonus provisions in the CAAA including: Phase I Extension Allowances; Early Reduction Credits; Small Diesel Allowances; and Conservation Allowances. A total of 1.35 million Phase I Extension Allowances were allocated to Phase I units that either reduce their emissions by 90% or transferred their reductions to other units that reduce their emissions by 90%. Approximately 314,000 Early Reduction Credits were allocated to units that voluntarily reduced their emissions between 1990 and 1995. Slightly more than 50,000 allowances were issued as conservation and small diesel allowances. Small diesel allowances were given to small diesel refineries in 1995 that manufactured and desulfurized diesel fuel in 1994, while conservation allowances were earned by plants that undertake efficiency and renewable energy measures.

During 1995 SO_2 emissions from Phase I generating units dropped significantly. [107] Phase I plants emitted only 4.9 million tons of SO_2, 4.6 million tons less than they emitted in 1990 – 3.2 million tons less than was required by Title IV. However, large decreases in SO_2 emissions were observed just after the passage of Title IV, even before the trading system was in place and plants were required to make large reductions. There have been several explanations offered to help explain the pre-1995 reductions. First, plants may have acted strategically by complying early with Title IV. Early compliance would allow utilities to pass on to consumers the additional higher cost of low-sulfur coal and/or the cost of installing scrubbers. Second, certain states revised their State Implementation Plans requiring electric utilities to lower their SO_2 emissions prior to 1995. However, the most probable explanation is that the deregulation of railroads made it much less expensive to ship low-sulfur coal from the Powder River Basin to Midwest, the geographic region which experienced the greatest SO_2 reductions between 1985 and 1993 (Ellerman and Montero, 1998).

Finally, the SO_2 cap-and-trade program builds in even more flexibility by letting allowances that are not used in one year to be 'banked' and used in any later year. In other

[107] Recall our analysis is done at the plant level, but regulation of the electric utilities takes place at the generating level. Phase I plants include the 110 plants (with 263 generating units) that were regulated under Phase I plus the 38 plants (111 generating units) that opted into Phase I.

words, a plant can lower its emissions below their annual allowance allocation, thereby not exhausting their allotment of allowance and 'deposit' the extra allowances in an 'emissions bank.' These 'banked' allowances are perfect substitutes for future year allowances, and may be used or sold. Phase I plants 'banked' many allowances from 1995-1999 most likely to smooth the transition the more stringent limits imposed under Phase II starting in 2000. In particular, plants banked more than 11.5 million allowances during Phase I (1995-1999). Plants then used 1.2 million of these banked allowances in 2000, the first year of Phase II, followed by 1.08 million allowances in 2001 and another 650,000 million allowances in 2002. This systematic drawing down of the allowance bank suggests that the over compliance during Phase I was intentional (rather than being an unexpected result of lower than expected prices for low-sulfur coal).

III. SO_2 Trading Program: Literature Review

Prior to the introduction of emissions trading, Gollop and Roberts (1985) showed that a cost-effective allocation of pollution abatement arising from allowance trading among electrical utilities could produce an almost 50% reduction in abatement costs, suggesting potentially huge savings from emissions trading. In the years since the advent of Title IV, many papers, including Burtraw et al (1997), Joskow et al (1998), Schmalensee et al (1998), Carlson et al (2000), Popp (2000), Keohane (2002,2003), Ellerman (2003), and Shadbegian and Morgan (2003), have examined many different aspects of the actual SO_2 allowance trading program including its cost savings, environmental effectiveness, spatial patterns of abatement, pollution control innovations, and the efficiency of the banking of allowances. The likely success of any pollution allowance-trading program depends critically on the efficiency of the allowance trading market. Joskow et al (1998) evaluate the efficiency of the SO_2 allowance market by comparing the price of allowances auctioned by EPA between 1993 and 1997 with private market allowance price indices. If the SO_2 allowance market is efficient then EPA auction prices and private market prices will be equal. Joskow et al find that by the end of 1994 EPA auction prices and private market prices for SO_2 allowances were virtually identical implying that the private market for tradable allowances was relatively efficient. Furthermore, Schmalensee et al (1998) also conclude that the private market for tradable allowances was relatively efficient by noting the tremendous growth in the number of market trades from 1995 to 1997: 1.6 million, 4.9 million, and 5.1 million allowances were traded, respectively.

Keohane (2003) concludes that Title IV's allowance trading system resulted in annual cost savings between \$150 million and \$270 million relative to a command-and-control uniform emissions-rate standard. On the other hand, Carlson et al. (2000) find that the sizeable decrease in pollution abatement costs during the beginning of Title IV relative to the initial estimates was due more to the technological progress that lowered the cost to switch to low sulfur coal and the reduction in the price of low sulfur coal rather than the ability to trade allowances per se. Shadbegian and Morgan (2003) examine the impact of the stringency of SO_2 regulations on the productivity of electric utilities before and after the implementation of Title IV. They estimate that a 10% increase in regulatory stringency lowered productivity by 0.66% prior to Title IV, while during Title IV that same increase in regulatory stringency had no significant impact on productivity. The productivity gain is equivalent to 31 million more kilowatts (kwh) of electricity – equivalent to \$1.5 million cost savings, evaluated at \$0.05/kwh.

Ellerman (2003), among other issues, examines whether or not the more than 11 million allowances 'banked' during Phase I was optimal. He concludes that, given a reasonable set of assumptions concerning both the discount rate and the expected growth of SO_2 emissions during the banking period, the level of banking that took place during Phase I was consistent with rational, cost-minimizing behavior on the part of the electric utilities.

Beyond the direct cost-savings that arise from the use of market-based mechanisms to protect the environment, economists have argued for their use because of the potential gains from induced technological change. Popp (2003) and Keohane (2002) have both provided empirical evidence that Title IV led to induced technological change. Popp shows that prior to the passage of the 1990 CAAA, regulation which mandated the use of scrubbers with a 90% removal efficiency rate in many new plants, created incentives which led to innovations that decreased the cost of operating scrubbers, yet did little to increase the ability of scrubbers to abate pollution. However, Popp provides evidence that since Title IV there has been technological innovations that have improved the removal efficiency of scrubbers. Keohane examines the choice of electric utilities' to install a scrubber or switch to low sulfur coal under command-and-control versus a more flexible system of allowance trading. He provides evidence that fossil-fuel fired electric utilities that were subject to Title IV were, for a given increase in the cost of switching to low sulfur coal, more likely to install a scrubber.

One potential reason why an allowance trading system may not maximize net benefits from emission reductions is that emissions from different sources may have different impacts on human health (or other benefits). Baumol and Oates (1988, Chapter 12) argue that differences in health impacts across different emission sources can lead to a suboptimal outcome when high marginal damage sources buy allowances from low marginal damage sources on a one-for-one basis. Tietenberg (1995) reviews the literature on the spatial effects associated with tradable allowances, arguing that the first-best option – potentially each source paying a different price for an allowance – significantly complicates the trading process, so a range of second-best options have been proposed. One second best option that has been proposed in the literature is to minimize the distortion which may arise from heterogeneous marginal damages across sources by dividing the control area into different zones. The zones should be defined such that emission sources are similar enough within a zone to allow unrestricted trading. On the other hand, trading will be permitted between zones only at a predefined trading ratio ('exchange rate') that is based on the relative marginal damages. Creating a system of trading zones is appealing since it should increase the level of net benefits relative to a completely unrestricted trading system. However, as Atkinson and Tietenburg (1982) point out, a system of trading zones has three undesirable effects: 1) it increases compliance costs by reducing the number of cost minimizing trades; 2) it makes the final allocation of air quality improvements more reliant on the initial allocation of allowances, since that allocation determines the overall level of emissions in each zone; and 3) it decreases the number of market participants which increases the likelihood of noncompetitive behavior. Furthermore, a system of trading zones places more burden on the regulator since the regulator would need to know the marginal damage function of all sources to set the optimal trading ratios ('exchange rates').

IV. The Benefits and Costs of Cleaner Air

A. Benefits from Cleaner Air

We estimate the human health benefits from SO_2 reductions (SO2BEN) from a given emission source by the change in mortality risk from exposure to ambient particulate concentrations caused by those SO_2 emissions. These human health benefits are calculated using a simplified linear damage function, based on estimated parameters from the literature:

$$SO2BEN = SO2DIFF*AIR\_QUAL\_TC * HEALTH\_CHG * POP * VSL.$$

AIR_QUAL_TC is the transfer coefficient – the change in air quality (ambient particulate matter – $PM_{2.5}$) per ton change in SO_2 emissions (SO2DIFF). HEALTH_CHG is the change in mortality risk to the impacted population corresponding to the changes in air quality. POP is the size of the impacted population, and VSL (value of statistical life) is the dollar value associated with reducing premature mortality.

We calculate air quality changes at any given location using the Source-Receptor (S-R) Matrix Model, as described in Latimer (1996) and Abt (2000). The S-R Matrix model was initially calculated using the Climatological Regional Dispersion Model (CRDM). The model includes data on air pollution emissions from 5,905 separate sources in the U.S., along with additional sources from Mexico and Canada.[108] The S-R Matrix relates emissions of each particular pollutant from each source to the resulting ambient concentrations of each pollutant in every county in the U.S. More specifically, the S-R Matrix provides the necessary transfer coefficients to calculate the county-by-county changes in annual average pollutant concentrations for a one unit change of emissions for a particular pollutant from each source. The S-R Matrix transfer coefficients are a complicated function of numerous factors including wet and dry deposition of gases and particles, chemical conversion of SO_2 and nitrogen oxide (NO_X) into secondary particulates, effective stack height, and several atmospheric variables (including wind speed and direction, stability, and mixing heights). We use the AIR_QUAL_TC to measure the impact of SO_2 emissions on ambient concentration of $PM_{2.5}$ in each county.

Our study concentrates on the human health benefits from lower ambient concentrations of secondary particulates ($PM_{2.5}$) that result from reductions in SO_2 emissions. We use the results from the American Cancer Society (ACS) study, the most complete analysis of long-term mortality effects from air pollution to date (Pope et al., 2002) to measure HEALTH_CHG. Pope et al. find that a 10 $\mu g/m^3$ increase in $PM_{2.5}$ concentrations leads to an approximate 4% (95% confidence interval: 2%, 6%) higher mortality rate in the exposed population. We assume that the secondary particulates formed from SO_2 have the same impact on premature mortality (Pope et al. found similar numbers for sulfate particles in their study).[109] We estimate the exposed population, POP, based on county-level data from the 1990 Census of Population, which provides the number of people living in each county (and thus the number of exposed people by the average ambient pollution concentrations in that county).

Finally, we use a recent EPA (1997) benefit-cost analysis that estimated the value of a statistical life (VSL) to put a dollar value of premature mortality. The EPA study combined contingent valuation and wage-risk studies to provide a central VSL estimate of $5.4 million (in

---

108 Emissions sources in the U.S. include ground-level sources, county-level sources and individual sources. Emissions from ground-level sources are estimated for each of the 3,080 contiguous counties (excludes Alaska and Hawaii, whereas elevated sources are grouped according to effective stack height. Point sources with an effective stack height taller than 500 meters are modeled as individual sources of emissions. All emission sources in the same county with an effective stack height less than 250 meters are aggregated into a single county-level source – the same is done for emission sources with an effective stack height between 250 meters and 500 meters. Ground-level emission sources are also aggregated to the county level. The S-R matrix models 5,905 U.S. emission sources.

109 Chay and Greenstone (2003a, 2003b) analyze the impact of the exposure of fine particulate matter on infant mortality, and find similar results to the ACS study, measured in terms of increased mortality rates.

1995 dollars) per life saved. Note that our study assumes constant values for the VSL and HEALTH_CHG terms for the entire population. In other words, each exposed person is assigned the same average dollar harm from exposures to fine particulates and the same level of sensitivity to fine particulates.[110] Note also that the very large estimates we find for the benefits of lowering SO_2 emissions are a combination of these two factors: one will get smaller benefits by assuming either smaller health effects or a lower VSL.

B. Costs of Cleaner Air

There are three basic options (or combinations of options) available to plants to comply with Title IV: install a scrubber, switch to lower sulfur coal, or buy allowances. We measure the cost of abating a ton of SO_2 emissions in two ways. Our first estimate of the cost of complying with Title IV (COST1) is based on the actual method each plant chose to use, given the option of purchasing allowances. From Ellerman et al (1997) we have an estimate of the average cost of SO_2 abatement for each of the 374 units (plant-boiler observations) regulated by Title IV during Phase I – this consists of the 263 units mandated to reduce their SO_2 emissions by Title IV plus the 111 units which 'opted' into Phase I. According to Ellerman et al (1997) the average cost of 'switching' and 'scrubbing' in 1995 was \$153 and \$265 per ton respectively, whereas the average price of an allowance was \$128.50.[111] Our second estimate of the cost of complying with Title IV (COST2) is based on Keohane (2003), which models each unit's abatement costs based on its decision to install a scrubber or not. The decision to install a scrubber is first evaluated given the Title IV allowance trading program and then given a traditional command-and-control regime (a no trading scenario) designed to produce the equivalent aggregate SO_2 emission reductions realized under the 1990 CAAA. Keohane estimates the emissions and SO_2 abatement costs at each of the plants assuming both an emissions trading regime and a command-and-control regime, and the difference in costs between the two regimes gives us our second measure of SO_2 abatement costs.[112]

Who pays these extra abatement costs? One possible answer is "nobody", if efficiency improvements resulting from the new allowance trading system (e.g. more flexible production switching, less uncertainty about regulatory requirements) outweighed the additional abatement costs on a plant-by-plant basis. However, a more likely scenario is that plants facing higher costs of pollution abatement will pass along these costs to their customers. We assume that all of the extra costs are passed through to the utility's customers, and that all customers live in the same state where the utility is located.[113] We use data from the 1990 Census of Population to allocate each plant's extra abatement costs equally to all people living within that state.

V. Sample Coverage

Phase I of Title IV regulated the emissions of 263 generating units (the Table A generating units) owned by 110 plants. An additional 38 substitution and compensation plants (111 generating units) opted into Phase I, bringing the final total to 374 generating units. Our

[110] Our data would readily allow our calculations to vary both in terms of sensitivity and valuation for different subpopulations – if one could generate a consensus on how to quantify such differences, a politically charged issue that we avoid here.

[111] We would like to thank Denny Ellerman for providing us with this data.

[112] We would like to thank Nat Keohane for providing us with this data.

[113] If we had data on cross-state electricity sales, we could adjust our cost calculations to reflect this.

sample consists of all 148 plants and their 374 generating units. The geographic distribution of these plants – heavily concentrated in the Midwest - is shown in Figure 1.

In Table 1 we present information on SO_2 emissions and the allocation of SO_2 allowances obtained from the EPA's Allowance Tracking System (ATS).[114] The 148 plants in our sample emitted a total of 9.5 million tons of SO_2 during 1990, the year Title IV was passed. By 1995, our 148 plants had reduced their SO_2 emissions by 4.6 million tons from their 1990 levels, cutting them almost in half, although Title IV had only required them to reduce emissions by 15%, to 8.1 million tons.

VI. Distribution of Benefit and Costs

In Table 2 we present two scenarios of health benefits and abatement costs. In Scenario 1 we calculate the benefits and costs associated with the actual 1995 SO_2 emissions reductions (costs are based on Ellerman et al (1997)): counterfactual SO_2 emissions minus actual emissions. The counterfactual emissions in 1995 are those we would have observed in the absence of the CAAA of 1990, based on calculations presented in Ellerman et al (1997). In Scenario 2 we take the actual reduction in SO_2 emissions as given, and compare the costs and benefits associated with achieving that aggregate reduction using two different policy regimes, allowance trading and command-and-control (reducing the allowable emissions rate uniformly across plants), based on calculations from Keohane (2003). A visual comparison of the benefits from reducing SO_2 emissions under the two scenarios can be seen in Figures 2 and 3. Not surprisingly, given the concentration of the plants in the Midwest and the pattern of airflow from west to east, the benefits that result from the large reductions in emissions in Scenario 1 are highly concentrated geographically. Scenario 2 involves a reallocation of emissions reductions across plants, so we see both losers and winners in Figure 3.

As expected, the aggregate benefits in 1995 resulting from reductions in SO_2 emissions from the 1995 counterfactual levels far outweigh their costs: we estimate benefits of nearly $56 billion and costs of only $558 million. An alternative assumption on abatement costs is that the actual cost of a ton of abatement is equal to the allowance price ($128.5 in 1995), which results in total abatement costs of only $496 million. In either case these increased abatement costs are dwarfed by the increased benefits from the SO_2 reduction, which are roughly 100 times as large.

Scenario 2 shows that allowance trading results in a sizable reduction in abatement costs ($94 million or 16.8%), relative to achieving the same aggregate emissions by a hypothetical command-and-control system. These cost savings are outweighed, however, by the changes on the benefits side. Plants with decreased emissions under allowance trading are more likely to be low-benefit plants, while plants with higher emissions under allowance trading are more likely to be high-benefit plants. In other words, we find that plants which buy allowances (to emit more SO2) are more likely to be high-benefit plants, while plants that sell allowances (and thereby emit less SO2) are more likely to be middle- or low-benefit. This is reflected in the average benefits at buying and selling plants: the buying plants have a mean benefit of $17,519 while the selling plants have a mean benefit of $14,777. These differences are not huge, but it is still the case that the plants which are buying (selling) allowances are those plants which yield the highest (lowest) benefits from abating a ton of SO_2. This result drives the negative impact of the trades on overall benefits observed in Table 2, and suggests that the allowance trading system

[114] We would like to thank Denny Ellerman for providing us with this data.

might benefit from a spatially-based 'exchange rate' based on differences in the impacts of emissions across these plants.

Tables 3A, 3B, and 3C explore in more detail the differences across plants in marginal benefits generated from reductions in SO_2 emissions. Table 3A shows the distribution of the benefits per ton of reduction across our 148 plants. The variation in these numbers across plants is based on a variety of factors, including effective stack height and meteorological conditions, though the principal determinant is the population density downwind. There are a few outliers at the top and bottom of the distribution, but most plants fall between $9,600 and $19,500 per ton in marginal benefits. The plants towards the top of the distribution tend to be in places like Pennsylvania, while plants in Alabama, Florida, Georgia, and Mississippi tend to be near the bottom, although there is some within state variation as well.

Table 3B examines the hypothetical results from Scenario 2 in more detail, comparing plants which had higher emissions under the allowance trading scenario to plants which had higher emissions under the command-and-control scenario. Table 3C contains a similar comparison, but this time we analyze the actual emission decisions of plants, seeing whether the plants are buying or selling allowances in 1995. The two tables give similar results – plants with low marginal benefits tend to be sellers of allowances, while plants with high marginal benefits tend to be buyers of allowances.

What causes these differences across plants in marginal benefits? The largest factor is the location of the plant, but stack height is also important. Table 4 illustrates that there are large differences in marginal benefits across EPA regions. In particular, EPA regions 3 and 5 tend to have more plants with higher marginal benefits, while there are more plants with lower marginal benefits in EPA regions 4 and 7. Table 4 also shows that the very highest marginal benefit plants all have relatively low stacks (under 250 feet in effective stack height). When this is coupled with being located near a metropolitan area, the emissions from the plant can have a relatively strong local effect. Most of the plants in our sample have considerably higher stacks, and such plants tend to have small or moderate marginal benefits. Also note that plants with higher benefits tend to have higher abatement costs. This helps explain the finding that allowance trading has tended to move emissions from low-benefit to high-benefit plants – plants with higher costs are more likely to buy allowances, and the current trading system provides them with no incentive to consider the extent to which their own emissions are likely to be especially harmful. An examination of the data for individual plants shows that large, newer plants with tall stacks with relatively low benefits tend to be doing much of the additional abating required under allowance trading.[115]

We now turn to an examination of the possibilities of spatially-based limits on trading between plants, in order to reduce the number of trades which increase emissions at high-benefit plants and reduce emissions at low-benefit plants. Since marginal benefits are connected to downwind population, which is expected to differ by plant location, one possible solution is to define a set of trading regions and to require that trades occur only between plants in the same region. If plants in the same region have the same marginal benefits, this will rule out problematic trades. Our data does not identify individual trades, but presents aggregate

[115] We have also examined the correlations among these variables (available from authors), but this did not add much additional information to the results presented here.

purchases (or sales) for each plant.[116] We can simulate the effect of trading regions by requiring the buying and selling of allowances to balance within each region, and seeing how this affects the aggregate benefits of reducing emissions, assuming that the changes in allowance trading lead to comparable changes in plant-level emissions.

Table 5A shows the distribution of buying and selling within each EPA region, while Table 5B shows the distribution for each state; each table also presents the national totals. As expected, the national-level data show that emissions from the buyers tend to have higher marginal benefits than emissions from the sellers (roughly 10% higher – benefits per ton of $16,500 vs. $15,000). We see considerable heterogeneity in the trading behavior and marginal benefits across states within the same region. Most states have some plants buying allowances and some plants selling them, and there is often a considerable difference in marginal benefits between buyers and sellers. We see that some regions have relatively consistent behavior across plants in different states (e.g. region 3 with allowance buying and region 7 with allowance selling in nearly all states of the region), but that others show more heterogeneity across states (e.g. region 4 with allowance selling by plants in Georgia and allowance buying by plants in Kentucky and Tennessee). The key element for the success of a trading zone approach is the distribution of the marginal benefits. The evidence that there is substantial within-region heterogeneity in marginal benefits indicates that trades between high- and low-benefit plants would continue, leading to possible problems for aggregate welfare.

Table 6 shows the results from two simulations of the impact of changing the allowance trading process by imposing trading zones. The first simulation splits the set of plants into groups based on EPA regions. The second creates two 'super-regions', one including regions 4 and 7 (the Southern and Midwestern regions) and the other including the rest of the sample (the Northeast regions).[117] In both cases we force balanced trading within each region. We first calculate the excess demand (or supply) for allowances within the region. If there is excess demand, we eliminate it by increasing sales and decreasing purchases of allowances within the region, in proportion to the size of the plants buying and selling allowances within that region (and similarly for excess supply). To the extent that this reduces purchases (or increases sales) by high-benefit plants, it will increase social welfare.

The results show some benefits from trading zones, but they are not very large. The baseline data indicates 867,000 allowances being traded across plants, for which the discrepancy in marginal benefits between buyers and sellers amounts to a shortfall in benefits of $1.055 billion. Imposing the 2-region trading zone model would result in excess demand (supply) of about 25,000 allowances in each region, which reduces the shortfall in benefits by $113 million, or about 11% of the original shortfall. A 6-region trading zone model takes advantage of the greater variation in excess demand and supply across those regions, reducing the shortfall in benefits by $143 million, or about 14% of the original shortfall. While the absolute change in the shortfall from these trading zones might seem large in absolute terms, it would still leave 80-90% of the shortfall in place, and at the cost of considerably complicating the trading process

[116] We have recently received the necessary data to identify individual trades – the buying plant, the selling plant, their location, and the total number of allowances traded. This will allow us to do more detailed simulations.

[117] We considered simulating the effects of state-level trading zones, but this ran into the problem that some states have no buyers (or no sellers) of allowances – so there is no natural way to force those states into equilibrium. Creating 22 separate trading zones also raises concerns with implementation in terms of the market power that it would generate for individual facilities within the smaller states.

(and possibly losing the political impetus that led to passing the enabling legislation). As noted earlier, the substantial within-region heterogeneity in marginal benefits is limiting the benefits from trading zones.

An alternative approach would be to assign each plant an 'exchange rate' proportional to its marginal benefits, and require that plants buy sufficient allowances to cover their emissions, after accounting for the exchange rate. This would tend to force high-benefit plants to abate their pollution (rather than buying many extra allowances to compensate for the high benefits). Our initial attempts to model an individual plant's actual decision about buying and selling allowances have not been very successful (not predicting very well the actual buy/sell decision), so we are not presenting those results here. We can note that the variation in marginal benefits across plants is somewhat larger than the variation in our measure of abatement costs, so the plants' final decisions about buying and selling allowances under an 'exchange rate' system are likely to be driven primarily by differences in marginal benefits, rather than costs.

VII. Concluding Remarks

In this paper we analyze plant-level information on fossil fuel fired electric utilities to examine the distribution of costs and health benefits associated with the air quality improvement achieved by Title IV of the 1990 CAAA and compare it to the distribution under a command-and-control regime. In addition to comparing the costs and health benefits that arise from reductions in SO_2 emissions under Title IV, we use data on abatement costs to simulate the impact of requiring a comparable reduction in SO_2 emissions under the old command-and-control regime, by assuming uniform emission standards at all plants. We examine the distribution of benefits and costs both in terms of the regions being affected and the socio-economic composition of the affected population.

Our results for Scenario 1 suggest that, as expected, the aggregate health benefits in 1995 caused by reductions in SO_2 emissions under Title IV greatly exceeded their costs. We estimate benefits of \$56 billion and costs of only \$558 million leading to \$55 billion dollars of net benefits from the SO_2 reductions.

Our results for Scenario 2 compare the results from allowance trading under Title IV versus a hypothetical command-and-control system with uniform emission standards that would achieve the same overall reduction. We find that allowance trading saves a substantial fraction of the abatement costs, but the geographic shift in SO_2 emissions induced by allowance trading goes in the other direction, generating a reduction in the abatement benefits. To understand the importance of shifts in emissions across plants for Scenario 2, we examine the distribution of the marginal benefits of reducing emissions across our 148 plants. The differences are not huge: the median benefit per ton is about \$15,000 and 80% of plants fall between \$10,000 and \$20,000. However, when we consider which plants are buying or selling allowances, we find that plants that buy allowances tend to be high-benefit and plants that sell allowances tend to be middle or low-benefit.

This helps explain the negative net benefits from allowance trading we find for Scenario 2, and raises the question of whether a spatially-based approach to trading would improve the results. We find that alternative trading zone models (with 2 and 6 trading zones) result in only modest reductions in the overall performance of the model (reducing the shortfall in benefits by about 11-14%). This arises from the considerable heterogeneity of marginal benefits across plants within the same region. Given the necessary increase in complexity for the trading system, the modest improvements may not be sufficient justification for making a change. Next steps in the evolution of this research will involve incorporating more detailed measures of abatement costs and data on actual individual allowance trades to generate a plant-level (or unit-level) model of the tradeoff between abatement costs and allowance purchases, allowing us to model the impact of marginal benefit-based exchange rates on the overall performance of the allowance trading system.

REFERENCES

Abt Associates, "The Particulate-Related Health Benefits of Reducing Power Plant Emissions," prepared for Clean Air Task Force (October 2000).

Atkinson, S.E. and T.H. Tietenburg, "The Empirical Properties of Two Classes of Designs for Transferable Discharge Permit Markets," *Journal of Environmental Economics and Management*, **9**, 101-121 (1982).

Baumol, W. J., and W.E. Oates, *The Theory of Environmental Policy*, Cambridge University Press, 1988.

Burtraw, D., A. Krupnick, E. Mansur, D. Austin, and D. Farrell, "The Costs and Benefits of Reducing Acid Rain," Resources for the Future Discussion Paper 97-31-REV, Washington, D.C.: Resources for the Future (1997).

C.P. Carlson, D. Burtraw, M. Cropper, and K. Palmer, "SO2 Control by Electric Utilities: What are the Gains from Trade?," *Journal of Political Economy* **108**, 1292-1326 (2000).

K. Chay and M. Greenstone, "The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession," Quarterly Journal of Economics, 1121-1167 (2003a).

____________, "Air Quality, Infant Mortality, and the Clean Air Act of 1970," NBER Working Paper 10053 (2003b).

A. D. Ellerman, R. Schmalensee, P. Joskow, J. Montero, and E. Bailey, <u>Emissions Trading Under the U.S. Acid Rain Program: Evaluation of Compliance Costs and Allowance Market Performance.</u>, MIT Center for Energy and Environmental Policy Research, 1997.

A. D. Ellerman, and J. Montero, "The Declining Trend in Sulfur Dioxide Emissions: Implications for Allowance Prices," *Journal of Environmental Economics and Management*, **36**, 26-45 (1998).

A.D. Ellerman, "Lessons from Phase 2 Compliance with the U.S. Acid Rain Program," presented at the EPA's Market Mechanisms and Incentives: Applications to Environmental Policy (May, 2003).

F. M. Gollop, and M.J. Roberts, "Cost Minimizing Regulation of Sulfur Emissions: Regional Gains in Electric Power," *Review of Economics and Statistics*, 81-90 (1985).

P.L. Joskow, R. Schmalensee, and E. Bailey, "The Market for Sulfur Dioxide Emissions," *The American Economic Review* **88**, 669-685 (1998).

N. Keohane, "Environmental Policy and the Choice of Abatement Technique: Evidence from Coal-Fired Power Plants." Working paper available at www.som.yale.edu/faculty/nok4/files/papers/so2.pdf. (2002)

N. Keohane, "What Did the Market Buy? Cost Savings Under the U.S. Tradable Allowances Market Program for Sulfur Dioxide", Yale Center for Environmental Law and Policy Working Paper ES #33 (2003).

D. A. Latimer, "Particulate Matter Source-Receptor Relationships Between All Point and Area Sources in the United States and PSD Class I Area Receptors," prepared for EPA, OAQPS (September 1996).

Pope III, C. A., Burnett, R. T., Thun, M. J., Calle, E. E., Krewski, D., Ito, K., Thurston, G. D. (2002). Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. *Journal of the American Medical Association,* **287**, 1132–1141.

D. Popp, "Pollution Control Innovations and the Clean Air Act of 1990," *Journal of Policy Analysis and Management* **22**, 641-660 (2003).

R. Schmalensee, P.L. Joskow, A.D. Ellerman, J.P. Montero, E.M. Bailey, "An Interim Evaluation of Sulfur Dioxide Emissions Trading," *Journal of Economic Perspectives* **12**, 53-68 (1998).

R. Shadbegian, W. Gray, and J. Levy, "Spatial Efficiency of Pollution Abatement Expenditures," presented at the Western Economic Association Meetings (June 1999), NBER Environmental Economic Meetings (April 2000), International Atlantic Economic Association Meetings (October 2000), and U.S. E.P.A. National Center for Environmental Economics (October 2000).

R. Shadbegian and C. Morgan, "Environmental Regulation in the Electric Utility Industry: Are There Productivity Gains From Emissions Trading?" Presented at the International Atlantic Economic Association Meetings (October 2002) and the Western Economic Association Meetings (July 2003).

R. Shadbegian, W. Gray, and C. Morgan, "Benefits and Costs From Sulfur Dioxide Trading: A Distributional Analysis" in Acid in the Environment: Lessons Learned and Future Prospects (ed.s Gerald R. Visgilio and Diana M. Whitelaw), Springer Science+Media (forthcoming 2006).

Tietenberg, T., "Tradeable Allowances for Pollution Control When Emission Location Matters: What Have We Learned?" *Environmental and Resource Economics*, March 1995.

U.S. Environmental Protection Agency, "The Benefits and Costs of the Clean Air Act, 1970 to 1990," October, 1997.

U. S. Environmental Protection Agency, EPA Acid Rain Program 2001 Progress Report, http://www.epa.gov/airmarkets/cmprpt/arp01/2001report.pdf, November 2002.

Table 1 – Phase I Plants

	Phase I Plants*
SO_2 Emissions in 1990 (tons)	9,468,183
SO_2 Emissions in 1995 (tons)	4,902,778
Allowances in 1995	8,076,472
Boilers	374
Plants	148

* = Includes the 110 Table A plants plus the 38 “Substitution and Compensation” plants

Table 2 – Benefits and Costs

	Scenario 1	**Scenario 2**
Benefits	$55.94 billion	-$1,255 million
Costs	$0.56 billion	-$94 million
Net Benefits	$55.38 billion	-$1,161 million

Table 3A – Distribution of Benefits per Ton Reduction Across Plants

Distribution	Benefits/Ton
Maximum	$35,868
90%	$19,662
75%	$17,477
50%	$15,414
25%	$12,575
10%	$9,601
Minimum	$3,763

Table 3B – Distribution of Benefits per Ton Reduction (Scenario 2 Outcomes)
Command-and-Control vs. Allowance Trading

	Low Benefits (<$12,500)	Middle Benefits ($12,500-$17,500)	High Benefits (>$17,500)
Higher Emissions under Allowance Trading	9	34	20
Lower Emissions under Allowance Trading	20	32	5

Table 3C – Distribution of Benefits per Ton Reduction
Actual Trading Outcomes - Buying and Selling

	Low Benefits (<$12,500)	Middle Benefits ($12,500-$17,500)	High Benefits (>$17,500)
Allowance Buyers	12	36	15
Allowance Sellers	19	28	9

Table 4 – Determinants of Benefits per Ton Reduction

	Low Benefits (<$12,500)	Middle Benefits ($12,500-$17,500)	High Benefits (>$17,500)
Region			
1 (MA,NH)	1	0	1
2 (NJ,NY)	2	3	1
3 (MD,PA,WV)	0	13	10
4 (AL,FL,GA,KY,MS,TN)	22	11	1
5 (IL,IN,MI,MN,OH,WI)	4	43	13
7 (IA,KS,MO)	12	7	1
Stack Height			
Low	2	12	14
Medium	17	24	13
High	22	41	3
Abatement Costs			
Low	20	33	7
Medium	15	22	10
High	6	22	13

Table 5A – Distribution of Buying and Selling Across EPA Regions

Region	Total	Buy	Sell	Total Buy	Total Sell	Net Buy	MB-Buy	MB-Sell
1	2	1	1	4612	-1848	2764	$18,155	$9,510
2	6	2	2	7791	-48537	-40746	$17,593	$10,366
3	23	14	7	199284	-156723	42561	$18,229	$20,962
4	34	16	10	277268	-225112	52156	$12,545	$11,332
5	63	27	26	371025	-350174	20851	$17,584	$17,330
7	20	3	10	6915	-84499	-77584	$18,441	$9,814
	148	63	56	866893	-866893	0	$16,498	$14,982

Table 5B – Distribution of Buying and Selling Across States

Region	State	Total	Buy	Sell	Total Buy	Total Sell	Net Buy	MB-Buy	MB-Sell
1	MA	1	0	1	0	-1848	-1848	-	$9,510
1	NH	1	1	0	4612	0	4612	$18,155	-
2	NJ	1	1	0	1161	0	1161	$19,507	-
2	NY	5	1	2	6629	-48537	-41908	$15,679	$10,366
3	MD	4	3	1	21347	-1837	19510	$18,517	$28,203
3	PA	12	7	3	86575	-27997	58578	$18,978	$19,057
3	WV	7	4	3	91362	-126889	-35527	$16,703	$20,453
4	AL	3	1	1	6743	-19045	-12302	$11,826	$9,324
4	FL	3	2	0	11668	0	11668	$8,283	-
4	GA	10	2	5	1728	-124781	-123053	$10,198	$10,928
4	KY	12	7	2	141832	-11484	130348	$15,196	$15,518
4	MS	2	1	1	9515	-431	9084	$5,588	$5,749
4	TN	4	3	1	105783	-69371	36412	$13,324	$12,575
5	IL	12	5	5	87372	-48005	39367	$14,848	$15,998
5	IN	15	11	4	147839	-26129	121710	$15,754	$18,249
5	MI	2	1	1	812	-16234	-15422	$30,354	$16,393
5	MN	2	0	1	0	-15	-15	-	$15,371
5	OH	22	9	8	134523	-180352	-45829	$20,195	$19,436
5	WI	10	1	7	478	-79439	-78961	$15,128	$15,762
7	IA	6	1	3	1543	-1725	-182	$4,322	$12,061
7	KS	2	0	1	0	-3636	-3636	-	$3,931
7	MO	12	2	6	5372	-79138	-73766	$25,500	$9,671
	TO	148	63	56	866893	-866893	0	$16,498	$14,982

Table 6 – Shortfalls in Benefits from Allowance Trading
Impacts of Trading Zones

Excess demand/supply	Shortfall in Benefits	$ Improvement over Baseline	% Improvement over Baseline
	Baseline model (no zones)		
0	-$1055 M	$0	0%
	2-region model (region 4+7, 1+2+3+5)		
(25429, -25429)	-$942 M	$113 M	10.7%
	6-region model (regions 1,2,3,4,5,7)		
(2764, -40746, 42561, 52156, 20851, -77584)	-$912 M	$143 M	13.6%

Figure 1
Distribution of Plants in Database
(148 Plants; scale=1995 SO_2 emissions in tons)

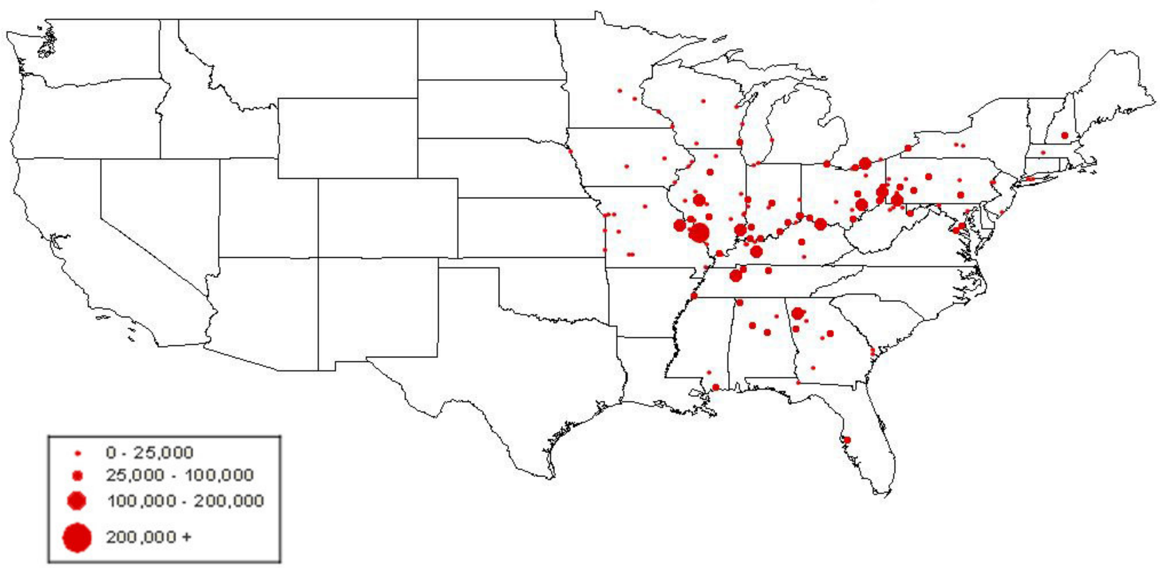


Figure 2
Geographic Distribution of Benefits
Scenario 1

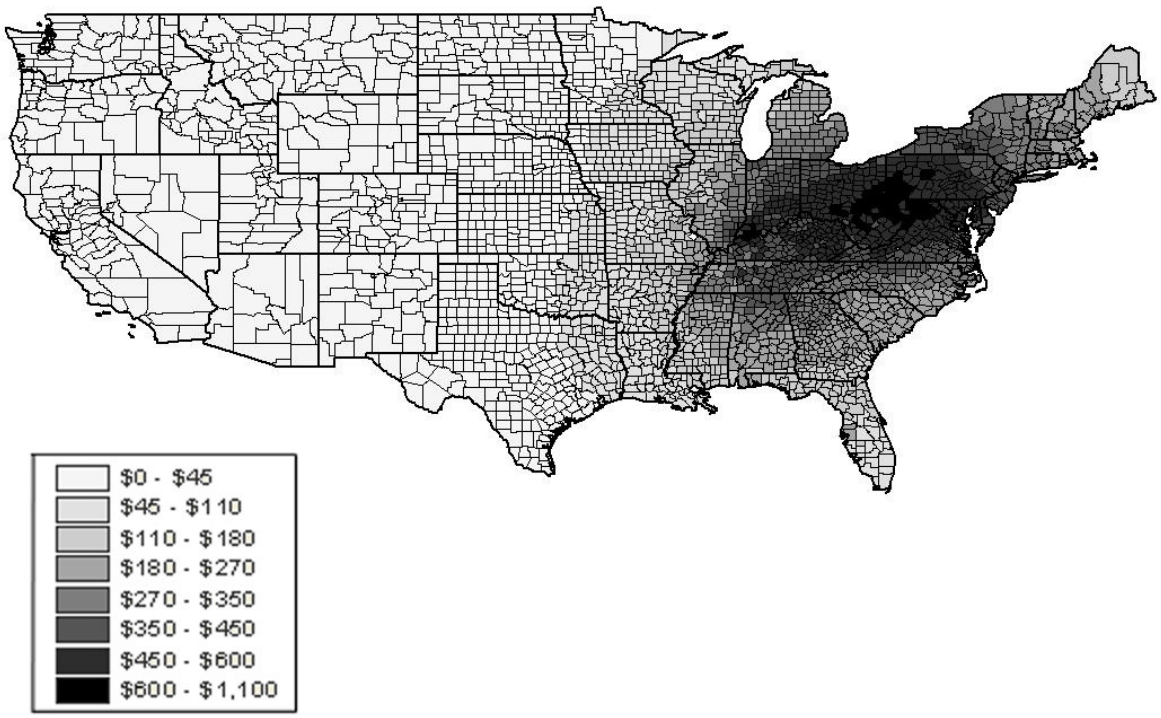
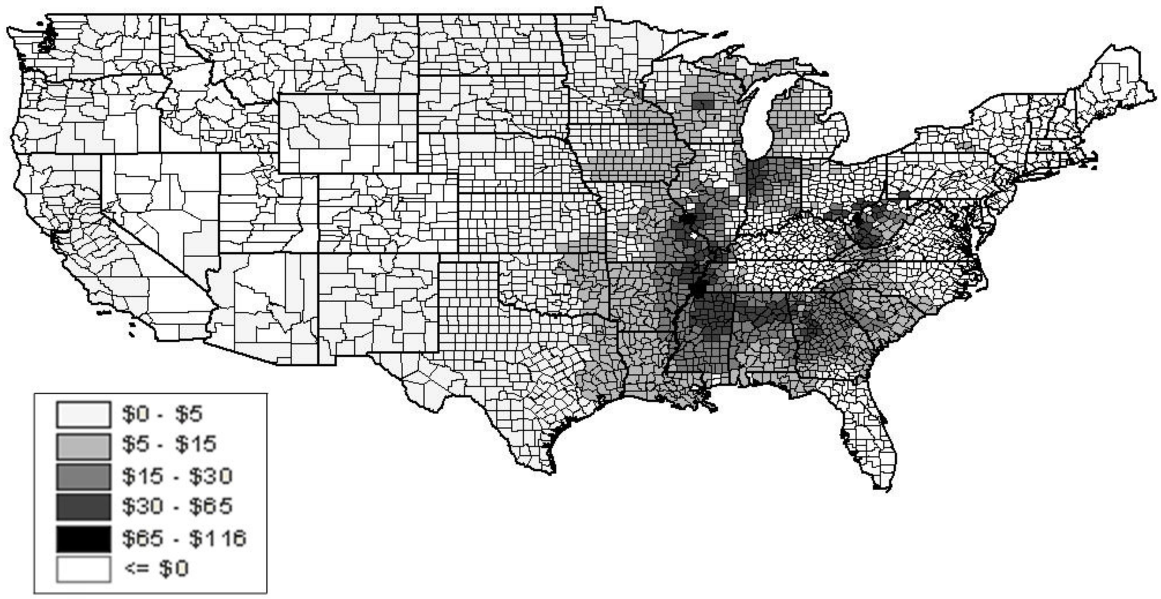


Figure 3
Geographic Distribution of Benefits
Scenario 2

Net Winners



Net Losers