PANEL DATA ANALYSIS OF REGULATORY FACTORS SHAPING ENVIRONMENTAL PERFORMANCE

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Abstract—This paper analyzes the regulatory factors shaping environmental performance at individual polluting facilities. In particular, it examines the influence of actual government interventions, namely, inspections and enforcement actions performed at specific facilities. This influence represents specific deterrence. This paper also examines general deterrence, that is, the threat of receiving an intervention. As important, it controls for differences in certain regulatory features of facility-specific pollution control permits. Unlike previous attempts to examine regulatory factors, this analysis uses panel data techniques to capture the heterogeneity across individual facilities, while exploring the dynamics of each facility; the analysis also captures heterogeneity across individual time periods.

I. Introduction

RECENTLY the Environmental Protection Agency (EPA) has been expressing a strong interest in understanding better the factors that shape environmental performance at individual polluting facilities. In particular, the EPA wishes to assess the effectiveness of government interventions, such as inspections and enforcement actions. To inform these interests, this paper analyzes the regulatory factors that shape the level of environmental performance at individual water-polluting facilities. For this purpose, I measure environmental performance by the level of wastewater discharges relative to the permitted effluent limits. In this way, I examine levels of both noncompliance and overcompliance. The primary research objective is to assess the effectiveness of government interventions for inducing better performance. For this purpose, I consider various government interventions: (1) federal inspections, (2) state inspections, (3) federal penalties, and (4) state penalties.

This examination of government interventions captures deterrence in two forms. Specific deterrence involves responses to interventions imposed on a specific facility. General deterrence involves responses to the threat of receiving an intervention. As important, this paper controls for differences in certain regulatory features of facility-specific water pollution control permits (for example, limit levels). To analyze the effects of these regulatory factors on environmental performance, this particular empirical analysis examines the wastewater discharges by large municipal wastewater treatment facilities in the state of Kansas for the years 1990 to 1998, which represents a very limited scope for analysis. Unlike all previous studies of environmental performance (or behavior), this paper uses panel data analysis to explore heterogeneity across individual facilities and individual time periods.[1] For this purpose, the paper uses these econometric models: pooled ordinary least squares (OLS), one-way and two-way fixed-effects models, and one-way and two-way random-effects models.

Economic analysis on the effects of regulatory factors on environmental performance and behavior is limited (Cohen, 1999). Few economic studies analyze the effects of government interventions on facility environmental performance involving standard emissions, and they focus solely on two industrial sectors—pulp/paperboard and steel (Gray & Deily, 1996; Magat & Viscusi, 1990; Nadeau, 1997; Laplante & Rilstone, 1996; Helland, 1998a, 1998b).[2] In the realm of wastewater management, previous studies examine only the former sector and consider only the effects of government inspections. The only studies of enforcement actions are in the realm of air emission management. Only two studies examine the effects of regulatory pressure on environmental behavior (Henriques & Sadorsky, 1996; Dasgupta, Hettige, & Wheeler, 2000). No previous study examines the effects of permit conditions on environmental performance or behavior.

Other studies examine the effects of nonregulatory factors, such as community pressure, on environmental performance (for example, Pargal & Wheeler, 1996; Arora & Cason, 1996).

None of these cited studies use panel data analysis to capture the influence of regulatory or nonregulatory factors on environmental performance or behavior.[3]

This present study draws upon these previous analyses to contribute to the literature in the following ways. First and foremost, this paper uses panel data analysis to assess the influence of regulatory factors and to explore heterogeneity across individual facilities and time periods. In particular, this paper demonstrates a strong heterogeneity across individual facilities and links this feature to critical facility characteristics. Second, this study analyzes the extent of noncompliance and overcompliance, which provides greater

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[1] Heterogeneity across facilities stems from factors such as different management styles. Heterogeneity across time periods stems from factors such as weather conditions.

[2] Other similar studies focus exclusively on agency behavior regarding inspections and/or enforcement actions (e.g., Deily & Gray, 1991; Earnhart, 1997, 2000a, 2000b).

[3] Some studies perform only cross-sectional analysis (Arora & Cason, 1996; Dasgupta et al., 2000; Pargal & Wheeler, 1996; Henriques & Sadorsky, 1996). Other studies utilize a panel data set while ignoring the data structure of repeated observations on individual facilities (Magat & Viscusi, 1990; Helland, 1998a, 1998b; Nadeau, 1997; Gray & Deily, 1996; Laplante & Rilstone, 1996).

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differentiation across polluters' performance.[4] Third, this study comprehensively incorporates regulatory factors. Fourth, this study analyzes a new category of polluter: municipal wastewater treatment plants, which are all publicly owned in Kansas. This type of polluter demands research attention in that municipal plants may not be effectively controlled by federal or state regulators. For example, public polluters are seldom the target of enforcement action by enforcement agencies (Naysnerski & Tietenberg, 1992). Yet, municipal plants represent one of the two main categories of polluters controlled by the Clean Water Act, and are 57% of all large wastewater dischargers.[5] As important, the federal government has strongly demonstrated, in the form of financial assistance, its desire to limit wastewater discharges by municipal plants.[6] Presumably the federal government would be interested in assessing the effectiveness of using government interventions to maintain a good return on its investment. Nevertheless, as with other studies that focus on one industry, the results of the present study most likely will not generalize to all industries.

II. Empirical Application

A. Selection of Research Site

To examine the effectiveness of government interventions and the influence of regulatory factors in general, this paper examines a specific demonstration of environmental performance: biological oxygen demand (BOD) wastewater discharges by large ("major") municipal wastewater treatment plants in Kansas during the years 1990 to 1998. This selection is appropriate for several reasons. First, unlike other media, regulators systematically record wastewater discharges and limits. Second, during the 1990s, Kansas had the dubious honor of suffering the worst ambient surface water quality in the entire United States.[7] Third, the EPA and the Kansas Department of Health and Environment (KDHE), the state environmental agency, focus their regulatory efforts on EPA-classified "major" facilities.[8] Municipal facilities represent 42 of the 58 major facilities in Kansas. Fourth, BOD represents the main type of pollutant discharged by municipal facilities.[9] Although this sample generates a large data set (4,320 observations) on environmental performance, it is very limited in scope.[10]

B. Government Regulatory Influence

Government efforts to control water pollution begin with the issuance of facility-specific permits. Although the EPA possesses the authority to issue permits, this authority has been delegated to states that meet federal criteria. Permits are issued generally on a 5-year cycle. Within a 5-year permit, agencies may impose interim limits, which serve as a transition to the final limits, which are generally more stringent. Or agencies may impose final limits immediately. The specific limit levels are based solely on effluent limitation guidelines promulgated by the EPA (40 CFR Part 133) and concerns over the ambient quality of the receiving waterbody.[11] To ensure compliance with issued permits, the EPA and relevant state agencies periodically inspect facilities and take enforcement actions as needed. Although the EPA retains authority to monitor and penalize facilities, state agencies are primarily responsible for monitoring and enforcement.

C. Data Collection

To examine the effects of these regulatory factors—permit conditions, inspections, and enforcement actions—on the environmental performance of Kansas municipal wastewater treatment facilities, I gather data from various databases. From the EPA's Permit Compliance System (PCS) database, I draw the following attributes for each facility: (1) permit issuance dates; (2) type of emission limit: interim or final; (3) flow capacity (millions of gallons/day); (4) type of treatment technology: secondary (for example, activated sludge) versus secondary equivalent (for

[4] The simple distinction between compliance and noncompliance is too limited in that many facilities overcomply with effluent limits (see, for example, Helland, 1998a). [McClelland and Horowitz (1999) report that aggregate emissions from pulp and paper plants in 1992 were roughly 50% of the permitted emissions.] Analysis of emissions without reference to limits is too limited in that it ignores variation in limits across facilities and time (see, for example, Helland, 1998b). Only Laplante and Rilstone (1996) consider emissions relative to limits.

[5] In 1990, municipal plants represented approximately 15,000 of the roughly 64,000 wastewater dischargers, almost 25% of the total (EPA, 1990); in 1994, municipal plants represented 57% of the 7,053 large dischargers.

[6] Between 1972 and 2001, the federal government issued more than $77 billion in grants and loans to municipal plants (Revkin, 2002).

[7] The Kansas Department of Health and Environment (KDHE) took limited steps to improve water quality in the 1990s by updating state water quality criteria (KDHE, 1994). The EPA also evaluated these water quality criteria in 1997 (Hall and Associates, 1997).

[8] Major facilities meet one of three criteria: (1) possess a discharge flow of 1 million gallons per day, (2) serve a population of 10,000 or greater, or (3) cause significant impact on the receiving waterbody.

[9] BOD is one of the five EPA-classified conventional pollutants, which are the focus of EPA control efforts. The EPA considers BOD the most damaging of the conventional pollutants and the focus of its control efforts (Helland, 1998a). All previous wastewater studies but one focus exclusively on BOD. Because technologies controlling BOD tend to reduce other pollutants, the relationship between regulatory factors and BOD emissions ought to be similar to the relationship between these factors and other pollutants (Magat & Viscusi, 1990).

[10] Being focused on one state, the results most likely will not generalize to all states; however, this tight focus should help to improve the accuracy of the analysis by avoiding the need to control for differences across states, especially the differences in state agency regulatory approaches. Being focused on wastewater and large facilities, the results need not generalize to all types of environmental performance and facilities of all sizes.

[11] Federal regulations establish upper bounds on limit levels. (Agencies may violate these federal standards by issuing higher limits. Only 0.5% of the Kansas data involve higher limits.) State agencies may legally issue more stringent effluent limits to maintain specific uses of particular waterways, such as fishing (EPA, 1990). In particular, the KDHE issues more stringent limits based on a state water quality standard for dissolved oxygen, which represents the ambient water quality parameter equivalent to the BOD pollutant.

TABLE 1.—STATISTICAL SUMMARY

A. Regression Variables

Variable	Units	Mean	Std. Dev.
Secondary equivalent treatment	0, 1	0.075	0.263
Flow capacity	Million gallons/day	6.301	8.695
Sales taxes	$1,000	48,747	75,084
Population	Millions	0.108	0.132
Monthly effluent limit level	mg/L	29.609	3.952
Permit expiration	1,000 days	0.194	0.403
Final limit type	0, 1	0.953	0.212
Nonreporting of effluent limit	0, 1	0.053	0.224
BOD relative emissions	Ratio	0.476	0.446
Log of BOD relative emissions	Log of ratio	−1.079	0.792
Nonreporting of emissions	0, 1	0.024	0.152
Winter season	0, 1	0.25	0.433
Spring season	0, 1	0.25	0.433
Summer season	0, 1	0.25	0.433
EPA inspection in current month	0, 1	0.036	0.040
KDHE inspection in current month	0, 1	0.102	0.049
Preceding 12-month cumulative KDHE inspections	Count	1.214	0.764
Preceding 12-month cumulative EPA inspections	Count	0.388	0.652
KDHE or EPA one-year lagged penalty	0, 1	0.031	0.174
Predicted KDHE inspection probability	Probability	0.098	0.048
Predicted EPA inspection probability	Probability	0.029	0.031
Annual KDHE enforcement of KS facilities	Count	4.750	3.382
Annual EPA enforcement of KS facilities	Count	1.750	2.488

B. Annual Number of Enforcement Actions Taken against Kansas Facilities

Year	EPA Actions	KDHE Actions
1990	0	5
1991	0	0
1992	1	5
1993	0	6
1994	0	9
1995	0	10
1996	1	5
1997	6	2
1998	6	1

example, stabilization ponds);[12] (5) BOD monthly emission limit levels; and (6) BOD monthly discharges. I calculate relative emissions by dividing discharges by the emissions limit. Thus, lower relative emissions reveal better performance.

From the PCS database, I also draw data on inspections performed by federal and state regulators within the state of Kansas. From these data, I generate separate measures of federal and state, specific and general deterrence, as described below.

From the EPA Docket and KDHE enforcement databases, I draw data on formal enforcement actions imposed against Kansas water polluters.[13] From these data, I create separate measures of federal and state, specific and general deterrence, as described below.

[12] The approval process for a facility's particular technology is highly technical and case by case.

[13] Formal actions include consent orders, corrective actions, remediation requirements, and fines.

From the Commerce Department Regional Economic Information Service (REIS) database, I gather annual data on county-level community characteristics: sales taxes and population.

For two of the 42 facilities, these databases provide severely limited information, especially on BOD limits and emissions. Consequently, I eliminate these two facilities from the sample.

D. *Statistical Summary*

Table 1 provides a statistical summary of the collected data used for the regression analysis. The average facility has the capacity to discharge approximately 6 million gallons per day. Over 90% of the facilities employ secondary treatment. Facilities face interim limits approximately 4% of the time. In any given month, the average permit has been expired for almost 194 days. The average BOD emission limit is slightly below 30 mg/L. Though facilities face a

30-mg/L a large majority of the time, limit levels vary across facilities, across years, and within years. This variation confirms the need to examine relative emissions.[14] In the average month, facilities face a 4% chance of an EPA inspection and a 10% chance of a state inspection.

Table 1B demonstrates the progression of enforcement over the 1990s. Between 1990 and 1998 inclusive, the EPA imposed 14 penalties against Kansas facilities; only one applied to a major municipal facility. The KDHE imposed 43 penalties, 10 of which applied to major municipal facilities. Given the limited number of EPA penalties against major municipal facilities, this analysis cannot effectively distinguish between the specific deterrence effects of federal enforcement and state enforcement. Instead, it merges these two enforcement categories when examining specific deterrence.

Finally, consider relative emission levels. Facilities on average overcomply with the BOD average limit by 52%. On the other hand, BOD relative emissions surge as high as 1,453% above the permitted limits. These figures confirm the need to analyze the *degree* of compliance and noncompliance rather than the status of compliance versus noncompliance.

Section III structures the econometric analysis of these collected data, including the creation of measures to capture specific and general deterrence. Section IV displays the analytical results.

III. Econometric Approach

A. Regression Model

This paper analyzes the effects of regulatory factors, including government interventions, on environmental performance. Toward this end, it estimates environmental performance, which stems from decisions made by treatment plants, and government interventions, which represent decisions made by agencies. I define these decision variables with the following notation. Let Y_{it} denote the level of relative emissions for facility i in time period t. Let I_{it}^{EPA} indicate the decision by the EPA to inspect facility i in time period t: $I_{it}^{\mathrm{EPA}} \in \{0,1\}$. Let I_{it}^{KD} indicate the decision by the KDHE to inspect facility i in time period t: $I_{it}^{\mathrm{KD}} \in \{0,1\}$. Let S_{it} indicate the decision by the EPA or KDHE to impose a sanction on facility i in time period t: $S_{it} \in \{0,1\}$.

To estimate the effect of interventions on performance, I must first sort out specific and general deterrence. Previous studies of specific deterrence examine the contemporaneous or lagged effect of a specific intervention at a specific facility (Magat & Viscusi, 1990; Helland, 1998a, 1998b). Previous studies of general deterrence examine the threat of intervention at a particular facility. To capture this threat, some studies use aggregate measures of government interventions within specified locations and time periods (for example, Epple & Visscher, 1984; Cohen, 1987). Similar studies focus directly on changes in the threat of an intervention (for example, Olson, 1999). In particular, Stafford (2002) examines the effect of a new EPA enforcement protocol regarding hazardous waste by analyzing facility compliance before and after the change. To capture the threat of an intervention directly, other studies use the predicted probability of an intervention (Laplante & Rilstone, 1996; Gray & Deily, 1996).

Consistent with previous studies, to capture specific deterrence, I focus on specific interventions at specific facilities. Facilities may be able to respond to interventions within the month of the intervention. In this case, performance and interventions are determined simultaneously. However, facilities most likely need several weeks, if not months, to respond to interventions (Magat & Viscusi, 1990). Therefore, I use lagged, not current, values of interventions to capture specific deterrence.[15] In the case of inspections, I generate the cumulative count of inspections performed by the KDHE at a specific facility in the preceding 12-month period, which I denote as $C_{i\ t-12}^{\ \mathrm{KD}}$, and I generate the cumulative count of inspections performed by the EPA, which I denote as $C_{i\ t-12}^{\mathrm{EPA}}$.[16] In the case of enforcement, I use the 1-year-lagged indicator of a state or federal sanction, which I denote as $S_{i\ t-12}$.

To capture general deterrence, I focus on the threat of an intervention. I denote the threat of an EPA sanction and of a KDHE sanction as SL_{it}^{EPA} and SL_{it}^{KD}, respectively, and denote the threat of an EPA inspection and of a KDHE inspection as IL_{it}^{EPA} and IL_{it}^{KD}, respectively. I capture these threats differently for sanctions and inspections. For enforcement, I generate two variables that separately measure the annual count of sanctions against all Kansas facilities by the KDHE and EPA, respectively.[17] For inspections, I predict their probability. Because these decisions are dichotomous, I employ a probit model to estimate each inspection decision separately (Maddala, 1983), as shown in the appendix.[18]

[14] The PCS database contains no information on emission limits for approximately 5% of the observations. Rather than dropping these observations, the empirical analysis adjusts for this lack of recorded limits by setting the level of relative emissions to the sample mean and including a dummy variable that indicates this alteration. The coefficient on this regressor is always statistically insignificant. Separate analysis of observations with recorded emission limits generates highly similar results.

[15] Within an instrumental variables approach for resolving potential simultaneity between performance and interventions, lagged interventions serve as proper instruments for current interventions, because lagged interventions are exogenous to current performance (Laplante & Rilstone, 1996; Magat & Viscusi, 1990). Thus, the assumed connection between lagged interventions and current performance need not be troubling.

[16] I chose a period of 12 months for various reasons: (1) major polluters should be inspected once per year, (2) the 12-month period fits with the annual recording of enforcement actions, (3) other time periods generate less significant results, and (4) Laplante and Rilstone (1996) examine a 12-month period.

[17] Conversations with KDHE and EPA officials confirm that aggregate measures of interventions properly proxy the threat of an intervention. Use of inspection aggregate measures generates unsatisfying results.

[18] I do not use the predicted probability of an enforcement action to proxy for the threat of enforcement. Probit estimation of the government

Regardless of the proxy for capturing an intervention threat, general deterrence does not meaningfully depend on current facility performance. The annual number of penalties imposed against all Kansas facilities is practically independent of a particular facility's performance. As well, the predicted probability of an intervention is based on past, not current, performance, as argued below.[19]

To support this last argument, I turn to agency behavior. First, although current interventions may depend on current performance, it is highly doubtful that agencies are cognizant of a facility's performance in the very month chosen for intervention. Agencies more likely base their intervention decisions on past performance, because they need time to evaluate performance before responding to it (Magat & Viscusi, 1990). In this case, performance and interventions are not simultaneously determined. Instead, lagged performance is predetermined relative to current interventions. To capture lagged performance, I use the mean level of relative emissions in the preceding 3-month period, $\check{Y}_{i\ t-3}$.[20]

Second, current KDHE inspections and EPA inspections may be simultaneously determined. To resolve this potential simultaneity, I employ an instrumental variables approach. As the instrumental variable for current KDHE inspections, I use preceding 12-month cumulative KDHE inspections at a specific facility, $C_{i\ t-12}^{\mathrm{KD}}$. As the instrumental variable for current EPA inspections, I use the similar count for EPA inspections, $C_{i\ t-12}^{\mathrm{EPA}}$. Both lagged values are exogenous to their current counterparts. This approach is proper in that agencies most likely need time to respond to each other.

Third, current inspections and sanctions may be determined simultaneously. To resolve this potential simultaneity, I again employ an instrumental variables approach. As the instrumental variables for KDHE inspections and EPA inspections, I use the respective lagged cumulative inspections. This approach is appropriate due to the sequential nature of enforcement: the regulator first inspects a facility, then later sanctions it. As the instrumental variable for current sanctions, I use the 1-year-lagged value of sanctions. Given the sequential nature of enforcement, one may not expect a connection from current enforcement to current inspections. However, after sanctioning a facility, the regulator may be more prone to inspect that same facility in the future (Harrington, 1988).

The described decision variables—Y_{it}, I_{it}^{EPA}, I_{it}^{KD}, and S_{it}—represent the endogenous variables in the regression system. Let X_{it} represent the vector of nondeterrence variables that determine performance. Z_{it} represents the vector of remaining variables that determine inspection decisions. M_{it} represents the vector of remaining variables that determine enforcement actions. The following set of equations captures the full regression system:

$$
\begin{aligned}
f(Y_{it}) = {} & \beta^{\mathrm{EPA}} C_{i\ t-12}^{\mathrm{EPA}} + \beta^{\mathrm{KD}} C_{i\ t-12}^{\mathrm{KD}} + \beta^{S} S_{i\ t-12} \\
& + \Omega^{EPA} IL_{it}^{\mathrm{EPA}} + \Omega^{\mathrm{KD}} IL_{it}^{\mathrm{KD}} + \Psi^{\mathrm{EPA}} SL_{it}^{\mathrm{EPA}} \\
& + \Psi^{\mathrm{KD}} SL_{it}^{\mathrm{KD}} + \eta X_{it} + \epsilon_{Yit},
\end{aligned} \tag{1}
$$

$$I_{it}^{\mathrm{EPA}} = \gamma\ \check{Y}_{i\ t-3} + \zeta C_{i\ t-12}^{\mathrm{KD}} + \xi\ \mathrm{S}_{i\ t-12} + \theta\ Z_{it} + \epsilon_{Eit}, \tag{2}$$

$$I_{it}^{\mathrm{KD}} = \delta\ \check{Y}_{i\ t-3} + \alpha\ C_{i\ t-12}^{\mathrm{EPA}} + \kappa\ S_{i\ t-12} + \pi\ Z_{it} + \epsilon_{Kit}, \tag{3}$$

$$S_{it} = \mu\ \check{Y}_{i\ t-3} + \tau\ C_{i\ t-12}^{\mathrm{EPA}} + \omega\ C_{i\ t-12}^{\mathrm{KD}} + \Phi\ M_{it} + \epsilon_{Sit}, \tag{4}$$

where $\in_{Yit}$, $\in_{Eit}$, $\in_{Kit}$, and $\in_{Sit}$ are error terms. For equation (1), I present estimates from a semilog specification, $f(Y_{it}) = \ln Y_{it}$,[21] using OLS regression.[22]

B. *Panel Data Structure*

The econometric analysis also addresses the panel structure of the collected data on environmental performance. Most important, the analysis uses panel data models to exploit the data along two dimensions: (1) heterogeneity across polluters and (2) heterogeneity across time periods.

The analysis utilizes two specific standard panel data models: the fixed-effects model and the random-effects model (Hsiao, 1986). Each specific model stems from a more general model that captures differences across the various polluters by incorporating an individual term for each facility. If it is uncorrelated with the other regressors in equation (1), then a random-effects model is appropriate. The one-way random-effects model captures differences across the various polluters by including a random disturbance term that remains constant through time and captures the effects of excluded factors specific to each facility. The two-way random effects model captures differences across time periods by additionally including a random disturbance

decision to take either a federal or a state enforcement action generates a very poor fit to the data; thus, the predicted probability serves as a very poor proxy, as noted in the appendix.

[19] Some previous studies use predicted probabilities of government interventions as instrumental variables within a two-stage simultaneous equations model that avoids potential simultaneity between performance and interventions (see, for example, Laplante & Rilstone, 1996; Gray & Deily, 1996).

[20] If current facility performance is determined simultaneously with government interventions, then fortunately the summary lagged value of relative emissions serves as a good instrumental variable in any instrumental variable approach, because the lagged value is exogenous with respect to current interventions.

[21] This paper also estimates a linear specification: $f(Y_{it}) = Y_{it}$. Based on a goodness-of-fit measure—adjusted R^2—and the prevalence of significant coefficients, I chose the semilog specification as the better model. The use of log values for the dependent variable also minimizes the effect of outliers (Gray & Deily, 1996).

[22] Legally all facilities must submit monthly discharge reports. This self-monitoring is the most important source of information utilized by regulators to assess environmental performance (EPA, 1990). [Stiff penalties for false reports and periodic inspections provide incentives to report discharges honestly (Magat & Viscusi, 1990).] However, the analysis must address the fact that all facilities do not always submit reports. It tackles this problem in four ways. Because the regression results are robust to the various approaches, I report only one set of results. For the reported approach, I fill the missing data on emissions with appropriate replacement values (Laplante & Rilstone, 1996). In this study, I use facility-specific annual mean values as replacements.

term that is generic to all polluters but captures the effects of excluded factors specific to each time period.

If the facility-specific term is correlated with the other regressors in equation (1), then a fixed-effects model is appropriate. The one-way fixed-effects model captures differences across facilities by estimating a constant term for each facility. The two-way fixed effects model captures differences across time periods by additionally estimating an individual constant term for each time period.

The next section uses these econometric models to examine the effects of regulatory factors.

IV. Estimation Results

A. *Explanatory Variables*

The analysis uses certain regressors to estimate environmental performance. Flow capacity permits identification of economies and/or diseconomies of scale. The type of treatment technology captures the general character of a facility's abatement technology. Sales taxes proxy for a community's level of resources available for wastewater treatment. Population proxies for the volume of wastewater being processed. The permit limit type, permitted limit level, and permit expiration capture permit conditions.[23] Lastly, I include the noted specific and general deterrence variables. (The full set of regressors is shown in Table 1A.)

B. *Pooled OLS Estimation of Environmental Performance*

In this subsection, I report and interpret the pooled OLS estimation results, shown in table 2. First, the effect of flow capacity indicates that larger facilities significantly underperform smaller facilities; that is, BOD treatment involves *dis*economies of scale. Second, facilities operating secondary-equivalent treatment technologies significantly underperform facilities operating secondary treatment technologies. Given their very large *t*-statistics, these two factors must be very important for explaining performance. Further analysis demonstrates that they prove critical for assessing the effects of certain regulatory factors. Third, facilities holding an expired permit significantly underperform those facilities holding a valid permit, and this underperformance grows as expiration increases. Perhaps facilities read the regulatory laxness involving permit issuance as a sign of regulatory laxness in general.[24] Fourth, facilities facing a final limit significantly outperform facilities facing only an interim limit; thus, the stringency of final limits improves performance. Fifth, more stringent limit levels undermine performance, as shown by the significantly negative effect of effluent limit levels.[25]

Finally, I examine deterrence. Both federal and state inspection-related specific deterrence improve performance, according to the effects of EPA and KDHE lagged cumulative inspections. However, only the latter effect is significant. Enforcement-related specific deterrence also significantly improves performance. As for general deterrence, the effects of predicted inspections demonstrate that the threat of federal and state inspections significantly improves environmental performance. Enforcement-related general deterrence also significantly improves performance, based on the effects of aggregate EPA and KDHE enforcement measures.

However, because these aggregate measures of enforcement possess no cross-sectional variation, they are vulnerable to changes in important yet unmeasured factors.[26] To mitigate this concern, I could argue that important unmeasured factors, such as other regulatory pressures and abatement technology, changed little. Over the sample period, the state of Kansas implemented no regulatory programs relating to the observed environmental performance. As important, very few facilities upgraded their abatement technologies, according to KDHE officials, and no facility changed its general technology. Still, I cannot rule out these factors' effects, especially given the time pattern of environmental performance, which I demonstrate by including individual year indicators in the regression, while excluding enforcement-related general deterrence factors.[27] As shown in the second column of table 2, the indicators collectively demonstrate a strong pattern of improving performance over the sample period. Enforcement-related general deterrence seems to explain some portion of this environmental performance pattern, especially when the two measures are examined jointly. As shown in Table 1B, increased state enforcement seems to help explain improved performance during the first half of the 1990s, and increased federal enforcement seems to help explain improved performance during the last 2 years of the sample period. However, the two enforcement measures could be merely picking up a baseline trend of improvement in facility performance. Thus, the reader should view the estimation results relating to enforcement-related general deterrence as merely suggestive.

[23] I do not lag the effects of permit conditions, because they are easily anticipated by facilities.

[24] One might expect permit expiration and environmental performance to be jointly determined. Facilities that expect to perform more poorly may more strongly stall the issuance of new permits expected to contain more stringent limits. Though facilities' objections certainly explain some of the cases of permit expiration, according to KDHE officials other reasons explain most of these cases. For example, the EPA and Kansas State Legislature objected to new state surface water quality standards, which tied up many permits. Most important, the KDHE was short on manpower. Still, I cannot rule out the possibility of joint determination.

[25] One might expect limit levels and environmental performance to be jointly determined. Facilities that expect to perform more poorly may bargain more strongly for weaker limits. Though I cannot rule out this possibility, analysis demonstrates that lagged performance does not seem to affect limit levels and the highly limited variation in limit levels would seem to mitigate any concern of joint determination.

[26] Although this vulnerability is certainly problematic, it need not be fatal. Recent studies of general deterrence effectively employ similar aggregate-based measures (Stafford, 2002; Olson, 1999).

[27] The other coefficients and standard errors remain mostly unchanged.

TABLE 2.—REGRESSION OF BOD RELATIVE EMISSIONS: POOLED OLS AND RANDOM-EFFECTS MODELS

	Pooled OLS		Random-Effects Models		
			One-Way		Two-Way
Variable	Model 1	Model 2	Model 1	Model 2	Model
Intercept	−0.091	0.007	0.231	0.325*	0.241
	(0.130)	(0.133)	(0.195)	(0.196)	(0.195)
Nonreporting of emissions	0.381***	0.404***	0.176***	0.180***	0.176***
	(0.080)	(0.080)	(0.065)	(0.066)	(0.065)
Winter season	0.222***	0.267***	0.105***	0.123***	0.106***
	(0.047)	(0.048)	(0.038)	(0.039)	(0.039)
Spring season	0.192***	0.207***	0.150***	0.156***	0.150***
	(0.036)	(0.036)	(0.028)	(0.028)	(0.029)
Summer season	0.001	0.004	−0.017	−0.015	−0.017
	(0.034)	(0.034)	(0.026)	(0.026)	(0.027)
Flow capacity	0.010***	0.014***	−0.005	−0.001	−0.005
	(0.002)	(0.003)	(0.011)	(0.011)	(0.011)
2nd equivalent treatment	0.794***	0.820***	0.820**	0.807**	0.818**
	(0.050)	(0.050)	(0.324)	(0.323)	(0.323)
Sales taxes ($1,000)	−1.2E − 6	−2.4E − 7	−8.4E − 7	2.2E − 7	−7.6E − 7
	(7.5E − 7)	(7.7E − 7)	(8.3E − 7)	(8.6E − 7)	(8.2E − 7)
Population (millions)	0.165	−0.365	1.528*	0.592	1.461*
	(0.433)	(0.447)	(0.882)	(0.910)	(0.882)
Monthly effluent limit	−0.012***	−0.012***	−0.025***	−0.025	−0.025***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Permit expiration (1000 days)	0.233***	0.255***	0.136***	0.152***	0.137***
	(0.032)	(0.033)	(0.031)	(0.032)	(0.031)
Final limit type	−0.574***	−0.559***	−0.723***	−0.718***	−0.724***
	(0.059)	(0.060)	(0.051)	(0.052)	(0.051)
Nonreporting of effluent limit	0.051	0.051	0.033	0.033	0.033
	(0.061)	(0.061)	(0.059)	(0.059)	(0.059)
KDHE/EPA 1-yr lagged penalty	−0.115*	−0.109*	0.1980***	0.205***	0.198***
	(0.070)	(0.060)	(0.057)	(0.057)	(0.057)
Cumulative EPA inspections	−0.008	−0.012	−0.031	−0.030	−0.031
	(0.023)	(0.024)	(0.021)	(0.021)	(0.021)
Cumulative KDHE inspections	−0.035*	−0.040**	−0.040**	−0.051***	−0.040**
	(0.019)	(0.020)	(0.017)	(0.017)	(0.017)
Annual EPA enforcement	−0.067***	N/A	−0.040***	N/A	−0.040***
	(0.008)		(0.007)		(0.007)
Annual KDHE enforcement	−0.019***	N/A	−0.009**	N/A	−0.010**
	(0.005)		(0.004)		(0.004)
Predicted EPA inspection	−1.392*	−2.550***	1.932***	1.477**	1.920***
	(0.808)	(0.857)	(0.687)	(0.747)	(0.695)
Predicted KDHE inspection	−0.849**	−1.107***	−0.359	−0.519*	−0.362
	(0.340)	(0.344)	(0.303)	(0.311)	(0.304)
1992 indicator	N/A	−0.124**	N/A	−0.087**	N/A
		(0.050)		(0.038)	
1993 indicator	N/A	−0.173***	N/A	−0.139***	N/A
		(0.050)		(0.039)	
1994 indicator	N/A	−0.238***	N/A	−0.154**	N/A
		(0.052)		(0.042)	
1995 indicator	N/A	−0.253***	N/A	−0.117**	N/A
		(0.056)		(0.045)	
1996 indicator	N/A	−0.312***	N/A	−0.153***	N/A
		(0.058)		(0.048)	
1997 indicator	N/A	−0.430***	N/A	−0.239***	N/A
		(0.062)		(0.052)	
1998 indicator	N/A	−0.628***	N/A	−0.409***	N/A
		(0.065)		(0.056)	
No. of Observations	3,840	3,840	3,840	3,840	3,840
Adjusted R^2	0.133	0.139	0.116	0.123	0.113

Standard errors shown in parentheses.
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.
N/A indicates that a particular regressor is not applicable to the noted model.

C. *One-Way Panel Data Models*

Random Effects: Although the pooled OLS model generates solid and interesting results, it disregards the expected heterogeneity inherent in the panel data. To exploit the heterogeneity across individual facilities, I turn to one-way panel data models. If appropriate, the one-way random effects model is preferred to the one-way fixed-effects model, which precludes estimation of two key yet time-invariant factors: flow capacity and treatment technology.

Much of the subsequent analysis focuses on these two factors when examining heterogeneity across individual facilities.

The one-way random effects model dominates the pooled OLS model according to a Lagrange multiplier (LM) test, but the one-way fixed effects model dominates the random effects model according to a Hausman test for random effects.[28] Therefore, I focus more on the fixed-effects model.

Table 2 reports the estimation results from the one-way random-effects model. The results for factors involving seasonal patterns, permit conditions, inspection-related specific deterrence, and enforcement-related general deterrence are very similar to the pooled OLS results in sign and statistical significance. Whereas the effect of treatment technology remains strongly significant, the effect of flow capacity reverses sign and becomes insignificant. The effect of population becomes significantly positive, indicating that greater pressure on a treatment system undermines performance, as one might expect. Most important, the significantly negative effects of the predicted EPA inspection probability and the lagged penalty indicator evaporate. Instead, each of these government interventions generates a positive effect. In the case of predicted state inspections, the effect remains negative but becomes insignificant. (The significance remains when individual year indicators are included, as shown in column 4 of table 2; the other coefficients are highly robust to this inclusion.) The inability to link some deterrence factors to environmental performance may stem from the disruption to another important factor—flow capacity. The results of the fixed-effects model buttress this conclusion.

Fixed-Effects Model: The one-way fixed-effects model not only dominates the one-way random-effects model but also the pooled OLS model. The F-test statistic of no fixed effects (83.1) strongly rejects the absence of fixed effects. Inclusion of these facility-specific factors dramatically increases the adjusted R^2 measure from 0.13 to 0.50. Thus, heterogeneity across individual facilities is strongly evident, and inclusion of facility-specific constant terms is definitely warranted.

Table 3 reports the estimation results. The fixed-effects model results for factors involving seasonal patterns, permit conditions, inspection-related specific deterrence, and federal enforcement-related general deterrence are very similar to the pooled OLS and random-effects model results in sign and statistical significance. Yet, differences are noteworthy. The effect of community resources becomes highly significant: as resources grow, performance improves. As in the random-effects model results, greater population pressure undermines performance. Most important, the significantly negative effects of the predicted EPA inspection probability and lagged penalty indicator again evaporate and become

[28] The Hausman test statistic equals 20.5 and is significant at levels below 5%.

TABLE 3.—ESTIMATION OF BOD RELATIVE EMISSIONS: FIXED-EFFECTS MODELS

Variable	One-Way Model 1[a]	One-Way Model 2[a]	Two-Way Model[b]
Nonreporting of emissions	0.169***	0.179***	0.175***
	(0.065)	(0.066)	(0.066)
Winter season	0.099***	0.121***	N/A
	(0.038)	(0.039)	
Spring season	0.148***	0.156***	N/A
	(0.028)	(0.028)	
Summer season	−0.018	−0.016	N/A
	(0.026)	(0.026)	
Population (millions)	8.977***	7.476***	7.51***
	(1.880)	(2.107)	(2.11)
Sales taxes ($1,000)	−3.09 E − 6***	−2.01 E − 6*	−2.04 E − 6*
	(9.66 E − 7)	(1.064 E − 6)	(1.07 E − 6)
Monthly effluent limit	−0.025***	−0.025***	−0.028***
	(0.004)	(0.004)	(0.004)
Permit expiration (1,000 days)	0.123***	0.143***	0.142***
	(0.032)	(0.032)	(0.032)
Final limit type	−0.727***	−0.726***	−0.730***
	(0.051)	(0.052)	(0.052)
Nonreporting of effluent limit	0.033	0.033	0.035
	(0.060)	(0.060)	(0.060)
KDHE/EPA 1-yr lagged penalty	0.208***	0.211***	0.209***
	(0.057)	(0.057)	(0.057)
Cumulative EPA inspections	−0.023	−0.029	−0.031
	(0.021)	(0.021)	(0.022)
Cumulative KDHE inspections	−0.037***	−0.047***	−0.047***
	(0.017)	(0.018)	(0.018)
Annual EPA enforcement	−0.036***	N/A	N/A
	(0.007)		
Annual KDHE enforcement	−0.005	N/A	N/A
	(0.004)		
Predicted EPA inspection	2.102***	1.532**	1.601*
	(0.687)	(0.748)	(0.861)
Predicted KDHE inspection	−0.235	−0.435	−0.351
	(0.304)	(0.312)	(0.322)
1992 indicator	N/A	−0.082**	N/A
		(0.038)	
1993 indicator	N/A	−0.108***	N/A
		(0.040)	
1994 indicator	N/A	−0.093**	N/A
		(0.045)	
1995 indicator	N/A	−0.100**	N/A
		(0.045)	
1996 indicator	N/A	−0.148***	N/A
		(0.048)	
1997 indicator	N/A	−0.226***	N/A
		(0.052)	
1998 indicator	N/A	−0.382***	N/A
		(0.056)	
Number of observations	3,840	3,840	3,840
Adjusted R^2	0.5038	0.5069	0.5166

Standard errors in parentheses.
*, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.
N/A indicates that a particular regressor is not applicable to the noted model.
[a] Regression also includes 40 facility-specific constant terms.
[b] Regression also includes 40 facility-specific constant terms and 95 month-specific constant terms.

positive. The negative effect of predicted state inspections becomes insignificant. Based on these results, I conclude that the link between some deterrence factors and environmental performance requires adequate control of facility characteristics—flow capacity and treatment technology—yet the facility-specific constant terms do not effectively control for more systematic differences across facilities.[29] In sum, the one-way fixed-effects model generates odd results for some deterrence factors and does not permit estimation of key facility characteristics.[30]

Fortunately, the estimated facility-specific constant terms may still provide useful information about the effects of facility characteristics on performance. In particular, these terms can be used to categorize facilities according to their relative performance. As the benchmark for comparison, I identify the median value of the 40 facility-specific intercept terms. Given the even number of facilities, no estimated intercept evenly divides the set of facilities. Instead, I arbitrarily choose the facility with the 20th largest intercept as the benchmark facility. Then I generate 39 facility-specific indicator variables, based on that median facility. By reestimating performance with this new set of regressors, in lieu of 40 generic facility-specific intercepts, I am able to categorize the facilities. The significance and signs of the 39 facility-specific indicators identify which facilities perform better, worse, or no different than the median facility. Better performers have a significantly negative indicator (15 facilities), worse performers have a statistically positive indicator (15 facilities), and neutral performers have an indicator insignificantly different from 0 (9 facilities). After categorizing each facility, I connect these categories to the two facility characteristics: flow capacity and treatment technology.

Flow capacity is a continuous variable ranging from 0.18 to 3.00 million gallons per day with a mean value of 6.30. To discern its effect on performance, I divide the sample into two subsamples using mean flow capacity: 26 smaller facilities below the mean, and 13 larger facilities above the mean.

Table 4 reports the cross-tabulations of capacity and performance based on the sign of the facility-specific indicator. Of the smaller-capacity facilities, most are worse performers. Of the larger facilities, most are better performers. This simple comparison need not adequately discern the link between capacity and performance. Instead, I evaluate pairwise comparisons between the three categories of performers: better versus neutral, better versus worse, and neutral versus worse. Rather than using a two-sample t-test, which requires normality, I use the Kruskall-Wallis nonparametric test. As reported in table 4, an increase in capacity increases the ratio of better to neutral performers, the ratio of neutral to worse performers, and the ratio of better to worse performers. These results indicate that increased capacity shifts the distribution toward better performance, that is, facilities face economies of scale with respect to treatment performance. This conclusion is opposite from the one generated by the pooled OLS model. Thus, the use of panel data models proves critical for interpreting the effect of facility size on performance.

Next, I link the type of treatment technology and environmental performance based on the sign of the facility-specific constant term. A cross-tabulation of treatment type and performance category, shown in table 4, easily demonstrates that all facilities using secondary equivalent treatment are worse performers. (Kruskall-Wallis tests confirm

TABLE 4.—EFFECT OF FACILITY CHARACTERISTICS ON CATEGORY OF ENVIRONMENTAL PERFORMANCE, ACCORDING TO THE SIGN AND STATISTICAL SIGNIFICANCE OF FACILITY-SPECIFIC INDICATORS FROM THE ONE-WAY FIXED-EFFECTS MODEL

A. Treatment Type

i. Frequency Distribution of Performer Category by Treatment Type

Treatment type	Performer Category[a] Better	Neutral	Worse
Secondary	15	9	12
Secondary equivalent	0	0	3

ii. Pairwise Comparison of Performer Category: Sample Division according to Treatment Type

Pairwise Comparison of Performer Category	Kruskal-Wallis Nonparametric Test: Test Statistic	p-Value
Better vs. neutral	N/A	N/A
Better vs. worse	359.9	0.01
Neutral vs. worse	222.1	0.01

B. Flow Capacity

i. Frequency Distribution of Performer Category by Flow Capacity Type

Flow Capacity Type	Performer Category[a] Better	Neutral	Worse
Smaller than average[b]	8	6	12
Larger than average[b]	7	3	3

ii. Pairwise Comparison of Performer Category: Sample Division According to Flow Capacity

Pairwise Comparison of Performer Category	Kruskal-Wallis Nonparametric Test: Test Statistic	p-Value
Better vs. neutral	44.4	0.01
Better vs. worse	259.1	0.01
Neutral vs. worse	57.6	0.01

[a] Relative to median facility, better performers (that is, facilities) possess a significantly negative indicator, worse performers possess a statistically positive indicator, and neutral performers possess an indicator insignificantly different from 0.
[b] Average flow capacity is 6.30 million gallons per day.

[29] As further evidence, I reestimate the pooled OLS model without flow capacity and treatment technology. Exclusion of these critical factors disrupts the link between the same deterrence factors and performance in a fashion similar to the disruption prompted by their exclusion in the fixed-effects model.

[30] As in the pooled OLS model, I revised the one-way fixed effects model by adding individual year indicators, while excluding enforcement-related general deterrence. As shown in table 3, the two sets of estimates—model 1 and model 2—are highly similar in coefficient signs, magnitudes, and significance.

this point.) This conclusion is consistent with the strongly significant result generated by the pooled OLS model.

D. Two-Way Panel Data Models

Having examined heterogeneity across facilities using one-way panel data models, I next examine heterogeneity across time periods using the two-way random-effects and fixed-effects models. As shown in table 2, the estimation results of the two-way random-effects model are highly similar to those of the one-way random-effects model. Thus, inclusion of time-specific factors does not significantly alter the previous conclusions. Lastly, I employ the two-way fixed-effects model, which estimates numerous individual month coefficients. Over one-third of these time-specific coefficients are significant. The appropriate *F*-test for joint significance of all the fixed effects—facility-specific and time-specific—confirms their importance at levels much below 1% (statistic equals 10.15).[31] Thus, the two-way fixed-effects model dominates the comparable pooled OLS model.[32] Nevertheless, the two-way fixed effects model results differ little from the one-way fixed-effects model results. Thus, the previous conclusions are robust to the presence of strong heterogeneity across individual time periods.

V. Summary

This paper analyzes the regulatory factors—inspections, penalties, permit conditions—shaping environmental performance by examining wastewater discharges from large Kansas municipal facilities between 1990 and 1998. To exploit the data set's panel structure, I employ pooled OLS and four panel data models: one-way and two-way random-effects models and one-way and two-way fixed-effects models.

First, I evaluate the robustness across these models using OLS as the reference point. Inspection- and enforcement-related specific and general deterrence significantly induce better performance. Lax permit conditions significantly undermine environmental performance. Incorporation of facility-specific factors disrupts only the link between two specific deterrence factors and performance.

Second, I analyze the heterogeneity across individual facilities. This analysis relates to key facility characteristics whose systematic control apparently proves critical for measuring the influence of certain deterrence factors. Fortunately, analysis of facility-specific indicators permits evaluation of facility-characteristic effects: facilities face economies of scale with respect to flow capacity, and facilities using secondary-equivalent treatment underperform their peers. Because the first conclusion is inconsistent with the pooled OLS results, panel data analysis proves important on this point.

Lastly, I evaluate heterogeneity across time periods. Even though strong time effects exist, the presence of time-specific factors does not alter the conclusions drawn from one-way panel data models.

Though interesting, these conclusions are based on a very limited data set.

[31] Because the two-way fixed-effects model must exclude the two enforcement-related general deterrence factors, no nested test can assess the joint significance of the additional time-specific coefficients.

[32] The two-way fixed-effects model also dominates the comparable random-effects model. The Hausman test statistic for random effects is 47.5 and significant at levels below 1%.

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APPENDIX

Predicted Probability of Government Interventions

This appendix separately estimates the probability of each government intervention decision. To estimate the probability of an EPA inspection and a KDHE inspection, I employ a probit model using these regressors: (1) a preceding 12-month cumulative count of KDHE inspections at a specific facility; (2) a preceding 12-month cumulative count of EPA inspections at a specific facility; (3) a 1-year lagged indicator of EPA and/or KDHE penalty; (4) the mean value of relative emissions in the preceding three-month period; (5) facility characteristics: (a) flow capacity, (b) type of treatment technology; (6) water conditions: (a) ambient water quality of receiving waterbody, (b) seasonal indicators, (c) time trend; (7) community factors: (a) population, (b) sales taxes per capita, (c) high school graduation rate, (d) Republican presidential vote in 1996, and (e) unemployment rate. (Details on the rationale for selecting these regressors and complete estimation results are available upon request.) If the predicted inspection probabilities were used within a simultaneous equation system, the following regressors would help to identify the system, because they are excluded from the performance equation: relative emissions in preceding 3-month period, ambient water quality, high school graduation rate, Republican presidential vote, and unemployment rate. (The time trend is similar to individual year indicators or the time-specific factors of the two-way fixed-effects model.) For the EPA inspection equation, none of these excluded factors, except time trend, are significant. Nevertheless, the nonlinearity of the normal distribution function is sufficient to identify the system regarding EPA inspections (Greene, 1997). For the KDHE inspection equation, preceding relative emissions, ambient water quality, and Republican vote are significant.

The estimation results indicate an excellent fit for each type of inspection. As one measure of goodness of fit, the Pearson χ^2 test statistics of 4,483 and 3,971, respectively, for the EPA inspection and KDHE inspection equations are both significant at the 1% level given 3,805 degrees of freedom.

To estimate the government decision to take either a federal or state enforcement action, I first aggregate the data to an annual level, because the dependent variable is recorded only on an annual basis. I employ a probit model and use the same explanatory variables as for the inspection equations. Estimation results indicate a very poor fit (the Pearson χ^2 test statistic of 241 is significant only at levels greater than 90% given 309 degrees of freedom), which is not surprising, given the limited number of enforcement actions. Use of this predicted probability in the estimation of performance generates coefficients of implausible sign and significance.