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Spillover effects across environmental programs: the case of hazardous waste regulation in Michigan

Abstract

This paper investigates the compliance behavior of firms that are simultaneously regulated by multiple environmental programs. Three possible relationships among compliances with multiple programs are considered: complementarity, substitution and independence. These relationships reflect the spillover effects across environmental programs. A theoretical model of firm decision making is developed to show the possibilities of these relationships. The theoretical results are tested using data on facilities in Michigan that are regulated by hazardous waste (Reservation and Conservation Recovery Act, RCRA) and air programs (Clean Air Act, CAA). Results show evidence of positive cross-program effects. Inspections under CAA have positive and significant effects on facility compliance with RCRA. In addition, facilities subject to other environmental programs such as Toxic Release Inventory (TRI) or water regulation (Clean Water Act, CWA) also show better compliance status. With the presence of positive effects across environmental programs coordination is required among regulators to achieve the optimal monitoring and enforcement strategies.

Keywords: air pollution, hazardous waste, compliance, complementary, substitution.
JEL Classification: Q53, Q58, L51.

Introduction

Firm compliance with environmental regulations has been the focus of numerous empirical studies in environmental policy analysis. Current literature examines environmental enforcement and compliance from various perspectives[1]. To date, the majority of the empirical literature has focused on single medium program, such as Clean Air Act (CAA), Clean Water Act (CWA), Resource Conservation and Recovery Act (RCRA), Toxic Release Inventory (TRI), etc. However, in practice many firms are regulated under more than one environmental program. According to the Environmental Protect Agency's (EPA) Facility Registration System (FRS), a total of 40,630 facilities are regulated under RCRA in Michigan. Among those facilities, 3057 of them are also regulated by one or more programs listed above. In addition, facilities may also be subject to other EPA environmental programs and Michigan state programs such as Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA) and Toxic Substances Control Act (TSCA). Thus the number of facilities regulated by multiple programs may be even higher. For firms regulated under multiple programs, an important question is: do stricter regulations under one program increase, decrease or have no effect on firm compliance with another program?

This paper endeavors to answer the above question by examining firm compliance behavior under multiple programs. When a firm is regulated under multiple programs, the relationships among these environmental regulations can be substituting, complementary or independent. Complementary (substituting) regulations arise when increasing the monitoring and enforcement intensity under one program causes the firm to increase (decrease) its abatement under other programs and hence results in higher (lower) compliance under other programs. When regulations are not independent, optimal monitoring and enforcement strategies require coordination between two programs. Consider the situation where an increase in a firm's abatement level under program A reduces 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 increases, although the monitoring and enforcement parameters under that program remain unchanged. From a society's perspective, this complementarity among regulations means reduced total abatement costs and thus reduced social optimal level of emissions, which benefits the overall environment. Following the same reasoning, substituting regulations, on the other hand, results in higher abatement costs and higher social optimal level of emissions. In either cases, coordination among regulations is required to achieve the social optimum.

The purpose of this paper is to uncover both the existence and nature of spillover effects that one regulatory program places on another regulatory program. Previous studies are suggestive. Firms may substitute away from one type of emissions to another due to technological change or optimization strategies during production. 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 medium

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[1] Cohen (1998, 2000) provides literature reviews of empirical works on environmental monitoring and enforcement. Grey and Shimshack (2011) summarize the empirical evidence of environmental monitoring and enforcement with more recent findings.

such as landfill or water[1]. These studies suggest substitution-inducing regulations (or negative spillovers), but do not explicitly consider regulatory programs simultaneously. In contrast, this paper tests for potential substitution in compliance across programs.

In practice complementary regulations are also possible. For example, 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 in general which 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. The existing literature does not provide evidence of such complementaries. However, a few papers investigate the complementarities across firms induced by a single environmental program (see Shimshack and Ward, 2005, 2008; Decker and Pope, 2005).

The theoretical model developed in this paper considers a representative firm regulated under two programs, i.e., two pollutants, and allows for abatement of one pollutant to have positive, negative or zero impacts on the marginal abatement cost of the other pollutant. Comparative statics results show that firms respond to more stringent regulations by increasing abatement as well as the compliance within the same program. The effects of changes in the regulation of one program on the compliance of the other program are ambiguous and depend on the nature of the abatement cost function.

The empirical work focuses on facilities in Michigan that are regulated under both RCRA and CAA. A panel data probit model with censoring is used to estimate the impacts of monitoring and enforcement under both RCRA and CAA on facility compliance with RCRA. The results confirm positive within program effects. As expected, higher RCRA inspection frequency increases the compliance rate within the same program. However, in a finding not previously documented, the cross-program effects turn out to be positive as well. Increasing CAA inspections frequency leads to a higher compliance rate under RCRA. Thus there is a complementary relationship between the two programs.

The rest of the paper is organized as follows. Section 1 develops the theoretical model of firm compliance decisions under multiple regulations. Section 2 discusses the data and the empirical model. Results and interpretations are given in Section 3. Robustness check is conducted in Section 4 and the final section concludes.

1. Theoretical model

A polluting firm is regulated under two environmental programs, denoted m and n. The regulations take the form of standards, denoted s_m and s_n, on the firm's total emissions of the regulated pollutants. The firm decides whether to comply by choosing the abatement levels a_m and a_m. Let $\overline{e}_i$ denote the level of emissions in the absence of regulation, and e_i the emissions after abatement, where $i = m, n$. It is assumed that there is measurement error associated with the inspection process, denoted v_i, such that the firms realized emissions are $e_i = \overline{e}_i - a_i + v_i$. Then $a_i = \overline{e}_i - e_i + v_i$. The abatement cost for the firm is $c(a_m, a_n)$, with $c_i = \frac{\partial c}{\partial a_i}$, $c_{ii} = \frac{\partial^2 c}{\partial a_i^2}$ and all being positive. Define the cross marginal abatement cost to be $c_{mn} = c_{nm} = \frac{\partial^2 c}{\partial a_m \partial a_n}$. As shown below, complementary or substitution relationships between the two regulatory programs arise when the cross marginal abatement cost is different from zero.

1. When $c_{mn} = c_{nm} < 0$, increasing abatement of one pollutant reduces the marginal abatement cost of the other, and
2. When $c_{mn} = c_{nm} > 0$, increasing abatement of one pollutant increases the marginal abatement cost of the other.

To ensure compliance, regulators of the two programs inspect the probabilities q_m and q_n, respectively. Emissions exceeding the standards are penalized with per unit fines, f_m and f_n. The probability that the firm is out of compliance under regulation i, denoted $P_i(a_i)$, is a function of the corresponding abatement level, where $P_i^{'} < 0$, $P_i^{''} < 0$, and $P_i(0) = 1$[2]. Define the firm's expected total cost, $g(a_m, a_n)$ as the sum of abatement costs and expected penalties. It follows that

[1] 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.

[2] To ensure the probability $P_i(a_i)$ to be differentiable, it is assumed that the firm cannot completely eliminate the potential of violation due to measurement errors associated with the inspection process.

$$g\left(a_m, a_n\right) = c\left(a_m, a_n\right) + f_m q_m P_m\left(a_m\right)\left(\overline{e}_m - a_m + v_m - s_m\right) + f_n q_n P_n\left(a_n\right)\left(\overline{e}_n - a_n + v_n - s_n\right). \tag{1}$$

The firm chooses abatement levels a_m and a_n to minimize $g(a_m, a_n)$. Assuming interior solutions, the associated first order conditions can be rearranged to yield:

$$c_m = f_m q_m P_m\left(a_m^*\right) - f_m q_m\left(\overline{e}_m - a_m^* - s_m\right) P_m^{'}(a_m^*), \tag{2}$$

$$c_n = f_n q_n P_n\left(a_n^*, s_n\right) - f_n q_n\left(\overline{e}_n - a_n^* - s_n\right) P_n^{'}(a_n^*), \tag{3}$$

where * denotes the optimal abatement levels. The left-hand sides of equations (2) and (3) represent the marginal costs and the right-hand sides are the expected marginal benefits of abatement effort respectively.

The relationship between the two regulatory programs m and n depends on the comparative static results for penalties (f) and inspections (q). The main results are stated as Proposition 1 and proofs are provided in Appendix.

Proposition 1. Assuming an interior solution for the firm's optimization problem, the comparative statics with respect to penalties f_i and inspections q_i are:

1. $\frac{da_i}{df_i} > 0$ and $\frac{da_i}{dq_i} > 0$ for $i = m,n$;
2. Sign ($\frac{da_i}{df_j}$) = sign ($\frac{da_i}{dq_j}$) = -sign(c_{ij}), where $i, j \in \{m,n\}$ and $i \neq j$.

Proposition 1 describes the effects of changes in penalties and inspections on abatement levels under the two programs. Within program effects refers to the impacts of monitoring and enforcement on the abatement (and hence compliance) within the same program; cross-program effects refer to the impacts of monitoring and enforcement under one program on the abatement (and hence compliance) under the other program as Statement (1) in Proposition 1 indicates that the within program effects are positive. Increasing fine or inspection probability under regulation *I* results in higher abatement of pollutant *i*. Statement (2) refers to cross-program effects. When the cross marginal abatement cost is negative (positive), higher monitoring and enforcement intensity under program *i* increases (decreases) abatement cost at the margin under program *j* for $i \neq j$ and thus the abatement and hence compliance under program *j* decreases (increases). The programs are substitutes (complements). Although the sign of the cross marginal abatement cost is usually not observed or cannot be estimated, it can be inferred from the sign of the comparative statistics. For example if $\frac{da_i}{df_j} > 0$ then the cross marginal abatement cost is negative and vice versa. In addition, if $\frac{da_i}{df_j} = 0$, the cross marginal abatement cost is zero and thus there is no cross-program effects.

Barring direct information on the cross marginal abatement cost, the existence of cross program effects is an empirical question. The theory implies the following testable hypotheses:

Hypothesis 1: The within program effects are positive.

Hypothesis 2: The cross-program effects are zero.

Hypothesis 2 tests the changes in abatement and thus compliance under one program in response to changes in monitoring and enforcement under the other program. Under the null hypothesis, there are no effects across the programs. If the null hypothesis is rejected, then it indicates that the two programs are correlated. Specifically, positive cross-program effects imply negative cross marginal abatement cost and hence the programs are complementary. On the other hand, if the cross-program effects are negative, then cross marginal abatement cost is negative and regulations are substitutes.

2. Data and econometric estimation

The major data source is EPA's Enforcement and Compliance History Online (ECHO). The ECHO database tracks the compliance, inspection and enforcement histories of all EPA-regulated facilities under air, water and hazardous waste programs. Under RCRA, facilities are inspected on a regular basis, although violations causing damage to human health or the environment may be self-reported or reported by third parties. Thus, compliance status is observable when a facility is inspected under RCRA. The RCRA compliance status is tabulated quarterly. If a facility is inspected during a specific quarter and found to be in compliance, then the facility is assumed to be in compliance in that quarter; if a facility is found to be out of compliance during the inspection, then it is assumed to be in violation in the corresponding quarter; for facilities that are not inspected, its compliance status remains unknown for that quarter. The total numbers of inspections and penalties under RCRA and CAA in each quarter are also obtained from the database. Overall a total of 1485 Michigan facilities with complete records in 40 quarters from 2001 to 2010 are included in the analysis[1].

[1] While determining facilities that are regulated under both CAA and RCRA, some facilities cannot be identified uniquely by CAA ID number or RCRA ID number. For example, a single ID under CAA can be matched to multiple IDs under RCRA according to EPA's facility registration system. Since there is no other identification method to aggregate the multiple RCRA IDs, each RCRA ID is treated as a unique facility although they share the same CAA information. Similarly, there are cases where a unique ID under RCRA are assigned multiple IDs under CAA. The multiple CAA IDs are treated as unique facilities. Therefore, each facility in the analysis is jointly identified by CAA and RCRA ID.

The ECHO database is linked to two other databases available through EPA: the Facility Registration System (FRS) database and the RCRA Info database. These databases provide information about facility characteristics and other environmental programs under which the facility is regulated.

Community characteristics are obtained from the U.S. Bureau of Economic Analysis to control for potential influence of community pressures on facility compliance. Specifically income per capital and population density at the county level are included in the analysis. For counties without income per capita and population density statistics, the corresponding state level statistics are used instead.

The empirical analysis focuses on the within program effects under RCRA and the cross-program effects of CAA monitoring and enforcement on RCRA compliance. Since compliance status under RCRA is available only when a facility is inspected, the empirical analysis must control for censoring.

Let $C^*_{k,t}$ denote the latent variable representing a facility's net benefit from complying with RCRA, where *k* denote the facility and *t* denote the time period. The corresponding compliance dummy variable is $C_{k,t}$ such that $C_{k,t}$ = 1 (facility complies) and $C_{k,t}$ = 0 (facility does not comply) otherwise. For the regulator, $I^*_{k,t}$ is the net benefit of inspecting facility *k* in period *t*. The corresponding dummy variable is $I_{k,t}$ such that $I_{k,t}$ = 1 (facility is inspected) if $I^*_{k,t} > 0$ and $I_{k,t}$ = 0 (facility is not inspected) otherwise. Due to censoring, $C_{k,t}$ is observed only when $I_{k,t}$ = 1. Thus the empirical model consists of the following two equations:

$$I^*_{k,t} = x'_{k,t}\alpha + u_{k,t}, \tag{4}$$

$$C^*_{k,t} = f'_{k,t}\beta + z'_{k,t}\gamma + \varepsilon_{k,t}, \tag{5}$$

with the corresponding dummy variables,

$$I_{k,t} = \begin{cases} 1 & if\ I^*_{k,t} > 0 \\ 0 & otherwise \end{cases},$$

$$C_{k,t} = \begin{cases} 1 & if\ C^*_{k,t} > 0 \\ 0 & otherwise \end{cases},$$

and $C_{k,t}$ is observed when $I_{k,t}$ = 1.

In equation (4), the inspection equation, $x'_{k,t}$ includes factors that affect the inspection probability for facility *k* in period *t* and *a* is the corresponding parameter vector to be estimated. In equation (5), the compliance equation, $f'_{k,t}$ are variables representing monitoring and enforcement actions. These variables include the number of inspections in the past four quarters and the total amount of penalty in $1000 in the past 4 quarters under both programs[1]. The coefficients of RCRA inspection and penalty represent within program effects, which are expected to be positive. The coefficients of CAA inspection and penalty variables represent the cross-program, which will be determined through estimation. Positive coefficients mean a higher penalty or inspection probability under CAA leads to more compliance under RCRA. Thus the cross-program effects are positive. This implies a complementary relationship between the programs. Similarly negative coefficients mean negative cross-program effect and a substitution relationship. In equation (5), $z'_{k,t}$ includes other control variables such as facility-specific characteristics and community characteristics. Parameter vectors β and γ will be determined through estimation.

The inspection equation and the compliance equation are jointly estimated using the Heckman two-step procedure. The error terms in the two equations are assumed to follow a bivariate normal distribution such that

$$\begin{bmatrix} u_{k,t} \\ \varepsilon_{k,t} \end{bmatrix} \sim N[0,\Sigma], \text{ where } \Sigma = \begin{bmatrix} 1 & \rho \\ \rho & \sigma^2_\varepsilon \end{bmatrix}.$$

The first step in Heckman two-step procedure is to estimate the selection decision. The inspection equation is estimated using a probit random effects model. The inverse Mill's ratio is obtained by

$$\hat{\lambda}_i = \frac{\phi\left(x'_{k,t}\hat{\alpha}\right)}{\Phi\left(x'_{k,t}\hat{\alpha}\right)},$$

where $\phi(\bullet)$ and $\Phi(\bullet)$ are the standard normal probability density function and cumulative distribution function.

In the second step, the compliance equation is estimated using aprobit random effects model as well. However only observations with compliance information available are included and the inverse Mill's is included as one of the control variables. Since the inverse Mill's ratio estimated in the first step, including it in the second step can introduce randomness and heterosckedascity. To correct for these, the standard error in the second step is computed using bootstrapping[1].

[1] The lagged variables instead of the contemporaneous variables are included in the model for two reasons. First, 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. Second, the current inspection or penalty may be correlated with the facility's current compliance status. Thus the lagged variables are used to control for potential endogeneity.

Table 1 provides variable descriptions and summary statistics. The first two dummy variables, *RCRA compliance* and *RCRA inspection*, are the dependent variables in the two equations. The mean quarterly inspection rate under RCRA is only 0.03[1]. However, the frequency of inspection varies across facilities. About 50% of the facilities are never formally inspected. Those facilities are still included in the analysis since they may be monitored or enforced through other channels like informal inspections. In contrast, 29 facilities are formally inspected in more than 10 quarters. The RCRA compliance rate for all inspected facilities is around 0.52, which means 52% of the quarterly inspections result in compliances. The set of variables from *RCRA penalty* to *CAA inspection* are inspections and penalties under both programs in the past four quarters. The average penalty in the past four quarters under RCRA is $220, which is much lower than the average under CAA, $940. The average number of inspections in the past four quarters under RCRA is slightly lower than the average under CAA.

Table 1. Variable description and summary of statistics

Variables	Description	Mean (standard deviation)
RCRA compliance	=1 if facility is in compliance with RCRA	.52 (.50)
RCRA inspection dummy	=1 if facility is inspected in current quarter under RCRA	.03 (.18)
RCRA penalty	Penalty under RCRA in the past four quarters, in $1000	.22 (7.15)
RCRA inspection	Number of inspections under RCRA in the past four quarters	.19 (.96)
CAA penalty	Penalty under CAA in the past four quarters, in $1000	.94 (41.38)
CAA inspection	Number of inspections under CAA in the past four quarters	.17 (.40)
CWA	=1 if facility is regulated by Clean Water Act	.20 (.40)
TRI	=1 if facility is subject to Toxic Release Inventory reporting	.51 (.50)
Manufacturing	=1 if facility is in manufacturing industry, with 2 digit SIC codes between 20 and 39	.58 (.49)
Large generator	=1 if facility is a large generator of hazardous wastes	.16 (.37)
Transporter	=1 if facility is a transporter of hazardous wastes	.003 (.06)
Income	Income per capita at the county level, in $1000	31.38 (6.92)
Population density	Number of persons per square miles	907.50 (1062.84)

Note: Standard errors are reported in parentheses.

The dummy variables, *CWA, TRI* and PSD, identify other environmental programs to which the facility is subject. More than half of facilities included in the analysis are subject to TRI reporting while bout 20% of the facilities are regulated by CWA. Industry differences are captured broadly using the variable *Manufacturing*. Facilities with 2 digit SIC codes between 20 and 39 are classified as manufacturing and 58% of facilities in the sample are classified as manufacturing. The next two variables, *Large generator* and *Transporter*, control for other RCRA-related characteristics of the facility. The remaining variables, *Income* and *Population density*, are selected to control for community characteristics. Those two variables are included in the estimation with natural log transformation.

3. Results

The estimation results of the two step probit model with random effects are shown in Table 2. Important parameters of interests are those related to past penalties and inspections in the compliance equation. Penalties in the past four quarters under both RCRA and CAA show positive and significant impacts on RCRA compliance, with RCRA penalty being significant at the 1% level and CAA penalty being significant at the 5% level. In terms of Hypothesis 1 in Section 1, the positive and significant coefficient of RCRA inspection provides evidence in support of it. The positive and significant coefficient of CAA inspection suggests that more monitoring actions under CAA are associated with better compliance with RCRA. Thus Hypothesis 2 can be

[1] Hill et al. (2003) provide summaries of various corrections for standard error in the Heckman two-step estimation and they also outline the advantages of using the bootstrapping method.

[2] For the 1485 facilities over a period of forty quarters, a total of 2808 inspections were carried out by the EPA and the state regulators.

rejected. In addition, the positive cross-program effects imply a complementary relationship between the two programs for the same facilities. In contrast, penalties under both programs show insignificant impacts on RCRA compliance. The coefficient RCRA penalty is negative and insignificant while the CAA coefficient is positive but insignificant. There are several possible explanations for the insignificant results. First, penalties especially those imposed under RCRA are generally results of violations revealed during inspections. The penalties can lag the corresponding inspections and violations by several quarters. By the time a facility receives a fine, the effect on compliance may have already been exerted on the facility through inspection a few quarters ago. Thus the penalty shows no further effects on compliance. Second, penalty is not the only cost imposed on the facilities during monitoring and enforcement. Facilities may incur inspection cost like filling paperwork and interruption of production during inspections. Given the relatively low level of penalties – an average of $220 under RCRA and $940 under CAA, the total inspection costs for facilities inspected frequently may be well above the expected penalty, thus those facilities will be more responsive to inspections than to penalties. Third a fine is usually the last enforcement action when a violation occurs and persists. Therefore penalties may reflect some inherent conditions that are hard for the violating facilities to overcome or correct. Even these facilities are fined frequently, there is no significant improvement in their compliances.

Table 2. Estimation results

Variables	RCRA compliance				Inspection	
	Coefficient	Std. error	Marginal effects	Std. error	Coefficient	Std. error
RCRA penalty	-.0001	.008			.001	.001
RCRA inspection	.072***	.027	.071***	.027		
CAA penalty	.018	.153				
CAA inspection	.214**	.097	.21***	.096		
TRI	.599***	.172				
CWA	.389**	.174				
Manufacturing	-.131	2.40			.393***	.046
Large generator	-2.50	5.15			.855***	.050
Transporter	-4.22	11.57			2.32***	.277
Income	1.19	2.91			-.463***	.016
Population density	-.294**	.119			.015	.016
Observations	1818				59400	

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

The finding of a complementary relationship between the two programs bears important policy implications. Complementary regulations imply that for a regulator, the benefit of increasing monitoring and enforcement of one program is not limited to the reduced emissions or increased compliance under the same program. When evaluating the effectiveness of monitoring and enforcement the regulator should also take into account the benefit of increased compliance under other programs. To achieve the social optimal levels of abatement and emissions, regulators of the two programs should coordinate their monitoring and enforcement actions.

To better interpret the within program and cross-program effects, the marginal effects for inspection variables are calculated at the mean of the independent variables. The marginal effect of *RCRA inspection* is 0.071, meaning one more RCRA inspection in the past four quarters increases the probability of RCRA compliance by 0.071. The marginal effect of *CAA inspection* turns out to be higher. A one unit increase in *CAA inspection* raises the RCRA compliance probability by 0.21. The higher marginal effects from *CAA inspection* may be due to the fact that facilities are inspected more frequently under CAA and thus the higher intensity of inspection gives facilities more incentive to deal with any violations.

Variables representing facility specific characteristics are insignificant in general except *CWA* and *TRI*, the dummy variables indicating whether a facility is subject to CWA and TRI. Facilities regulated under TRI are required to report their usage, manufacturing, transportation or releases of certain toxic chemicals to state and local governments. Previous empirical analysis of information disclosure programs can be used to explain this positive effect of *TRI*. For example, Konar and Cohen (1997) show that firms with stock prices declining due to the release of the TRI information subsequently reduce their emissions by a larger amount than other firms in the same industry. Thus, facilities reporting to TRI have more incentive to reduce emissions, resulting in better compliance with RCRA. According to Table 2, facilities regulated by CWA are also more likely to be in compliance. This finding adds more evidence in support of the positive cross-program effects.

Variables related to community characteristics seem to provide limited effects. The coefficient of income per capita is positive but insignificant. This finding is similar to the result in Shimshack and Ward (2005), who find community characteristics insignificant in their analysis of firm compliance. As explained in their paper, community characteristics may affect firm compliance through their influence on monitoring and enforcement, which has been included in the model. The other control variable, *Population density*, shows significant and negative effects on compliance. Similar results on population density are also found in previous works. For example, Earnheart (2004) finds that population density is positively related to BOD relative emissions among Kansas municipal wastewater treatment facilities.

The inverse Mill ration estimated in the first step turns out to be negative and insignificant in the second step. This implies that the selection bias resulted from censoring is small and insignificant. As a robustness check, a probit panel data model using data on inspected facilities is estimated and reported in the next section. The estimation results in the first step is also report in the last column in Table 1. Most of the control variables are significantly related to the inspection probability of a facility.

4. Sensitivity check

To check for robustness of the empirical results, two different models are considered here. Given that the selection bias resulted from censoring is insignificant, a probit panel model is estimated using a subsample of the inspected facilities. In the second model the sample data is treated as pooled cross-sectional data and a Heckman probit model is estimated using STATA's Heckprob. To control for the potential correlation over time within the same facilities clustering is used to control for within groups (facilities) correlation[1]. The estimation is reported in Table 3.

Table 3. Robustness check

	Probit Panel Model		Cross-sectional Heckman probit			
			Compliance		Inspection	
Variables	Estimation	Std. error	Estimation	Std. error	Estimation	Std. error
RCRA penalty	.002	.005	-.002	.001	.004***	.001
RCRA inspection	.07**	.032	.070***	.027		
CAA penalty	.018	.114	.015	.009		
CAA inspection	.211***	.088	.153*	.082		
TRI	.594***	.149	.312**	.142		
CWA	.388***	.134	.359**	.155		
Manufacturing	-.330*	.169	.001	.145	.127***	.081
Large generator	-.383***	.112	-.637**	.272	.776 ***	.075
Transporter	.041	.359	-.544	.668	1.96	.234
Income	.040	.359	.437*	.246	-.267	.163
Population density	-.256***	.045	-.20***	.069	.050**	.025
Observations	1818		55400		55400	

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

The results are consistent across the two models listed in Table 3 and the model discussed in the previous section in general. The coefficients of inspections under both programs are positive and significant while the coefficients of penalty under the two programs are insignificant and the signs vary. Variables representing other environmental programs like TRI and CWA are positive and significant. The coefficient of population density remains negative and significant. Other control variables show certain differences across models. For example, income per capita shows positive and significant effects on compliance in the cross-sectional Heckman probit model. Large generators of hazardous waste tend to comply less with RCRA according to the two models in Table 5.

Conclusion

This paper investigates firm compliance behavior under multiple environmental regulations. Three possible relationships among compliance decisions are considered and tested: (1) complementarity, where regulatory measures under one program positively affect firm compliance with other programs; (2) substitution, where firms reduce compliance with one program in response to more stringent regulations under other programs; (3) independence, where facilities make compliance decisions independently.

Using data on facilities that are regulated under both CAA and RCRA in Michigan probit model with censoring is estimated. As expected, the within program effects are positive: RCRA inspections have significantly positive effects on compliance under RCRA. A novel and important finding is the posi-

[1] See Rogers (1993), Williams (2000) and Wooldridge (2002) for details about clustering.

tive cross-program effects: increases in CAA inspections induce facilities to comply more often with RCRA. Therefore, the CAA regulatory program has positive spillovers on the RCRA program and the two programs are complementary. Facilities subject to other environmental programs like CWA and TRI are also shown to be more likely to comply with RCRA, which provide further evidence in support of the complementarity. Given the findings, coordination among regulators is called for achieving social optimum.

One potential limitation of the results is that the positive spillover effects are found among facilities in Michigan that are subject to RCRA and CAA. To establish the nature of the spillover effect at the national level further research may be needed.

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Appendix

The second order effects that are used in deriving the comparative statics include:

$$g_{11} = c_{mm} + q_m f_m P_m^{''}(\overline{e}_m - a_m - s_m) - 2q_m f_m P_m^{'},$$

$$g_{22} = c_{nn} + q_n f_n P_n^{''}(\overline{e}_n - a_n - s_n) - 2q_n f_n P_n^{'}.$$

When second order is satisfied, $g_{11} > 0$ and $g_{22} > 0$.

The following are second-order partial derivatives:

$$g_{12} = c_{mn},$$

$$g_{1f_m} = q_m P_m^{'}(\overline{e}_m - a_m^* - s_m) - 2q_m P_m\left(a_m^*, s_m\right) < 0,$$

$$g_{2f_n} = q_n P_n^{'}(\overline{e}_n - a_n^* - s_n) - 2q_n P_n\left(a_n^*, s_n\right) < 0,$$

$$g_{1q_m} = f_m P_m^{'}(\overline{e}_m - a_m^* - s_m) - 2f_m P_m\left(a_m^*, s_m\right) < 0,$$

$$g_{2q_n} = f_n P_n^{'}(\overline{e}_n - a_n^* - s_n) - 2 f_n P_n\left(a_n^*, s_n\right) < 0,$$

$$g_{2f_m} = g_{1f_n} = g_{2q_m} = g_{1f_n} = 0.$$

The within program effects and their signs are given below, where $SOC = g_{11}g_{22} > 0$,

$$\frac{da_m^*}{df_m} = \frac{1}{SOC}\begin{vmatrix} -g_{1f_m} & g_{12} \\ -g_{2f_m} & g_{22} \end{vmatrix} = -\frac{g_{1f_m}g_{22}}{SOC} > 0,$$

$$\frac{da_m^*}{dq_m} = \frac{1}{SOC}\begin{vmatrix} -g_{1q_m} & g_{12} \\ -g_{2q_m} & g_{22} \end{vmatrix} = -\frac{g_{1q_m}g_{22}}{SOC} > 0.$$

The same reasoning holds for $\frac{da_n^*}{df_n}$ and $\frac{da_n^*}{dq_n}$.

The cross-program effects include:

$$\frac{da_m^*}{df_n} = \frac{1}{SOC}\begin{vmatrix} -g_{1f_n} & g_{12} \\ -g_{2f_n} & g_{22} \end{vmatrix} = \frac{g_{2f_n}g_{12}}{SOC} = \frac{c_{mn}g_{2f_n}}{SOC},$$

$$\frac{da_n^*}{df_m} = \frac{1}{SOC}\begin{vmatrix} -g_{1f_m} & g_{12} \\ -g_{2f_m} & g_{22} \end{vmatrix} = \frac{g_{2f_m}g_{12}}{SOC} = \frac{c_{mn}g_{2f_m}}{SOC},$$

$$\frac{da_m^*}{dq_n} = \frac{1}{SOC}\begin{vmatrix} -g_{1q_n} & g_{12} \\ -g_{2q_n} & g_{22} \end{vmatrix} = \frac{g_{2q_n}g_{12}}{SOC} = \frac{c_{mn}g_{2q_n}}{SOC},$$

$$\frac{da_n^*}{dq_m} = \frac{1}{SOC}\begin{vmatrix} -g_{1q_m} & g_{12} \\ -g_{2q_m} & g_{22} \end{vmatrix} = \frac{g_{2q_m}g_{12}}{SOC} = \frac{c_{mn}g_{2q_m}}{SOC}.$$

The signs of the cross-program effects depend on the sign of c_{mn}. Assume that the second-order condition is satisfied. If $c_{mn} > 0$, then the cross-program effects are negative since the second order partial derivatives are negative and the Hessian matrix is positive. If $c_{mn} < 0$, then the cross-program effects are positive.