How do Voluntary Pollution Reduction Programs (VPRs) Work? An Empirical Study of Links between VPRs, Environmental Management, and Environmental Performance

By

Abdoul G. Sam,

Department of Agricultural, Environmental, and Development Economics

The Ohio State University

E-mail: sam.7@osu.edu

Robert Innes,

Department of Agricultural and Resource Economics

University of Arizona

E-mail: innes@ag,arizona.edu

Madhu Khanna,

Department of Agricultural and Consumer Economics

University of Illinois at Urbana-Champaign

E-mail: khanna1@uiuc.edu

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Abdoul G. Sam*, Robert Innes**, and Madhu Khanna***

Abstract

EPA-sponsored voluntary pollution reduction programs (VPR) have gained increased prominence in U.S. environmental policy. However, as commitments to these programs are not enforceable by design, the empirical literature has mostly focused on studying the motives for their adoption and their efficacy in curbing pollution. This paper seeks (i) to shed light on the bi-directional links between participation in a VPR and adoption of firm-structured environmental management strategies (EMS), and (ii) the joint impact of VPRs and EMS adoption on the environmental performance of participant firms. Our econometric analysis reveals that participation in the 33/50 program, helped spur the adoption of Total Quality Environment Management (TQEM), which in turn had a significant negative effect on 33/50 pollutant releases. We also find that 33/50 participation produced additional direct benefits in pollution reduction both during and after the program years, and that it enhanced the effectiveness of TQEM in reducing pollution during the post-program years.

Keywords: Voluntary Pollution Reductions, 33/50 Program, Environmental Management Systems, Total Quality Environmental Management.

JEL codes: D230, L510, Q 530

* Assistant Professor, Department ofAgricultural, Environmental, and Development Economics, The Ohio State University.
** Professor, Department of Agricultural and Resource Economics, University of Arizona.
*** Professor, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign.
Senior authorship not assigned.

I. Introduction

Government-sponsored voluntary pollution reduction programs are an increasingly common feature of the contemporary approach to environmental protection in the U.S. These approaches are being used by environmental agencies to encourage firms to take a holistic perspective towards pollution control and to achieve reductions in pollutants that are otherwise not directly regulated, such as toxic releases and greenhouse gases. The 33/50 program was the first such voluntary program established by the U.S. Environmental Protection Agency in 1991. The program sought to reduce emissions of seventeen high priority toxic chemicals reported to the Toxics Release Inventory (TRI) through voluntary action by firms. It got its name from its two numeric goals of reducing the level of on-site releases and off-site transfers of 17 designated chemicals (referred to as 33/50 releases, hereafter) by 33% reduction by the end of 1992 and by 50% by 1995 relative to their 1988 levels. The program emphasized prevention of pollution upstream rather than managing wastes after they have been generated; the EPA thereby hoped to instill a pollution prevention ethic among firms and promote efforts to make continuous environmental improvement through pollution prevention (EPA, 1992).

The first purpose of this paper is to examine whether the 33/50 program was effective in instilling such an ethic among participants, as reflected in their adoption of a management system that values proactive efforts at pollution prevention and continuous improvement in product quality and in increasing process efficiency. A management system that embodies this philosophy is based on total quality management principles. Since 1990 many firms began to apply these principles to environmental management and adopted Total Quality Environmental Management (TQEM)[1]. TQEM views pollution as a quality defect to be continuously reduced through the development of products and processes that minimize waste generation at source.

A second purpose of this paper is to examine if participation in the 33/50 program was effective in reducing 33/50 releases and if program participants that also adopted TQEM were able to achieve greater reduction in 33/50 releases than other firms. In particular, we seek to examine if the adoption of TQEM enabled 33/50 participants to identify more cost-effective opportunities for pollution reduction and thereby achieve greater reduction in 33/50 releases than otherwise.

We undertake this analysis for a sample of 107 S&P 500 firms that responded to an Investor Research Responsibility Center (IRRC) survey in 1994 on the adoption of TQEM, that were in manufacturing industries eligible for participation in the 33/50 program and that reported 33/50 releases in 1988. We first use a recursive system of discrete choice regressions to examine the incentives for firms to participate in the 33/50 program in 1991 and its implications for the adoption of TQEM in 1994. We then examine the implications of program participation and TQEM adoption on 33/50 releases over the period 1991-1995 while correcting for endogeneity in the two discrete choice decisions and controlling for firm-specific effects that could have influenced environmental performance.

A number of studies have sought to explain why profit-driven firms might voluntarily agree to costly pollutant reductions by participating in a VPRP. Theorists have suggested that firms might participate in voluntary programs in order to attract a clientele of "green consumers" (Arora and Gangopadhyay, 1995), deter lobbying by environmental groups for tighter government standards (Maxwell, Lyon and Hackett, 2000), preempt mandatory environmental regulations (Segerson and Micelli, 1998), spur tighter environmental standards that "raise rivals' costs" (Innes and Bial, 2002), avoid future environmental liability, deter boycotts by environmental interest groups (Baron, 2001; Innes, 2006), and/or lessen the costly scrutiny of environmental regulatory authorities (Maxwell and Decker, 2002). There are also several empirical studies that have examined the motivations for firms to participate in voluntary programs such as the 33/50 program (Arora and Cason, 1995, 1996; Khanna and Damon, 1999; Videras and Alberini, 2000; Sam and Innes, 2005; Gamper-Rabindran, forthcoming), Green Lights and Waste Wise (Videras and Alberini, 2000) and the Climate Challenge program (Welch et al.). A number of studies have examined the factors motivating firms to proactively adopt environmental management systems in general (Khanna and Anton, 2002a, b; Anton et al., 2004) and TQEM in particular (Harrington et al., 2005). The findings of these empirical studies are reviewed at greater length in the next section.

Since voluntary environmental efforts often involve no enforceable commitment to improve environmental performance, there are several studies that seek to determine whether such efforts have actually succeeded in reducing pollution from levels that would otherwise have been produced. A few studies have examined the extent to which the 33/50 program in particular was effective in reducing releases (Khanna and Damon, 1999; Sam and Innes, 2005; Gamper-Rabindran (forthcoming) while others have examined the impact of EMSs on toxic releases (Anton et al. 2004) and the impact of TQEM on adoption of pollution prevention technologies by firms (Khanna et al., 2005).

This paper extends that literature by examining not only the impact of the program on 33/50 releases but also the *mechanism* by which the program may have achieved pollution reduction. In particular, it examines if the program increased environmental consciousness among the management and motivated firms to adopt TQEM. It then examines if the interaction between participation in the 33/50 program and adoption of TQEM led to greater reductions in 33/50 releases than non-participation or participation by itself, unaccompanied by TQEM adoption. Section II describes the background and reviews the empirical literature examining motivations for voluntary environmental efforts. Section III describes the empirical framework and variable construction. Section IV describes the data; the results are presented in Section V, and conclusions in Section VI.

II: Background and Literature Review

The 33/50 program was two years after the first TRI report was made publicly available in 1989. After release of the first TRI report in 1989, hundreds of articles singling out the top polluters – "the dirty dozens" in states and counties – had appeared in local and national media (see for example, New York Times, 1991). The 33/50 program provided these large polluters a means of having their progress towards toxic pollution reduction recognized through a formal EPA program that would receive broad public attention. It also offered the potential for firms to reduce emissions and waste generation, forestall tougher regulations, gain stakeholder goodwill and thereby increase profits. Many firms recognized that the alternative of command-and-control regulations to control toxic releases would give them much less autonomy on issues such as chemicals to reduce, technology to use and the time frame for reduction and could be much more costly as compared to a voluntary approach.

The growing public concern with the environmental impact of firms' products and processes, of EPA's emphasis on prevention of pollution instead of control at the end-of-the-pipe (following the passage of the Pollution Prevention Act in 1990) and the threat of more stringent regulations created incentives for firms to make broader changes in their organizational culture and integrate the environment into their production decisions. Leading firms began to shift away from a regulatory driven, reactive approach to a proactive and beyond-compliance strategy towards environmental management. A survey of S&P manufacturing firms found that 43% of the firms had adopted TQEM by 1995 (Florida, 1996).

Several empirical studies have examined the factors that increased the likelihood of a firm participating in the 33/50 program[2]. These studies show the importance of public recognition provided by the program as a motivator for participation. Firms that are primarily producing final goods and in closer contact with consumers or in industries with a higher advertising expenditure per unit sales and, therefore, more visible to consumers, were found to be more likely to participate in the 33/50 program (Khanna and Damon, 1999; Arora and Cason, 1995, 1996). Sam and Innes (2005), Videras and Alberini (2000) and Gamper-Rabindran (forthcoming), on the other hand, found that proximity to final consumers had an insignificant effect on program participation. Instead, these studies found that participation in the program was motivated by a desire to offset adverse publicity from previous boycotts (Sam and Innes, 2005), a desire for a positive public image by firms that published annual environmental reports (Videras and Alberini, 2000) and a desire to appeal to investors in publicly owned firms likely to prefer firms facing fewer environmental liabilities and lower costs of compliance in the future

(Gamper-Rabindran, forthcoming). Concerns about adverse publicity could also explain the finding that firms producing larger volumes of 33/50 releases or other toxic releases were more likely to participate in the 33/50 program (Arora and Cason, 1996; Khanna and Damon, 1999; Sam and Innes, 2005; Gamper-Rabindran forthcoming).

Additionally, the threat of liabilities, more stringent enforcement of existing regulations and high costs of compliance with anticipated regulations also motivated firms to participate in the 33/50 program. While Khanna and Damon (1999) and Videras and Alberini (2000) find that firms that were listed as potentially responsible parties for a relatively large number of Superfund sites were more likely to participate in the 33/50 program, Sam and Innes (2005) find that this was the case only for large firms. They also found that firms with higher rates of inspections in the past were more likely to have participated in the program, while Gamper-Rabindran (forthcoming) found this to be the case for firms in the chemical industry only. Videras and Alberini (2000) found that firms subject to corrective actions for violations of the Resource Conservation and Recovery Act were more likely to participate in the 33/50 program. Additionally, Khanna and Damon (1999) and Gamper-Rabindran (forthcoming) found that firms in the chemical industry that had a high share of hazardous air pollutants in total toxic releases, and therefore, faced a stronger threat of high costs of compliance with anticipated regulations, were more likely to participate in the 33/50 program.

Several studies have also sought to examine the motivations for voluntary adoption of environmental management practices by firms, such as an environmentally responsible plan, ISO 14000 and environmental management systems, defined to include a wide range of practices (Henriques and Sadorsky, 1996; Dasgupta et al., 2000; Khanna and Anton, 2002a, b; Anton et al., 2004). The former two studies find that regulatory pressure was the most important factor in motivating firms to adopt environmentally friendly management practices while the latter three studies find that consumer contact, the threat of liabilities, and the volume of emissions were important in motivating the adoption of environmental management systems. Harrington et al (2005) and Khanna et al. (2005) focus on examining the factors that motivated firms to adopt TQEM. They find that TQEM was driven primarily by factors that originated within the firm rather than by external considerations. Firms that were more innovative and had higher technical capacity, that had a larger size and therefore greater ability and experience in instituting complex organizational changes and lower costs of adoption and firms with large toxic releases and greater incentives to find ways to significantly reduce waste in production generation, disposal costs, and future liabilities were more likely to adopt TQEM.

Among the studies examining the impact of voluntary efforts by firms on environmental performance, Khanna and Damon (1999) and Sam and Innes (2005) find that the 33/50 program did spur a reduction in 33/50 releases in the Chemical sector (Khanna and Damon, 1999) and for all eligible manufacturing firms (Sam and Innes, 2005). Gamper-Rabindran (forthcoming) on the other hand, examines the impact of the 33/50 program in reducing releases of 15 toxic chemicals, after excluding the two chemicals that were considered to be ozone depleting and were targeted for a phase out by the Montreal Protocol. Industry-specific analysis of the impact of the program on the change in releases between 1991-1996 shows that the impact of the program varies across sectors; the program led to a statistically significant reduction in releases in the Paper and Fabricated Metals sector only, while it led to significant increases in releases in the

Chemicals and Primary Metals sector (1991-1995). The effects of the program on releases from the Electric, Transport, Rubber and Stone sectors were statistically insignificant. Studies on the impact of environmental management systems show that they have been effective in reducing toxic releases (Anton et al., 2004) and that TQEM motivated firms to adopt more pollution prevention techniques (Khanna et al., 2005).

III. Empirical Framework

Motivations for Voluntary Efforts

The initiation of a voluntary program, such as the 33/50 program, could induce a firm to participate if the firm's expected discounted benefits from participation are greater than its expected discounted net benefits without participation in the program. While the program did not specify fixed practices/technologies for pollution reduction or particular levels of pollution reduction, it could motivate adoption of environmentally friendly practices if those practices increase the discounted net benefits from participation in the program. In particular, we seek to examine if the 33/50 program served as a catalyst for firms to expand their notion of product quality to include environmental attributes of products and to make efforts to increase process efficiency by using quality management principles that encourage prevention of pollution at source rather than controlling it after it is generated. This systems approach to waste management is compatible with the philosophy of total quality management that emphasizes continuous progress in preventing defects and increasing efficiency through process management. It also seeks to design products that more than meet customer expectations about quality (Powell, 1995). TQEM involves using tools that enable managers to focus on the causes of their difficult environmental problems and to rely on performance measures that allow isolation of the contribution of particular activities to performance. Firms that adopt TQEM may therefore be more likely to identify opportunities for waste reduction and select cost-effective practices for reducing pollution. TQEM also emphasizes customer and quality improvements to meet or exceeding customer expectations and firms that adopt TQEM firms are likely to be more outwardly focused and to have closer relationships with customers which would enable them to identify the practices that customers' value. They are also more likely to have the tools, such as life-cycle analysis, to evaluate the environmental impacts of alternative product specifications, raw materials and disposal options, from "cradle to grave." The desire for public recognition could, therefore, lead a firm to not only participate in the 33/50 program but to adopt TQEM to increase the appeal of its products to environmentally conscious consumers. This discussion leads to the first main hypothesis that we seek to test in this paper[3]:

Hypothesis 1: 33/50 program participation spurred the adoption of TQEM.

In testing Hypothesis 1, it is important to recognize that 33/50 participation could be an endogenous variable. For example, (unobserved) managerial preferences could influence the adoption of *TQEM* and participation in the 33/50 program, implying correlation between one decision and the error in the other decision's structural equation. We therefore estimate the following two equations.

(1) $P_i^{*}=\alpha X_i+\mu_{1i}$

where P_i* measures the net benefits from 33/50 participation. The indicator variable for 33/50 participation is $P_i=1$ *if* $P_i*>0$ and *0* otherwise. The error component μ_{1i} is assumed to be normally distributed with mean zero and variance $\sigma^2_{\mu 1}$.

(2) $T_i* = \beta P_i + \gamma W_i + \mu_{2i}$

The indicator variable for *TQEM* is $T_i = 1$ if $T_i* > 0$ and 0 otherwise. The error component μ_{1i} is assumed to be normally distributed with mean zero and variance $\sigma^2_{\mu 2}$. Some of the variables included in W_i are likely to be also included in X_i. If the random errors in the two equations are correlated then a bivariate probit model should be used to estimate the two equations consistently and efficiently. If the errors in the two equations are uncorrelated then the two equations can be estimated independently to obtain consistent and efficient estimates of the parameters (Maddala, 1983, p 123). We use the Lagrange multiplier (Kiefer, 1983) and the conditional moment (Newey, 1985) tests to test for correlation between these error terms. For both tests (see table 4) we fail to reject the null of no correlation between the disturbances; we therefore estimate two separate probit equations. A biavariate probit model was unable to converge and provide estimates for the regression parameters.

While testing Hypothesis 1 it is also important to control for other factors that could motivate firms to adopt TQEM. We now turn to a discussion of these factors. Since many of these factors could also have influenced the decision to participate in the 33/50 program, we discuss the role of these factors in both regression equations together.

The first set of explanatory variables in the regression equations for 33/50 participation and TQEM adoption is designed to capture the desire to gain an environmentally friendly image to appeal to green consumers and to reduce the threat of consumer boycotts organized by environmental interest groups, through participation in the 33/50 program and/or adoption of TQEM (Baron, 2001; Innes, 2006; Arora and Gangopadhyay, 1995). We construct several variables to capture these motivations. As in Khanna and Damon (1999) we include a dummy variable FG that takes a value of one if the firm sells a product directly to final consumers.[4] We follow Sam and Innes (2005) by measuring the strength of potential boycott threats using a dummy variable that takes on a value of one if a firm is in an industry that was contemporaneously targeted for boycott (BC).[5]

By abating pollution voluntarily, firms may be able to preempt lobbying by environmental groups for tighter government standards (Maxwell, Lyon and Hackett, 2000). This motive for proactive environmental efforts are likely to be greater in states with larger environmental constituencies, where the public sensitivity to pollution is likely to be greater, as are environmental groups' incentive and ability to successfully lobby the government for change. To test for these effects, we use the per-capita Sierra Club membership in a plant's home state, averaged across plants to obtain a firm-level variable (SIERRA). Because boycott threats are likely to be more acute when firms operate in states with larger environmental constituencies, we also consider an interaction variable between BC and the average per capita Sierra Club membership in the home states of a firm's plants (SIERRA).[6]

Firms may also participate in the 33/50 program and adopt TQEM to “raise rivals' costs.” Firms in concentrated industries that are relatively research-intensive and innovative (and thereby have relatively low pollution abatement costs) may have a stronger motive to show exceptional environmental conduct in order to spur tighter government environmental standards and disadvantage rivals firms (Innes and Bial, 2002). Previous empirical evidence on this has been mixed. Arora and Cason (1995) and Khanna and Damon (1998) do not find strong evidence that innovative firms or firms in more innovative industries as were more likely to participate in the 33/50 program. Arora and Cason also find that firms in more competitive industries were more likely to participate in the 33/50 program. On the other hand, Sam and Innes (2005) find that more research intensive firms and those in more concentrated industries and were more likely to participate in the 33/50 program. Among the studies on environmental management systems, Khanna and Anton (2001) find that innovative firms were statistically significantly more likely to adopt a comprehensive environmental management system while Harrington et al (2005) find that they were more likely to adopt TQEM. As in previous studies we attempt to capture such effects with variables measuring industry concentration (HERF), firm-level R&D expenditures (RD), and the interaction between these two measures (HRD=HERF*RD).

Larger firms, with deeper pockets, may also have incentives to make voluntary efforts to reduce pollution in order to avoid potential liability for harm caused. Such incentives will be greater in states that levy strict liability for environmental harm, as opposed to negligence liability (Alberini and Austin, 1999). Hence, we measure the liability motive for proactive efforts using a dummy variable taking a value of one if a plant's home state has a strict liability statute, again averaged across a firm’s plants to obtain a firm-level variable (STRICT). We also capture the threat of liabilities by a variable measuring the number of Superfund sites for which a firm is a potentially responsible party (PRP).

We also include socio-economic indicators for the states in which each firm operates, including measures of the public's educational status (EDUC), the number of lawyers per capita (LAWYERS), state spending on air quality (SPENDAQ), and presence of right-to-work laws (RTW). In addition, we control for industry effects by including dummy variables for the seven industries most heavily represented in our sample (SIC 28, 33, 34, 35, 36, 37, and 38). These variables control for location specific effects and industry specific effects on the incentives for proactive environmental efforts.

A number of other variables that differ across the two regression equations are included in our estimations. The additional variables that are hypothesized to affect 33/50 participation include a measure of each firm's 1990 33/50 pollutant releases (33/50 RELEASES). Several studies (Arora and Cason, 1996; Khanna and Damon, 1999; Sam and Innes, 2005; Gamper-Rabindran forthcoming) find that firms emitting a larger volume of 33/50 releases were more likely to participate in the program. In addition, firms that had already achieved large reductions in emissions prior to 1991 are likely to have had greater incentives to join the 33/50 program because their prior (1988-1990) emission reductions already placed them in near reach of the program's goals. However, existing studies show that the extent of reduction achieved by firms prior to 1991 did not have a statistically significant effect on the program participation decision, after controlling for the effects of the other factors that differed across firms (Arora and Cason, 1995; Khanna and Damon, 1999; Sam and Innes, 2005; Gamper-Rabindran, forthcoming). We control for this effect by including a variable measuring a firm's 33/50 pollutant reductions from 1988 to 1990 (DIFREL).

Previous studies show that participation in the 33/50 program may have been motivated by an implicit bargain with regulatory authorities whereby they could anticipate fewer costly government inspections and enforcement actions (Sam and Innes, 2005). The extent of such a benefit is likely to be higher for firms that have recently experienced higher levels of regulatory scrutiny. Hence, to measure the "enforcement" motive for 33/50 participation, we consider three variables: (i) the number of government inspections of firm facilities in 1989-1990, per facility (INSP89-90), (ii) the number of facilities operated by each firm (FAC), and (iii) an indicator that takes a value of one if a firm had an enforcement action in the period 1989-1990 (ENFORCE). As a growing literature documents the impacts of government enforcement activity on pollution levels, we also include a variable measuring each firm's lagged government environmental inspections per facility in our pollution equation (INSP-FAC). Both INSP and ENFORCE are highly correlated with 33/50 participation in our sample and not highly correlated with TQEM decisions.[7] Moroever, prior evidence indicates that enforcement variables such as these are significant determinants of 33/50 participation (Videras and Alberini, 2000; Sam and Innes, 2005) and not significant determinants of EMS decisions (Khanna and Anton, 2002; Anton, et al., 2005). On an intuitive level, the close link between regulatory enforcement and the 33/50 program – as a program initiated and promoted by regulatory authorities – is to be expected, whereas predictable links to internal environmental management decisions are much less clear.

To explain TQEM adoption – a decision that potentially affects overall environmental performance, not just 33/50 pollutants – we include a measure of each firm's overall TRI releases for 1989-1990 (TRI).[8] We also include the vintage of a firm's assets, and firm growth, can affect emissions levels, with newer equipment and the financial resources made available by rapid growth both enabling pollutant reductions. We measure firm growth by the rate of sales growth (SG). We measure the vintage of assets with two variables. The first (NEWASSETS) is defined as the ratio of net assets to gross assets (as in Khanna and Damon, 1999), and is employed in our pollution equation. The second (OLDASSETS) is defined as the interaction between a firm's TRI releases (TRI) and one minus the NEWASSETS variable; this second vintage measure is designed to reflect the extent to which a firm is an older, more highly polluting production operation, and is employed in our EMS adoption equation (more below).

TRI releases (TRI) and the vintage of company assets (OLDASSETS) are included in the TQEM equation but not in the 33/50 participation equation. Both variables are significant determinants of TQEM adoption in our sample, as are related variables in prior empirical work (Khanna and Anton, 2002; Anton, et al., 2005). Conversely, both variables exhibit low correlation with 33/50 participation in our sample (less than .1). TRI releases are logical explanatory variables for overall firm-level environmental management decisions, versus the subset of these releases that are targeted in the 33/50 program. In our sample, the correlation between these two release measures is approximately .57, indicating both substantial covariation and measure-specific variation that may distinctly drive firms' 33/50 and EMS decisions, respectively. With regard to our OLDASSETS measure, the potential benefits of EMSs are likely to be higher when productive assets are older and more highly polluting (as reflected by higher values of OLDASSETS); in such cases, there is simply more pollution to reduce and more scope for management measures that achieve significant reductions. Conversely, scope for significant emission improvement for newer, less polluting assets is likely to be lower. The 33/50 program, on the other hand, calls for proportionate emission reductions that may or may not be more costly when assets are older; with older assets, there may be lower costs per unit emission reduction, but more emissions to reduce. Hence, the link between our asset vintage variables (both OLDASSETS and NEWASSETS) and 33/50 participation is conceptually ambiguous and found to be statistically insignificant in preliminary estimations of the participation equation.

Finally, we include two variables measuring firm size (the number of employees, EMPL) and the number of facilities (FAC), since larger firms have had lower costs and larger resources for adopting TQEM. We also include an interaction between EMPL and STRICT because liability effects are likely to be more pronounced for larger firms.

Implications of Voluntary Efforts for Releases

In investigating the effects of 33/50 participation and TQEM adoption on 33/50 releases the two main hypotheses we seek to test are:

Hypothesis 2. 33/50 program participation increased the effectiveness of TQEM in reducing pollution.

Hypothesis 3. 33/50 program participation directly spurred long-term pollutant reductions.

We test these hypotheses by including firms' 33/50 program participation and TQEM adoption decisions and their interaction as regressors in the pollution equation with 33/50 releases as the dependent variable.

As 33/50 program participation occurred in 1991, we model participation effects only from 1992 onwards. Although participation decisions were pre-determined in these years, there may nevertheless be an endogeneity issue. Specifically, if the error in the participation equation is correlated with the error in the pollution equation, then using actual participation decisions in the pollution equation leads to biased and inconsistent estimates. For example, due to attributes that we do not observe in our data, 33/50 participants may have been more likely to reduce pollution even had they not joined the program. This is "the endogenous treatment problem" identified by Heckman (1978). Similarly, due to unobservable firm attributes, TQEM adopters may have been more likely to reduce pollution even had they not adopted TQEM. We circumvent any source of inconsistency in two ways. First, we allow our data to reveal any correlation between the error terms by using actual adoption and participation decisions and constructing two correction variables (augmented Inverse Mills Ratios) to remove any source of inconsistency.[9] Second, we use predicted probabilities of TQEM adoption and participation in the 33/50 program obtained from Probit estimates of the two equations as regressors in the pollution equation in lieu of actual adoption and participation data.

Third, because 33/50 participation effects may (or may not) be different in the short-run and the "long-run," we distinguish between effects during the program years, 1992-96, and during the post-program years, 1997-98. We construct interaction effects for both the program years (1994-96) and post-program years (1997-98), which we denote by PART-TQ9496 and PART-TQ9798, respectively. In addition, as noted earlier, there is some question about the timing of TQEM adoption decisions and, hence, of their potential effect on pollution. As surveys were completed in 1994, it is natural to model

TQEM effects from 1994 through the end of our sample (1998), as we do in the estimations that are reported in the next section. However, we also test for TQEM effects during 1992-93, finding in all cases that TQEM has no significant impact on pollution in these years.

Finally, when predicted regressors are used to obtain consistent parameter estimates, standard error estimates obtained by conventional methods need to be adjusted to account for the first-stage estimation. Following List, et al. (2003) and Fredriksson, List and Millimet (2003), we implemented a nonparametric bootstrap to obtain the correct standard errors whenever predicted values are used.[10]

We control for several factors that could have directly influenced the level of 33/50 releases. These include the size of the firm, measured by EMPL and FAC. To the extent that firms participate in the 33/50 program and adopt TQEM to raise rival's costs it would be reasonable to expect that innovative firms and those in more concentrated markets may have greater incentives to lower 33/50 releases to raise environmental standards for competing firms. We therefore include RD, which also control for technological capability of the firm and HERF.

IV: Data

Data on TQEM adoption is obtained from a survey of S&P 500 firms in 1994 by the Investor Research Responsibility Center (IRRC).[11] In the survey, respondents indicate whether they have adopted each of a number of different environmental policies (see Khanna and Anton, 2002). We limit attention to examining the impact of the 33/50 program on adoption of TQEM because the philosophy underlying TQEM was most directly compatible with the ethic that the EPA sought to promote through the 33/50 program. Our sample of firms is obtained by the intersection of (i) the S&P 500 (those firms that responded to the IRRC surveys), (ii) firms eligible for participation in the 33/50 program in 1991 (those reporting 33/50 releases in 1988), and (iii) firms in the manufacturing industries responsible for the bulk of 33/50 releases (belonging to SIC codes 20-39). This intersection gives us a sample of 107 firms, and an associated unbalanced panel of 33/50 pollutant releases over 1989-1998. We include pre- and post-program years in order to assess pre-program trends and long-term effects of the 33/50 program and EMS adoption on pollutant releases.

For these 107 firms, we constructed our data from several sources. Financial and employment data was obtained from the Standard & Poor's Compustat database. The EPA's Office of Environmental Information Records provided data on 33/50 participation, Federal and State enforcement actions under the Clean Air Act (CAA) and the Resource Conservation and Recovery Act (RCRA) (1988-1990), and facility-level government inspections under the CAA (1988-1998).[12] The Toxic Release Inventory (TRI) provided facility-level data on 33/50 chemical releases, primary standard industrial codes (SIC), parent company names, and facility locations. Firm-level 33/50 pollutant releases and inspections were obtained by aggregating across each firm's facilities. The Sierra Club provided data on its state membership (from 1989-1998, measured per capita). The Maxwell, Lyon and Hackett (2000) dataset provided information on state characteristics (1988), including per capita state spending on clean air laws, educational status (the number of bachelors degrees per capita), the number of lawyers per capita, and indicators for whether the state had a right-to-work law or strict environmental liability.[13]

The number of 1988 Superfund sites for which a firm was a potentially responsible party (PRP) was obtained from the EPA's Superfund Office. Tables 1 and 2 present variable definitions and descriptive statistics for our sample.

Since we have TQEM adoption data only from survey respondents, a sample selection issue arises in the TQEM adoption equation. As argued by Videras and Alberini (2000), firms that have returned the EMS questionnaire may not constitute a random sample, i.e. these firms may also have been more likely to adopt TQEM. We investigate this potential source of inconsistency issue by estimating a censored bivariate model for EMS adoption and response to the IRRC survey. Our results indicate that the unobservables in the two equations are uncorrelated.

V. Results

Tables 3 and 4 present results from estimations of the 33/50 participation and TQEM adoption equations, respectively.[14] Consonant with prior work, Table 2 provides some evidence that 33/50 participation was motivated in part by regulatory enforcement scrutiny (with significant positive coefficients on PRP, ENFORCE, INSP-FAC), the potential threat of boycott (with a significant positive coefficient on BC), and the potential to "raise rivals costs" (with significant coefficients on RD, and HRD).

Although our EMS variable is measured using responses to a 1994 survey, firms may have adopted TQEM before the time of the survey. For this reason, there is potential for TQEM adoption to precede, or be contemporaneous with, a firm's 33/50 participation decision. We therefore test if a firm's TQEM adoption decision is a determinant of its 33/50 participation decision. The probit results (available from authors upon request) indicate that TQEM adoption is not a significant predictor of 33/50 participation, as expected (Hypothesis 1). Conversely, in Table 3, the coefficient on the 33/50 participation variable is positive and statistically significant. Hence, we find evidence in favor of our main hypothesis in this equation, namely, that the 33/50 program helped spur adoption of TQEM (Hypothesis 1). Like prior work, Table 3 also indicates that TQEM adoption is positively (and significantly) related to our "green marketing" proxy (the final good variable FG) and to our OLDASSETS measure. As expected, firms with older and more highly polluting assets have more potential to gain significant emission reduction benefits from TQEM programs, thus favoring their implementation. Higher levels of R&D (RD) and industry concentration (HRD) tend to favor TQEM adoption as well. Such effects are consistent with the "raising rivals cost" theory of corporate environmentalism, whereby concentrated research-intensive firms adopt environmentally progressive practices in order to spur tighter government regulations that disadvantage their higher-cost rivals. R&D may also be a spur to TQEM adoption if research lowers the cost of implementing such environmental management systems. We did not find evidence that pressures by public interest groups tend to spur EMS programs such as TQEM. The coefficient of the interaction variable between environmental membership and boycott threats (BC-SIERRA) has the expected positive sign but is not statistically significant.

Turning to the pollution equation, Table 5 presents selected coefficient estimates for models estimated both using actual participation and adoption data, and using fitted values (estimated probabilities) for this data obtained from our Table 2 and 3 estimations (see discussion in Section III). We find in all our four specifications that TQEM adoption has a direct effect on 33/50 pollutant releases that is negative and statistically significant. In addition, we find that 33/50 participation tends to increase the effectiveness of TQEM in reducing pollution during the post-program years (as indicated by the negative and significant coefficient on PART-TQ9798 in model III). These effects tend to support our original conjectures that the 33/50 program served to reduce pollution in both the short-run (during the program years) and the long-run (after the program ended) in two ways: (1) by spurring the adoption of environmental management programs (like TQEM) that are effective mechanisms to curb episodes of excessive pollution from failures in equipment, servicing and/or oversight, and (2) by helping to create a corporate culture of environmentalism that makes EMS programs more successful (Hypothesis 2).

We find evidence that the 33/50 program produced additional direct benefits in pollution reduction both during and after the program (with significant negative coefficients on PART9296 and PART9798). Such effects may be due to other environmental management practices, beyond TQEM, that the 33/50 program may have tended to promote, and/or direct benefits of the corporate environmental consciousness promoted by 33/50 participation. The coefficients on the "augmented" Inverse Mills ratios indicate that the error terms in the pollution equation is uncorrelated the error terms in the 33/50 and TQEM equations.

VI. Conclusions

In this paper we have studied the bi-directional links between EPA-sponsored voluntary pollution reduction programs and firm-structured environmental management strategies; and their joint impact on the environmental performance of adopting firms. We find evidence that participation in the 33/50 program, the EPA's first formal voluntary pollution reduction program, motivated the adoption of Total Quality Environment Management, the key Environmental Management System, by a sample of S&P 500 firms. This finding suggests that participation in the 33/50 program lowered the costs of adopting the Environmental Management Systems possibly thanks to the technical assistance provided by the EPA for 33/50 participants and/or the corporate culture of environmentalism created by participation in the 33/50 program.

Consonant with prior work (Sam and Innes, 2005; Khanna and Damon, 1999), we find that the 33/50 program led to a reduction in the production of target chemicals during the program years (short-run effects). In addition, we also find that the 33/50 had long-run effects in that it enhanced the effectiveness of TQEM in reducing pollution during the post-program years.

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Table 1: Variable Definitions

RELEASE	Total firm releases of 33/50 pollutants (millions of pounds) (annual)
PSTATUS	Firm's participation status (dummy) in 33/50 program in 1991
PART91 -95	Dummy that equal 1 if a firm is a 33/50 participant and year is between 1991 and 1995, and 0 otherwise
PART96 -98	Dummy that equal 1 if a firm is a 33/50 participant and the year is between 1996 and 1998, and 0 otherwise
TQEM	Dummy that equal 1 if a firm is a TQEM adopter between 1994 and 1996
FAC	Number of a firm's facilities (annual)
INSP-FAC	Lagged Number of a company's CAA inspections (annual) per facility
DIFREL	Change in total firm releases of 33/50 pollutants from 1988-1990
ENFORCE	Dummy that equals 1 if firm had an enforcement action in 1989-90
PRP	Number of Superfund sites for which a firm is a PRP, 1990
SIC28 - SIC38	Dummies for a firm's primary two-digit SIC class
RD	Lagged firm expenditures on R&D ($millions) (annual)
EMPL	Lagged number of firm employees (1000's) (annual)
HERF	Herfindahl index for firm's two-digit SIC class
BC	Dummy that equals one if firm operates in an SIC that was subject to contemporaneous boycott, 1992
FG	Dummy that equals one if firm produces a final good (determined by a firm's primary four-digit SIC class)
SG	Firm percentage sales growth (annual)
SIERRA	Sierra Club members per capita in firm/facility home state (annual)
STRICT	Dummy that equals one if firm's/facility's home state has a strict liability statute, 1988
RTW	Dummy that equals one if firm's/facility's home state has a right-to-work statute, 1988
SPENDAQP	State expenditures on air quality programs in the firm's/facility's home state, 1988
LAWYERS	Number of lawyers per capita in firm/facility home state, 1988
EDUC	Percentage of college degrees in firm/facility home state population, 1990

Table 2: Probit estimation of 33/50 participation

	Variable	Mean	Standard Deviation	Model I Estimate	Model I T-value		Model II Estimate	Model II T-value	
Prior reductions	DIFREL	0.2504	0.7281	-1.4978	-1.09082		-1.2179	-0.8951856	
	PRP	5.9813	10.662	0.1877	2.12812	**	0.1473	1.9986431	**
Enforcement	ENFORCE	0.4019	0.4926	2.0043	2.23994	**	2.1274	2.4902259	**
Effects	INSP-FAC	1.1433	1.1491	0.7285	2.33568	**	0.6884	2.2533552	**
	FAC	7.486	7.8673	0.1401	1.64244		0.0887	1.0435294	
Raising rival's	RD	357.72	814.93	0.009	3	**	0.0099	2.8285714	**
costs	HERF	0.4502	0.1352	21.897	2.07714	**	18.1903	1.7410984	*
Preemption of	SIERRA	2.1562	0.9664	-0.3997	-0.99726		1.5559	0.9767719	
regulations	SIERRA^2	5.5746	6.3465				-0.3074	-1.3607791	
Liability effects	STRICT	0.8103	0.2443	-2.436	-1.70171	*	-1.2884	-0.8307434	
Boycott	BC	0.3832	0.4884	9.0611	2.50189	**	6.5129	2.0683753	**
deterrence	BC-SIERRA	0.8445	1.2283	-0.5239	-0.96714				
Green marketing	FG	0.6542	0.4779	0.2923	0.22518		-0.214	-0.1541343	
	RELEASE	0.6329	1.2701	-0.4929	-0.72764		-0.4463	-0.7050553	
Firm-specific	SPENDAQ	1.1998	0.5809	0.0508	0.09104		-0.0247	-0.04553	
characteristics	LAWYERS	2.8393	0.6506	-0.7546	-0.88371		-0.9347	-1.0632465	
	EDUC	19.9341	2.3309	0.4456	1.76196	*	0.3955	1.5909091	
	RTW	0.311	0.2995	-1.5707	-1.48165		-1.0889	-1.0690163	
	Constant			-23.7131	-2.64889	**	-21.6118	-2.5284056	**
No. Observations					107			107	
Log-L					-27.1327			-26.54655	
AIC					0.97444			0.96349	

Notes: The dependant variable is the 33/50 program participation dummy. The dataset is a cross-section of 107 firms, with time-varying variables measured as of 1990. The hypothesis that all the slope coefficients are jointly insignificant is rejected. Squared variables are denoted by an addition of “^2” to the variable and interactions variables are denoted with hyphens. ** Statistically significant at the 5% level or better (two-tail). * Statistically significant at the 10% level. Both models includes industry dummies for SIC codes 28 and 33-.38.

Table 3: Probit estimation of TQEM adoption

	Variable	Mean	Standard Deviation	Model I Estimate	Model I t-ratio	Model II Estimate	Model II t-ratio
33/50 participation	PSTATUS	0.7347	0.3443	1.6335	2.75 **	1.4164	2.6138 **
Superfund sites	PRP	5.9813	10.662	-0.0481	-1.60	-0.0637	-0.797
	PRP^2					0.0005	0.2083
Raising rivals' costs	RD	357.7239	814.9375	0.009	2.31 **	0.0088	2.3158 **
	HRD	154.5725	370.5258	-0.019	-2.13 **	-0.018	-2.169 **
Preemption of	SIERRA	2.1562	0.9664	-1.0195	-0.77	0.5288	1.6639 *
Regulations	SIERRA^2	5.5746	6.3465	0.1877	0.97		
Liability effects	STRICT	0.8103	0.2443	2.3443	1.09	2.8601	1.3952
	STRCT-EMPL	27.9534	35.7018	-0.049	-1.12	-0.0618	-1.475
Boycott	BC	0.3832	0.4884	-1.141	-0.67		
Deterrence	BC-SIERRA	0.8445	1.2283	0.6254	1.18		
Green marketing	FG	0.6542	0.4779	1.6966	1.84 *	1.9118	1.8871 *
	FG-SIERRA					-0.0892	-0.434
	TRI	36.3905	62.4455	-0.0617	-1.86 *	-0.0668	-1.85 *
Firm-specific effects	OLDASSETS	17.8365	30.1482	0.1301	1.80 *	0.1459	1.7924 *
	EMPL	43.3214	81.4452	0.0661	1.69 *	0.0748	1.9479 **
	EMPL^2	8448.06	55175.95			0	0
	FAC	7.486	7.8673	-0.0552	-1.40	-0.0608	-1.643
	SPENDAQ	1.1998	0.5809	0.1384	0.26	0.2911	0.5325
	RTW	0.311	0.2995	0.693	0.76	0.8387	0.9424
	LAWYERS	2.8393	0.6506	0.9674	1.09	0.7392	0.8374
	EDUC	19.9341	2.3309	-0.417	-1.57	-0.4311	-1.662
	Constant			1.9743	0.56	0.2527	0.0835
No. Observations					90		90
Log-L					-33.46		-34.58
AIC					1.344		1.3685

Notes: The dependant variable is the TQEM adoption dummy. The dataset is a cross-section of 90 firms, with time-varying variables measured as of 1990. The hypothesis that all the slope coefficients are jointly insignificant is rejected. Squared variables are denoted by an addition of “^2” to the variable and interactions variables are denoted with hyphens. ** Statistically significant at the 5% level or better (two-tail). * Statistically significant at the 10% level. Both models includes industry dummies for SIC codes 28 and 33-.38.

Table 4: Lagrange Multiplier (LM) and Conditional Moment (CM) test statistics.

		33/50	
	LM Tests	Model I	Model II
TQEM	Model I	1.2449	1.5082
	Model I	1.0474	1.2836

		33/50	
	CM Tests	Model I	Model II
TQEM	Model I	-0.02263	-0.0211
	Model I	-0.01979	-0.01738

Both tests fail to reject the null of zero correlation between the error terms in the 33/50 and the TQEM equations at any conventional level of significance.

Table 5: Random Effects Estimation of the Pollution Equation

	Actual Adoption and Participation Data								Predicted values of Adoption and Participation Data							
	Model I		Model II		Model III		Model IV		Model I		Model II		Model III		Model IV	
Variable	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio	Estimate	t-ratio
YEAR	-0.0305	-1.91 **	-0.0712	-5.68 ***	-0.0611	-4.73 ***	-0.0652	-5.00 ***	0.0014	0.08	-0.0547	-4.31 ***	-0.0323	-2.38 **	0.0016	0.09
FAC	0.0332	4.10 ***	0.0337	4.13 ***	0.0353	4.34 ***	0.0338	4.15 ***	0.0291	3.80 ***	0.0295	3.82 ***	0.0326	4.25 ***	0.0293	3.85 ***
FAC^2	-0.0002	-3.33 ***	-0.0002	-3.41 ***	-0.0002	-3.43 ***	-0.0002	-3.48 ***	-0.0002	-3.10 **	-0.0002	-3.14 **	-0.0002	-3.30 ***	-0.0002	-3.11 **
EMPL	0.0090	3.08 **	0.0085	2.89 **	0.0084	2.86 **	0.0087	2.93 **	0.0082	2.96 **	0.0079	2.82 **	0.0076	2.74 **	0.0081	2.94 **
EMPL^2	0.0000	-4.56 ***	0.0000	-4.46 ***	0.0000	-4.55 ***	0.0000	-4.46 ***	0.0000	-4.39 ***	0.0000	-4.40 ***	0.0000	-4.42 ***	0.0000	-4.40 ***
RD	-0.0003	-2.31 **	-0.0003	-2.68 **	-0.0003	-2.57 **	-0.0003	-2.58 **	-0.0002	-1.58	-0.0003	-2.21 **	-0.0002	-1.55	-0.0002	-1.58
HERF	-1.2906	-2.53 **	-1.1707	-2.28 **	-1.1597	-2.27 **	-1.2303	-2.39 **	-1.1071	-2.31 **	-1.2523	-2.59 **	-1.0811	-2.25 **	-1.1016	-2.30 **
PART9296	-0.3426	-4.09 ***	-0.1235	-1.93 **	-0.2067	-2.98 **	-0.1646	-2.41 **	-0.4641	-5.07 ***	-0.1613	-2.46 **	-0.3381	-4.44 ***	-0.4697	-5.19 ***
PART9798	-0.5789	-3.83 ***					-0.2047	-1.70 *	-0.7802	-4.47 ***					-0.7450	-4.88 ***
TQEM	-0.4052	-2.88 **	-0.4347	-4.67 ***	-0.3405	-3.48 ***	-0.4277	-4.59 ***	-0.5331	-2.89 **	-0.5968	-5.62 ***	-0.4818	-4.45 ***	-0.5961	-5.68 ***
PART-TQ9496	-0.0173	-0.11							-0.0814	-0.42						
PART-TQ9798					-0.4358	-2.98 **							-0.7758	-4.44 ***		
IMR-PART			0.0443	0.13	0.0739	0.21	0.0621	0.18								
IMR-EMS			0.2140	0.68	0.2203	0.70	0.2123	0.68								
CONSTANT	4.3666	1.47	8.0445	2.80 **	7.0817	2.44 **	7.5481	2.62 **	1.2265	0.42	6.6324	2.38 **	4.3819	1.56	1.2191	0.41

All models include a constant, the additional regressors NEWASSETS, SG, PRP, PRP^2, INSP-FAC, STRICT, RTW, EDUC, LAWYERS, SPENDAQ, SIERRA, SIERRA^2, BC, BC-SIERRA, FG, and the industry dummies (for SICs 28 and 33-38). "*", and "**" indicate statistical significance at the 10% level, 5% or 1% levels, respectively. t-statistics are in parentheses.

[1] The Global Environmental Management Initiative (GEMI) is recognized as the creator of total quality environmental management (TQEM) which embodies four key principles: customer identification, continuous improvement, doing the job right first time, and a systems approach. GEMI) was formed in April 1990 by a coalition of 21 companies including IBM, AT&T and Kodak. The goal of the organization is to develop strategies and standards for corporate environmental performance.(http://www.bsdglobal.com/tools/ systems_TQEM.asp).

[2] These include: Arora and Cason (1995, 1996); Celdren et al. (1996); Alberini and Videras (2000); Khanna and Damon (1999); Sam and Innes (2005); Gamper-Rabindran (forthcoming). . Among these, the analysis by Khanna and Damon (1999) is based on firm-level data for the chemical industry only while the analysis by Gamper-Rabindran (forthcoming) is based on facility level data disaggregated across six different industries: Paper, Fabricated Metal, Primary Metal, Chemical, Electronic and Electric and Transport. The other studies, with the exception of Arora and Cason (1996) which is using facility level data, use firm level data pooled from many different industries.

[3] Although TQEM is measured using responses to a 1994 survey, many firms may have adopted TQEM before the time of the survey. For this reason, there is potential for TQEM adoption to precede, or be contemporaneous with, a firm's 33/50 participation decision. TQEM however became popular only after 1990 when it was first introduced by GEMI. Hence it's adoption is unlikely to have been widespread enough in 1990 to have influenced 33/50 participation.

[4]In principle, "green marketing" effects may be more pronounced for larger, more polluting firms for which perceived benefits of "green" practices are greater. We therefore tested for effects of interaction variables between FG and measures of firm pollutant releases (33/50 releases in the 33/50 participation equation, and TRI releases in the EMS equation). However, none of these interaction effects was found to be statistically significant.

[5]The 1992-1993 issue of the *National Boycott News* lists products subject to contemporaneous organized consumer boycott, including over 400 products made by over 100 firms. If a firm or plant in our sample is in an industry that produces a targeted product (based on the firm's or plant's primary SIC classification), our boycott variable is assigned a value of one for that firm or plant. We should point out that actual boycotts are rare. In fact, theory predicts that boycotts will generally be deterred by cooperating firms (Baron, 2001). Hence, none of the firms in our sample were actually boycotted. Rather, our boycott variable attempts to measure the potential likelihood that a firm might face a boycott threat.

[6]In principle, boycott effects may also be more acute for larger polluters. We therefore considered an interaction between BC and a firm's 33/50 releases, but found no significant effects.

[7]The variables INSPECT89-90 and ENFORCE exhibit raw (Pearson) correlations of .29 and .41 with 33/50 participation, and .19 and .17 with TQEM adoption, respectively. In preliminary estimations, these variables were statistically insignificant explanators of TQEM adoption.

[8]Initiated in 1988, the Toxic Release Inventory (TRI) is a database of toxic releases by all firms with ten or more employers producing one or more of 320 targeted pollutants. The 33/50 pollutants are seventeen of these 320 toxic compounds considered particularly important by regulators in the early 1990's.

[9] Inconsistency due to an endogenous dummy variable can be removed by using the actual values for the dummy and adding an "inverse Mills ratio" for the entire sample, (see Vella (1998)). In our case we have two endogenous dummies (33/50 participation and EMS adoption). If the disturbances in the 33/50 participation and EMS adoption equations are correlated, the "inverse mills ratios" have to be evaluated numerically (see Fishe, Trost, and Lurie (1981), Muller and Riedel (2002)). However, if the error terms are uncorrelated then the inverse mills ratios for the entire sample are given by IMR-PART$_{ti}$, and IMR-TQEM$_{ti}$ where

$$\text{IMR-PART}_{ti}=P_i[\phi(\hat{\gamma}'W_i)/\Phi(\hat{\gamma}'W_i)]+(1-P_i)[-\phi(\hat{\gamma}'W_i)/(1-\Phi(\hat{\gamma}'W_i))] \text{ for } t>1991 \text{ and 0 otherwise, and}$$
$$\text{IMR-TQEM}_{ti}=T_i[\phi(\alpha'Z_i)/\Phi(\alpha'Z_i)]+(1-T_i)[-\phi(\alpha'Z_i)/(1-\Phi(\alpha'Z_i))] \text{ for } t>1993 \text{ and 0 otherwise.}$$

P_i is the participation dummy for firm i, $\hat{\gamma}$ is the estimated parameter vector for the probit estimation of the participation equation, W_i is the firm i set of explanatory variables in the participation equation, and $\phi()$ ($\Phi()$) are normal density (distribution) functions. Similarly T_i is the TQEM adoption dummy for firm i. α is the estimated parameter vector of the TQEM adoption equation, and Z_i is a vector is covariates in the TQEM equation. Using the Lagrange multiplier and conditional moment tests (see Table 5), we find that the disturbances in the participation and adoption equations are uncorrelated at all conventional levels of significance, allowing us to use IMR-PART and IMR-TQEM as regressors in the pollution equation to control for self-selection.

[10] Specifically, we obtain 250 bootstrap samples (of 107 companies each) from our data; perform our multi-step estimation for each sample; and construct standard error estimates for our parameters from the resulting distribution of bootstrapped parameter estimates.

[11] IRRC data on EMS adoption is available for other years. However, because data quality is much superior in 1994 (and responses highly correlated across proximate years), we restrict our analysis to the 1994 data.

[12] We restrict attention to CAA inspections because the 33/50 program was principally an air toxics program.

[13] We owe thanks to John Maxwell and Tom Lyon for generously providing us with their data. We also owe thanks to Chris Decker for providing invaluable advice on navigating the EPA's information services.

[14] In both tables, the first model specification (without the jointly endogenous right-hand variable) provides the basis for constructing fitted values in the other equation.