Voluntary Pollution Abatement: Testing Alternative Theories

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Abstract

We broaden the existing empirical literature on environmental regulation and voluntary pollution abatement programs by testing the effects of implicit boycott threats and a firm's participation in a partnership program on its subsequent regulatory oversight using EPA's 33/50 program as a research experiment. Our results are consistent with the hypothesis of a preemptive self-selection to deter consumer boycotts. The findings also indicate that (1) predetermined corrective actions constitute a significant determinant of voluntary participation and (2) EPA reciprocated to voluntary participation by easing regulatory oversight on participants.

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1 Introduction

An economic puzzle is posed by private firms' voluntary over-compliance with environmental regulations. For example, over 1200 firms signed up for the U.S. Environmental Protection Agency's (EPA) 33/50 program. In this program, firms pledged to reduce emissions of 17 key toxic pollutants beyond targets required by law. The program specifically sought to reduce targeted chemical releases by 33 percent by 1992 and by 50 percent by 1995, from 1988 baseline levels. Voluntary programs have been advanced as a cost-effective approach to pollution regulation in part because they lessen tensions and facilitate negotiations between enforcement agencies and polluting firms (Segerson and Miceli, 1998). However, EPA views these voluntary programs as complementary not an alternative to the traditional command and control approach to environmental regulation. Current EPA voluntary programs include the "Energy Star" program, which aims at decreasing carbon dioxide emissions and the "National Environmental Performance Track" designed to encourage environmentally proactive firms through rewards and public recognition.

Economists have offered a number of theories to explain why profit-driven firms might voluntarily agree to costly pollution reduction efforts beyond what is required by law. Arora and Cason (1995, 1996) explain firms' environmentally "friendly" conduct by a prospect of a reward of such conduct in the marketplace. If "green" consumers are willing to pay a premium for the environmental quality of a product, firms may seek to be certified as "green" in order to capture this premium (Arora and Gangopadhyay, 1995; Cason and Gangadharan, 2002; Teisl, Roe and Hicks, 2002; Feddersen and Gilligan, 2001; Kirchhoff, 2000). As a result, Arora and Cason (1995,1996) hypothesize that firms closer to final consumers, that is those producing final goods are more likely sign up for voluntary over compliance.

Maxwell, Lyon and Hackett (2000) offer an alternative explanation of voluntary over compliance; they argue that the main determinant of over-compliance is the deterrence of new and more severe pollution regulations. This is a case where private firms' voluntary over-compliance with pollution standards may influence government policy to the firms' advantage; by reducing pollution through partnership programs firms may prevent environmental groups from lobbying the government for tighter and costlier government environmental regulations. The Emergency Planning and Community Right to Know Act (EPCRA) passed in 1986 by the U.S. Congress lowered the cost to consumers of gathering information on polluting firms; in such a situation, firms' voluntary pollution abatement can deter hostile actions of "green" residents who could exercise political lobbying to seek tougher environmental standards. Henriques and Sadorsky (1996) found that Canadian firms in their sample perceived the threat of tighter government regulations as the most important source of pressure for formulating an environmental policy.

Over-compliance may also prompt regulators to exercise less enforcement effort, with reductions in any sanctions for regulatory infractions (Maxwell and Decker, 2003). Alternatively, in an imperfectly competitive market, a firm with a "clean" production technology may wish to over-comply with government pollution standards in order to spur tighter standards that relatively disadvantage its rivals (Salop and Scheffman, 1983). This is an issue of imperfect competition where the innovating firm would lobby for its standards - which are higher than the rest of the industry- to be set as the industry standards. If the innovator were victorious in doing so, it would indirectly compel competitors to invest in the new technology thereby raising their costs of compliance dramatically. The innovating firm may gain an optimal financial reward for the environmental R&D that produces its "clean" technology (Innes and Bial, 2002) as a result of tighter government pollution regulations.

Firms may be also "altruistic" not in order to obtain a consumer reward, but to avoid the cost of a consumer boycott threatened by environmental interest groups (Baron, 2001; Innes, 2003). The issue of forestalling consumer boycotts as a determinant of voluntary pollution abatement has not yet been explored empirically; we hypothesize that the concern for boycott has driven firms to self-select into the 33/50 program.

In this paper, we present an empirical investigation of the determinants of voluntary over-compliance using the 33/50 program as a research experiment. In doing so, we build upon related work (principally, Arora and Cason (1995, 1996) and Khanna and Damon (1999)) by seeking to (i) distinguish effects of incentives to raise rivals' costs (Innes and Bial, 2002), deter lobbying (Maxwell, Lyon and Hackett, 2000), and obtain a price premium from green consumers (Arora and Gangopadhyay), (ii) discern the effect of implicit consumer boycott threats on firm participation in the 33/50 program, and (iii) identify the impact of a firm's environmental enforcement experience on voluntary participation and pollution reduction performance.

The remainder of the paper is organized as follows. Section II provides a summary of the 33/50 program; section III presents the main theories of voluntary over-compliance to be tested in this paper. In section IV we lay out the econometric modeling for the empirical analysis. Section V discusses the sources of the data herein used and the results of the regressions. Finally section VI offers concluding remarks.

2 Outline of EPA's 33/50 program

The 33/50 program was initiated in 1991 as EPA's pioneer voluntary program. Although it had a specific goal of chemical release reduction, its primary objective was to experiment the effectiveness of voluntary programs as a viable mechanism for pollution control and the promotion of a pollution prevention ethic among polluting firms. Specifically, the program sought to reduce the releases associated with seventeen toxic chemicals by a third by 1992 and by a half by 1995 from 1988 levels by encouraging firms to voluntarily abate releases of the targeted chemicals. The program did not emphasize on media-specific releases, rather it aimed at reducing the aggregated releases on air, land or water. As a reward for their responsiveness, pledging firms enjoy a public recognition of their efforts by the EPA and national and regional awards as well. Public recognition is designed to help firms portray a better image of environmental awareness, which is important to "green" consumers, environmental groups, and financial markets (Hamilton, 1995).

Table 1: **List of The Chemicals Targeted By The 33/50 Program.**

Benzene	Lead and Compounds	Tetrachloroethylene
Cadmium and Compounds	Mercury and Compounds	Toluene
Carbon Tetrachloride	Methyl Ethyl Ketone	Trichloroethane
Chloroform	Methyl Isobutyl Ketone	Trichloroethylene
Chromium and Compounds	Methylene Chloride	Xylenes
Cyanides	Nickel and Compounds	

Source: 33/50 Program The final record, EPA march 1999

In its final report on the 33/50 program, EPA claims that the 33/50 program achieved its goal one year ahead of schedule. However, Khanna and Damon (1999) report that 40% of the release reduction that occurred during the period 1988-1993 took place prior to the program being launched, therefore the 33/50 program cannot be credited for those reductions. During the period 1991-1993 non-participants reduced their 33/50 releases by 18% while participants cut their 33/50 releases by 41%. Furtermore, a significant amount of pollution reduction is directly attributable to the Montreal Protocol.[1] One of the goals of this paper is to estimate the pollution abatement that is attributable to the 33/50 program after controlling for selection bias. Under the provisions of the EPCRA, the EPA created the Toxic Release Inventory (TRI), a database compiling information on toxic releases of all facilities and firms with ten or more employees producing one or more of 320

[1]Two of the targeted chemicals are ozone-depleting chemicals: 1,1,1-Trichloroethane and Carbon Tetrachloride, as a result they fall directly under regulations set forth by the Montreal Protocol, which calls for phasing out ozone-depleting chemicals. The Montreal Protocol was ratified in 1988 by the United States.

targeted chemicals. The TRI served as a barometer of progress for pledging firms. In March 1991, 509 parent companies of facilities with substantial releases of the 33/50 chemicals were invited to participate in the program. In July of the same year EPA mailed out invitations to another 4,534 companies. By 1995, a total 10,167 firms (more than 20,000 facilities) releasing any one type of the targeted chemicals were offered to join the 33/50 program. Of those invited 1,294 firms chose to self-select into the program; the majority of which (1,066) set specific reduction goals (EPA 33/50 Program, the final record, march 1999, page 4). However, because of the voluntary nature of the program, commitments are not enforceable by law and participants can always renege on them [2]. EPA made clear to participants that pledging does not liberate them from their legal responsibilities of compliance with pollution laws; regulatory oversight will not be altered as a result of participation:

> "The voluntary nature of the Program means that a company's decision to participate does not change its responsibilities for complying with all other laws and regulations. Participation in the program is *enforcement neutral*: a company will receive no special scrutiny if it elects not to participate and receive no relief from normal enforcement attention if it does elect to participate. (emphasis added; EPA, 1992 p. 11)".

Yet, EPA cites the improvement of the corporate image with regulating agencies as an incentive of voluntary participation:

> "Many partnership programs offer recognition, such as national awards for exceptional performance that can *enhance corporate image* with customers, *regulators*, neighbors, and the media. Participants who receive awards or other recognition can highlight their environmental commitment and motivate their employees or customers."

(Source: http://www.epa.gov./partners/benefits/index.htm#recognition, Emphasis added).

Previous work on the 33/50 program has not examined the relationship between voluntary over-compliance and regulatory relief. One of the empirical questions we seek to answer in this paper is whether or not regulatory oversight was neutral to voluntary participation. Gray and Deily (1996) found that firms in their sample with a good compliance record received less inspections visits and that fewer enforcement actions were levied upon them.

[2] None of the 1,294 firms that pledge participation reneged on their decision, they all remained committed until the end of the program. (EPA, march 1999)

3 Motivations of voluntary over-compliance

EPA rewards volunteers by making their involvement and performance in partnership programs known to the general public via press releases, rewards and other means of public recognition. This is believed to be one of the main incentives driving participation. If a firm operates in a market where consumers respond to the environmental quality, commitment to a "clean" technology plays a role of product differentiation for otherwise identical products (Arora and Gangopadhyay, 1995). Hence we hypothesize that the closer a firm is to final consumers the more likely it will sign up for the 33/50 program in order to capture the premium that "green" consumers are willing to pay. Arora and Cason (1995,1996) used industry-aggregated advertisement expenditures to measure closeness to final consumers; the idea being that firms with higher advertisement expenditures a more likely to be firms producing final goods. They found that an increase of one standard deviation in the advertisement intensity ratio raises the probability of participation to the 33/50 program by 20%. However, the use of industry-aggregated advertising expenditures as a proxy for closeness to final consumers is delicate for the same advertising expenditures could also be proxying for market power.[3] This problem can be dealt with by running an auxiliary regression of the advertising expenditures on market shares and then using the residuals -which represent the portion of advertising expenditures purged of the market power effect- as a measure of closeness to final consumers. Unfortunately because of the substantial missing values for firm-level advertising expenditures in the Compustat database, the use of advertising expenditure (even industry-aggregated) could provide misleading results. To test the "green" consumer theory, Khanna and Damon simply use a dummy variable that takes the value 1 if a firm sells a final product. Their result corroborated that of Arora and Cason (1996). In this paper, we follow Khanna and Damon's approach of a final good dummy. We use the four-digit primary Standard Industrial Classification (SIC) code to classsify firms between producers of final and intermediate goods. [4]

Another theory of voluntary over-compliance tested in previous work is the preemption of government action. According to this theory firms self-select into voluntary programs as a means to dissuade any political action

[3] A more reliable approach to estimating the importance of final consumers in the participation decision would be to survey the firms through a direct questionnaire as done by Henriques and Sadorsky (1996) for Canadian firms. Conversely, such an approach would be costly to implement in the U.S given the immense number of firms involved in the 33/50 program and the potential of misreporting by the firms.

[4] This product classification scheme is possibly problematic because some firms have more than one line of business.

by legislators towards stricter pollution laws. Maxwell Lyon and Hackett (2000) found that the threat of government intervention plays a major role in stimulating release reduction. Government intervention can be spurred by powerful environmental groups such as the Sierra Club and the National Resources Defense Council. The launching of the TRI not only reduced informational asymmetries between consumers and polluting firms but it also shrunk information cost since obtaining the data is free of charge; release information on any firm or facility producing one or more of the targeted chemicals can be obtained by downloading from EPA's website.[5] We test the hypothesis that firms volunteered for the 33/0 program in order to preempt political action by lawmakers towards more stringent pollutions standards. To measure the threat of government action we have the per capita Sierra Club membership as well as the League of Conservation voters' scorecard of state congressional delegations, which grades members of the House and the Senate on their votes on environmental issues. Delegates more responsive to environmental issues (generally democrats) get high scores while delegates "pro-business" (generally republicans) tend to get low scores. Maxwell, Hackett and Lyon (2000) found that states with higher per capita "green" residents and high initial pollution levels abated pollution faster. We interact the number of green "residents" with contemporaneous sales. The prior here is that sizeable firms (easier targets) headquartered in state with many "green" residents are more likely to sign up for voluntary programs to avoid facing tougher pollution standards as a result of lobbying efforts of environmental groups.

Boycott deterrence has been recently advanced as voluntary over-compliance engendering-factor. Innes (2003) develops a theoretical model that examines how boycott threats from environmentally conscious consumers can elicit voluntary over compliance. Besides being the target of a direct boycott, firms are also often the victims of secondary boycotts aimed at their business partners (Henriques and Sadorsky, 1996). Boycotts are more likely to be successful when a firm is vulnerable, that is when its product is substitutable, perishable, sold through retail outlets and publicly purchased (author's name). Boycotts are also more likely to strike sizeable firms that are highly visible. Over the recent past we have seen consumer groups and animal rights activists have challenged "powerful" firms with a threat to boycott. For example, thanks a strong pressure by animal rights groups, fast food restaurants such as McDonalds, Burger King and Wendy's agreed to require from their suppliers of chicken and eggs to make the production process more "humane". Similarly, other companies (Mc Cain, Frito Lay) have responded to

[5] Using an event study method, Hamilton (1995) found that publicly traded firms reporting to the TRI were adversely affected by the first release of the TRI data, they experienced significant abnormal returns that slumped the value of their stock by $ 4.1 million.

boycott threats by renouncing the use of genetically modified content (Innes, 2003). In this paper we examine the effects of implicit boycott threats on self-selection into EPA's 33/50 program.

The extent to which firms might have signed up for EPA's partnership program in order to obviate probable boycott has yet to be investigated empirically. Part of the reason is the scarcity of boycott-related data such as product substitutability and/or perishability. In this paper we hypothesize that the concern for consumer boycott is a determinant of voluntary over-compliance. To test for boycott threat effects, we use data obtained from the issues of the *Boycott Quarterly* on contemporaneous boycott targets, as well as an interaction variable between the per capita environmental membership and the boycott dummy (takes the value 1 for firms in an industry targeted for boycott as listed in the issues of the *Boycott Quarterly.*) [6] The interaction variable is designed so as to test the combined effects of a strong environmental membership and implicit boycott threats on pollution abatement.

Innovation is also cited as a motivation for participation for two reasons. First, environmentally driven technological innovation could make it easier for successful innovators to meet pollution abatement goals hence providing a greater enthusiasm for participation. Similarly an innovator may wish to over-comply with government pollution standards in order to provoke more stringent standards that relatively disadvantage its rivals (Salop and Scheffman, 1983). ARCO's strategy perfectly illustrates the latter point. In 1988 the California Air Resources Board (CARB) decided to find ways to bring the state in compliance with the federal mandates of the Clean Air Act. The CARB considered doing so by tightening the pollution standards of automotive fuel content. Anticipating more stringent standards, ARCO developed an innovative gasoline (EC-X) promising that it would diminish the emissions of carbone monoxide and ozone precursors by 30% (ARCO, 1990). As a successful innovator, ARCO campaigned strongly to have its new gasoline be set as the new standard in the state (Platt's Oilgram News, 1991). Obviously setting ARCO's reformulated gasoline as the state's standard would have raised ARCO's competitors costs of compliance dramatically. In general the innovating firm could gain a financial reward for the environmental R&D that produces its "clean" technology (Innes and Bial, 2002). In the context of this paper, the innovation hupothesis states that successful innovators and firms with "cleaner" technologies are likely to sign up for partnership programs because of the relative technological advantage they hold over their competitors. We therefore hypothesize that R&D expenditures influence participation and abatement decisions.

[6] It would have been better to include variables that capture the perish ability and the substitutability of the product; unfortunately this information is unavailable.

A plausible motivation of voluntary over-compliance is to seek regulatory relief. Gray and Deily (1996) show that regulatory oversight is not neutral; compliance behaviour influences inspections and enforcement actions and vice versa. Then the question is whether firms self-selected into the 33/50 program in order to get less scrutiny from regulators. In this paper we hypothesize (i) that a firm's history of inspections/enforcement actions is a predictor of voluntary over-compliance and (ii) that facilities whose parent companies were participants benefited from less regulatory scrutiny. To investigate our claims, we use facility-level inspections and enforcement data as well as the number of superfund sites where a firm is listed as a Potentially Responsible Party (PRP). PRPs are notified by the EPA about their potential responsibilities for cleanup costs due to environmental damages in superfund sites. We can expect that firms that have received more PRP notifications will be more aware of their potential liabilities and hence reciprocate by abating pollution more.

There are other firm-specific factors that influence a firm's decision to sign up for a partnership program with the EPA. Some of the these are factors are measurable such as firm's size proxied by its workforce, sales, prior reduction efforts etc. Other factors are not measurable: the managerial team's inclination for a "clean" technology for example.

A summary of the main theories

- "Green" consumer theory: firms selling final products are more likely to participate in partnership program with the EPA than those producing intermediate products.
- Threat of government action: firms self-select into EPA's voluntary programs to dissuade any political action by legislators towards stricter pollution laws.
- Boycott deterrence: firms participate in order to avoid the cost of a consumer boycott.
- Environmental R&D: firms with higher R&D are more likely to participate in EPA's voluntary programs.
- History with mandatory environmental standards: firms with a poor compliance history are more likely to join EPA's partnership programs, hoping to improve their image with regulators.
- Participation is not enforcement neutral: participants will get a relief in regulation with respect to mandatory environmental laws as a result of their participation.

4 Econometric modeling

To test the theories underlined above we estimate three equations: a participation (selection) equation, a pollution equation and an inspections equation. The participation equation investigates the determinants of voluntary participation in the context of the 33/50 program while the pollution equation examines the motivating factors of pollution abatement for both participants and non-participants. The objective of course is to test the theories of participation and performance underlined in the previous section. The third equation considered here tries to study the impact of participation in the 33/50 program on inspection rates, which is testing if self-selection into the 33/50 program provided regulatory breaks for participants. The first two equations are estimated using data at the firm level because the invitations to join the program were sent to parent companies not to facilities. The inspection equation is estimated using facility level data as done in previous related work; the reason is that inspections both state and federal are directed to a facility, not to the parent company. Before laying out the econometric modeling, we first address the selection problem, which is very much relevant in the case of the 33/50 program.

4.1 A note on the selection issue

Evaluating the impact of the 33/50 program entails a serious consideration for potential self-selection bias. Firms that signed up for the program do not necessarily constitute a random sample. There may exist observed and unobserved cross-sectional differences that affect both participation and pollution decisions. Failure to account for these effects could result in "self-selection bias". For example, a firm whose managers/stakeholders are committed to an environmentally friendly technology will abate pollution even absent any 33/50 program. Similarly, firms that invest more in environmental R&D might find it easeir to abate pollution than others, as a result will be more willing to self-select into the 33/50 program (khanna and Damon,1999). Such discrepancies in firm condition prior and during to the implementation of the program could seriously influence observed difference between participants and non-participants. Therefore when analyzing the impact of the 33/50 program we must discern between the differences in firm conditions and the intrinsic effects of the program; not doing so would result in biased (generally upward) pollution abatement attributable to the 33/50 program.

In terms of econometric modeling, what we are saying is that the error term in the participation equation (which represents unobservable variables driving participation) would be correlated with the disturbance of the pollution equation. The correlation between the disturbances in the two equations simply means that the unobserved factors motivating a firm's participation to a voluntary program also affect its performance. To solve the selectivity problem we estimate a two-stage model. In the first stage we estimate the probability of participation into the 33/50 program. The participation equation is essential in that in allows us to test the theories of voluntary participation. It also provides the predicted probabilities, which are then used in the second stage of the estimation process to correct for the self-selection. A complete description of the estimation process is offered next.

4.2 Modeling the pollution and participation equations

An important and unfortunately overlooked empirical question regarding voluntary pollution reduction program is the performance of participants.[7] While the EPA claims that the goals of the program were met one year ahead of schedule, a closer look at the reductions prior to the implementation of the program and reductions of non-participants makes us wonder about the effectiveness of the partnership program. In this paper we propose an estimation method that accounts for self-selection bias to estimate the net impact of the 33/50 program. Our sample of firms is based on the 6,000 firms that constitute the first and second invitation groups. We are interested in finding the driving forces of pollution abatement for firms in our sample over the duration of the program. Since we have a panel data, the pollution equation can be specified as:

$$Y_{it} = X_{it}\beta + \lambda P_i + \zeta_{it} \tag{1}$$

where α_i represents a firm-idiosyncratic disturbance, β is the parameter vector and X_{it} is a vector of exogeneous/predetermined regressors. P_i represents the participation dummy, we include the participation decision in order to control for the effects of participation on pollution abatement. [8]

The parameter λ represents the estimate of the difference in mean pollution between participants and non-participants. To see that let us take the conditional expectation of the pollution equation:

$$E(Y_{it}|X_{it}, P_i = 1) = X_{it}\beta + \lambda + E(\zeta_{it}|X_{it}, P_i = 1) \tag{2}$$

[7] Except for Khanna and Damon previous research merely focused on investigating the determinants of voluntary participation.

[8] All of the firms considered in our estimation sample were invited in to join the program 1991; furthermore, firms that joined the program stayed in while those that declined stayed out for the rest of the program (EPA march 1999), which is why we omit the time subscript for the participation decision.

$$E(Y_{it}|X_{it}, P_i = 0) = X_{it}\beta + E(\zeta_{it}|X_{it}, P_i = 0) \quad (3)$$

It follows from the above equations that:

$$\lambda = \{E(Y_{it}|X_{it}, P_i = 1) - E(Y_{it}|X_{it}, P_i = 0)\}$$

Clearly this result was obtained by assuming that the random component is not only orthogonal to the covariates in X_{it} but also to the participation decision. While the former is generally assumed to hold, the latter restriction can be easily violated. The restriction of orthogonality between the participation decison and ζ_{it} has two consequences. First it rules out potential self-selection bias, which arises whenever the orthogonality restriction is violated:

$$\{E(\zeta_{it}|P_i = 1) - E(\zeta_{it}|P_i = 0)\} \neq 0 \quad (4)$$

The orthogonality restriction also implies that the average pollutions elicited by participants and non participants absent the 33/50 program would have followed a parralel path. In other words, the change in pollution elicited by non participants after the program is a reasonable estimate of the couterfactual (unobservable) pollution that would have been elicited by participants if they did not adopt the 33/50 program.

As sad earlier, the restriction in (4) is likely not to hold in the case of the 33/50 program. There are two ways this restriction could be violated: if ζit is acquainted with the covariates in the participation equation ("selection on the observables") or if the ζit is correlated to the disturbance in the participation equation ("selection on the unobservables"). We solve the potential selection bias due to "observables" by including a linear control function in the participation equation as descibed in Heckman and Hotz (1989). To overcome the selectivity bias due to "unobservables" we replace the participation dummy in the pollution equation by its predicted values (see below); in the limit this amounts to replacing the particpation dummy by its conditional mean which is purged of the random component.

Consider the following theoretical setup:

$$\text{Selection equation: } P_i = \mathbf{1}(P_i^* > 0) \; ; \; P_i^* = W_i\gamma + u_i \quad (5)$$

$$\text{Regression equation: } Y_{it} = X_{it}\beta + \lambda P_i + \zeta_{it} \quad (6)$$

This is known as an "Endogenous Treatment Model". (Heckman,1978; Vella, 1998). The correlation between the error processes operates via the participation dummy P_{it}. To obtain consistent estimates of β, and λ, Heckman (1978) proposes that P_i be replaced by its predicted values obtained by consistently estimating (5). Asymptotically this is equivalent to replacing the conditional mean of the participation dummy (which is unrelated to u_{it}), as a result the correlation between ζ_{it} and u_{it} vanishes. The correct model to be estimated is then:

$$Y_{it} = Z_{it}\beta + \lambda\hat{P}_{it} + \eta_{it}, \;\; \eta_{it} = \alpha_i + \epsilon_{it} \tag{7}$$

Z_{it} is a vector of regressors in the pollution or participation equations (due to the inclusion of a linear control function for the selection on "observables"). This model rules out Fixed effects since we treat α_i as random draw. The main reason for eschewing a Fixed effects model is the presence of time-invariant regressors such as the final product dummy. Fixed effects models are also discouraged when the estimation sample is a subset of the population of interest, which is the case in our study. We will test later between Random effects and Ordinary Least Squares (OLS).

However, because the predicted probability $\hat{P}_i$ is an imputed regressor from the selection equation, the standard errors obtained by treating the predicted probability as a known regressor are incorrect. Murphy and Topel (1985) derive the correct asymptotic variance covariance matrix for the parameters in the second stage when at least one of the regressors is an imputed regressor. We extend Murphy and Topel's derivation to generate the correct variance-covariance matrix of the second stage parameters (See appendix for the extension of Murphy and Topel's derivation to an "error components" model).
Let's now turn to the estimation of the participation (selection) equation.

Assume that firms behave rationally, that is a firm would choose to participate in a voluntary program if the net present value (NPV) of participation is positive. Let P_i^* denote the NPV of participation for firm i. We further assume that $P_i^* = W_i\gamma + u_i$ where W_i is a vector of exogenous/predetermined variables and γ a parameter vector. However, P_i^* is not observed, rather we observe a firm's decision to participate or not. We therefore estimate the following binary choice model:

$$P_i = 1(P_i^* > 0) \text{ and } \; E(P_i|W) = F(W_i\gamma)$$

We assume that the error term is normally distributed and run a probit model which provides consistent estimates under the null.

4.3 Modeling the inspection equation

In this section we test the "neutrality hypothesis" mentioned earlier: is self-selection into voluntary pollution abatement programs really enforcement neutral or does participation negatively affect regulatory oversight? We posit that the EPA reciprocated to the voluntary participation by easing the enforcement of mandatory pollution laws. To test this conjecture we estimate the following equation:

$$\text{Inspection equation: } Insp_{it} = f(X_{it}\theta + \delta\hat{P}_i) + \mu_{it} \quad (8)$$

The dependant variable is the number of inspection visits received by facility i in year t=1989 to 1995, X_{it} represents a vector of explanatory variables such as 33/50 releases, population density in the county where facility i is located in etc. $\hat{P}_i$ is the predicted probability of participation of the parent company of facility i. Due to the discreteness of the dependant variable (number of inspection visits for facility i) we use a count data model to estimate (8). As a reminder, invitations to participate in the 33/50 program were not sent to the facilities but to their parent companies.

If our conjecture were correct then the sign of $\hat{\delta}$ would be negative and significant. Unlike the two pollution and participation equations, the inspections equation is estimated using facility-level data. This is mainly because inspections are conducted at the facility-level not at the parent-company level. All related previous work has used facility-level information as well.

5 Data and Results

Several data sources are combined in this research. Financial and employment data was obtained from the Standard and Poor's Compustat database. The Compustat (North America) database compiles information on more than 21,000 active and inactive publicly traded firms. To test the effects of industry concentration we computed the herfindahl index for each two-digit SIC code. Boycott related information was found in the back issues of the *Boycott Quarterly*. The Toxic Release Information (TRI) provided facility-level data on off site and on site (air, water and land) 33/50 chemical releases, the primary standard industrial (SIC) code of the facilities, parent companies of the facilities and their Dun and Bradsheet numbers. A firm can have several facilities. So to get the firm level data we aggregated the releases of its facilities. EPA's Office of Environmental Information Records, FOIA and Privacy Branch provided data on enforcement actions and inspections. The enforcement actions are mainly based on violations of the Clean Air Act (CAA) and the Resource Conservation and Recovery Act (RCRA); the inspections are exclusively undertaken under the regulations of the CAA. It makes sense to focus on the CAA in this study because roughly 70% of the 33/50 chemical releases are into the air (Arora and Cason, 1996) which makes it essentially an air toxics program. Data on Sierra Club state membership was obtained directly from the Sierra Club. We also obtained the data on state characteristics such as the right-to-work law, the per capita spending on the implementaion of clean air laws, the average income, the strict liability incator etc. used in Maxwell, Lyon and Hackett (2000).

Our study focuses on the manufacturing industry corresponding to SIC codes 20 to 39. We used the parent company's name to merge the compustat database with the environmental data. A total of 496 firms were identified as being in all databases for the manufacturing industry. However only 325 had three years or more of complete data over the period 1988-1995. As a result our sample size consists of 325 firms (all in the manufacturing industry) observed between 1988 and 1995. Due to lagging we our time series was shrunk to 7 years. We include the 1989-1990 data to capture pre-program trends.

Table 2: Summary statistics.

Descriptive statistics for some of the explanatory variables				
Variable	Participants		Non-Participants	
	Mean	St.error	Mean	St. error
Herfindhal index /1000	0.4418	0.1442	0.49	0.16
Number of PRPs	5.4	9.74	1.08	2.23
Sierra Club Membership per capita*1000	2.33	1.20	2.86	1.94
33/50 Releases (M of lbs.)	0.82	1.53	0.10	0.17
Sales (M. of dollars)	6.84	16.09	0.63	0.94
Employement (thousands)	34.42	71.47	5.00	7.10
R&D	211.75	549.19	18.38	46.86
Number of Facilities	8.47	8.84	2.61	2.97
Enforcement dummy	0.42	0.49	0.10	0.30
Inspections (89-90)	13.45	19.95	2.60	4.77
Lawyers per thousand residents	3.19	1.01	3.23	1.02
Per capita spending on air quality	1.32	0.73	1.34	0.73
Final Good dummy	0.66	0.47	0.62	0.48
Boycott dummy	0.38	0.48	0.25	0.43
Right to work law	0.18	0.38	0.20	0.40
% Educated in a state (Bachelor and higher)	20.96	3.89	21.01	3.74
Strict liability	0.8	0.39	0.76	0.42
Sample size:	165		160	

Note: The values in this table are computed using 1990 data.

5.1 Results of the selection equation

To test the theories of voluntary self-selection underlined previously, we have estimated two alternative models. The dependant variable in both models is the decision of a firm to sign up for the 33/50 program. For simplicity we have considered only the firms in the first and second invitation groups as our sample space. Both the first and the second group were invited to join the program in the same year, 1991. We assume that the error process in our participation equation has a normal distribution. One serious concern here is the endogeneity between the time-dependant variables and the participation decision; we address that issue by using predetermined levels of 1990 for all time-dependant variables. The results of the estimation are presented in table 3.

Perhaps surprisingly, our findings reject the "green" consumer theory of Arora and Cason (1995,1996): the coefficient of the final good dummy is statistically insignificant at all conventional levels. As a reminder the final good dummy is used as a proxy of a firm's closeness to final consumers. However our results corroborate those of Videras and Alberini (2000) who similarly found an insignificant coefficient for the final good dummy.

Another interesting result we find is that environmental membership as captured by state per-capita Sierra Club membership does not constitute a predictor of voluntary participation. The variable has the expected positive sign but is statistically insignificant. We should caution though that we use membership in the state where the parent company is headquartered in rather then the environmental membership in the state of the facility, which would be preferable. [9]

We test the hypothesis that firms self-selected into the 33/50 program to forestall consumer boycotts by including a "boycott" dummy. As a reminder the boycott dummy takes the value 1 if a firms operates in the same industry (a four-digit SIC code) as that of firms listed for boycott in the issues of the *Boycott Quarterly* as of 1990. Therefore this dummy measures implicit boycott threats. The hypothesis that firms pledge pollution abatement to obviate probable boycotts has not been tested in earlier work. The coefficient on the boycott dummy seems to substantiate the theory of a boycott-induced self-selection. The marginal effect of the boycott dummy indicates that implicit boycott threats increase the probability of participation by a statistically significant 12.19%.

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[9] We do so because most parent companies have several facilities some of which are located in different states, so that it is impossible to aggregate back to the firm level.

Table 3: **Probit estimation of the participation equation.**

Hypothesis Tested	Variable	Mean	Model I	Model II
The effects of prior corrective actions	Intercept		-7.4538** (0.3916)	-1.2963 (0..8130)
	Enforcement	0.26		0.6700*** (0.2401)
	Number of Inspections	8.11		0.0375*** (0.014)
	Number of PRPs	3.28	0.0527** (0.0216)	
The preemption of Government entry	Sierra club	2.59		0.3544 (0.6252)
	Sierra squared	9.93		-0.03385 (0.1344)
	Strict liability	0.78	0.0657 (0.2077)	0.2609 (0.2224)
The effects of boycott deterrence	Boycott dummy	0.32		0.3961* (0.2121)
The "green" consumer theory	Final good	0.64	0.1043 (0.1830)	0.0158 (0.2077)
The innovation hypothesis	R&D intensity	116.55	0.0047*** (0.0013)	0.0043** (0.0018)
The effects of industry concentration	Herfindahl index	0.47	-0.8032 (0.6182)	
Firm characteristics	Employment (thousands)	19.94		0.02845*** (0.0112)
	Employment squared	3216.68		-0.00007*** (0.000032)
	Number of facilities	5.58	0.1495*** (0.0363)	
	Facilities squared	83.64	-0.0024* (0.0014)	
	SIC 28 dummy	0.17	0.2547 (0.2677)	0.4970** (0.2536)
State characteristics	Right-To-Work law	0.19	0.1744 (0.2106)	0.1029 (0.2318)
	Education	20.98		-0.0205 (0.0293)
	χ^2\{p-value\}		133.79\{0.00\}	156.11\{0.00\}
observations: 325	-LogL		158.33	147.17

Notes: The dependant variable is the dummy for participation in the 33/50 program. Standard errors are in parentheses. The hypothesis that all the slope coefficients are jointly insignificant is clearly rejected by the likelihood ratio test.
****Statistically significant at the 1% level*
***Statistically significant at the 5% level*
**Statistically significant at the 10% level*

Another interesting finding in both models is that previous infringements to mandatory environmental regulations constitute a motivation of participation. The previous enforcement actions inspections and the number of potentially responsible parties capture this fact. The coefficients of these variables are positive and significant as expected. This result indicates that participation was partly driven by a concern to project a better image to regulators and to seek regulatory breaks (later we will test formally if EPA reciprocated by diminishing regulatory oversight on participants). Also, the significance of past enforcement actions and inspections seems to downplay the idea of firm altruism as a motivation of voluntary participation. The 22.53% marginal effect of enforcement suggests that predetermined violations of environmental regulations were a significant motivating factor of participation.

Both models exhibit a significant relationship between participation and firm size as proxied by a firm's workforce. This result is consistent with findings in similar studies. Arora and Cason (1996) argue that the size effect can be explained by the greater liability that larger firms might have for creating environmental damages. An alternative explanation is that sizeable firms might find it easier to absorb the costs of pollution abatement due to economies of scales (Videras and Alberini, 2000). We also find a decreasing effect of firm size as measured by employment square.

Similarly we find that a higher number of facilities increases the probability of participation This is not surprising since a firm is considered a participant even if only one of its facilities is a participant in the program. Therefore a firm with N facilities has up to N chances to sign up for the program.

Unlike in Khana and Damon (1999), we find that innovativeness of a firm positively impacts participation decisions. Both models show a positive and significant coefficient on R&D intensity, hence substantiating the "environmental R&D" hypothesis according to which firms involved in research for "cleaner" technology will find it easier to pledge pollution abatement.

In model I the coefficient on the Herfindahl index is negative but insignificant. The negative sign seems to indicate that firms operating in less concentrated industries (lower index) are more likely to sign up. Finally we included a dummy variable for firms operating in the Chemicals and Allied Products industry (SIC 28). We do so because the American Chemical Association (formerly known as the Chemical Manufacturers Association) launched the Responsible Care Program in 1988 with a specific goal of pollution reduction by its members. Hence we expect that firms that are members of the ACC (not all firms in SIC 28 were members!) would free ride on their commitment to the Responsible Care Program. The positive and significant coefficient on the SIC 28 dummy supports the free-riding argument.

5.2 Results of the participation equation

To study the performance of the 33/50 program we have estimated a pollution equation described in section 3. This is an interesting empirical question because participation (pledge of abatement) is not enforceable. The estimation of the pollution equation will answer two major questions: did participants respect their pledges of pollution abatement and how much of pollution abatement can be attributed to the program after controlling for potential selection bias.

Our dataset consists of a panel of 325 firms observed over the period 1989 to 1995. Because we have two imputed regressors (the predicted probability of participation in the 33/50 program and the predicted number of inspection visits), it is adequate to use the procedure of Murphy and Topel (1985) described in the appendix to generate corrected standard errors that accounts for the extra randomness introduced by the "predicted" regressors.

The results of the estimation as shown in table 4. The LM test of OLS versus One-way random effects favors the latter. The dependant variable is the aggregate releases of 33/50 chemicals in millions of lbs. We present the results of two alternative specifications. The second model differs from the first in that we replace the common intercept by industry dummies, none of which were found to be significant.

Consistent with expectations, the coefficient of the predicted probability of participation is negative and significant, meaning that participants leaved up to their pledges of pollution reduction. Khana and Damon also report the same finding. We find that participation is associated approximativeley with 30% pollution abatement which translated to a 14.58% pollution reduction on average relative to 1990 basline levels (far from the 50% reduction goal). This percentage of pollution reduction attributeable to the 33/50 program is lower than the one reported in Khanna and Damon (1999) who estimated an average effect of 27.92%. This difference in the estimate of the intrinsic effects of the 33/50 program could be due to two factors among others. First Khanna and Damon restrict their study to SIC 28 (Chemical and Allied

Table 4: **Random effects estimation of the pollution equation.**

Hypothesis Tested	**Variable**	**Model I**	**Model II**
	Intercept	1.0195	
		(1.3591)	
Prior inspections	Predicted inspections	-0.12695***	-0.1685***
		(0.0238)	(0.0266)
	Spending on air quality	-0.1057	
		(0.4483)	
	Strict liability	0.1245	
		(0.7482)	
The preemption of	Sierra club	-0.0774**	-0.07567**
Government entry		(0.0357)	(0.0355)
	Sierra*Boycott	-0.0976**	-0.19**
		(0.0581)	(0.058)
The effects of	Boycott dummy	0.7402	
boycott deterrence		(0.6085)	
Testing the "green" consumer theory	Final good	-0.12867	
		(0.5743)	
Testing the innovation hypothesis	R&D	-0.00062***	-0.00063**
		(0.000084)	(0.000085)
Industry concentration	Herfindahl index	-0.2465	
		(0.1862)	
Testing the effects of participation	Predicted probability of participation	-0.2992***	-0.30***
		(0.0319)	(0.0318)
	Release intensity	0.06877***	0.0672***
		(0.0155)	(0.0154)
Firm	Employment (thousands)	0.0258***	0.0254***
		(0.00225)	(0.00250)
	Employment squared	-0.00003***	-0.00003***
characteristics		(4.195E-06)	(4.25E-06)
	Number of facilities	0.06604***	0.06701***
		(0.00537)	(0.00536)
	Right-to-work law	-0.4395	
		(0.7355)	
	Lawyers per-capita	-0.06995	
State characteristics		(0.3013)	
	Education		0.03495
			(0.0318)
Number of observations: 1879	LM test of OLS vs RE	909.2307	879.18
	$\chi^2_{0.05}(1)$	3.84	3.84
	Adjusted R^2	0.3096	0.3132

Note: The dependant variable is the aggregated 33/50 release. The data set is an unbalanced panel of 325 firms and 1879 firm-year observations (1989-1995). The Breush-Pagan LM test of OLS vs RE favors RE.

Products) while our study encompasses SIC's 20-39 of the manufacturing industry. Their estimate could also be substantially affected by participants in the Responsible Care program. Second our time span (1989-1995) is longer than that in Khanna and Damon (1988-1993).

To test the effects of mandatory pollution laws on 33/50 releases, we included the predicted number of inspections visits received a firm (aggregated across its facilities). We do not include the levels because of the simultaneity between inspections and releases. The coefficient on this variable is negative and significant, meaning that state and federal inspections have pollution abatement-inducing effects.

Unlike the participation regression, we find that environmental membership does have a deterrent effect on polluters. This is captured by the coefficients on the sierra club membership as well as the coefficient on the interaction between sierra club and the boycott dummy. The coefficient on R&*D* supports our claims that innovative firms will find it easier to achieve pollution abatement thanks to a "cleaner" production technology. Not surprisingly we find that bigger firms and firms with more facilities tend to pollute more.

5.3 Results of the inspections equation

As our findings in the previous regressions show, participation and pollution decisions were partly driven by the prior regulatory burden. All measures of actual and potential violations of pollution laws were found to have significantly induced participation and or pollution reduction; which is certainly in line with the findings in earlier studies (Hamilton, 1995; Khanna and Damon, 1999; Videra and Alberini, 2000). In this section we test our model of EPA's responsiveness to participation in the 33/50 program. Explicitely, we test if regulatory oversight as measured by the number of inspections visits at the facility level was altered by participation in the partnership program in favor of participants. To the best of our knowledge the "neutrality" hypothesis as it relates to voluntary programs has not been formally tested in previous literature. Because of the discrete nature of inspections we use a random effects Poisson to estimate the model. The results are displayed in table 5. We have an unbalanced panel of 1263 facilities and 6075 observations over the 1989-1995 period.

Table 5: Poisson (Random effects) estimation of the inspections equation.

Variable	**Model I**	**Model II**
Intercept	-0.3727** (0.1686)	-0.0987 (0.2763)
Inspections (t-1)	0.02463*** (0.002843)	0.02396*** (0.00284)
Predicted probability of participation	-0.09588* (0.0559)	-0.0855* (0.0518)
Sierra club	0.0469 (0.1017)	
Sierra squared	-0.01361 (0.01272)	
County density	0.000025 (0.00024)	
Attainement status of the county	0.2783** (0.1168)	0.3599*** (0.1180)
Predicted 33/50 releases	0.0001767* (0.000094	0.00018* (0.000097)
Sales of parent company	0.0199*** (0.005414)	0.01574*** (0.004288)
Sales squared	-0.0001*** (2.75E-5)	-0.00008*** (2.43E-5)
Strict liability adopted by the state		-0.1468 (0.1369)
State Per capita spending on air quality	-0.2338** (0.0963)	-0.2287** (0.0974)
Right-to-work law		-0.00039 (0.1410)
Lawyers per-capita	0.0603 (0.0687)	
Education (Bachelor and higher)		0.00056 (0.01484)
No. of observations	6075	6075
-LogL	6630.917	6635.875

Notes: The dependant variable is the number of inspections visits received by a facility in year t=1989-1995. Standard errors are in parentheses.
****Statistically significant at the 1% level*
***Statistically significant at the 5% level*
**Statistically significant at the 10% level*

The results show that indeed participation negatively impacted on the number of inspection visits, indicating that participation was not enforcement neutral as claimed by the EPA. This finding goes against anecdotal evidence in Arora and Cason (1995) which suggests that participants in voluntary programs did not get any preferential treatment in terms of fines. The marginal effect of the predicted probability of participation is a statistically significant 10%, meaning that on average participants received a 10% reduction in the number of CAA-related inspection visits over the 1991-1995 period.

6 Conclusion

In a situation of low informational asymmetries between consumers and polluting firms and an ever growing concern for a clean environment, corporate responsibility is no longer confined just to compliance with mandatory pollution regulations. As the evidence has suggested in recent literature, corporate responsibility in environmental matters also necessitates a proactive behavior of self-policing. What are the determinants of such a proactive behavior is one of the research questions of this paper.

We have tested alternative hypotheses of self-selection in voluntary programs using the 33/50 program as a research experiment. Our findings substantiated our prior expectations, that is (1) firms elected for preemptive self-selection in order to deter consumer boycotts, (2) previous infringements to mandatory environmental laws constitute a significant motivation of voluntary participation and (3) that EPA responded to voluntary participation by reducing regulatory oversight on participants. The results also indicate that the intrinsic effects of the 33/50 program are far lower than the goal of a 50% pollution abatement. After controlling for all sources of self-selection bias, we found that just 14.5% of the average pollution abatement over the 1991-1995 period can be attributed to the existence of the partnership program. Interestingly, our results have not lent support to the "green" consumer theory which has echoed in previous related literature. The finding that enforcement and inspection actions are a significant predictor of voluntary participation suggests that partnership programs work better when combined with the traditional command and control approach.

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A Adapting the Derivation of Murphy and Topel (1985) to Random effects

We present here an extension of the derivation by Murphy and Topel (1985) of a consistent variance-covariance matrix for the second-stage parameters when at least one of the regressors is imputed from the first stage. The interested reader is directed to the original paper for a more complete discussion of the derivation. We first present an outline of the original derivation. We will then provide the steps necessary to generalize the derivation to one-way random effects models.

Assume the following simple theoretical framework:

$$1^{st} \text{ stage equation: } P_i = F(W_i, \gamma) + \eta_i \tag{9}$$

$$2^{nd} \text{ stage equation: } Y_i = X_i\beta + \lambda\hat{P}_i + \mu_i \quad ; i = 1...N \tag{10}$$

Here we have a simple case of only one "first-stage imputed" regressor is P_i. Further assume that the imputed regressor is consistently estimated by Maximum likelihood with a variance-covariance denoted V_γ. Under the classical assumptions of OLS, we have $V_\beta = \hat{\sigma}^2(Z'Z)^{-1}$ where Z is a horizontal concatenation of X and $\hat{P}$.

Let

$$W^0 = \hat{\lambda}\frac{dF(W,\hat{\gamma})}{d\gamma}$$

$$S(\hat{\gamma}, W) = \frac{dlogL(\hat{\gamma},W)}{d\gamma}$$

$$V_\gamma = \{-\frac{d^2 LogL(\hat{\gamma},W)}{d\gamma d\gamma'}\}^{-1}$$

Define the following matrices:

$$Q_0 = N^{-1}(Z'Z)$$

$$Q_1 = N^{-1}(Z'W^0)$$

$$Q_2 = N^{-1}\sum_{i=1}^{N} Z_i'\hat{\mu}_i S_i(\hat{\gamma}, W_i)$$

Then the formula for the "correct variance" for the second stage parameters as derived by Murphy and Topel is given by:

$$V_\beta^* = V_\beta + Q_0^{-1}\{Q_1 V_\gamma Q_1' - Q_1 V_\gamma Q_2' - Q_2 V_\gamma Q_1'\}Q_0^{-1} \tag{11}$$

Now assume the following model allowing for a possibly unbalanced panel data structure:

$$1^{st} \text{ stage equation: } P_{it} = 1(P_{it}^* > 0) \;\; ;P_{it}^* = W_{it}\gamma + \eta_{it} \tag{12}$$

$$2^{nd} \text{ stage equation: } Y_{it} = X_{it}\beta + \lambda \hat{P}_{it} + \zeta_{it} \;\; ; t = 1...T_i \;\; ; i = 1...N \tag{13}$$

Let $\zeta_{it} = \alpha_i + \epsilon_{it}$. This is a general notation for an Error components model where α_i is an cross-section-specific and time-invariant disturbance. It is well-know that (13) suffers from serial correlation, that is $E\{\zeta_{it}.\zeta_{is}\} \neq 0$ for $t \neq s$ hence OLS is inefficient. Therefore we cannot directly apply (11) to obtain correct standard errors. The following steps are necessary and suffiscient however to apply (11).

- Estimate (12) by maximum likelihood
- Use the procedure described in Greene (Pages 570-71; Equations 14-24 through 14-32) to obtain estimates of σ_ϵ^2 and σ_α^2
- Define Z as a horizontal concatenation of X and $\hat{P}$
- Compute $Y_{it}^* = Y_{it} - \hat{\theta}_i \bar{Y}_i$ and $Z_{it}^* = Z_{it} - \hat{\theta}_i \bar{Z}_i$ where $\hat{\theta}_i = 1 - \frac{\hat{\sigma_\epsilon}}{(T_i \hat{\sigma_\alpha}^2 + \hat{\sigma_\epsilon}^2)^{1/2}}$
This overcomes the inefficiency in (13)
- Compute V_γ, $S(\hat{\gamma}, W)$, Q_0, Q_1 and Q_2.
For example for the Logit model, we have $S_i(\hat{\gamma}, W_i) = (P_i - \Lambda_i)W_i$ where Λ is the CDF of the logistic distribution. For a linear model, $S_i(\hat{\gamma}, W_i) = \hat{\eta}_i W_i$
- Regress Y_{it}^* and Z_{it}^* using pooled OLS to get the naive variance of β: $V_\beta = \hat{\sigma}_\epsilon^2 * (Z^{*\prime} Z^*)^{-1}$.
- Use (11) to get the correct standard errors of $\hat{\beta}$

The generalization to more than one imputed regressor is straightforward. These steps can be followed to generate "correct" second-stage standard errors when the second-stage equation violates the classical assumptions of homoscedasticity and/or serial correlation. One simply needs to correct for either or both problems and run OLS on the transformed model.