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The Environmental Performance of Polluting Plants: A Spatial Econometric Approach

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Abstract

This paper uses plant-level data from EPA and Census databases to incorporate spatial components in models of the environmental performance (compliance and emissions) of manufacturing plants. The spatial approaches include creating explanatory variables based on information related to the plant's location and the location of nearby plants, testing for spatial autocorrelation in environmental performance and the explanatory variables, examining whether spatial factors in the explanatory variables explain the spatial factors in environmental performance, and directly modeling the spatial component of environmental performance with spatially lagged dependent variables. Our analysis uses data for 521 manufacturing plants in the compliance analysis and 102 plants in the emissions analysis.

Our results indicate a significant, but limited, role for spatial factors in modeling environmental performance. We find positive spatial autocorrelation in the analysis of compliance status, but no such spatial effects are observed for emissions. In fact, very few variables in our model show significant impacts on emissions. The positive spatial autocorrelation of compliance status holds in most cases, whether or not we control for other explanatory variables, though these results depend in part on the way in which the spatial effects are assumed to operate across plants. Some of the models indicate that the spatial autocorrelations in the explanatory variables help explain part of the spatial autocorrelation observed in compliance status, though much of the autocorrelation in compliance usually remains unexplained. Models which directly incorporate spatially-lagged compliance status in the estimation often (but not always) find significant positive effects for those spatial lags.

Much of the explanatory power of the compliance models comes from plant-specific characteristics, with larger, older, and more pollution-abatement-intensive plants, and those in single-plant firms, showing less compliance. Neither the local demographic characteristics nor measures of political activity have much impact on compliance. Our measures of inspection activity tend to have the expected signs – having more inspections at the plant, at nearby plants, and at plants in the same state is associated with greater compliance – but these effects aren't always significant. As expected, inspections at nearby plants in other states don't seem to increase compliance.

1. Introduction

This paper examines the determinants of environmental performance at a sample of U.S. manufacturing plants, focusing on correlations across the performance of nearby plants. We measure environmental performance by a plant's compliance status with air pollution regulations and by its air pollution emissions. Our model of performance allows for a variety of potential determinants, including plant characteristics, regulatory activity, and demographics of the local population. In addition to the measured factors affecting the plant, we use a variety of spatial econometric methods to test for similarities in performance across nearby plants, and then to see whether controlling for these spatial effects influences the estimated effects of the other explanatory variables in the model.

There exists a substantial body of research examining the determinants of air pollution compliance status and emissions. Gray and Deily (1996) examine compliance status at steel mills, Gray and Shadbegian (2003b) look at compliance status at paper mills, and Nadeau (1997) considers the duration of non-compliance at paper mills. The determinants of air pollution emissions have been studied by Kahn (1999) and Gray and Shadbegian (2002, 2003a). Performance with respect to water pollution regulations has been studied by Magat and Viscusi (1990), Laplante and Rilstone (1996), Helland (1998) and Shimshack (2003). This research generally finds some impact of enforcement activity on compliance, as well as demonstrating the important role of plant-level characteristics in the models, with firm-level characteristics (when included) tending to play a less important role.

Attention to spatial factors in prior research has tended to focus on generating particular explanatory variables to enter in the model, without paying any particular attention to their spatial nature. For example, Gray and Deily (1996) calculate state-level measures of regulatory activity, to use as instruments for plant-level enforcement that may be correlated with plant-level compliance status. Kahn (1999) and others use the location of political borders to identify which plants might face less regulatory attention, due to the costs from their pollution being spread to people in other states. Gray and Shadbegian (2002) and others in the Environmental Justice vein use demographic information for the neighborhood surrounding a plant to help explain air and water pollution emissions.

The present paper attempts to bring a more systematic approach to the spatial nature of environmental performance. In order to get a manageable set of plants in reasonably close proximity to each other, we select three medium-sized US cities, all near or on state borders (St. Louis, Cincinnati, and Charlotte). We use EPA datasets to identify the location of polluting manufacturing plants near these cities. We then link these plants to Census datasets (Longitudinal Research Database and Pollution Abatement Costs and Expenditures Survey) providing additional plant-level information for the model including plant size, age, productivity, and pollution abatement spending.

Because the focus of our work is on the spatial factors influencing performance, we use a single cross-section of data, rather than putting together a panel of data (panel data might have more observations, but the need for multiple years of data would reduce the number of plants with data, limiting the available variation for spatial analyses). We chose to collect data from 1997, and wound up with a sample of 521 plants with data on air compliance status and the set of explanatory variables. A subsample of 102 plants had emissions data for particulates, sulfur dioxide, and nitrogen oxides.

Our analysis takes advantage of spatially-based information in several ways. First, as other studies noted above have done, we generate explanatory variables that have a spatial component. These include measures of state-level air pollution regulatory activity and demographic characteristics of the area around each plant. In addition, we take advantage of the spatial relationship among plants to create a measure of general deterrence measured by the spatially-lagged inspection history of nearby plants, to supplement the usual specific deterrence measure of the plant's own inspection history. We also test whether this spatial lagging operates across state borders, or whether nearby plants in another state are irrelevant because they are under the jurisdiction of a different regulatory agency.

Second, we test for the existence of spatial autocorrelation in both the dependent and explanatory variables in the model, along with tests for spatial autocorrelation in the residuals from non-spatial models of environmental performance. This allows us to see whether any spatial component in environmental performance is explained by a spatial component in the measured explanatory variables, or whether there is some unmeasured spatial factor influencing performance. This part of the analysis incorporates a variety of tests, as well as a variety of assumptions about the nature of the spatial relationships among plants embodied in different spatial weighting matrices.

Finally, we incorporate the spatial dimension explicitly in our models of environmental performance. This involves testing whether the performance at one plant is directly affected by the performance of nearby plants, even after controlling for the influence of the other explanatory variables. Both instrumental variables and maximum likelihood versions of the models are considered, along with different spatial weighting matrices.

Our results indicate that compliance status is significantly positively correlated across nearby plants, but no such spatial effects are observed for emissions. In fact, very few variables in our model showed significant impacts on emissions. The positive spatial autocorrelation of compliance status holds in most cases, whether or not we control for other explanatory variables, though these results depend in part on the way in which the spatial effects are assumed to operate across plants. Some of the models indicate that the spatial autocorrelations in the explanatory variables help explain part of the spatial autocorrelation observed in compliance status, though much of the autocorrelation generally remains. The models which directly incorporate spatially-lagged compliance status in the estimation often (but not always) find significant positive effects for those spatial lags.

Much of the explanatory power of the compliance models comes from plant-specific characteristics, with larger, older, and more pollution-abatement-intensive plants, and those in single-plant firms, having less 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. As expected, inspections at nearby plants in other states don't seem to increase compliance. Neither the local demographic characteristics nor measures of political activity have much impact on compliance.

Section 2 examines the various factors expected to influence environmental performance, including possible spatial characteristics of these models. Section 3 discusses some issues relating to spatial econometrics that are important for estimating our models. Section 4 describes the data used in the analysis. Section 5 presents the results, and Section 6 contains some concluding comments.

II. Determinants of Environmental Performance

Our model of the determinants of environmental performance begins with a profit-maximizing manufacturing plant[1], choosing how much effort to put into reducing pollution and complying with environmental regulations. Although the two dimensions of performance, compliance with air pollution regulations and emissions of air pollutants, are likely to be similar, there can certainly be discrepancies between them (e.g. paperwork-based violations). Because pollution is an externality, we would not expect a profit-maximizing plant to voluntarily reduce its pollution or improve its environmental performance, without some external incentives being provided for those improvements.

The major external influence on a plant's environmental performance is government regulation, provided in the US by state environmental regulators and the federal EPA. These agencies define a set of requirements for plants, ranging from permitted levels of pollution emissions to reporting of emissions and other paperwork requirements. In order to encourage plants to comply with the regulations, the agencies perform inspections and direct other enforcement actions at the plants, with the aim of identifying (and punishing) those plants which are not in compliance. For the set of plants we are considering, the bulk of the regulatory activity is carried out by state regulators, with some oversight by the federal EPA.

We expect that more vigorous regulatory activity will be associated with greater incentives for a plant to improve its environmental performance. As noted by Becker (1968), we can model the actions of a regulatory agency as increasing the expected costs of violating regulations. One component of the agency's actions is related to inspection activity, with a greater number of inspections increasing the probability that a violation will be detected. The

[1] We speak of profit-maximizing plants, rather than firms, since all of our data is for plants, not firms.

other component involves increasing the penalties imposed on any violations that are detected. The overall impact of regulation provides a 'deterrent' effect, by making the cost of poor performance greater than the costs of improving that performance.

In the case of environmental regulations the incentives to comply often seem quite limited, raising the question of why plants spend millions of dollars on pollution abatement. Regulatory agencies have limited resources to perform inspections and are limited in the amount of penalties they can impose (so the regulator can't impose an infinitely large penalty to make up for the relatively infrequent inspections). Harrington (1988) provides an explanation for compliance under these circumstances in the context of a repeated game, where the regulator can impose a bigger effective penalty by taking aggressive regulatory activity towards a plant for several periods after the initial violation, and making it difficult for the plant to earn its way back to being treated as a 'complier'.

Not all penalties for poor environmental performance are imposed by regulators. Plants may be reluctant to incur the bad publicity associated with being found in violation of environmental regulations, or being found to be one of the largest polluters in an area (even if the emissions levels are within the legal requirements). Poor performance may lead to boycotts by consumers, while good performance may lead to higher product demand through environmental labeling (more common in Europe than in the U.S.). Local community environmental groups might direct complaints about the plant to regulatory agencies, or become involved in the process of granting environmental permits to the plant. The strength of these external incentives to reduce pollution and increase compliance are likely to differ across plants, depending on the particular agency or local pressure groups involved.

Plants differ in other characteristics that may affect environmental performance, including age, size, industry, and multi-plant firm status. Older plants may have been designed without consideration for environmental issues, and might be very difficult to retrofit to meet new environmental regulations. On the other hand, older plants are often explicitly exempted from new regulations through grandfathering. This could generate a discrepancy between emissions-based and compliance-based measures of performance, where older plants might do worse on emissions and better on compliance, with the degree of this discrepancy providing a measure of the importance of grandfathering. Plants that are larger may find it cheaper to reduce emissions if there are economies of scale in pollution abatement, but they might also be more visible and subject to greater regulatory attention, providing another reason for discrepancies among the performance measures. The industry in which the plant is located is likely to be important, with some industries being associated with greater pollution emissions and more regulatory attention. Single-plant firms might be at a disadvantage in dealing with compliance issues, as they would need to rely on their own resources, rather than drawing on the expertise of a corporate-level environmental staff.

The deterrent effect of increased regulatory activity can be separated into 'general' and 'specific' deterrence. General deterrence refers to the impact of regulatory activity directed at other plants. More inspections at other plants cause uninspected plants to raise their own estimates of how likely they are to get caught if they choose to have poor environmental performance. One approach to measuring general deterrence is to incorporate the overall inspection rate into the model, assuming that each individual plant has rational expectations about this probability of being inspected. These overall inspection rates could be narrowed down to particular industries or particular states, if there are large differences in inspection rates across plants that should be knowable by the plants, with this variation making it possible to estimate the size of the general deterrence effects.

Specific deterrence refers to the impact of regulatory activity directed against this particular plant. It is expected that plants which have been inspected frequently in the past will feel more pressure to have good environmental performance. Specific deterrence may be associated with the regulatory process, where first offenses are sometimes presumed to have arisen through ignorance of the regulatory requirements, while repeat offenders who fail to abate problems pointed out on prior inspections are treated much more harshly. Another interpretation of specific deterrence is that plants are involved in Bayesian updating, so that having an inspection one year raises their expected probability of being inspected the following year. Some support from the Bayesian view comes from Scholz and Gray (1990), looking at OSHA enforcement, where inspections that imposed penalties improved performance (reduced injuries) while inspections that didn't impose penalties tended to worsen performance – arguably because being inspected and not penalized encourages the plant to be less worried about inspections in the future. In either event, the inspection history at a plant can be included in the model to capture specific deterrence effects, measured by a count of the number of inspections that happened in some prior time period or simply by a dummy variable indicating that the plant was inspected at least once during the period.

This paper is focused on looking for a spatial component in environmental performance, where the performance of one plant is correlated with the performance of other plants nearby. These spatial effects could arise for several different reasons, with different implications for the modeling and econometric solutions. First, spatial effects could be driven by spatially correlated exogenous variables driving environmental performance. If these exogenous variables are not explicitly included in the model they would result in spatially correlated residuals. One example of a spatially correlated exogenous variable is the tendency of plants in the same industry to cluster together (as found in Henderson (1999)). If plants in the same industry have similar problems with pollution abatement, we would observe spatially correlated environmental performance. If manufacturing plants were developed in different areas at different times, plants near each other would tend to be of similar age, and thus be affected in similar ways by inflexibility of their production processes and regulatory grandfathering. We might also expect to see similarities in the external pressures faced by plants. One area might have especially active local environmental groups, putting more pressure on all plants in the area. Some states might have more aggressive regulatory agencies, doing more inspections and imposing more penalties across all plants in the state (Gray and Deily (1996)).

Spatial effects could provide a way of testing for the importance of general deterrence effects. Plants could be especially attentive to the regulatory attention paid to nearby plants, so that a localized definition of the inspection rate for general deterrence might be more meaningful than a state-wide inspection rate. Different definitions of 'nearby' plants could be incorporated in the model, and interpreted as measuring the span of attention of individual plants. Since most of the regulatory activity is carried out at the state level, we would also expect that inspections at nearby plants would only matter when they are located in the same state – the experience of plants across the state border should be completely 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. This would involve a connection through the dependent variables, and could reflect behavior either of the plants or of the regulators involved. If one plant is doing especially well, it might provide a demonstration effect (that good performance is possible), putting more pressure on neighboring plants to perform well. This would be especially true if we broadened the objective function of the plant to include having good community relations, since measuring performance locally is likely to include comparisons of performance across the plants in the area.

Regulators might also have a preference for the spatial pattern of environmental performance. This could involve a negative relationship in the performance of neighboring plants. If the regulators are concerned about 'hot spots' developing when several poor performers are located nearby, they might tend to put extra pressure on the neighbors of a poorly performing plant. On the other hand, regulators might prefer to have bad performers clustered together, perhaps in a location far from politically influential residents. Such a motivation is assumed in Environmental Justice models, where poor and minority neighborhoods face the worst of the pollution due to regulatory indifference. Gray and Shadbegian (2002) test this for paper mills, finding greater pollution emissions in poor, but not minority, neighborhoods. This would lead to positive correlations in the performance of nearby plants.

III. Spatial Econometric Methods

As described in Anselin (1988), spatial econometrics incorporates information about the spatial orientation of data points into traditional economic models. At one level, spatial econometrics allows us to test whether the spatial dimension is an important component of the data. The spatial autocorrelation of variables provides an indication of whether data points near each other in space tend to be more similar than those further apart. This is comparable to examining correlation coefficients in an ordinary dataset, to see which variables have a significant relationship to each other, or to examining the autocorrelation of the residuals in a time-series dataset to see whether there seems to be an important time-dimension in the data. In this way, spatial autocorrelation is about testing for an effect, rather than using the effect to improve the overall model of the dependent variable.

Another level of spatial econometrics is to incorporate the spatial nature of the data into the model being examined. This can be done by including a spatially lagged version of the dependent variable (or of some of the explanatory variables) in the model. This is similar to including lagged dependent variables in a time-series model. Sometimes an explicit interpretation of the coefficient on the lagged variable is possible, as in models of capital investment or inventory accumulation, where the error term in one period reflects the discrepancy between desired and actual levels of the variable, and the coefficient reflects the costs of adjustment that keep the firm from completely adjusting to the desired level immediately. In other cases the lagged dependent variable simply provides a simple way to capture the tendency for time-series variables to change slowly over time. A model of adjustment costs could also be incorporated in an error-correction model, where the error terms in the model are explicitly included in the model (rather than being implicitly captured within the lagged dependent variable), with coefficients reflecting the adjustment process.

In our modeling we consider both spatial autocorrelation and spatially lagged estimation. The first step in our spatial analysis involves looking at the spatial autocorrelation of the environmental performance variables and the various explanatory variables. The second step measures the spatial autocorrelation of the residuals from regression models of environmental performance. The difference between the spatial autocorrelations measured in the first and second steps helps us categorize the tendency for similarity in environmental performance across nearby plants. If most of the spatial effects in the first step remain in the second step, then the spatial effects are due primarily to other factors influencing environmental performance that are not captured in our model. In this case, there may be a real spatial component to the model, with regulators paying attention to the performance of nearby plants – putting pressure on plants either to avoid 'hot spots' (if there is negative spatial autocorrelation) or to concentrate pollution in some areas while keeping other areas clean (if there is positive spatial autocorrelation). If the spatial effects from the first step disappear in the second step, then the spatial effects in environmental performance could be an artifact of the underlying spatial effects captured by the model, and our model does not require as much attention to spatial details.

The third step of the spatial analysis involves estimating a model that incorporates a spatially lagged error structure in the model itself. This presumes that we identified the presence of spatial effects in the first step, and concluded that they are not fully captured by the other explanatory variables in the model in the second step. Incorporating the spatially lagged dependent variable in model can be done in two different ways. If we are willing to assume that the underlying error terms in the model follow a normal distribution, we can use a maximum likelihood estimation model of the whole process, including the coefficient on the spatially lagged dependent variable. If we are unwilling to make that distributional assumption, we need a set of exogenous variables that can be used as instruments to predict the value of the spatially lagged dependent variable (predicting the value for the dependent variable for each of the nearby plants and then averaging them together to form the spatial lag). This predicted value can then be included in a regression model without fear of introducing a simultaneous-equations bias in the estimation – as long as the exogeneity of the instrumental variables holds.

We use the SpaceStat package (from TerraSeer) to perform all of our spatial econometric analyses.[2] This has the advantage of providing relatively simple procedures to do the major spatial econometric routines, along with close connections to the modeling discussions in Anselin (1988). However, the use of SpaceStat (combined with the authors' relative inexperience with spatial analysis) does limit the range of spatial analyses performed in this paper. One example is that we are unable to estimate limited dependent variable models, and instead use a linear probability model of compliance rather than a more suitable logit or probit analysis. We also had some difficulty in getting the maximum likelihood (ML) version of the spatially lagged models to run with the full dataset, so in this version of the paper we concentrate on an instrumental-variables (IV) based model of the spatial lag for the full dataset (running both IV and ML on a subsample of the dataset, and hoping to include the full-sample ML in a later version).

IV. 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 all near state borders, allowing us to test for differences in spatial impacts and regulation across states. The cities involved (and the states) are St. Louis (Missouri and Illinois), Cincinnati (Ohio, Kentucky, and Indiana), and Charlotte (North and South Carolina). An initial set of plants was drawn from EPA databases, selecting those within 50 miles of one of the cities. We use plant location information (latitude and longitude) from EPA's Envirofacts database, taken from the Permit Compliance System and the Toxic Release Inventory modules. The final sample

[2] Our preliminary, non-spatial analyses were done using Stata.

of 521 plants came from a merger of plant-level Census microdata and EPA data, requiring plants to have both Census and EPA data, including air pollution compliance information for 1997. A subsample of 102 plants have complete air pollution emissions data for particulates, sulfur dioxide, and nitrogen oxides.

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) to scale many of the other variables, as well as a direct measure of the plant's size, deflated and in log form (SIZE). Our control for plant age, AGE, is the plant's age in 1997 (1997 – year of birth).[3] We control for the plant's efficiency using labor productivity, LPROD, measured as real output per employee. Another dummy variable, SINGLE, for plants which are owned by single-plant 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 used the average value from 1991-1994,

[3] We would like to thank John Haltiwanger for providing the plant age information.

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.[4]

Our regulatory measures come from EPA databases. From the Integrated Database for Enforcement Activity (IDEA) 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).[5] To measure air pollution enforcement activity, we used 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.[6] We also created INSPNB, a spatially lagged version of INSPECT, which consisted of the total number of inspections during 1993-1995 at all manufacturing plants within 10 miles, and INSPNBOUT, the total number of inspections during 1993-1995 at all manufacturing plants located within 10 miles of the plant, but located in a neighboring state. For a state-level measure of overall regulatory activity, STACT, we calculated the average number of regulatory actions in 1997 per plant in the Air Facility Subsystem part of Envirofacts database for each state (in this calculation we included all regulatory activity, including enforcement actions as well as inspections, since this state-level average is not endogenously determined by an individual plant's compliance status).

Data on air pollution emissions come from EPA's 1996 Emissions Inventory database (only collected every few years). These represent the tons of emissions per year for three

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[4] We imputed PAOC based on published 4-digit industry data for plants which didn't have PACE data.
[5] There are several different codes for compliance status in the EPA data, but only one or two of the non-compliance codes are very frequent, so it wasn't practical to consider a multinomial measure of compliance. We follow EPA's categorization of which codes refer to non-compliance.
[6] We didn't want to include other enforcement actions because of their potential endogeneity with compliance status at the plant level.

different pollutants: particulates under 2.5 microns (PM25TVS), sulfur dioxide (SO2TVS), and nitrogen oxides (NOXTVS). Each of these variables have been scaled by the plant's total value of shipments in 1997, so they represent a pollution intensity in terms of tons of pollution per thousand dollars of shipments.

We use demographic information at the block group level from the 1990 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). Two groups potentially more sensitive to air pollution are the old and the very young. We measure these by ELDERS, the fraction of the population who are 65 or older, and KIDS, the fraction of the population who are under 6. For "Environmental Justice" reasons we might expect plants located in poor and minority neighborhoods to face less pressures to improve environmental performance. We measure these factors by POOR, the fraction of the population living below the poverty line, and MINORITY, the fraction of the population which 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 candidate in 1992. ENVSPEND is the percentage of the budgets of all local governments within the county which 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. We found some evidence for this effect in earlier work (Gray and Shadbegian (2002)).

V. Results

We begin by examining the determinants of environmental performance in a traditional econometric setting, without spatial considerations. Table 1 presents summary statistics for the variables used in our analysis. Note that our analysis of the determinants of emissions is limited to 102 plants, while our analysis of the determinants of compliance can use all 521 plants. Plants with emissions data don't seem very different from the other plants. They are less likely to be in compliance with air regulations (81% vs 88%) and have a history of receiving slightly more air inspections – though neither sample is getting very many inspections, with only 37% of the plants in the full sample receiving any air inspections in the 1993-1995 period. The plants with emissions data are slightly larger, slightly less productive, and have about the same demographics in the nearby population. More surprisingly, they have lower average pollution abatement operating costs, and are less likely to be in one of the industries we designated as 'dirty'.

Table 2 presents the results from our basic models of air compliance. As noted above, the spatial econometric analyses we perform later didn't include options for limited dependent variables, so most of the models we present are for ordinary regressions. We did comparable sets of logit models (shown here in models 2e and 2f), which gave nearly identical results for all the variables. Most of the significant results we find are for the plant characteristics. Larger plants are significantly less likely to be in compliance. Plants with higher pollution abatement costs are also less likely to be in compliance, probably reflecting (endogenous) pressures for increased abatement efforts at plants with chronically poor compliance. Both of these effects are reasonably large: a one standard deviation change in either SIZE or PAOC is associated with 5-6% lower compliance, and only 12% of the plants in the sample are out of compliance. Plants that belong to single-plant firms also have significantly lower compliance.[7] Plants in dirty industries are less likely to be in compliance, reducing compliance by about 7%, though this effect is only marginally significant. The effects of plant age and productivity are not significant, though they do go in the expected direction (younger and more productive plants are more often in compliance).

The demographics of the surrounding population show some reasonable signs, but not much significance. Plants surrounded by a more elderly population are more likely to be in compliance, as are plants with more young children nearby. Both are groups expected to be more sensitive to air pollution, and would therefore result in more pressure on plants to improve their performance. Though not significant, we find worse performance in poor neighborhoods, but better performance in minority neighborhoods (similar to Gray and Shadbegian (2002)).

The political variables are not significant, although their signs are consistent across models 2c-2f. Plants located in counties which spend more on environmental activities, counties with higher voter turnout, and (surprisingly) counties with more Republican voting, have higher compliance rates. Plants located near state borders also show greater compliance, possibly surprising if we expect regulators to pay less attention to those plants (though perhaps a lack of

[7] The table shows the sign for SINGLE, but not its numerical coefficients, for disclosure reasons. SINGLE is not included in the emissions subsample analyses because very few of those samples are in single-plant firms

attention would correspond to imposing less stringent standards, which might make it easier for the plant to be in compliance).

The results for regulatory activity generally show the expected signs, but are not always significant. Plants that had more inspections themselves in 1993-1995 (INSPECT) have higher compliance rates, but only approach significance in the logit model. Plants in states that are doing more air regulatory actions per plant in 1997 (STACT) are more often in compliance; this effect is significant in model 2b, but becomes smaller and less significant as other explanatory variables are added to the model. Of these two regulatory variables, INSPECT represents a specific deterrence effect and STACT represents general deterrence. An alternative measure of general deterrence is provided in Models 2d and 2f, when we look at inspections at nearby plants, differentiating between those in the same state and those in different states. The main effect (INSPNB), reflecting the effect of having more inspections at nearby plants in the same state, is positive and marginally significant. The differential effect of having more inspections at nearby plants in another state (INSPNBOUT) is negative and also marginally significant. Since the out-of-state coefficient is larger than the overall one, the net effect of more inspections at nearby plants in another state is negative (though not significant). This pattern of signs is consistent with state regulators, concerned about local hot spots, not bothering with areas where neighboring regulators are already putting on their own pressure.

In Table 3 we turn to air pollution emissions, finding somewhat weaker and less expected results. Since we are examining data for three pollutants, we present fewer models for each pollutant, but the general results are consistent across the wider range of models corresponding to Table 2. We expected to find opposite coefficients from those in Table 2 – plants with more emissions being less likely to be in compliance. Instead, nearly all of the plant characteristics have the same signs in Tables 2 and 3 (though most coefficients in Table 3 are statistically insignificant). The only consistently significant result is for SIZE, where larger plants are likely to emit less air pollution, an apparent contradiction of the results in Table 2, while larger plants had poorer compliance levels. This 'contradiction' may be explained by larger plants having more opportunities to be in violation, or facing greater scrutiny from regulators. Emissions are greater at older plants, but this is only significant for particulate. The demographic variables are generally not significant, and tend to have the same sign as the compliance results more often than not. The political variables are also insignificant. A surprising result is that a past history of having had more air pollution inspections (INSPECT) is associated with having more emissions for sulfur dioxide and nitrogen oxides; the state-level general deterrence measure is at least negative, though not significant.

We now turn to the spatial dimension of the data. In Table 4 we examine the degree of spatial autocorrelation in our data, using Moran's I test and two spatial weighting matrices.[8] The first weighting matrix gives equal weight to all plants within 10 miles (DIS10), while the second weighting matrix gives weights inversely proportional to the squared distance between the plants, again applied only to plants within 10 miles (DISSQ). Most of the explanatory variables show some evidence of positive spatial autocorrelation, especially with the DIS10 weighting matrix.[9] INSPECT is the only explanatory variable which shows no evidence of spatial effects in any specification.

Of the measures of environmental performance, only compliance shows strong evidence of spatial effects. A plant's compliance status tends to be positively correlated with the

[8] We don't bother calculating spatial correlations for the neighborhood- or county-based variables which would be strongly correlated by their construction.

[9] Given the relatively scattered nature of our plants, the DISSQ measure might be placing too much weight on a few plants that happen to be especially close together

compliance status of nearby plants, especially using the DIS10 weights (the DISSQ weights in the full sample show no spatial effects). None of the emissions measures show any significant evidence of spatial autocorrelation, with sulfur dioxide and nitrogen oxides showing negative autocorrelation (though not significant).[10]

Table 4 also presents the results of tests for spatial dependence in the regression residuals for the dependent variables. As expected from the spatial autocorrelation results, only COMPLY shows any evidence of spatial effects, and these appear (to some degree) in all cases except the full-sample model using DISSQ weights. However, depending on the test statistic used, we sometimes see a significant reduction in the strength of the spatial autocorrelation of the residuals, compared to the original COMPLY spatial autocorrelations. This suggests that at least some of the apparent spatial effects in COMPLY are due to the effects of spatially autocorrelated explanatory variables in the model.

Having found some evidence for spatial autocorrelation, at least for compliance, we now examine whether controlling for these spatial effects has any impact on the estimated coefficients for other explanatory variables. Tables 5-7 show the results for models of the compliance decision that incorporate spatially lagged effects. Table 5 shows the results for the full sample using an IV model, Table 6 shows the results for the emissions subsample using an IV model, and Table 7 shows the results for the emissions subsample using a ML model.[11] We see a significantly positive impact of the spatially lagged compliance of nearby plants for the emissions subsample, with stronger results for the ML estimates (but surprisingly not much effect for the full sample IV model). The coefficients and significance on the other explanatory

[10] A few specifications we tested did show spatial effects for one or more pollutants, but none as strong or as consistent as those for compliance status.
[11] As noted earlier, we haven't gotten the maximum likelihood estimation with the full sample to work yet.

variables in the full sample model have not changed much, when compared to Table 2.[12] The results are quite similar, regardless of the spatial weights used.

Tables 8 and 9 show similar results for the various emissions measures, with IV results in Table 8 and ML results in Table 9. The results for the spatially lagged performance of nearby plants are not significant, consistent with the earlier results in Table 4. As we found back in Table 3, the other explanatory variables aren't very often significant, but the pattern of signs and significance in Tables 8 and 9 is similar to that seen in Table 3, including the puzzling relationship between the plants with more inspections having higher emissions of sulfur dioxide and nitrogen oxides.

VI. Conclusions

We have examined a variety of ways in which models of the environmental performance (compliance and emissions) of manufacturing plants can incorporate spatial components. The spatial approaches include creating explanatory variables based on information related to the plant's location and the location of nearby plants, testing for spatial autocorrelation in environmental performance and the explanatory variables, examining whether spatial factors in the explanatory variables explain the spatial factors in environmental performance, and directly modeling the spatial component of environmental performance with spatially lagged dependent variables. Our analysis used data from EPA and Census datasets on 521 manufacturing plants in the compliance analysis and 102 plants in the emissions analysis.

Our results indicate significant positive spatial autocorrelation for compliance status, but no such spatial effects are observed for emissions. In fact, very few variables in our model show

[12] Though not presented here, the coefficients for the explanatory variables in Tables 6 and 7 are very similar to those for non-spatial regression analyses on the emissions subsample.

significant impacts on emissions. The positive spatial autocorrelation of compliance status holds in most cases, whether or not we control for other explanatory variables, though these results depend in part on the way in which the spatial effects are assumed to operate across plants. Some of the models indicate that the spatial autocorrelations in the explanatory variables help explain part of the spatial autocorrelation observed in compliance status, though much of the autocorrelation in compliance usually remains unexplained. Models which directly incorporate spatially-lagged compliance status in the estimation often (but not always) find significant positive effects for those spatial lags.

Much of the explanatory power of the compliance models comes from plant-specific characteristics, with larger, older, and more pollution-abatement-intensive plants, and those in single-plant firms, having less 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. As expected, inspections at nearby plants in other states don't seem to increase compliance. Neither the local demographic characteristics nor measures of political activity have much impact on compliance.

These results indicate a significant, but limited, role for spatial factors in modeling environmental performance. Controlling directly for spatial factors doesn't substantially change the estimated impact of the other explanatory variables in the model, nor do the spatial factors explain a huge amount of the variation in compliance across plants. In the near term we plan to test a variety 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. In the longer term, we hope to expand the analysis to include panel data on air pollution performance and information from other regulatory datasets such as EPA's Toxic Release Inventory and

OSHA's inspection data. This will help us provide a richer picture of the spatial connections across plants, and may increase our ability to explain what determines them (our initial hope to include an analysis of water pollution performance here was frustrated by the small number of these plants with any water pollution data, so a comparable analysis on the water side will have to wait for an alternative set of plants).

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Table 1
Descriptive Statistics
Compliance Sample (N=521) and Emissions Sample (N=102)

Sample: Variable	Emissions mean (s.d)	Compliance mean (s.d.)	Description
Dependent Variables			
COMPLY	0.814 (0.391)	0.877 (0.329)	Dummy variable=1 if a plant is in compliance with air regulations in 1997
PM25TVS	0.360 (0.718)		Particulates emissions under 2.5 microns/shipments (1000's tons) in 1996
SO2TVS	3.613 (17.933)		Sulfur dioxide emissions/shipments (1000's tons) in 1996
NOXTVS	2.886 (15.182)		Nitrogen oxide emissions/shipments (1000's tons) in 1996
Inspection Activity			
INSPECT	0.500 (0.793)	0.473 (0.709)	Number of plant inspections (1993-1995)
STACT	0.622 (0.257)	0.557 (0.229)	Average number of regulatory actions per plant in state (1997)
INSPNB	15.951 (14.121)	16.837 (15.513)	Total number of inspections at all manufacturing plants within 10 miles (1993-1995)
INSPNBOUT	3.853 (12.115)	2.516 (7.837)	Total number of inspections at all manufacturing plants located within 10 miles of the plant, but located in a neighboring state (1993-1995)
Plant Characteristics			
SIZE	10.776 (1.305)	10.408 (1.541)	Log of real shipments in 1997
AGE	40.522 (20.667)	41.535 (19.530)	Age of the plant = 1997- year plant was opened
LPROD	0.303 (0.376)	0.331 (0.436)	Log of real shipments/employment
PAOC	0.796 (0.918)	0.917 (1.481)	Pollution abatement operating costs/shipments (1991-1994)
DIRTYSIC	0.314 (0.466)	0.361 (0.481)	Dummy variable =1 if a plant is in SIC 26, 28, 29, 33, or 34
Demographic Variables			
POOR	11.390 (4.270)	11.106 (4.122)	Percentage of the local population living below the poverty line in 1990
ELDERS	12.214 (1.827)	11.947 (2.183)	Percentage of the local population 65 or older in 1990
MINORITY	18.359 (11.686)	18.989 (12.067)	Percentage of the local population nonwhite in 1990
KIDS	8.408 (0.704)	8.683 (0.734)	Percentage of the local population 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 local government spending on environmental amenities
DEMOCRAT		0.401 (0.107)	Fraction in the county voting for the Democratic candidate in 1992
TURNOUT		0.549 (0.488)	Fraction of registered voters in the county voting in the 1992 Presidential election

Note: some of the N=521 numbers really refer to an earlier sample of 349 plants; these numbers will be corrected in the next version.

TABLE 2
BASIC COMPLIANCE MODELS
(N=521)

DEPVAR	2a COMPLY	2b COMPLY	2c COMPLY	2d COMPLY	2e COMPLY	2f COMPLY
INSPECT		0.015 (0.817)	0.025 (1.372)	0.028 (1.513)	0.325 (1.456)	0.376 (1.650)
INSPNB				0.002 (1.590)		0.027 (1.699)
INSPNBOUT				-0.004 (-1.650)		-0.047 (-1.744)
STACT		0.171 (2.776)	0.140 (1.222)		1.113 (0.961)	
SIZE	-0.036 (-3.212)		-0.035 (-3.001)	-0.035 (-3.024)	-0.380 (-2.898)	-0.374 (-2.867)
AGE	-0.001 (-0.677)		-0.001 (-1.094)	-0.001 (-1.365)	-0.010 (-1.155)	-0.012 (-1.485)
LPROD	-0.003 (-0.082)		-0.004 (-0.093)	-0.006 (-0.151)	-0.023 (-0.059)	-0.067 (-0.172)
SINGLE	--		--	--	--	--
DIRTYSIC	-0.066 (-2.122)		-0.066 (-2.004)	-0.070 (-2.168)	-0.811 (-2.316)	-0.865 (-2.459)
PAOC	-0.032 (-3.046)		-0.032 (-3.008)	-0.032 (-2.940)	-0.220 (-2.454)	-0.209 (-2.195)
POOR			-0.005 (-0.673)	-0.006 (-0.833)	-0.035 (-0.469)	-0.033 (-0.497)
MINORITY			0.003 (1.391)	0.003 (1.747)	0.026 (1.188)	0.028 (1.312)
ELDERS			0.019 (1.850)	0.018 (1.765)	0.190 (1.664)	0.184 (1.626)
KIDS			0.018 (0.633)	0.015 (0.582)	0.136 (0.504)	0.152 (0.590)
BORDER			0.033 (0.958)	0.023 (0.655)	0.255 (0.654)	0.229 (0.583)
ENVSPEND			0.006 (1.121)	0.004 (0.695)	0.125 (0.818)	0.080 (0.600)
DEMOCRAT			-0.095 (-0.488)	-0.275 (-1.343)	-1.136 (-0.513)	-3.156 (-1.294)
TURNOUT			0.337 (1.285)	0.148 (0.677)	3.664 (1.191)	2.825 (1.001)
R2	0.070	0.016	0.102	0.106	0.138	0.147
ESTIMATOR	OLS	OLS	OLS	OLS	LOGIT	LOGIT
-LOG-L					-155.13	-153.53

Notes: (T-Statistics)

TABLE 3
BASIC EMISSION MODELS -- OLS
(N=102)

DEPVAR	3a PM25TVS	3b PM25TVS	3c SO2TVS	3d SO2TVS	3e NOXTVS	3f NOXTVS
INSPECT	0.102 (1.019)	0.089 (0.875)	5.602 (2.190)	5.691 (2.204)	4.139 (1.930)	4.039 (1.860)
INSPNB		-0.000 (-0.041)		0.065 (0.250)		0.028 (0.130)
INSPNBOUT		0.003 (0.203)		-0.122 (-0.293)		-0.081 (-0.232)
STACT	-0.954 (-1.204)		-0.352 (-0.017)		-12.007 (-0.710)	
SIZE	-0.106 (-1.595)	-0.113 (-1.672)	-3.541 (-2.085)	-3.524 (-2.067)	-2.796 (-1.963)	-2.857 (-1.993)
AGE	0.011 (2.995)	0.011 (3.000)	0.047 (0.500)	0.044 (0.455)	0.065 (0.817)	0.063 (0.783)
LPROD	0.028 (0.125)	0.079 (0.354)	0.837 (0.148)	0.903 (0.159)	-0.630 (-0.132)	-0.076 (-0.016)
DIRTYSIC	-0.143 (-0.686)	-0.076 (-0.371)	-0.234 (-0.044)	-0.180 (-0.035)	-1.264 (-0.284)	-0.235 (-0.054)
PAOC	0.007 (0.079)	0.008 (0.088)	-0.439 (-0.186)	-0.450 (-0.188)	-0.637 (-0.322)	-0.698 (-0.347)
POOR	-0.027 (-0.655)	-0.021 (-0.512)	0.049 (0.048)	0.058 (0.056)	-0.068 (-0.079)	0.018 (0.021)
MINORITY	0.010 (1.028)	0.007 (0.649)	0.035 (0.136)	0.053 (0.187)	0.086 (0.400)	0.086 (0.360)
ELDERS	-0.005 (-0.081)	-0.004 (-0.063)	0.957 (0.571)	1.056 (0.615)	0.281 (0.200)	0.380 (0.263)
KIDS	-0.017 (-0.081)	0.059 (0.279)	1.383 (0.257)	1.836 (0.346)	-1.466 (-0.325)	-0.160 (-0.036)
BORDER	-0.261 (-1.151)	-0.187 (-0.817)	-0.889 (-0.154)	-0.615 (-0.106)	-2.530 (-0.521)	-1.037 (-0.213)
ENVSPEND	-0.014 (-0.508)	0.001 (0.035)	-0.321 (-0.464)	-0.339 (-0.526)	-0.152 (-0.262)	-0.005 (-0.009)
DEMOCRAT	0.356 (0.193)	1.786 (1.207)	5.375 (0.114)	7.381 (0.198)	4.881 (0.124)	22.987 (0.732)
TURNOUT	-1.797 (-0.911)	-1.024 (-0.511)	-21.321 (-0.425)	-16.078 (-0.317)	-41.695 (-0.990)	-24.646 (-0.579)
R2	0.207	0.194	0.175	0.176	0.191	0.187

Notes: (T-Statistics)

TABLE 4

A. MORAN'S I TEST FOR SPATIAL AUTOCORRELATION IN THE DEPENDENT VARIABLES (normal approximation)

VARIABLE	OBS	WEIGHT	I	ST DEV	Z-VALUE	P-VALUE
COMPLY	521	DIS10	0.0593	0.0190	3.230	0.001
COMPLY	521	DISSQ	0.0276	0.0360	0.821	0.412
COMPLY	102	DIS10	0.1484	0.0731	2.165	0.030
COMPLY	102	DISSQ	0.1512	0.0969	1.662	0.097
PM25TVS	102	DIS10	0.0222	0.0731	0.434	0.660
PM25TVS	102	DISSQ	0.0441	0.0969	0.557	0.578
SO2TVS	102	DIS10	-0.0194	0.0731	-0.130	0.897
SO2TVS	102	DISSQ	-0.0150	0.0969	-0.053	0.958
NOXTVS	102	DIS10	-0.0121	0.0731	-0.030	0.976
NOXTVS	102	DISSQ	-0.0109	0.0969	-0.010	0.992

B. TESTS OF SPATIAL AUTOCORRELATION IN THE ERRORS

DEPVAR	LM-ERR	LM-ERR	MORAN I	MORAN I	LM-LAG	LM-LAG
WEIGHT	DIS10	DISSQ	DIS10	DISSQ	DIS10	DISSQ
COMPLY (n=521)	2.061	0.875	2.346	-0.444	0.420	0.998
	(0.15)	(0.35)	(0.02)	(0.66)	(0.52)	(0.32)
COMPLY (n=102)	5.585	3.191	4.075	2.917	5.212	4.551
	(0.02)	(0.07)	(0.00)	(0.00)	(0.02)	(0.03)
PM25TVS	0.129	0.007	0.877	1.110	0.085	0.000
	(0.72)	(0.94)	(0.38)	(0.27)	(0.77)	(1.00)
SO2TVS	1.370	0.122	-0.075	0.654	0.751	0.197
	(0.24)	(0.73)	(0.94)	(0.51)	(0.39)	(0.66)
NOXTVS	0.924	0.143	0.170	0.623	0.439	0.132
	(0.34)	(0.70)	(0.86)	(0.53)	(0.51)	(0.72)

C. MORAN'S I TEST FOR SPATIAL AUTOCORRELATION IN THE EXPLANATORY VARIABLES (normal approximation)

VARIABLE	OBS	WEIGHT	I	ST DEV	Z-VALUE	P-VALUE
INSPECT	521	DIS10	0.0062	0.0190	0.430	0.667
INSPECT	521	DISSQ	-0.0049	0.0360	-0.083	0.934
LPROD	521	DIS10	0.0729	0.0190	3.951	0.000
LPROD	521	DISSQ	0.1192	0.0360	3.370	0.001
AGE	521	DIS10	0.1136	0.0190	6.096	0.000
AGE	521	DISSQ	0.1440	0.0360	4.058	0.000
PAOC	521	DIS10	0.0516	0.0190	2.825	0.005
PAOC	521	DISSQ	0.1043	0.0360	2.956	0.003
SIZE	521	DIS10	0.0689	0.0190	3.737	0.000
SIZE	521	DISSQ	0.0867	0.0360	2.465	0.014
INSPECT	102	DIS10	0.0670	0.0731	1.053	0.293
INSPECT	102	DISSQ	0.1040	0.0969	1.176	0.240
LPROD	102	DIS10	0.1229	0.0731	1.817	0.069
LPROD	102	DISSQ	0.1863	0.0969	2.025	0.043
AGE	102	DIS10	0.0306	0.0731	0.554	0.580
AGE	102	DISSQ	0.0129	0.0969	0.235	0.814
PAOC	102	DIS10	0.1407	0.0731	2.061	0.039
PAOC	102	DISSQ	0.0892	0.0969	1.023	0.306
SIZE	102	DIS10	0.1346	0.0731	1.976	0.048
SIZE	102	DISSQ	0.2424	0.0969	2.604	0.009

TABLE 5
SPATIAL LAG COMPLIANCE MODELS
(N=521) -- INSTRUMENTAL VARIABLES

	5a	5b	5c	5d	5e	5f
DEPVAR	COMPLY	COMPLY	COMPLY	COMPLY	COMPLY	COMPLY
WEIGHT	DIS10	DIS10	DIS10	DISSQ	DISSQ	DISSQ
W_COMPLY	-0.144	-0.023	0.002	-0.018	-0.004	0.007
	(-1.18)	(-0.23)	(0.02)	(-0.15)	(-0.04)	(0.07)
INSPECT	0.015	0.025	0.028	0.015	0.025	0.028
	(0.81)	(1.36)	(1.51)	(0.83)	(1.37)	(1.50)
INSPNB			0.002			0.002
			(1.56)			(1.53)
INSPNBOUT			-0.004			-0.004
			(-1.65)			(-1.62)
STACT	0.197	0.146		0.176	0.142	
	(2.98)	(1.24)		(2.52)	(1.18)	
SIZE		-0.035	-0.035		-0.035	-0.035
		(-3.00)	(-3.02)		(-3.00)	(-3.02)
AGE		0.001	-0.001		0.001	-0.001
		(-1.07)	(-1.36)		(-1.09)	(-1.36)
LPROD		-0.004	-0.006		-0.003	-0.006
		(-0.10)	(-0.15)		(-0.09)	(-0.15)
PAOC		-0.032	-0.032		-0.032	-0.032
		(-2.98)	(-2.93)		(-3.00)	(-2.94)
SINGLE		--	--		--	--
DIRTYSIC		-0.066	-0.070		-0.066	-0.070
		(-2.01)	(-2.16)		(-2.00)	(-2.15)
POOR		-0.005	-0.006		-0.005	-0.006
		(-0.71)	(-0.79)		(-0.66)	(-0.74)
MINORITY		0.003	0.003		0.003	0.003
		(1.38)	(1.59)		(1.32)	(1.54)
ELDERS		0.020	0.018		0.019	0.018
		(1.86)	(1.74)		(1.80)	(1.70)
KIDS		0.019	0.015		0.018	0.015
		(0.66)	(0.58)		(0.63)	(0.58)
BORDER		0.034	0.023		0.034	0.023
		(0.98)	(0.65)		(0.95)	(0.64)
ENVSPEND		0.006	0.004		0.006	0.004
		(1.14)	(0.68)		(1.10)	(0.67)
DEMOCRAT		-0.099	-0.274		-0.096	-0.272
		(-0.51)	(-1.31)		(-0.49)	(-1.30)
TURNOUT		0.338	0.149		0.338	0.151
		(1.29)	(0.67)		(1.28)	(0.68)
R2	0.023	0.102	0.106	0.016	0.102	0.106
LM-ERR	5.173	0.978	0.602	0.061	0.192	0.260
	(0.02)	(0.32)	(0.44)	(0.81)	(0.66)	(0.61)

TABLE 6
SPATIAL LAG COMPLIANCE MODELS
(N=102) -- INSTRUMENTAL VARIABLES

	6a	6b	6c	6d	6e	6f
DEPVAR	COMPLY	COMPLY	COMPLY	COMPLY	COMPLY	COMPLY
WEIGHT	DIS10	DIS10	DIS10	DISSQ	DISSQ	DISSQ
W_COMPLY	0.281	0.498	0.508	0.265	0.528	0.512
	(1.36)	(2.93)	(2.73)	(1.20)	(3.45)	(2.91)
INSPECT	-0.021	-0.006	-0.013	-0.021	0.001	-0.007
	(-0.43)	(-0.12)	(-0.26)	(-0.43)	(0.02)	(-0.14)
INSPNB			-0.004			-0.005
			(-0.68)			(-0.88)
INSPNBOUT			0.003			0.004
			(0.34)			(0.49)
STACT	0.066	-0.223		0.081	-0.193	
	(0.44)	(-0.54)		(0.55)	(-0.46)	
SIZE		-0.079	-0.081		-0.074	-0.076
		(-2.30)	(-2.35)		(-2.10)	(-2.17)
AGE		-0.004	-0.004		-0.004	-0.004
		(-2.00)	(-1.98)		(-1.83)	(-1.82)
LPROD		-0.036	-0.037		-0.056	-0.059
		(-0.31)	(-0.32)		(-0.47)	(-0.49)
PAOC		-0.117	-0.122		-0.118	-0.123
		(-2.44)	(-2.49)		(-2.40)	(-2.47)
DIRTYSIC		0.147	0.176		0.127	0.153
		(1.34)	(1.60)		(1.14)	(1.39)
POOR		-0.013	-0.011		-0.004	-0.002
		(-0.58)	(-0.50)		(-0.17)	(-0.08)
MINORITY		0.003	0.004		0.001	0.002
		(0.59)	(0.61)		(0.28)	(0.37)
ELDERS		0.029	0.027		0.022	0.018
		(0.86)	(0.77)		(0.62)	(0.50)
KIDS		0.001	0.005		-0.001	-0.004
		(0.01)	(0.04)		(-0.01)	(-0.04)
BORDER		-0.112	-0.071		-0.173	-0.137
		(-0.90)	(-0.54)		(-1.43)	(-1.11)
ENVSPEND		0.001	0.004		0.003	0.006
		(0.10)	(0.31)		(0.22)	(0.42)
DEMOCRAT		-0.049	0.156		0.080	0.176
		(-0.05)	(0.21)		(0.08)	(0.23)
TURNOUT		-0.560	-0.276		-0.517	-0.265
		(-0.55)	(-0.27)		(-0.49)	(-0.25)
R2	0.049	0.344	0.337	0.057	0.415	0.388
LM-ERR	0.001	0.087	0.133	0.205	3.364	2.503
	(0.98)	(0.77)	(0.72)	(0.65)	(0.07)	(0.11)

Notes: (T-Statistics)

TABLE 7
SPATIAL LAG COMPLIANCE MODELS
(N=102) -- MAXIMUM LIKELIHOOD

	7a	7b	7c	7d	7e	7f
DEPVAR	COMPLY	COMPLY	COMPLY	COMPLY	COMPLY	COMPLY
WEIGHT	DIS10	DIS10	DIS10	DISSQ	DISSQ	DISSQ
W_COMPLY	0.297	0.266	0.270	0.214	0.198	0.200
	(3.00)	(2.75)	(2.70)	(2.46)	(2.34)	(2.32)
INSPECT	-0.021	-0.002	-0.006	-0.020	0.002	-0.002
	(-0.44)	(-0.05)	(-0.13)	(-0.43)	(0.03)	(-0.04)
INSPNB			-0.001			-0.001
			(-0.29)			(-0.25)
INSPNBOUT			0.002			0.002
			(0.23)			(0.25)
STACT	0.064	-0.169		0.085	-0.140	
	(0.44)	(-0.46)		(0.58)	(-0.38)	
SIZE		-0.078	-0.079		-0.075	-0.077
		(-2.51)	(-2.55)		(-2.42)	(-2.46)
AGE		-0.004	-0.004		-0.004	-0.004
		(-2.17)	(-2.11)		(-2.09)	(-2.02)
LPROD		-0.015	-0.010		-0.015	-0.010
		(-0.15)	(-0.09)		(-0.15)	(-0.10)
PAOC		-0.111	-0.112		-0.110	-0.110
		(-2.57)	(-2.58)		(-2.53)	(-2.52)
DIRTYSIC		0.113	0.129		0.094	0.105
		(1.17)	(1.37)		(0.96)	(1.12)
POOR		-0.005	-0.004		0.001	0.002
		(-0.24)	(-0.19)		(0.08)	(0.12)
MINORITY		0.002	0.002		0.001	0.001
		(0.43)	(0.33)		(0.22)	(0.11)
ELDERS		0.028	0.027		0.025	0.024
		(0.92)	(0.87)		(0.81)	(0.76)
KIDS		0.023	0.031		0.030	0.035
		(0.24)	(0.32)		(0.31)	(0.36)
BORDER		-0.167	-0.148		-0.209	-0.197
		(-1.55)	(-1.37)		(-1.94)	(-1.82)
ENVSPEND		0.004	0.007		0.006	0.008
		(0.35)	(0.58)		(0.48)	(0.71)
DEMOCRAT		-0.157	0.055		-0.146	0.034
		(-0.18)	(0.08)		(-0.17)	(0.05)
TURNOUT		-0.427	-0.285		-0.366	-0.284
		(-0.47)	(-0.31)		(-0.40)	(-0.31)
R2	0.054	0.271	0.270	0.040	0.267	0.266

Notes: (T-Statistics)

TABLE 8
SPATIAL LAG EMISSION MODELS
(N=102) -- INSTRUMENTAL VARIABLES

	8a	8b	8c	8d	8e	8f
DEPVAR	PM25TVS	PM25TVS	SO2TVS	SO2TVS	NOXTVS	NOXTVS
WEIGHT	DIS10	DISSQ	DIS10	DISSQ	DIS10	DISSQ
W_X	0.368	0.154	0.284	0.051	0.260	0.114
	(0.91)	(0.71)	(1.07)	(0.13)	(1.08)	(0.36)
INSPECT	0.083	0.090	4.548	5.645	3.165	3.956
	(0.79)	(0.87)	(1.58)	(2.15)	(1.33)	(1.79)
INSPNB	-0.002	0.001	0.077	0.064	0.043	0.028
	(-0.14)	(-0.09)	(0.29)	(0.25)	(0.19)	(0.13)
INSPNBOUT	0.004	0.005	-0.130	-0.120	-0.073	-0.059
	(0.21)	(0.29)	(-0.30)	(-0.29)	(-0.20)	(-0.16)
SIZE	-0.109	-0.107	-3.838	-3.513	-3.170	-2.863
	(-1.57)	(-1.54)	(-2.14)	(-2.04)	(-2.11)	(-1.97)
AGE	0.012	0.012	0.027	0.046	0.053	0.067
	(3.00)	(3.00)	(0.27)	(0.47)	(0.64)	(0.81)
LP	0.102	0.093	1.727	0.974	0.827	0.207
	(0.44)	(0.41)	(0.29)	(0.17)	(0.17)	(0.04)
PAOC	0.016	0.013	-0.248	-0.415	-0.514	-0.622
	(0.17)	(0.13)	(-0.10)	(-0.17)	(-0.25)	(-0.30)
DIRTYSIC	-0.054	-0.081	-0.282	-0.245	-0.322	-0.389
	(-0.26)	(-0.39)	(-0.05)	(-0.05)	(-0.07)	(-0.09)
POOR	0.001	-0.008	-0.066	0.073	-0.070	0.063
	(-0.01)	(-0.19)	(-0.06)	(0.07)	(-0.08)	(0.07)
MINORITY	0.005	0.006	0.054	0.050	0.079	0.070
	(0.39)	(0.48)	(0.18)	(0.17)	(0.32)	(0.29)
ELDERS	-0.033	-0.026	0.845	0.975	0.181	0.213
	(-0.43)	(-0.34)	(0.47)	(0.53)	(0.12)	(0.14)
KIDS	-0.015	0.011	1.880	1.756	-0.429	-0.440
	(-0.06)	(0.05)	(0.34)	(0.33)	(-0.09)	(-0.10)
BORDER	-0.169	-0.188	0.357	-0.601	0.180	-0.978
	(-0.72)	(-0.81)	(0.06)	(-0.10)	(0.04)	(-0.20)
ENVSPEND	0.005	0.003	-0.318	-0.335	-0.009	-0.005
	(0.17)	(0.10)	(-0.48)	(-0.51)	(-0.02)	(-0.01)
DEMOCRAT	1.265	1.495	14.132	7.740	23.927	21.380
	(0.78)	(0.96)	(0.36)	(0.20)	(0.74)	(0.67)
TURNOUT	-1.219	-1.129	-10.513	-15.750	-15.984	-23.341
	(-0.59)	(-0.55)	(-0.20)	(-0.31)	(-0.36)	(-0.54)
R2	0.213	0.207	0.196	0.176	0.205	0.191
LM-ERR	0.914	0.436	3.294	0.072	2.609	0.247
	(0.34)	(0.51)	(0.07)	(0.79)	(0.11)	(0.62)

Notes: (T-Statistics)
X = PM25TVS, SO2TVS, NOXTVS

TABLE 9
SPATIAL LAG EMISSION MODELS
(N=102) -- MAXIMUM LIKELIHOOD

	9a	9b	9c	9d	9e	9f
DEPVAR	PM25TVS	PM25TVS	SO2TVS	SO2TVS	NOXTVS	NOXTVS
WEIGHT	DIS10	DISSQ	DIS10	DISSQ	DIS10	DISSQ
W_PM25TVS	-0.053	-0.0002	-0.122	-0.058	-0.086	-0.045
	(-0.39)	(-0.002)	(-0.88)	(-0.56)	(-0.63)	(-0.44)
INSPECT	0.090	0.089	6.179	5.742	4.328	4.071
	(0.98)	(0.97)	(2.67)	(2.47)	(2.22)	(2.08)
INSPNB	-0.000	0.000	0.059	0.065	0.023	0.029
	(-0.03)	(-0.05)	(0.26)	(0.28)	(0.12)	(0.15)
INSPNBOUT	0.003	0.003	-0.119	-0.124	-0.084	-0.090
	(0.22)	(0.22)	(-0.32)	(-0.33)	(-0.27)	(-0.29)
SIZE	-0.113	-0.113	-3.390	-3.536	-2.753	-2.854
	(-1.86)	(-1.85)	(-2.21)	(-2.30)	(-2.13)	(-2.21)
AGE	0.011	0.011	0.051	0.042	0.067	0.062
	(3.31)	(3.32)	(0.59)	(0.48)	(0.92)	(0.85)
LPROD	0.076	0.079	0.550	0.821	-0.375	-0.187
	(0.38)	(0.39)	(0.11)	(0.16)	(-0.09)	(-0.04)
PAOC	0.007	0.008	-0.536	-0.489	-0.759	-0.728
	(0.08)	(0.10)	(-0.25)	(-0.23)	(-0.42)	(-0.40)
DIRTYSIC	-0.079	-0.076	-0.136	-0.106	-0.206	-0.175
	(-0.43)	(-0.41)	(-0.03)	(-0.02)	(-0.05)	(-0.04)
POOR	-0.024	-0.021	0.111	0.041	0.047	0.000
	(-0.64)	(-0.56)	(0.12)	(0.04)	(0.06)	(0.00)
MINORITY	0.008	0.007	0.053	0.057	0.088	0.092
	(0.75)	(0.71)	(0.21)	(0.22)	(0.41)	(0.43)
ELDERS	0.000	-0.004	1.146	1.147	0.445	0.445
	(-0.00)	(-0.07)	(0.74)	(0.74)	(0.34)	(0.34)
KIDS	0.069	0.059	1.817	1.926	-0.071	-0.050
	(0.36)	(0.31)	(0.38)	(0.40)	(-0.02)	(-0.01)
BORDER	-0.189	-0.187	-1.030	-0.630	-1.439	-1.060
	(-0.92)	(-0.91)	(-0.20)	(-0.12)	(-0.33)	(-0.24)
ENVSPEND	0.000	0.001	-0.348	-0.344	-0.004	-0.005
	(0.02)	(0.04)	(-0.60)	(-0.59)	(-0.01)	(-0.01)
DEMOCRAT	1.861	1.786	4.496	6.974	22.676	23.619
	(1.39)	(1.34)	(0.13)	(0.21)	(0.80)	(0.83)
TURNOUT	-0.996	-1.024	-18.456	-16.450	-27.513	-25.160
	(-0.55)	(-0.56)	(-0.41)	(-0.36)	(-0.72)	(-0.66)
R2	0.194	0.194	0.179	0.177	0.189	0.187

Notes: (T-Statistics)
X = PM25TVS, SO2TVS, NOXTVS