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Keywords: air pollution, hazardous waste pollution, compliance, complementary, substitution

JEL Classification: Q53, Q58, L51

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I. Introduction

When a firm is regulated by multiple environmental programs, the firm may manage its compliance with these programs systematically so that regulation of one program can affect firm decisions regarding compliance with other programs. Specifically, this cross program effects on compliance can be complementary or substituting, in that regulations of one program may either increase or decrease firm compliance with other programs. Such relationships reflect the spillover effects across environmental programs. This paper examines the existence and nature of the spillover effects by asking whether monitoring and enforcement actions taken under one program increase, decrease or have no effects on firm compliance with other programs.

The study of spillover effects across environmental programs can reveal important policy implications. When regulations are not independent, optimal monitoring and enforcement strategies require coordination between the two programs. Consider the situation where an increase in a firm's abatement level under program A increases its marginal abatement cost under program B. As a result of the increase, the firm's optimal abatement level (and hence its compliance under program B) decreases, although the monitoring and enforcement parameters under that program remain unchanged.[1] This substitution within regulations means certain emissions are crowded out from one program to the other. That is, a firm reduces its emissions under program A, but emits more under program B due to the increased marginal abatement costs under program B. From a society's perspective, substituting programs result in increased total abatement costs and higher social optimal level of emissions. Following the same reasoning, complementary regulations result in lower total abatement costs and lower social optimal level of emissions. In either case, coordination among regulators is required to achieve the social optimum.

To date, the majority of the empirical literature on the effectiveness of environmental monitoring and enforcement has focused on single medium program. Grey and Shimshack (2011) provided the most

[1] Theoretically, a firm's optimal abatement level is determined by the point at which the marginal abatement cost is equal to the marginal benefit of abatement. For a convex abatement cost function, when marginal abatement cost increases and marginal benefit of abatement remains unchanged, the optimal abatement level decreases, as does the compliance.

recent literature review on this topic. In their review, the spillover effects are defined as the impact of regulatory actions aimed at one facility on the environmental performance of other facilities. Such spillover effects are found in Shimshack and Ward (2005), Gray and Shadbegian (2007), and Decker and Pope (2005). The spillover effects discussed in this paper refer to the effects of regulatory actions under one program on facility compliance with other programs. The only paper that discusses such spillover effects is Liu (2012). Using data on facilities in Michigan, Liu (2012) finds that inspections under Clean Air Act (CAA) have positive and significant effects on facility compliance with Reservation and Conservation Recovery Act (RCRA).

This paper differs from Liu (2012) in the following aspects. First, instead of focusing on one state, facilities in all states across the nation are considered. The results from the study of facilities in one state cannot be readily extended to facilities in other states. Thus the positive spillover effects found among Michigan facilities may not hold across the nation. Analysis of a national sample can provide a more comprehensive view. Second, Liu (2012) focuses on the effects of CAA regulations on RCRA compliance. In comparison, this study examines the effects of RCRA regulations on CAA compliance. Unlike the RCRA program in which compliance status is available only if a facility is inspected, the CAA program requires regulated facilities to self-report; therefore, compliance status at the source level is available on a monthly basis.[2] The detailed compliance data produce better econometric analysis for the purpose of investigations of the effects of monitoring and enforcement on compliance. Third, the panel data model selected for this study explicitly controls for potential heteroscedasticity and auto-correlation; these issues are not considered in Liu (2012).

Other empirical literature on monitoring and enforcement is suggestive. For example, Botre et al. (2007) show that technological innovation in automotive catalytic converters results in lower nitrogen oxides but increased ozone. Sigman (1996) and Gamper-Rabindran (2006) find that changes in regulations can lead firms to transfer pollutants from a regulated medium such as air to a different

[2] The issue of self-reporting will be discussed in details in the next section.

medium such as landfill or water.[3] These studies suggest substitution-inducing regulations (or negative spillover effects), but do not explicitly consider regulatory programs simultaneously. However, complementary regulations are also possible. Installing new abatement equipment or expanding current environmental pollution controls to accommodate the requirements of one program may also help the firm control other emissions. It could be that new personnel provide expertise in pollution control which may benefits the abatement of emissions under other programs. Intensive monitoring and enforcement under one program may also induce firms to adopt cleaner inputs for production or upgrade manufacturing processes in ways that reduce emissions in general. Thus, actions taken to reduce emissions under one program may have positive spillover effects such that they also reduce emissions regulated under other programs. Given that the spillover effects, if exist, can be either positive or negative, this paper employs empirical analysis to determine the nature of such effects.

The empirical work focuses on facilities regulated under both RCRA and CAA programs. A panel data model with panel corrected standard error (PCSE) is used to estimate the impacts of monitoring and enforcement under both RCRA and CAA on facility compliance with CAA. The results confirm positive within-program effects—higher CAA penalty or the threat of a CAA inspection increases the compliance rate within the same program. In contrast to previous findings, negative spillover effects are found across programs. Increasing RCRA inspection frequency and penalty as well as the threat of an RCRA inspection leads to less compliance with CAA. Thus there is a substituting relationship between the two programs.

The rest of the paper is organized as follows. Section II discusses the data and the empirical model. Results and interpretations are given in Section III and Section IV concludes.

[3] Alberini (2001) also addresses substitution, but from a different perspective. She examines the relationship between underground and aboveground storage tanks for petroleum products and hazardous substances due to extensive regulations on underground storage. She finds the relationship changes from complementing to substituting following the regulatory changes.

II. Data and Econometrics model

A. Data

Facility compliance data are obtained from the Environmental Protection Agency's (EPA) Enforcement and Compliance History Online (ECHO) database. The ECHO database tracks the compliance, inspection and enforcement histories of all EPA-regulated facilities. Other information obtained from the ECHO database includes facility characteristics and other environmental programs under which a facility is regulated.

Under CAA program, facilities are required to self-report their emissions. CAA compliance data are available on a monthly basis at the source level. The use of self-reported data may raise the question of strategic misreporting. A theoretical model developed in Kaplow and Shavell (1994) shows that under certain conditions individuals can be induced to truthfully self-report their status. Empirically self-reported data are widely used in studies of monitoring and enforcement (see Laplante and Rilstone, 1996; Earnhart, 2004a; Shimshack and Ward, 2005). Some of the literature uses self-reported data directly without addressing potential issues. When self-reported data are tested explicitly in other studies, their accuracy cannot be rejected. In addition, as stated in Shimshack and Ward (2005), sanctions on intentional misreporting range from criminal fines to jail time. Thus, facilities face strong incentives to truthfully report their status.

According to Earnhart (2004a), community characteristics may also play important roles in facility emissions and compliance decisions. Therefore, community characteristics are obtained to control for potential influence of community pressures on facility compliance. The major data sources for these characteristics include the U.S. Bureau of Economic Analysis, the U.S. Bureau of Labor Statistics, and the U. S. Census Bureau. The control variables include real annual income per capita, unemployment rate, college graduate rates, minority rate, and population density at the county level. For counties without detailed statistics, the corresponding state level statistics are used instead.

In selecting facilities to be included in the analysis the following criteria are used. First, the facilities must be regulated under both CAA and RCRA since the purpose of this study is to investigate the effects of RCRA regulation on CAA compliance. Second, the facilities should be federally reportable since enforcement and compliance data on such facilities are more reliable. [4] Third, government facilities are excluded from the sample since their compliance behavior and enforcement history can be systematically different from non-government facilities. Overall, a total of 5,849 facilities are included in the analysis; the time frame for the sample is 2001-2010.[5, 6] The distribution of facilities across the nation is summarized in Table 1. Among all the states considered in the sample, Pennsylvania has the highest number of facilities (about 11% of the 5,849 facilities) while Vermont has the lowest number with about 9 facilities.

Table 1

Distribution of facilities across states

State	Count	Percentage	State	Count	Percentage
Alabama	276	4.71	Montana	22	0.38
Arizona	21	0.36	Nebraska	57	0.97
Arkansas	36	0.61	Nevada	20	0.34
California	302	5.15	New Hampshire	28	0.48
Colorado	43	0.73	New Jersey	65	1.11
Connecticut	41	0.70	New Mexico	19	0.32
Delaware	49	0.84	New York	242	4.13
District of Columbia	19	0.32	North Carolina	362	6.18
Florida	179	3.05	North Dakota	17	0.29
Georgia	230	3.92	Ohio	127	2.17
Idaho	16	0.27	Oklahoma	113	1.93
Illinois	152	2.59	Oregon	85	1.45
Indiana	256	4.37	Pennsylvania	645	11.00
Iowa	142	2.42	Rhode Island	16	0.27
Kansas	125	2.13	South Carolina	209	3.57
Kentucky	74	1.26	South Dakota	23	0.39

[4] According to EPA, "A facility is federally reportable if its emission classification is 'major' or 'synthetic minor', or it is subject to NSPS or NESHAP requirements and its source-level compliance status is not equal to 'no applicable state regulation.' (EPA, AFS document)"
[5] Due to the lack of complete compliance records, 19,900 facilities in the ECHO downloadable dataset are excluded from the analysis, although they satisfied the selection criteria stated above.
[6] Compliance records in April 2002 are missing for about 90% of the facilities that satisfy the selection criteria. Instead of excluding those facilities, it is assumed that their compliance status in April remained the same as in March 2002. Changing this assumption did not significantly affect the results.

Louisiana	162	2.76	Tennessee	288	4.91
Maine	31	0.53	Utah	38	0.65
Maryland	78	1.33	Vermont	9	0.15
Massachusetts	209	3.57	Virginia	435	7.42
Michigan	112	1.91	Washington	101	1.72
Minnesota	64	1.09	West Virginia	74	1.26
Mississippi	44	0.75	Wisconsin	63	1.07
Missouri	116	1.98	Wyoming	26	0.44

*Hawaii, Puerto Rico, Alaska, and Virginal Island are not included.

Variable descriptions and summary statistics are provided in Table 2. The first variable, *CAA compliance*, is the number of months that facilities are in compliance in a given year. Overall, the facilities are in compliance for 10.61 months on average. About 54.3% of the facilities are in compliance throughout the ten years while 24.6% of them are never in compliance over the same period. The set of variables from *CAA inspection to RCRA penalty* are inspections and penalties under the two programs in the previous year. The average annual CAA penalty lagged one year is $6400, while the average annual RCRA penalty lagged one year is $540. The penalties variables are included with natural log transformation. The average number of annual CAA inspections lagged one year is 0.79; one particular facility is inspected 28 times in a certain year. The number of annual RCRA inspections lagged one year is just 0.33, but the maximum number of inspections is as high as 71 in a certain year for one particular facility. The average number of annual CAA inspections of other facilities than the given facility in the same state is .78, which is similar to the average number of inspections on the given facility.

Table 2

Variable Description and Summary of Statistics

Variables	Description	Mean (Standard deviation)	Min, Max
CAA compliance	Number of months in a given year that facilities are in compliance	10.67 (3.42)	0, 12
CAA inspection	Annual number of CAA inspections, lagged one year	.79 (.75)	0, 28

CAA penalty	Annual amount of CAA penalty in $1000, lagged one year	6.4 (152)	0, 1.65e+04
RCRA inspection	Annual number of RCRA inspections, lagged one year	.33 (1.43)	0, 71
RCRA penalty	Annual amount of RCRA penalty in $1000, lagged one year	.54 (35.8)	0, 7700
Other CAA inspections	Average annual number of CAA inspections on other facilities in the same state	.78 (.20)	0, 1
CWA	=1 if facility is regulated by Clean Water Act	.52 (.50)	0, 1
TRI	=1 if facility is subject to Toxic Release Inventory reporting	.67 (.47)	0, 1
MACT	=1 if facility is regulated under Maximum Achievable Control Technology	.44 (.50)	0, 1
SIP	=1 if facility is regulated under State Implementation Plan	.12 (.32)	0, 1
Manufacturing	=1 if facility is in manufacturing industry, with 2 digit SIC codes between 20 and 39	.62 (.49)	0, 1
Race	Percentage of white in population	81.27 (15.68)	13.54, 100
Income	Annual income per capita at the county level, adjusted by CPI, in $1000	33.10 (8.84)	14, 112
High	Percentage of population with high school education or above	85.28 (4.42)	62.1, 97
Rate	Unemployment rate	6.36 (2.61)	1.9, 29.7
Population Density	Number of persons per square miles	1043 (4180)	.64, 69,121

The dummy variables, *CWA* and *TRI,* identify other environmental programs to which the facility is subject. More than half of the facilities included in the analysis are subject to TRI reporting while about 51% of the facilities are regulated by CWA. The next two dummy variables *MACT* and *SIP* denote two specific programs within the CAA program. About 44% of the facilities are regulated under MACT and 12% regulated under SIP. Industry differences are captured broadly using the variable *Manufacturing*. Facilities with 2 digit SIC codes between 20 and 39 are classified as manufacturing and 62% of facilities in the sample belong to that category. The remaining variables, *Race*, *Income*, *College*, *Rate,* and *Population Density*, are selected to control for community characteristics. Those variables are included in the estimation after natural log transformation.

B. Econometrics model

Following the theoretical model developed in Liu (2012), empirical methods are used to test the following hypotheses:

1. Within program effects hypothesis: controlling for other influences, regulatory actions against the facilities should have positive impact on their compliance within the same program.
2. Cross program effects hypothesis: the nature of the spillover effects depends on the impacts of regulatory actions taken under one program on compliance with another program. This is the cross program effects. If the impacts are positive (negative), then the spillover effects are positive (negative).

The dependent variable is facility compliance with CAA regulation. Due to estimation consideration, monthly compliance data are summarized on a yearly basis. The summarized yearly data might lose certain information that is embedded with the detailed monthly data. However, if monthly data are used and estimated using panel data models for binary dependent variables such as logit or probit models, facilities whose compliance status never changed are dropped from the estimation due to the lack of variation. About 54.3% and 24.6% of facilities are either always in compliance or never in compliance. If binary estimations are carried out, only 21.1% of the original sample are used and thus information provided by those excluded facilities are ignored. Therefore, the dependent variable is the number of month a facility is in compliance in a given year.

Following previous literature on compliance, the monitoring and enforcement measures considered here are sorted into specific and general deterrence (Grey and Shimshack, 2011). The specific deterrence included monitoring and enforcement actions taken at a specific facility. The general deterrence included the threat of enforcement actions and the spillover effects defined in Grey and Shimshack (2011)—the impact of enforcement at a specific facility on other facilities in general. To capture the specific effects, inspections and penalties under CAA and RCRA are included. Those variables are included as lagged effects instead of contemporaneous effects for the following reasons. First, the current inspection or penalty may be correlated with the facility's current compliance status and this can cause endogeneity. Including lagged variables can alleviate the issue to certain extent. Second, it may take time for the monitoring and enforcement actions to have an impact on the facilities, and it takes time for facilities to correct violations revealed during inspections. The general deterrence is represented by two measures: the threat of inspections and inspections on other facilities within the same state. The probability of inspection at a facility is calculated using a fixed-effects panel logit model, in which the dependent variable is equal to one if a facility is inspected during that period and zero otherwise. The estimation results are reported in the Appendix.

Heteroscedasicity and autocorrelation are among the issues that should be considered in panel data analysis when selecting econometric models. A modified Wald test for groupwise heterscedascity described in Greene (2000) is employed for the sample data and the results confirmed heterscedascity with p-value of 0. To test for autocorrelation, a Lagram-Multiplier test for serial correlation discussed in Wooldridge (2002) is used and the results show strong serial correlation with a p-value of 0.[7] Given the presence of both heteroscedasticity and autocorrelation, the model selected for estimation is a panel data model with panel corrected standard error (PCSE) with controls for both issues. [8] Furthermore, year dummies are included to control for the trend in environmental regulations and state dummies are used as proxies to state specific environmental regulations. [9]

In summary, the econometric model can be expressed as follows:

$$C_{it} = \alpha + \beta E + \gamma G + \delta Y_t + \rho S_k + \varepsilon_{it},$$

where C_{it} denotes the number of compliance months in a given year, *i* denotes the facility, *t* denotes time, *E* includes all monitoring and enforcement measures, *G* denotes other control variables

[7] The heteroscedasticity test is carried out using Stata's xttest3, while the test for autocorrelation is carried out using Stata's xtserial.

[8] Another concern is fixed-effects versus random-effects. While fixed-effects models may have advantages over random effects models, adopting fixed-effects models can be problematic since some of the important facility characteristics are time-invariant and thus will be excluded from the estimation. Excluding important facility characteristics may result in certain variables being insignificant or even showing the opposite signs. A similar issue is documented in Earnhart (2004b), where certain monitoring and enforcement variables are either insignificant or show the opposite signs when "systematic differences across facilities" are not adequately controlled for.

[9] Even though the dependent variable is the number of months a facility is in compliance, the typical panel data count model is inappropriate. The count model requires the events of the counts to be independent. However a facility's compliance status can be dependent from one month to the next. In particular, a facility's violation status can last for months if a major violation is found, and it difficult to correct.

including facility specific characteristics and community characteristics, Y_t is the year dummy, $S_k$is the state dummy, k denotes the state, and ε_{it} is PCSE error.

III. Results and Discussion

Table 3 provides the estimation results of two models using the panel data model with PCSE correction that controls for both heterscedasticity and autocorrelation. Model 1 includes the predicted probabilities of CAA and RCRA inspections while Model 2 excludes them. The discussion of results will focus on Model 1; Model 2 is used to check the robustness of Model 1. Important parameters of interests are those related to monitoring and enforcement measures.

Overall both general and specific deterrence under CAA shows positive and significant effects on CAA compliance. Thus, positive within-program effects are confirmed, and there is sufficient evidence in support of hypothesis 1 stated in Section II. The threat of a CAA inspection can increase facility compliance by 3.013 months on average in a given year, *ceteris paribus*. The other general deterrence variable, CAA inspection of other facilities within the same state, shows positive effects but it is insignificant. In terms of the specific deterrence, one unit increase in the log of *CAA penalty* increases facility compliance by 0.02 month on average in a given year, which translates to an increase of roughly 0.14 month of compliance for every $1000 increase in *CAA penalty*. *CAA inspection* shows significant but negative effects on CAA compliance at the 10% level with a coefficient of -0.03. The negative effects of *CAA inspection* is unexpected and deserve further examination. First, this may arise from targeting enforcement. According to Harford (1991), who first proposed the targeting enforcement theory, targeting noncompliant facilities with more frequent inspections or higher penalties can achieve efficiency while minimizing regulatory costs. Empirical evidence in support of targeting regulation is found later in Helland (1998). Facilities with noncompliance behavior under CAA may be targeted by the regulators with more frequent inspections, and therefore negative relationship is found between compliance and inspection. Second, it is also possible that facilities inspected in the previous year expect lower inspection probabilities in the current year and thus put less effort in abatement and compliance. This possibility is further supported by the results of the logit model shown in the Appendix. The negative and significant coefficient of *lagged CAA inspection* in the logit model indicates that facilities inspected in the previous year face lower probability of being inspected in the current year. If facilities correctly anticipated this, they may have reduced compliance in response.

Table 3

Estimation results

VARIABLES	(1)	(2)
Predicted CAA inspection	3.013*** (0.9)	
Other CAA inspection	1.43 (1.02)	2.24** (1.04)
CAA inspection	-0.03* (0.015)	-0.05*** (0.015)
CAA penalty	0.02*** (0.005)	0.02*** (0.005)
Predicted RCRA inspection	-2.57*** (0.81)	
RCRA inspection	-0.05*** (0.01)	-0.03*** (0.01)
RCRA penalty	-0.02* (0.01)	-0.02* (0.01)
TRI	-0.51*** (0.06)	-0.51*** (0.06)
CWA	-0.58*** (0.05)	-0.59*** (0.05)
MACT	-0.38*** (0.05)	-0.39*** (0.05)
SIP	0.17*** (0.06)	0.17*** (0.06)
Manufacturing	-0.06 (0.06)	-0.06 (0.06)
Race	0.15 (0.13)	0.15 (0.12)
Income	-0.15 (0.13)	-0.17 (0.13)
College	-0.03	-0.03

	(0.08)	(0.08)
Unemployment Rate	-0.16** (0.08)	-0.16** (0.08)
Population Density	0.05** (0.02)	0.05** (0.02)
Observations	52,641	52,641
R-squared	0.319	0.317
Number of groups	5,849	5,849

Standard errors are shown in parentheses.

***Significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

State and year dummies are included in the regression but not reported here.

In terms of the spillover effects across programs, all RCRA monitoring and enforcement variables are associated with negative and significant coefficients. Thus, negative cross program effects are confirmed and the relationship between CAA and RCRA is substituting. Among the RCRA variables, the threat of an RCRA inspection shows the highest impact on CAA compliance with a coefficient of -2.57. *RCRA inspection* is significant at the 1% level with a coefficient of -0.05. That is, for every additional RCRA inspection, a facility's compliance is expected to decrease by 0.05 month on average in a given year, *ceteris paribus*. Lastly, *RCRA penalty* also shows significant and negative effects on CAA compliance. A unit increase in the log of *RCRA penalty* can reduce facility compliance with CAA by 0.02 month on average in a given year, which is equivalent to a decrease of about 0.14 month for every $1000 increase in *RCRA penalty*. In addition, the negative cross program effects are further supported by the dummy variables that represent other environmental programs. Facilities regulated under TRI or CWA show less compliance than others, based on the negative and significant coefficients associated with *TRI* and *CWA*.

The finding of a substitution relationship between the two programs bears important policy implications. When evaluating monitoring and enforcement actions, regulators usually consider the benefits and cost of such actions and make decisions within the same program. However, substituting regulations imply that for a regulator, the effects of monitoring and enforcement actions are not limited to the benefit of improved compliance within the same program. Given the negative spillover effects across the two programs, CAA and RCRA, regulators should also take into account the decreased compliance with CAA caused by monitoring and enforcement actions in RCRA. To achieve the social optimal levels of abatement and emissions, regulators of the two programs should coordinate their monitoring and enforcement actions.

The negative spillover effects confirmed in this study is in contrast to the findings in Liu (2012), in which positive spillover effects are found. Notice that this study focus on facility compliance with CAA while Liu (2012) examines facility compliance with RCRA. The two programs can be different in various aspects and these differences may cause the contrasts in the findings of the two studies. Also the abatement technology under each media can be different and thus contributes to the contrast in findings. In addition, results from one state may not be readily extended so as to be applicable to the whole nation.

The rest of the control variables have limited impacts on compliance. Within the CAA program, facilities subject to MACT comply less while those regulated under SIP have better compliance record. In terms of the community characteristic, unemployment rate is negatively related to compliance with a coefficient of -0.16 and population density shows positive effects on compliance with a coefficient of 0.05. Both of these two variables are significant at the 1% level.

Given that certain monitoring and enforcement variables are also included in the logit models to predict the probabilities of CAA and RCRA inspections, one concern is that the predicted probabilities may interact with those monitoring and enforcement variables when they are all included in Model 1. In fact, the coefficients associated with the predicted probabilities are much higher than those associated with the actual monitoring and enforcement variables, which further confirms the concern.[10] To check the consistency of the findings in Model 1, a second model is estimated in which the predicted probabilities

[10] In Earnhart (2004b), it is also found that the predicted EPA inspections are associated with much higher coefficients than other deterrence variables.

are excluded. The results are shown in the last column of Table 3. Most of the variables show consistent estimations with the same signs and similar magnitude except the inspection variables. Specifically, both *CAA inspection* and *RCRA inspection* show larger effects than in Model 1. O*ther CAA inspections*, which is insignificant in Model 1, becomes significant in Model 2, indicating that CAA inspections imposed on other facilities in the same state have positive impacts on the compliance of the specific facility. This verifies that the predicted probabilities do pick up some of the effects of inspection variables. However, given that the signs of the coefficients are consistent between the two models, the conclusion of positive within program effects and negative cross program effects remain valid. Therefore, the spillover effect is negative and the relationship between the two programs is substituting.

IV. Conclusion

This paper investigates firm compliance with multiple environmental regulations. Using data on facilities that are regulated under both CAA and RCRA across the nation, a panel data model with PCSE correction is used to examine the within-program effects and cross program effects. The within-program effects refer to the impact of regulatory measures on compliance within the same program, while the cross-program effects refer to the impact of regulatory measures under one program on compliance under other programs.

As expected, the within program effects are positive. The threat of inspections and actual penalties under CAA improve facility compliance with CAA significantly. In comparison to previous findings, the cross-program effects are found to be negative. The threat of inspections and actual inspections as well actual penalties under RCRA induce facilities to comply less with CAA. Therefore, the RCRA program has negative spillovers on the CAA program and the two programs are substituting. In addition, facilities subject to other environmental programs like CWA and TRI are also shown to comply less with CAA, which provides further evidence in support of the substitution. Given the findings, coordination among regulators is called for to achieve social optimum. When regulators take monitoring and enforcement actions under RCRA, further consideration should be given to the effects of those actions on facility compliance with other programs such as CAA.

References

Alberini, A.(1993). Environmental regulation and substitution between sources of pollution: an empirical analysis of Florida's storage tanks. *Journal of Regulatory Economics*, 19, 55–79.

Botre, C., Tosi, M., Mazzei, F., Bocca, B., Petrucci, F., Alimonti, A. (2007). Automotive catalytic converters and environmental pollution: role of the platinum group elements in the redox reactions and free radicals production, *International journal of environment and health*, 1, 142-152.

Decker, C. S., Pope, C. R. (2005). Adherence to environmental law: the strategic complementarities of compliance decisions. *The Quarterly Review of Economics and Finance*, 45, 641–661.

Earnhart, D. (2004a). The Effects of community characteristics on polluter compliance levels. *Land Economics*, 80, 208-432.

Earnhart, D. (2004b). Panel Data Analysis of Regulatory Factors Shaping Environmental Performance. *The Review of Economics and Statistics*, 86(1), 391-401.

EPA, AFS Download Summary: Description of the IDEA AFS Data Set, http://www.epa-echo.gov/echo/idea_download.html, last accessed on 8/20/2012.

Gamper-Rabindran, S. (2006). Did the EPA's voluntary industrial toxics program reduce emissions? A GIS analysis of distributional impacts and by-media analysis of substitution. *Journal of Environmental Economics and Management*, 52, 391–410.

Gray, W., Shadbegian, R. (2007). The Environmental Performance of Polluting Plants: A Spatial analysis. *Journal of Regional Science*, 47 (1), 63-84.

Gray, W., Shimshack, J. (2011). The Effectiveness of Environmental Monitoring and Enforcement: A Review of the Empirical Evidence. *Review Environmental Economics and Policy*, 5(1), 2-24.

Greene, W. (2000). *Econometric Analysis*. Upper Saddle River, NJ: Prentice-Hall.

Harford, J. (1991). Measurement Error and State-Dependent Pollution Control Enforcement. *Journal of Environmental Economics and Management*, 21, 67-81.

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

Kaplow, L. Shavell, S. (1994). Optimal Law Enforcement with Self-reporting of Behavior. *Journal of Political Economy*, 102(3), 583-606.

Laplante, B. Rilstone, P. (1996). Environmental Inspections and Emissions of the Pulp and Paper Industry in Quebec. *Journal of Environmental Economics and Management*, 31, 16-36.

Liu, L. (2012). Spillover Effects across Environmental Programs: the Case of Hazardous Waste Regulation in Michigan. *Environmental Economics*, 3 (2), 35-43.

Shimshack, J. P., Ward, M.B. (2005). Regulator Reputation, Enforcement, and Environmental Compliance. *Journal of Environmental Economics and Management*, 50, 519–540.

Sigman, H. (1996). Cross-media pollution: Responses to restrictions on chlorinated solvent releases. *Land Economics*, 72, 298–312.

Wooldridge, J. (2002). *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.

Appendix

Results of the fixed-effects logit estimation

VARIABLES	CAA Inspection	RCRA inspection
Lagged CAA inspection	-1.06***	
	(0.02)	
Lagged CAA penalty	0.02***	
	(0.005)	
Lagged CAA compliance	0.0002	
	(0.005)	
Lagged RCRA inspection		-0.45***
		(0.024)
Lagged RCRA penalty		0.01
		(0.01)
Race	2.12**	1.53
	(1.00)	(1.28)
Income	-0.34**	0.17
	(0.16)	(0.21)
College	-0.19**	0.18*
	(0.09)	(0.10)
Unemployment Rate	0.76***	0.09
	(0.10)	(0.13)
Population Density	0.34	0.33
	(0.34)	(0.42)
Year 2002	-0.47***	0.01
	(0.06)	(0.08)
Year 2003	-0.23***	-0.006
	(0.06)	(0.08)
Year 2004	-0.17***	-0.02
	(0.06)	(0.07)
Year 2005	-0.25***	-0.02
	(0.05)	(0.06)
Year 2006	-0.13***	-0.06
	(0.05)	(0.06)
Year 2008	-0.31***	-0.18***
	(0.05)	(0.07)
Year 2009	-0.79***	-0.008
	(0.09)	(0.11)
Year 2010	-0.85***	-0.01
	(0.09)	(0.12)
Observations	40,671	30,402

Standard errors are shown in parentheses.

***Significant at the 1% level; ** significant at the 5% level; * significant at the 1% level.

Year 2001 and 2007 dummies are dropped due to collinearity.