Adoption of Pollution Prevention Techniques: The Role of Management Systems and Regulatory Pressures

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This paper investigates the extent to which firm level technological change that reduces unregulated emissions is driven by existing and anticipated regulatory pressures, and technological and organizational capabilities of firms. Using a treatment effects model with panel data for a sample of S&P 500 firms over the period 1994-96, we find that organizational change in the form of Total Quality Environmental Management leads firms to adopt techniques that prevent pollution even after we control for the effects of various types of regulatory pressures and firm-specific characteristics. Moreover, we find that the presence of 'complementary assets', in the form of technical capability of the firm, is important for creating an internal capacity to undertake incremental adoption of pollution prevention techniques.

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1. Introduction

Command and control environmental regulations in the U.S. have typically sought to control pollution after it has been generated. The steeply rising costs of these regulations (these costs increased by more than 50% between 1990-2000)[1] and their negative impact on the productivity of regulated firms (see survey in Gray and Shadbegian, 1994) have shifted the attention of environmental regulators and firms towards flexible environmental strategies that target the reduction of pollution at source. The U.S. National Pollution Prevention Act of 1990 emphasizes pollution prevention rather than end-of-pipe pollution control as the preferred method of pollution reduction. However, it does not mandate adoption of pollution prevention technologies. Instead, the USEPA has sought to induce voluntary adoption of such technologies through the promotion of environmental management systems that induce firms to take a holistic view of pollution control and reduce waste generation at source (Crow, 2000; USEPA, 1997, 1998; USGAO, 1994). This paper investigates the influence of a firm's environmental management system and other internal and external factors on the extent to which the firm adopts pollution prevention technologies.

An environmental management system typically embodies the concept of Total Quality Management which emphasizes prevention over detection, continuous progress in product quality by minimizing defects, and quality improvement across all aspects of the industrial process. Application of these principles to environmental management, referred to as Total Quality Environmental Management (TQEM),[2] can lead firms to apply the same systems perspective to prevent pollution problems. Under TQEM, pollution is viewed as a quality defect to be continuously reduced through the development of products and processes that minimize waste generation at source. Case studies of leading firms, such as Kodak, Polaroid, Xerox and L'Oreal show how TQEM principles and tools led them to implement techniques that reduce waste and improve the quality and environmental friendliness of their processes and products (Ploch and Wlodarcyzk, 2000; Breeden et al., 1994; Wever and Vorhauer, 1993; McGee and Bhushan, 1993; Nash et al., 1992). An in-depth study of firms led the President's Commission on Environmental Quality (1993) to conclude that quality management principles and pollution prevention are complementary concepts; a finding reinforced by subsequent surveys of firms which show that firms that adopted pollution prevention practices were more likely to be those practicing TQEM.[3] However, there has been no systematic empirical determination of a link between TQEM and the adoption of new pollution prevention technologies. Moreover, while TQEM can provide a framework that encourages pollution prevention, it does not guarantee that firms will choose to do so. Firms may instead resort to other ways to control pollution such as recycling or reusing waste. Alternatively, firms may adopt TQEM simply to convey a visible signal of an environmentally responsible firm and gain legitimacy among external stakeholders (Shaw and Epstein, 2000).[4]

In addition to the firm's management system, its technical capabilities can also influence the extent to which it adopts pollution prevention technologies. This is based on the premise that even though generic knowledge about ways to prevent pollution already exists, strategies to prevent pollution need to be customized to the particular production processes and products of the adopting firm. Therefore, pollution prevention is likely to require technical expertise and related experience.[5] Indeed, surveys of firms suggest that adopters of pollution prevention techniques are more innovative in general, with higher R&D intensity and a history of more frequent new product introductions and product design changes (Florida and Jenkins, 1996). This suggests that proactive efforts at reducing pollution do not occur in a vacuum. Instead, they are associated with broader and previous efforts of a firm to be innovative.

Furthermore, external pressure from mandatory regulations could have an impact on the environmental innovativeness of firms. While these regulations do not directly require firms to adopt pollution prevention technologies, they can create incentives to adopt such technologies if these technologies have synergistic effects on reducing emissions of regulated pollutants and thereby reducing current or anticipated costs of compliance. Several authors have also suggested that regulators are responsive to good faith efforts put forth by firms to reduce releases of pollutants not currently regulated or to limit releases of pollutants beyond what is required by statute or permit (Hemphil, 1993/1994; Cothran, 1993). This may create incentives for firms to voluntarily adopt pollution prevention technologies to serve as a signal of environmentally responsibility and reduce regulatory scrutiny and the stringency with which environmental regulations are enforced.

We conduct this analysis using an unbalanced panel of 167 firms from the S&P 500 list which reported to the Toxics Release Inventory (TRI) and responded to the survey on adoption of environmental management practices conducted by the Investor Research Responsibility Center over the period 1994-96. Our study controls for the heterogeneity among firms in a broad range of characteristics while analyzing the impact of technological capabilities, regulatory pressures and TQEM on the adoption of pollution prevention technologies.

Previous studies have used conceptual analysis and case studies in management and organizational theory to show that organizational structure of the firm can affect its speed in adopting productivity enhancing innovations and its ability to realize the benefits of technology adoption. In particular, an effective management system with clear policies, organizational structure, tracking and reporting mechanisms and performance measures is needed to induce environmental innovations (DeCanio et al., 2000; Breeden et al., 1994). Several empirical studies find that environmental regulatory pressures led to environmental innovation (Lanjouw and Mody, 1996; Jaffe and Palmer, 1997; Gray and Shadbegian, 1998; Brunnermeier and Cohen, 2003; Pickman, 1998). These studies use either industry expenditures on R&D or aggregate number of patents as a proxy for innovation and industry pollution abatement costs as a measure of regulatory pressures (with the exception of Gray and Shadbegian (1998) who use plant level data). A related study by Cleff and Rennings (1999) examines the perceived importance of various types of environmental policy instruments on the discrete self-classification of firms as being environmentally innovative and finds that firms perceived voluntary programs (eco-labels and voluntary commitments) to be important in encouraging product and process innovation.

Studies of environmental management systems (survey in Khanna, 2001) have examined the motivations for adopting an environmental plan (Henriques and Sadorsky, 1996), seeking ISO certification (Anderson et al., 1999; Dasgupta et al., 2000; King and Lenox, 2001; Nakamura et al., 2001), adopting a more comprehensive environmental management system (Khanna and Anton, 2002 a, b; Anton et al., 2004) and participating in the Responsible Care Program (King and Lenox, 2000).[6] Another related set of studies has examined the implications of such initiatives by firms for their environmental performance, measured by toxic releases (King and Lenox, 2000; Anton et al., 2004) or by compliance status (Dasgupta et al. 2000). More recently, Arimura et al (2007) and Frondel et al (2007) examine the impact of management systems on the environmental innovation behavior of facilities in various OECD countries. The former study uses R&D expenditure as a proxy for environmental innovation and finds that management systems did not lead to more environmental R&D. The latter study uses a multinomial logit model to examine whether a facility adopted an end-of-pipe technology or a cleaner production technology and finds that management systems motivated adoption of both types of technologies. Both these studies, however, do not control for the endogeneity of the management system adoption decision, which may be determined simultaneously with its environmental innovativeness.

This paper makes several contributions to the literature on the determinants of environmental innovations. Unlike the previous literature which has used either aggregate and broad measures of innovation such as industry expenditures and patent counts or has used discrete indicators of technology adoption, we use detailed micro data on a specific type of environmental innovation, namely count of adoption of 43 types of pollution prevention techniques adopted by firms to reduce their toxic releases as reported annually to the USEPA's Toxics Releases Inventory (TRI). These pollution prevention practices include product and process changes, raw material substitutions and good operating practices. Moreover, we analyze the effects of organizational structure on environmental innovation using a treatment effects model that allows us to control for the endogeneity of the TQEM adoption decision. We also analyze the impact of various types of environmental regulations, both existing and anticipated, on pollution prevention.

2. Conceptual Framework

We consider profit maximizing firms that are emitting toxic releases which are not directly subject to any penalties or other regulations. Despite the absence of regulation, firms may have several motivations to reduce the releases of these pollutants voluntarily. These motivations could be internal, that is, generated by the firm's management philosophy and technical capacity, or external, that is, arising from the firm's interaction with external stakeholders, including environmental regulators, environmental interest groups and consumer groups. These stakeholders have the potential to take actions that affect the costs of compliance, market share, reputation and image of firms. All of these developments have increased the incentives for firms to make proactive efforts to reduce their unregulated toxic releases. In the absence of any mandated technology standards, firms have flexibility in choosing either pollution prevention or end-of-pipe technologies for controlling such releases.

Interest in pollution prevention has grown among firms with the passage of the Pollution Prevention Act and due to increasing costs of end-of-pipe disposal. Underlying the concept of pollution prevention is the premise that pollution is caused by a wasteful use of resources; thus, a reduction in these wastes through changes in production methods that increase production efficiency can lead to input cost-savings, higher productivity, lower costs of pollution control and disposal and lower risk of environmental liabilities relative to using end-of-pipe technologies (Porter and van der Linde, 1995; Florida, 1996). The adoption of pollution prevention activities could also confer a second benefit to firms seeking to improve their environmental image. While emissions reductions from some unobserved counterfactual level may be sometimes hard to ascertain, pollution prevention activities provide tangible evidence to the public and to regulators that the firm is proactively engaged in abatement using methods not mandated by law. Although, recognition of the net benefits of adopting pollution prevention technologies is likely to have been increasing among all firms, we expect these benefits to differ across heterogeneous firms. We next discuss our measure of adoption of pollution prevention techniques.

Our dependent variable is the count of new pollution prevention techniques adopted by a firm during a year. Since pollution prevention is popularly referred to as P2, we call this variable *New P2*. Each facility of a firm is required to report new adoption of any of 43 different activities to prevent pollution for each toxic chemical to TRI in a given year. These activities are broadly categorized into changes in operating practices, materials and inventory control, spill and leak prevention, raw material modifications, equipment and process modifications, rinsing and draining equipment design and maintenance, cleaning and finishing practices, and product modifications. Each facility can report up to four different P2 activities adopted for controlling the level of releases of each chemical.

We use several different methods for aggregating the number of P2 practices across categories of practices, across chemicals, and across facilities belonging to the same parent company. First, we simply aggregate the number of all P2 practices adopted in a year across all chemicals for each facility and then across all facilities belonging to a parent company to obtain *New P2* at the firm-level for that year.[7] Second, we consider the count of chemicals for which a facility had undertaken any P2 activity and aggregate these across chemicals and across facilities belonging to a parent company to obtain *Chem-Count P2* at the firm-level for that year. Third, we weight each facility's P2 activities (summed over chemicals as under the first method above) by its share in the five-year lagged toxic releases of the parent company and obtained a *Weighted Sum of New P2* at the firm level. Facilities with fewer P2 activities per chemical, fewer number of chemicals and a smaller share in lagged toxic releases of the firm would contribute less to this measure of firm level *Weighted Sum of New P2*. The hypotheses and the discussion below are framed in terms of the determinants of *New P2*, for ease of presentation, but apply as well to the alternative aggregations of P2 discussed above. We now discuss the specific factors, first the external and internal factors and then the management system that can explain environmental innovativeness of firms.

Profit maximizing firms can be expected to adopt the lowest cost methods to comply with existing and anticipated regulations. Existing regulations, that are primarily in the form of end-of-pipe technology standards, may create disincentives for voluntary adoption of pollution prevention technologies. Theoretical studies by Downing and White (1986) and Milliman and Prince (1989) show that the incentive to innovate is stronger under market-based systems (e.g. emission fees or permits) than under command and control regulations because the gains through lower costs of compliance with innovation are much higher with market based policies. Additionally, by diverting resources towards compliance with technology standards and promoting a reactive approach to compliance, command and control regulations can reduce incentives to be innovative. However, these studies ignore the potential for firms to influence the stringency with which regulations are enforced, to preempt future regulations or to indirectly lower costs of compliance through synergistic reductions in related pollutants.

Existing mandatory regulations could lead firms to adopt pollution prevention technologies that might be directly targeted at reducing (unregulated) toxic releases but could indirectly lower the costs of regulatory compliance through at least two different channels. First, efforts to prevent toxic releases could reduce the compliance costs for regulated pollutants (if regulated pollutants and toxic releases are complementary by-products of the production process). Surveys find that firms are proactively adopting P2 and seeking to eliminate harmful emissions to avoid complex, inflexible and costly regulatory processes and legal liabilities (Rondinelli and Berry, 2000; Florida and Davison, 2001).

Second, frequent inspections and penalties associated with enforcement of mandatory regulations are not only costly for firms but they can also have a negative impact on a firm's reputation. Empirical studies show that firms that had lower toxic releases were less likely to be subject to inspections and enforcement actions. Such firms were also subject to fewer delays in obtaining environmental permits (Decker, 2003; 2004). Sam and Innes (forthcoming) find that participation in USEPA's voluntary 33/50 program led to a significant decline in the frequency with which firms were inspected. To the extent that adoption of P2 practices can signal good faith efforts by firms to be environmentally responsible and reduce compliance costs, there would be incentives for firms to adopt such practices. We expect both of these channels to create incentives for firms that face greater enforcement pressure in the form of more frequent inspections and a larger number of penalties to adopt more *New P2* not only to reduce pollution at source but also to earn goodwill with regulators and possibly reduce the frequency of future inspections and severity of penalties.

Furthermore, future regulations, particularly if targeted at toxic releases, can also impact adoption of pollution prevention technologies. Anticipation of stringent environmental regulations for reducing currently unregulated pollutants could induce technological innovation by firms to reduce pollution at source (Porter and van der Linde, 1995).[8] By taking actions to control pollution ahead of time through product and process modifications, firms may be able to lower costs of compliance as compared to the costs of retrofitting abatement technologies in the future (Christmann, 2000). Firms may also adopt pollution prevention technologies to reduce the potential for environmental contamination and avoid future liabilities. The anticipation of future stringent environmental regulations may also induce firms to be innovative to gain a competitive advantage by establishing industry standards and creating potential barriers to entry for other competitors (Dean and Brown, 1995; Barrett, 1992; Chynoweth and Kirschner, 1993).

This suggests the following:

Hypothesis 1: The higher the costs of compliance with existing and anticipated mandatory regulations, the greater the incentives to adopt pollution prevention techniques.

As proxies for the costs of existing regulations, we include the variable, *Inspections*, defined as the number of times a firm was inspected by state and federal environmental agencies to monitor compliance with mandatory regulations.[9] We also include *Civil Penalties* received for noncompliance with environmental statutes, such as the Clean Air Act, the Clean Water Act, Toxic Substances Control Act and the Resource Conservation and Recovery Act.

Additionally, as a measure of the stringency of the existing regulatory climate of the county, we construct a measure based on the non-attainment status of all counties in the US. As per the 1977 Clean Air Act Amendments, every county in the US is designated annually as being in attainment or out of attainment (non-attainment) with national air quality standards in regards to six criteria air pollutants: carbon monoxide, sulfur dioxide, total suspended particulates, ozone, nitrogen oxide and particulate matter. Regulatory requirements are commonly understood to be more lax in attainment counties compared to non-attainment counties. These amendments, therefore, led to significant spatial differentials in air quality regulation across counties within states. Within any of the six criteria air pollutant categories, county status may range from attainment of the primary standard to non-attainment. Because a county can be out of attainment in several air pollutant categories, and many heavy polluters emit numerous pollutants, we construct a dummy variable for each of the six pollutants for each facility based on its location: for each pollutant a value of 1 is given to facilities located in a non-attainment county for that pollutant and 0 otherwise. Each of the six dummy variables is summed up for all the facilities of each parent company and the resulting counts are then summed up over the six pollutants to derive the *Non-attainment* variable (as in List, 2000). Higher values indicate that a larger number of the facilities of a parent company are located in counties with non-attainment status for a larger number of pollutants.

A few states have also initiated mandatory P2 programs since 1988 to encourage source reduction of toxic emissions. These programs impose mandatory reporting requirements for P2 activities adopted, similar to the federal TRI, and provide technical assistance to firms in the state. Six states have numerical goals for P2 adoption, while two states provide financial assistance to firms.[10] We hypothesize that facilities located in states with mandatory P2 programs are more likely to adopt *New P2* activities. We include a dummy equal to one if a facility is located in a state with a mandatory P2 program and zero otherwise. These dummies are then summed over the facilities of a firm to obtain the *Mandatory P2 Policy* variable, which provides a measure of the extent to which a firm is facing regulatory pressure to report/adopt P2 activities.

We include another variable, the *Number of Superfund Sites* for which a firm has been listed as a potentially responsible party under the provisions of the Comprehensive Environmental Response, Compensation and Liability Act. This provides a measure of the potential threat of liabilities for harmful contamination caused by disposal of pollution (as in Khanna and Damon 1999; Videras and Alberini 2000). As a proxy for anticipated costs of compliance, we include the volume of *Hazardous Air Pollutants* (*HAP*) consisting of 189 toxic chemicals listed in Title III of the 1990 Clean Air Act Amendments. These were expected to be regulated under New Emissions Standards for HAP from 2000 onwards. We expect that firms with a larger *HAP* face a greater threat of anticipated regulations and are more likely to adopt pollution prevention technologies to obtain strategic advantages over competitors by reducing HAP emissions ahead of time.

In addition to external pressures to adopt P2 activities, two internal factors may also play an important role by influencing a firm's ability to identify profitable techniques and its learning costs of adoption. The first of these is the firm's technological capabilities. These are also referred to as "complementary internal expertise/assets" or "absorptive capacity" (Cohen and Levinthal, 1994). These capabilities depend on the level of in-house technical sophistication.[11] Several scholars have demonstrated the relationship between the knowledge resources and capabilities/competencies of a firm and its innovativeness (Teece, Pisano and Shuen, 1997; Cohen and Levinthal, 1994, 1989).[12] Based on this literature we hypothesize that:

Hypothesis 2: Firms that have stronger technical capabilities are likely to adopt more pollution prevention techniques.

We measure a firm's absorptive capacity by its *R&D Intensity*, defined as the ratio of its annual R&D expenditures over its annual sales. Cohen and Levinthal (1989) contend that R&D expenditures not only generate new information but also enhance the firm's ability to assimilate and exploit existing information, that is, a firm's 'learning' or 'absorptive' capacity.

The second internal factor that could influence the adoption of pollution prevention technologies is the organizational structure of the firm. The managerial literature argues that organizational systems are critical to the innovativeness of firms because they condition firm responses to challenges and ability to realize the full benefits of cost-reducing or productivity enhancing technologies (Teece and Pisano, 1994; DeCanio et al., 2000). In particular, TQEM creates an organizational framework that encourages continuous improvement in efficiency and product quality through systematic analysis of processes to identify opportunities for reducing waste in the form of pollution. The TQEM tool-kit of senior management commitment, team-work, empowerment of employees at all levels, and techniques such as process mapping, root cause analysis and environmental accounting can enable the firm to become aware of inefficiencies that were not recognized previously and to find new ways to increase efficiency and reduce the costs of pollution control (Wlodarczyk et al., 2000). This may lead the firm to see the value of developing products and processes that minimize waste from "cradle to grave" rather than focusing only on end-of-pipe pollution control. The conceptual relationship between TQEM and pollution prevention suggests:

Hypothesis 3: Firms which adopt TQEM will adopt more pollution prevention techniques.

We define *TQEM* as a dummy variable equal to 1 if a firm adopted TQEM in a particular year and zero otherwise. In testing Hypothesis 3, it is important to recognize that *TQEM* could be an endogenous variable. For example, (unobserved) managerial preferences could influence the adoption of both *TQEM* and pollution prevention techniques. We discuss this issue and our methods for accounting for it in the next section.

While testing the above three hypotheses we control for other factors that could also influence the adoption rates of pollution prevention practices. In addition to regulatory pressures, market pressures from consumers and environmental organizations could also lead firms to undertake pollution prevention.[13] Several studies have shown that consumer willingness to pay premiums for environmentally friendly products and the desire to relax price competition can lead some firms to produce higher quality environmental products to differentiate themselves from other firms (Arora and Gangopadhyay, 1995). For example, Starbucks consumers pressured the coffee chain to purchase only from suppliers who grow coffee beans in a bird-friendly-fashion (GreenBiz News, 2004). We extend the demand-side pressures to include the demand for innovation by other stakeholders, such as environmental and citizen groups. These groups can express their preferences through boycotts and adverse publicity which can affect the reputation of a firm.

We proxy consumer pressure by a dummy variable, *Final Good*, which is equal to one for firms that produce final goods and zero for those that produce intermediate goods.[14] We measure pressure by environmental groups through an explanatory variable, *Environmental Activism*, which is defined as the ratio of per capita membership in environmental organizations in a state relative to that in the entire U.S. We obtain a measure of environmental activism for each parent company by averaging the values for all its facilities located in different states.[15] Higher values of this variable indicate that a firm has its facilities in states with relatively high per capita membership in environmental organizations.

Additionally, we recognize that the costs of adopting pollution prevention practices and the effectiveness of pollution prevention as a strategy for reducing emissions may vary with the scale of toxic releases. If larger toxic polluters face larger (smaller) costs of abatement using pollution prevention methods, then one would observe a negative (positive) association between the emissions reported to the TRI and pollution prevention activities. Since current emissions are endogenous, as they are affected by the level of pollution prevention activities, we use lagged *Toxic Releases* (choosing a five year lag to ensure that endogeneity is not an issue even in the presence of serial correlation). In some specifications, of which we report one, we replace lagged

Toxic Releases by current *Toxic Releases* as an explanatory variable. We avoid endogeneity bias from doing so by using lagged *Toxic Releases* as an instrument for current *Toxic Releases*. It is also possible that firms emitting releases with a higher toxicity index may be more concerned about regulatory or public scrutiny and potential liabilities. Such firms may have greater incentives to adopt P2 techniques. We, therefore, also include the lagged *Toxicity-Weighted Releases* as an explanatory variable in one model.

We control for the number of pollution reduction opportunities a firm has by including the *Number of Chemicals* emitted as an explanaotry variable. This variable is the count of chemicals reported by the firm which is obtained by summing up the chemicals reported by each facility over all facilites of that firm. This controls for the possibility that firms emitting a larger number of chemicals or having a larger number of facilities may adopt more pollution prevention practices simply because they have more opportunities to do so.

We also include the *Age of Assets* of a firm, its *Market Share of Sales* and its *Sales* as explanatory variables. *Age of Assets*, measured by the ratio of total assets to gross assets (as in Khanna and Damon, 1999), indicates how depreciated a company's assets are and is thus a proxy for the cost of replacement of equipment. Higher values of this variable indicate newer assets. The newer the equipment, the more costly it would be to replace it, which may be a barrier to innovative activities to prevent pollution. Newer equipment may also be more efficient and less polluting; there may, therefore, be less of a need for making the modifications needed to prevent pollution. We, therefore, expect that firms with older assets may be more likely to adopt more *New P2*.[16]

We include the *Market Share* of a firm in terms of industry sales as an explanatory variable to control for any effects of industry leadership on the incentives for innovation. There is a considerably large theoretical and empirical literature analyzing these effects and yielding ambiguous predictions (see survey by Cohen and Levin 1989). Some have supported the Schumpeterian argument that monopolists or market leaders can more easily appropriate the returns from innovative activity. Others argue that insulation from competitive pressures breeds bureaucratic inertia and discourages innovation.[17] Market share can also be a proxy for a firm's innovativeness and technical capabilities as innovative and technically capable firms tend to dominate their markets. Finally, we include the *Sales* of a firm as a measure of firm size. Larger firms may have more resources to adopt pollution prevention practices. They are also likely to be more visible and thus targets of social pressure by stakeholders because they may be held to higher standards. Such firms may also be more vulnerable to adverse effects of a tarnished reputation.[18]

3. Empirical Model

Our empirical model consists of a *New P2* adoption equation (1) which relates the number of *New P2* techniques Y_{it}, adopted by the i^{th} firm at time t to a vector of observed exogenous variables, X_{it}, the *TQEM* adoption decision, T_{it} , and unobserved factors, ε_{1it}.

$$Y_{it} = \alpha X_{it} + \beta T_{it} + \varepsilon_{1it} \qquad (1)$$

Contemporaneous values of explanatory variables X_{it} are used to explain *New P2* in equation (1), except for five-year lagged values of toxic releases and *HAP*, because emissions might be jointly determined with the *New P2* adoption decisions; unobserved factors influencing *New P2* adoption are likely to influence current emissions. However, our results are robust to using current emissions as a regressor with past emissions as an instrument. Since the distribution of *HAP*, *Toxic Releases* and *Toxicity-Weighted Releases* in our sample is highly skewed to the right and to allow for diminishing marginal effects these variables on *New P2*, we include the square roots of these variables as explanatory variables. We also estimated models using levels of these variables and found that the signs and significances of these and other explanatory variables were unaffected. Because we have multiple years of observations, the error terms may be serially correlated. We allow for serial correlation of the form $\varepsilon_{1it} = \rho_1 \varepsilon_{1it-1} + u_{it}$ where $E(u_{it}) = 0$, $E(u_{it}^2) = \sigma_u^2$ and $Cov(u_{it}, u_{is}) = 0$ if $t \neq s$ and estimate all models using the Prais and Winsten (1954) algorithm.[19]

The coefficient of *TQEM* represents the average treatment effect of *TQEM* adoption on *New P2* adoption levels. We recognize that the *TQEM* adoption decision, T_{it}, may be endogenous because the unobserved variables that influence *TQEM* may be correlated with the unobserved variables that influence *New P2* equation. For example, one such unobserved variable could be the 'green' preferences of the current management which would affect both the decision to undertake *TQEM* and undertake more *New P2* even after conditioning for observed variables. The bias on β in (1) could be positive if *TQEM* is more likely to be adopted by such firms. However, the bias could be negative if firms with an inherently low scope for pollution prevention activities find the adoption cost of *TQEM* not worthwhile. A test for the endogeneity of *TQEM* (Wooldridge, 2002) rejects the null hypothesis that it is an exogenous variable at the 1% significance level. To deal with this endogeneity problem, we can use a two-stage least squares method to estimate the effect of T_{it} on Y_{it} consistently if the following conditions are satisfied (Wooldridge 2002): the error term has zero conditional mean; the variance of the error is constant; the standard rank condition is satisfied; and the TQEM adoption is adequately described by a probit model (Wooldridge 2002). The optimal instrumental variable for *TQEM* in such a model is the predicted probability of *TQEM*, $\hat{T}_{it}$, which we obtain by estimating the *TQEM* adoption equation using a probit model with a vector of explanatory variables, W_{it-5} (that capture the factors that influence the benefits and costs of adopting TQEM). In particular, we posit the following selection equation based on the latent variable T_{it}* which measures the net benefits from adoption of TQEM.

$$T_{it}^* = \gamma_1 W_{it-5} + \varepsilon_{2it} \qquad (2)$$

The indicator variable for *TQEM* is $T_{it} = 1$ if $T_{it}^* > 0$ and 0 otherwise. Some of the variables included in W_{it-5} are likely to be also included in X_{it}. The *i.i.d.* error component ε_{2it} is assumed to be normally distributed with mean zero and variance $\sigma^2_{\varepsilon 2}$. We estimate the probit model pooling all observations from the three year panel. The parameter estimates obtained thereby are consistent but the standard errors are incorrect because they ignore the panel nature of the data. We correct for the standard errors by allowing for correlation in the disturbance of the latent variable across time for the same firm.

The explanatory variables included as instruments for TQEM in estimating equation (2) are based on the findings about the determinants of TQEM adoption described in Harrington et al. (forthcoming). They hypothesize that the incentives for firms to adopt TQEM depend on external stakeholder pressures from environmentally aware consumers and public interest groups, regulatory pressures from environmental agencies, and internal factors which depend on the production related benefits and costs of making such organizational changes and the capabilities of firms to make them. The internal production-related benefits arise because TQEM focuses on process improvement to reduce input waste, which is seen as the cause of pollution, and input use while increasing productivity and value-added activities. The adoption of TQEM may also impose production-related and managerial costs due to a need for process and product modifications.[20] We include lagged values of *Civil Penalties*, *Inspections*, *Superfund sites* and *HAP* as proxies for regulatory pressures. We include *Final Good* as a measure of consumer pressure and lagged *Sales* as a measure of visibility to the public. *Sales* is also a proxy for the economies of scale and firm size could influence the firm's ability to bear the fixed costs of adoption. We include lagged *Toxic Releases* reported to the TRI as a measure of the scale of the environmental problem. Additionally, lagged *R&D Intensity* and *Number of Facilities* could influence the net benefits of adopting TQEM. *R&D Intensity* is a proxy for the technical capacity of firms. The *Number of Facilities* of a firm could influence the firm's visibility to the public, the costs of coordinating a common management system within the corporation and the gains from implementing a uniform approach towards environmental management. In equation (2) all time dependent explanatory variables (other than *Number of Facilities*) are measured with a five-year lag (for the years 1989-91) to avoid possible endogeneity bias since the year that a firm adopts TQEM for the first time is not known. However, adoption may have occurred during or after 1991, since TQEM was first introduced by the Global Environmental Management Facility that was formed in April 1990. The use of five-year lagged explanatory variables avoids the possibility that TQEM adoption in the past could have influenced any of the explanatory variables included above. While *Number of Facilities* is expected to influence the adoption of TQEM, it is not expected to influence the adoption of P2 activities by a firm after we have controlled for the *Number of Chemicals* emitted by the firm aggregated over facilities. The exclusion of this variable from equation (1) enables identification of its parameters.

4. Data Description

The sample consists of S&P 500 firms which responded to the Investor Research Responsibility Center (IRRC) survey on corporate environmental management practices adopted by them and whose facilities reported to the TRI at least once over the period 1994-1996 or 1989-1991 (since we are using five-year lagged values of toxic releases as explanatory variables). The IRRC data provides information about the adoption of TQEM by parent companies. The TRI contains facility-level information on releases of chemical-specific toxic pollutants and on the pollution prevention activities adopted by firms since 1991. It also provides data on *HAP* and the *Toxicity-Weighted Releases*.[21] To match the TRI dataset with the IRRC, we construct unique parent company identifiers for each facility in the TRI database, and then aggregate all chemical and facility level data to obtain parent company level data.[22] We dropped the chemicals which had been added or deleted over the period 1989-1996 due to changes in the reporting requirements by the USEPA. This ensures that the change in toxic releases in our sample over time is not due to differences in the chemicals that were required to be reported. Of the S&P 500 firms, only 254 firms reported to the TRI at least once during the period 1989-1996. Of these firms, an unbalanced panel of 184 firms responded to the survey by the IRRC in at least one of the three years. Restricting our sample to the firms for which complete data for estimating equations (1)-(2) were available resulted in 463 observations belonging to 174 firms for estimating equation (1) and 422 observations belonging to 167 firms for estimating equation

(2). Summary statistics for the variables used here are presented in Table 1.

The TRI instructs firms to report the new P2 activities adopted by them in that year. However, it is possible that some firms might be reporting all (cumulative) P2 activities adopted by them instead of only the incremental ones. To check if this was the case we examined the annually reported P2 counts by each facility belonging to S&P 500 firms and reporting to TRI, for each chemical for the period 1992-1996 and compared it with their reports for the previous period (1991-1995). We then derived the change in the reported *New P2* count for a total of 74,780 instances at the chemical-facility level. If firms were inadvertently reporting all P2 activities adopted instead of New P2 activities, we would expect that the annual count of P2 reported would be increasing or stay constant over time for all years. Our investigation focused at the facility level on the premise that any misinterpretation of the instructions in the TRI would be at the facility rather than chemical level. In particular, we have calculated the number of facilities for which the reported P2 counts were non-decreasing for all chemicals. We found that this was the case for only 236 facilities (5.68% of all S&P facilities reporting to TRI) and represents only 0.67% of the chemical-facility pairs (because these facilities have a much lower than average number of chemicals). Therefore, even if there was any misinterpretation of the survey question, it impacted at most a small fraction of the data. [23]

The number of environmental *Civil Penalties* and the number of *Inspections* are derived from USEPA's Integrated Data for Enforcement Analysis (IDEA) database. Since these data are reported at the sub-facility level, inspections and penalties of all sub-facilities of each parent company are added up to get parent company level data. The number of *Superfund Sites* is derived from the Comprehensive Environmental Response, Compensation, and Liability Information System (CERCLIS) of the USEPA. Superfund data are at the facility level and were aggregated to the parent company level.

The S&P 500 Compustat database, now known as Research Insight, is the source of parent-company level financial data on net sales, total assets, gross assets and R&D expenditures. *Market share* data are obtained from Ward's Business Directory using parent company names. The *Final Good* dummy is constructed based on the firm's four-digit SIC code (as described in Harrington et al., 2005). The primary SIC code of a parent company is that reported in the Research Insight database. If that was missing, then we use the SIC code in Ward's Business Directory to construct the *Final Good* dummy.

The *Non-attainment* status of counties is obtained from the USEPA Greenbook.[24] These data are matched with the TRI using the location information of each facility. The data on *Environmental Activism* are obtained at the state level for 1993 from Wikle (1995).[25] Data on state P2 policies are obtained from the National Pollution Prevention Roundtable.[26]

5. Results

We estimated three alternative first-stage probit models to explain TQEM adoption (Table 2). In Model I-A the explanatory variables are measured in levels while in Model I-B they are measured in square roots (except for *Number of Facilities*). The Schwarz Information Criterion and Akaike Information Criterion indicate that explanatory variables measured in square-roots provide a better fit to the data on *TQEM*. We then estimate Model II, which is a parsimonious version of Model I-B and includes only the variables that have a statistically significant effect on *TQEM*. We find that firms that have larger *R&D intensity*, larger *Sales*, larger *Toxic releases* and a fewer *Number of Facilities* are more likely to adopt TQEM. Consumer pressure, proxied by *Final Good*, and regulatory pressure proxied by *Number of Superfund Sites*, *HAP*, *Civil Penalties* and *Inspections*, is not found to have any effect on TQEM adoption. These results are consistent with those reported in Harrington et al. (forthcoming) which find that internal considerations were more important in motivating adoption of TQEM than external factors.

We estimate several different models to examine the determinants of *New P2* adoption. All linear models are estimated assuming an AR1 error process. The estimates of ρ_1, the autocorrelation parameter, in all models strongly support the validity of assuming an AR1 error process against the alternative of an *i.i.d.* error distribution. Since the dependent variable is a count variable, we also estimate a negative binomial model. The dispersion parameter of the negative binomial is statistically significant, indicating the validity of using this model instead of a Poisson model. The standard errors of the negative binomial models allow for correlation in the disturbance of the latent variable across time for the same firm.

We first examine the results of models that include only the exogenous explanatory variables and exclude *TQEM*. Model III-A (Table 3) examines the determinants of *New P2*. Model III-B is a negative binomial version of Model III-A. Model IV A includes the square root of *Toxicity-Weighted Releases* as an additional explanatory variable. Model V and Model VI have *Chem-Count P2* and *Weighted P2* as dependent variables, respectively. These models examine only hypotheses I and II. The coefficients of all variables will also include any indirect effects the associated factors will have through their influence on TQEM adoption. We then estimate and report results of the full structural system which includes the TQEM variable, appropriately instrumented.

Results from the linear regressions consistently support Hypothesis 1 and show that current and anticipated regulatory pressures, as proxied by *Penalties, Inspection, HAP and Non-Attainment*, had a statistically significant positive impact on *New P2* and *Chem-Count P2* adoption. In the negative binomial model, however, only the regulatory pressure proxied by *Non-Attainment* had a statistically significant impact on *New P2*. Surprisingly, we find that the effect of *Superfund Sites* is negative and statistically significant across all models, suggesting that firms that were responsible for fewer *Superfund Sites* were more likely to adopt *New P2* and *Chem-Count P2*. This could be because firms that are potentially responsible for a larger number of *Superfund Sites* are those that typically dispose large amounts of waste off-site. An effective way to manage their environmental impacts may be through end-of-pipe treatment rather than pollution prevention. It could also be that such firms are expecting to incur a substantial financial burden to address current liabilities and have fewer resources to invest in pollution prevention technologies.

Model VI shows that existing mandatory regulations did not have a statistically significant impact on the *Weighted P2* measure of adoption of pollution prevention techniques. Recall that *Weighted P2* differs from *New P2* in that it attaches a higher weight to P2 adoption by facilities with a higher share of toxic emissions within the firm. Therefore, the finding that regulatory pressures influence *New P2* adoption but not *Weighted P2* adoption suggests that existing regulations primarily impact the P2 activities of those facilities that have a smaller share of the firm's toxic releases. Existing regulations do not appear to have motivated the relatively pollution intensive facilities within the firm to undertake more P2 activities, possibly because the costs of undertaking P2 may have been much higher for these facilities. Anticipated HAP regulations, however, did motivate a higher level of *Weighted P2* adoption in addition to a higher level of *New P2* adoption. This indicates that regulations targeted at toxic releases were more effective in motivating P2 adoption by the pollution intensive facilities within firms as compared to command and control regulations aimed at other pollutants. We also find robust support for Hypotheses 2 in the linear and negative binomial model and across alternative measures of P2 activity. All models in Table 3 show the positive effects of technological capabilities, as proxied by *R&D Intensity* on *New P2*.

In Table 4, we present the results of models that include the impact of TQEM adoption on P2 activity. Model VII-A estimates an OLS model that disregards the endogeneity of the TQEM adoption decision. Model VII-B examines the impact of TQEM on *New P2* using the predicted probability of TQEM estimated from Model II as an instrument for TQEM. Model VII-C uses the variables from Model II directly as instruments for TQEM (except *Number of facilities* which is included to explain *TQEM* but is not expected to influence *New P2* and hence excluded from that equation). We find that the conclusions of our paper regarding the determinants of *New P2* techniques do not depend materially on whether the parsimonious or larger specification of the first stage models is used. Model VII-D includes current toxic releases as an explanatory variable and lagged toxic releases as an instrument, while Model VII-E includes toxicity-weighted releases as an explanatory variable. Model VII-F estimates a two-step negative binomial model.

Model VII-A which is estimated without correcting for the endogeneity of *TQEM* shows that the effect of *TQEM* on *New P2* is positive but small and statistically insignificant. The other Models VII B-E, however, consistently support Hypothesis 3 and show that *TQEM* has a positive and statistically significant impact on *New P2*. The coefficient of *TQEM* in the models that instrument for *TQEM* is much larger than in Model VII-A, indicating the presence of a negative selection bias in its estimation, i.e., that TQEM adopters are firms with lower than average *unobserved* propensity to adopt pollution prevention activities. The two-step negative binomial in Model VII-F is implemented using the predicted value of *TQEM* as an explanatory variable. Since we are using a generated regressor, the standard errors are corrected using the Murphy-Topel method.

The magnitude of the *TQEM* coefficient in the base models (VII-B and VII-C) suggests that the average effect of TQEM adoption on the annual count of *NewP2* practices is equal to approximately 18 practices. In our sample, the average annual count of pollution prevention practices by adopters of TQEM is equal to 27. This suggests that if these firms had not adopted TQEM, their average annual count would be only about 9. The non-adopters of *TQEM* average about 16 *New P2* practices per year in our sample. The fact that adopters would have introduced fewer pollution prevention practices per year in the absence of *TQEM* is consistent with our finding that there is negative selection into the adoption of TQEM (though this simple difference in means is partially due to differences in observable firm characteristics). In comparing the results of Table 4 with those of Table 3, the most important observation is that with the inclusion of TQEM as a variable, the magnitude of the coefficient of *R&D Intensity* and its statistical significance diminishes. This suggests that *R&D intensity* has an indirect effect on the adoption of *New P2* through the adoption of TQEM and after accounting for that, its direct effect is smaller. On the other hand, the effects of variables proxying for regulatory pressure appear to be primarily direct effects on *New P2*. This is consistent with the results obtained in Table 2 which show that R&D intensity has a significant influence on TQEM adoption while regulatory pressures do not.

In Table 5, we examine the effect of *TQEM* on alternative measures of pollution prevention. Models VIII-A and VIII-C use predicted probability of *TQEM* as an instrument while Models VIII-B and VIII-D use lagged variables as instruments. We find that *TQEM* has a statistically significant and positive effect on *Weighted P2* and on *Chem-Count P2*, while the effects of other variables remain as discussed above. These results suggest that *TQEM* leads even the more pollution intensive facilities within firms to adopt more pollution prevention activities.

Among the other firm characteristics, *Market Share*, and *Number of Chemicals*, have a statistically significant effect on P2 adoption. The effect of *Number of Chemicals* was as expected; the more opportunities a firm has to adopt pollution prevention technologies the more such technologies it will adopt. We find a fairly robust negative and statistically significant sign for *Toxic Releases* (whether lagged or not) suggesting that firms that were relatively small toxic polluters had lower costs of abatement of toxic releases using pollution prevention technologies. After controlling for the effects of the volume of toxic releases, we find that *Toxicity-weighted releases* had a positive and significant impact on *New P2*. The effects of other firm characteristics, such as *Sales* and *Age of Assets*, are not robustly significant across all the models. The effects of other external pressures from environmental groups, communities or consumers on adoption of pollution prevention techniques, as proxied by *Environmental Activism* and *Final Good*, are also not statistically significant. The effects of firm characteristics and the magnitudes of their coefficients are very similar in models that include *TQEM* and those that exclude *TQEM* as a variable.

6. Conclusions

The objective of this paper is to study the factors that influence the voluntary adoption of technologies that reduce toxic pollution at source in a sample of S&P 500 firms. Particular attention is devoted to examining the impact of a firm's management system and of external regulatory pressures on the adoption of pollution prevention technologies. In addition, we investigate the role played by internal capabilities in influencing incremental adoption of these technologies. More generally, our study makes a contribution to the broader literature that studies the determinants of environmental innovation by firms.

Our main econometric findings are as follows. First, regulatory pressure from current and anticipated regulations plays an important role in motivating voluntary environmental innovation. In contrast, market pressures are found to have an insignificant effect on firm behavior. Pressure from existing regulations is found to be more important in motivating the relatively cleaner facilities within firms to adopt pollution prevention technologies. Second, adoption of TQEM does indeed motivate the adoption of more pollution prevention technologies. Thus, managerial innovations, such as adoption of TQEM, lead firms to be innovative in their approaches towards environmental management. Third, technological capability is an important determinant of a firm's adoption of pollution prevention technologies. Fourth, firms with a relatively smaller volume of toxic releases face higher costs of abatement using pollution prevention technologies. To the extent that this is also the case for facilities within firms, it would explain the finding above that regulatory pressures were more likely to motivate the less toxic release intensive facilities to undertake pollution prevention. High toxicity-weighted releases in the past do, however, motivate more pollution prevention activities by firms. This suggests that firms perceive the benefits from preventing such pollution and reducing potential liabilities and public concern.

These results indicate that firms' adoption of TQEM is not simply a 'greenwash' or done only to achieve social legitimacy. Such firms are indeed changing their operations to make them more environmentally friendly. While our study cannot shed light on whether strategies to induce voluntary adoption of pollution prevention techniques are sufficient (or more effective than mandatory approaches requiring pollution prevention) for achieving the goals of the Pollution Prevention Act, they do show that efforts to encourage voluntary changes in a firm's management system while maintaining a strong regulatory framework and a credible threat of mandatory regulations can be effective in moving firms towards those goals.

This analysis has several policy implications. It shows the extent to which policy makers can rely on environmental management systems to induce voluntary pollution prevention. It also shows the role that regulations can play in motivating innovative methods for pollution control. By distinguishing between different types of regulatory pressures, this analysis shows that regulatory pressures targeted towards hazardous toxic releases are more effective than others in inducing the pollution intensive firms and facilities within firms to adopt pollution prevention practices. The results obtained here also highlight the importance of providing technical assistance to firms that may not have the capacity to undertake innovative pollution prevention activities. Lastly, by identifying the types of firms less likely to be self-motivated to voluntarily adopt pollution prevention practices, this analysis has implications for the design and targeting of policy initiatives that seek to encourage greater pollution prevention.

[1]http://yosemite1.epa.gov/ee/epalib/ord1.nsf/77e34926d19d5664852565a500501ed6/335eadf8201059108 52565d00067efc6!OpenDocument

[2] 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 (http://www.bsdglobal.com/tools/ systems_TQEM.asp).

[3] A survey of U.S. manufacturing firms in 1995 by Florida (1996) found that 60% of respondents considered pollution prevention to be very important to corporate performance and two-thirds of them had also adopted TQEM. Of the 40% firms that considered pollution prevention to be only moderately important, only 25% had adopted TQEM. A survey of U.S. manufacturing plants in 1998 found that among the pollution prevention adopters, the percentage of firms practicing TQM was twice that for other plants (Florida, 2001). A survey of Japanese manufacturing firms found that plants adopting a green design were more likely to be involved in TQM than other plants (Florida and Jenkins, 1996).

[4] For example, Howard et. al (2000) found that Responsible Care participants were more likely to implement practices visible to external constituencies but they varied a great deal in implementation of practices such as pollution prevention and process safety that were visible only internally. Shaw and Epstein (2000) argue that firms adopt popular management practices, such as total quality management, to gain legitimacy and find that implementation of such practices leads to gains in external reputation regardless of whether there is an improvement in the firm's financial performance.

[5] More generally, prior research suggests that firms cannot costlessly exploit external knowledge, but must develop their own capacity to do so, through the pursuit of related R&D activities and cumulative learning experience (Cohen and Levinthal, 1989; 1994).

[6] Several studies also investigate the motivations for firms to participate in public voluntary programs such as EPA's 33/50 program, Waste Wise and Green Lights (for a survey of those studies see Khanna, 2001).

[7] It is extremely rare in our sample that a firm reports four P2 activities for a particular chemical. Thus, censoring through top coding is not a concern in our data.

[8] Several theoretical studies show that the threat of mandatory regulations can induce voluntary environmental activities to preempt or shape future regulations (see survey in Khanna, 2001). Empirical analyses show that regulatory pressures (Henriques and Sadorsky, 1996; Dasgupta, et al., 2000), threat of liabilities and high costs of compliance with anticipated regulations for hazardous air pollutants (Anton et al., 2004; Khanna and Anton, 2002) did motivate adoption of environmental management practices, but their direct effect on environmental technology adoption has not been examined.

[9] Information about the pollution prevention practices adopted by firms is available to regulators only with a lag of one or two years. Hence we do not expect current inspections and penalties to be influenced by current pollution prevention decisions.

[10] Mandatory P2 programs started in 1988 with Washington, followed by Massachusetts and Oregon in 1989. Four states adopted them in 1990 (Maine, Minnesota, Mississippi, and Vermont) while three adopted them in 1991 (Arizona, New Jersey, and Texas). Arizona, Massachusetts, Maine, Mississippi, New Jersey and Washington have set numerical goals for P2 activities; while Arizona and Minnesota provide financial assistance to firms.

[11] These capabilities or specialized assets are firm-specific. They are acquired over time, are non-substitutable and imperfectly imitable, such as firm-specific human capital, R&D capability, brand loyalty. They can enable firms to adopt new technologies at lower cost (Dierickx and Cool, 1989).

[12] Blundell et. al. (1995) find that the stock of innovations accumulated in the past was significant in explaining current innovations. Christmann (2000) finds that complementary assets in the form of R&D intensity of the firm determine the competitive advantage that a firm receives from adopting P2 strategies.

[13] Consumer preferences for green products may manifest themselves through movements in demand and relative prices in the product markets. This parallels the argument put forth by Schmookler (1962) and

Grilliches (1957) that demand-pull can explain innovative activity by firms as they strive to deliver the preferred goods in the market (Dosi, 1982).

[14] Empirical evidence does suggest that firms that produce final goods and that were larger toxic polluters in the past were more likely to participate in voluntary environmental programs and adopt EMSs (see survey in Khanna, 2001; Anton et al., 2004).

[15] Studies also show that community characteristics can influence the level of public pressures for reducing pollution (Arora and Cason, 1999; Hamilton, 1999). Pressure from environmental groups, proxied by membership in environmental organizations, was found to influence participation in voluntary programs (Welch et al., 1999; Karamanos, 2000) and reduction in intensity of use of certain toxic chemicals (Maxwell et al., 2000). Using this measure of environmental activism, Welch et al. (1999) find that firms headquartered in states with greater environmentalism were more likely to participate in the voluntary Climate Challenge program.

[16] Studies find that firms with older assets were more likely to participate in voluntary environmental programs (Khanna and Damon, 1999) and adopt a more comprehensive environmental management system (Khanna and Anton, 2002).

[17] In the context of quality provision, Spence (1975) shows that this depends on the relationship between the marginal value of quality and the average value of quality to the firm while Donnefeld and White (1988) show that it depends on the differences in the absolute and marginal willingness to pay for quality.

[18] Larger firms have been found to be more likely to participate in the chemical industry's Responsible Care Program (King and Lenox, 2000), Green Lights, Waste Wise, and 33/50 programs (Videras and Alberini, 2000) and in Climate Challenge (Karamanos, 2000).

[19] A fixed effects model could not be estimated because we have several regressors that are time-invariant. A random effects model failed to converge and hence could not be estimated.

[20] Empirical studies show that regulatory pressures, threat of liabilities and high costs of compliance with existing and anticipated regulations motivated the adoption of environmental practices. (Henriques and Sadorsky, 1996; Dasgupta, et al., 2000; Anton et al., 2004; Khanna and Anton, 2002a). They also find that firms that were large toxic polluters and likely to face greater public scrutiny, that were in closer contact with consumers and were more visible to the public were also motivated to adopt EMSs (Anton et al., 2004; Khanna and Anton, 2002; King and Lenox, 2000). Some empirical studies have found a positive significant effect of R&D on the adoption of EMSs (Khanna and Anton, 2002), on participation in the 33/50 program (Arora and Cason, 1996) and in Waste Wise (Videras and Alberini, 2000). In contrast, Khanna and Damon (1999) and Videras and Alberini (2000) did not find the R&D level to significantly influence participation in 33/50 and Green Lights.

[21] We construct toxicity weighted releases using toxicity weights defined by the Threshold Limit Values (TLV) for each toxic chemical. TLVs are set by the American Conference of Governmental and Industrial Hygienists (ACGIH, 2003) as the maximum average air concentration of a substance to which workers can be exposed without adverse health effects during an 8-hour work shift, day after day. The TLV index is calculated by multiplying the quantity of emissions of each toxic chemical with the inverse of the TLV of the chemical and then summing across all chemical releases by the firm.

[22] To match the facilities with their parent companies, a combination of the Dun and Bradstreet number, facility name, location, and SIC code were used (these additional identifiers were used for some facilities when the Dun and Bradstreet number was missing). The ticker symbol, which identifies the parent companies in the Research Insight database, was used to match the IRRC data with financial data from Research Insight. Since some parent company names have changed over our study period, Market Insight, a database tool linked with Research Insight was used to trace the parent company's history. The historical information included mergers, acquisitions, changes in names, SIC codes and ticker symbols.

[23] These 236 facilities consistently reported P2 counts that were the same or higher than in preceding year(s) for all their chemicals, and they comprise 5.68% of all unique 4155 facilities that belonged to S&P 500 firms and reported to the TRI. They can be suspected of incorrectly reporting their P2 activities (though an equally likely possibility is that the P2 count was indeed non-decreasing for all the chemicals

and time periods for these facilities). In terms of total sample, this translates to 502 out of 74,780 chemical-facility pairs. Additionally, these 236 facilities belong to 113 different parent companies. Hence, we can rule out systemic and large scale misinterpretation of TRI instructions at the parent company level. Even if it occurred at the facility level, the number of facilities and the number of P2 activities affected by it is negligible.

[24] Can be found at http://www.epa.gov/oar/oaqps/greenbk/anay.html.

[25] It is based on data on membership in 10 environmental organizations, namely African Wildlife Foundation, American Birding Association, The Nature Conservancy, World Wildlife Fund, Zero Population Growth, American Rivers, Bat Conservation International, Natural Resources Defense Council, Rainforest Action Network, and Sea Shepherd Conservation Society.

[26] http://www.p2.org/inforesources/nppr_leg.html.

Table 1. Descriptive Statistics (1994-96).

Variable	Mean	Std. Dev.	Minimum	Maximum
TQEM	0.68	0.47	0.00	1.00
New P2	23.40	37.13	0.00	284.00
Chem-Count P2	14.65	23.28	0.00	173.00
Weighted Sum of New P2	2.49	4.16	0.00	28.93
R&D Intensity	0.03	0.04	0.00	0.24
Final Good	0.56	0.50	0.00	1.00
Environmental Activism	0.90	0.28	0.26	2.43
Lagged Toxic Releases (Millions of pounds)	14.87	42.34	0.00	382.88
Current Toxic Releases (Millions of pounds)	31.88	69.85	0.00	519.18
Superfund Sites	66.32	173.28	0.00	1376.00
Lagged HAP (Million of pounds)	3.05	6.86	0.00	57.97
Penalties	1.49	3.43	0.00	33.00
Inspections	50.66	82.79	0.00	491.00
Non-attainment	12.24	16.87	0.00	96.00
Mandatory P2 Policy	1.69	2.87	0.00	18.00
Market Share of Sales	0.26	0.22	0.00	0.98
Net Sales ($ Billion)	12.96	22.40	0.18	165.37
Age of Assets	0.75	0.10	0.46	0.93
Number of chemicals	80.69	113.86	1.00	625.00
Number of Facilities	17.64	20.73	1.00	111.00

Summary statistics are presented for N=422.

Table 2: Determinants of TQEM Adoption

Explanatory Variables	Model I-A	Model I-B	Model II
Constant	0.207 (0.188)	-0.446* (0.259)	-0.391 (0.248)
R&D Intensity	2.328 (2.365)	1.797** (0.880)	1.818** (0.881)
Final Good	0.042 (0.201)	0.032 (0.209)	
Toxic Releases	0.005 (0.003)	0.063 (0.040)	0.115*** (0.040)
Superfund	0.0004 (0.001)	0.011 (0.032)	
HAP	0.008 (0.016)	0.012 (0.110)	
Penalties	0.053* (0.064)	0.108 (0.129)	
Inspections	0.002 (0.002)	0.042 (0.042)	
Sales	0.0001 (0.0001)	0.006* (0.003)	0.007** (0.003)
Number of Facilities	-0.014** (0.006)	-0.017** (0.007)	-0.011** (0.005)
Schwarz I.C.	611.86	586.83	561.82
Akaike I.C.	1.23	1.18	1.17

N= 463 in all these regressions. Values in parentheses are standard errors.
All models allow for correlation of disturbances across time for each firm:
*significant at 10%, **significant at 5%, ***significant at 1%. All variables in Model I-A are in linear terms. All variables in Model I-B and II are in square root with the exception of Number of Facilities.

Table 3: Determinants of the Adoption of Pollution Prevention Techniques

Explanatory Variables	MODEL III-A New P2: OLS	Model III-B New P2: Negative Binomial	Model IV New P2: OLS	MODEL V Chem-Count P2: OLS	MODEL VI Weighted P2: OLS
Constant	12.349 (9.640)	-0.832** (0.383)	10.763 (9.678)	5.655 (5.525)	5.110*** (1.687)
Innovative Capabilities					
R&D Intensity	67.584** (28.455)	2.772* (1.528)	66.438** (28.419)	43.416*** (4.984)	15.998*** (16.329)
Regulatory Pressures					
Superfund	-0.025*** (0.009)	-0.080* (0.045)	-0.025*** (0.009)	-0.010* (0.005)	-0.001 (0.001)
HAP	4.038*** (1.524)	-0.158 (0.129)	4.506*** (1.550)	1.580* (0.876)	1.168*** (0.267)
Penalties	0.639* (0.358)	-0.076 (0.068)	0.562 (0.361)	0.578*** (0.207)	0.073 (0.063)
Inspections	0.047** (0.021)	0.054 (0.071)	0.046** (0.021)	0.031** (0.012)	0.004 (0.004)
Non-attainment	0.391*** (0.093)	0.161** (0.078)	0.404*** (0.093)	0.161*** (0.053)	0.030* (0.016)
Mandatory P2Policy	-0.581 (0.562)	-0.147 (0.089)	-0.422 (0.571)	0.062 (0.322)	-0.243** (0.098)
Other Firm Characteristics					
Final good	0.194 (2.367)	-0.255* (0.152)	0.632 (2.379)	-0.269 (1.362)	0.408 (0.416)
Environmental Activism	2.589 (3.493)	0.066 (0.232)	2.751 (3.486)	-0.570 (2.018)	2.162*** (0.616)
Toxic Releases	-0.816* (0.426)	0.099 (0.068)	-1.288** (0.520)	-0.410* (0.248)	0.061 (0.076)
Toxicity Weighted Releases			0.347^{+} (0.221)		
Market share	16.359*** (5.029)	0.090^{+} (0.058)	15.050*** (5.091)	7.854*** (2.892)	1.988** (0.883)
Net Sales	-0.012 (0.074)	0.094 (0.079)	-0.009 (0.074)	0.035 (0.042)	0.026** (0.013)
Age of Assets	-24.720** (12.028)	-0.488 (0.558)	-23.180* (12.047)	-9.630 (6.907)	-8.801*** (2.108)
Number of Chemicals	0.186*** (0.027)	0.900*** (0.110)	0.184*** (0.027)	0.124*** (0.016)	-0.009** (0.005)
Year	-1.140 (0.965)	-0.130** (0.052)	-1.161 (0.962)	-0.843 (0.563)	-0.245 (0.171)
Log- Likelihood	-1886.65	-1424.55		1643.47	-1143.69
ρ_1	0.597*** (0.039)			0.565*** (0.0401)	0.569*** (0.040)

N=422. Values in parentheses are standard errors. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.
$^{+}$ Significant at 15% level. Dispersion parameter for Negative Binomial is 0.533 and statistically significant at 5%.

Table 4: Impact of TQEM Pollution Prevention (New P2) Adoption

Variables	Model VII-A OLS	Model VII-B 2SLS: Predicted probability as IV	Model VII-C 2SLS: Variables as IV	Model VII-D 2SLS: Predicted probability and lagged releases as IV	Model VII-E 2SLS: Predicted probability as IV	Model VII-F Two-Step Negative Binomial
Constant	12.586 (9.672)	-2.346 (11.107)	-2.242 (11.618)	3.775 (11.015)	-3.223 (11.140)	1.546* (0.903)
Internal Managerial and Innovative Capabilities						
TQEM	0.197 (2.058)	17.496*** (6.679)	18.519*** (6.674)	22.507*** (7.426)	16.656** (6.634)	1.786** (0.830)
R&D Intensity	70.292** (28.036)	46.928 (29.284)	48.924* (29.849)	40.143 (29.543)	47.810* (29.170)	-2.289 (2.009)
Regulatory Pressures						
Superfund	- (0.009)	-0.029*** (0.009)	-0.029*** (0.009)	-0.027*** (0.009)	0.029*** (0.009)	-0.001** (0.000)
HAP	3.953*** (1.506)	3.648** (1.520)	3.034* (1.637)	4.333*** (1.604)	4.300*** (1.543)	0.108 (0.110)
Penalties	0.634* (0.342)	0.750** (0.361)	0.762** (0.368)	1.139*** (0.404)	0.671* (0.363)	0.032 (0.020)
Inspections	0.045** (0.021)	0.051** (0.021)	0.052** (0.022)	0.068*** (0.023)	0.049** (0.021)	0.000 (0.001)
Non-attainment	0.401*** (0.090)	0.418*** (0.092)	0.405*** (0.094)	0.402*** (0.094)	0.423*** (0.093)	0.032*** (0.007)
Mandatory P2 Policy	-0.643 (0.549)	-0.378 (0.561)	-0.150 (0.576)	-0.378 (0.559)	-0.225 (0.570)	-0.047 (0.034)
Other Firm Characteristics						
Final good	0.029 (2.336)	-0.747 (2.375)	-0.521 (2.446)	-1.627 (2.404)	-0.114 (2.381)	-0.391** (0.182)
Environmental Activism	2.681 (3.389)	3.614 (3.505)	3.125 (3.901)	2.440 (3.541)	3.748 (3.500)	-0.382 (0.381)
Toxic Releases	-0.708* (0.401)	-1.148** (0.447)	-1.205*** (0.456)	-2.373** (0.932)	-1.738*** (0.554)	0.070* (0.041)
Toxicity-Weighted Releases					0.432* (0.224)	
Market share	16.703** (4.899)	10.890** (5.385)	12.651** (5.491)	7.814[+] (5.601)	9.727* (5.465)	0.701* (0.380)
Net Sales	-0.014 (0.074)	-0.029 (0.074)	-0.022 (0.076)	-0.108 (0.082)	-0.263 (0.074)	-0.005 (0.007)
Age of Assets	- (11.829)	-18.897 (12.149)	-19.832 (12.754)	-22.254* (12.201)	-17.795 (12.167)	-0.398 (0.959)
Number of chemicals	0.188*** (0.027)	0.182*** (0.027)	0.181*** (0.028)	0.214*** (0.032)	0.179*** (0.271)	0.003* (0.002)
Year	-1.078 (0.945)	-0.521 (0.998)	-0.453 (1.046)	-1.587* (0.939)	-0.579 (0.994)	-0.084 (0.055)
Log – likelihood	1931.45	1935.43	1861.03	-1955.08		-1535.25
ρ_1	0.598*** (0.0386)	0.569*** (0.400)	0.561*** (0.041)	0.545*** (0.0408)		

Values in parentheses are standard errors. * Significant at 10%, ** Significant at 5%, *** Significant at 1%. [a/] Model VII-D has current toxic releases as explanatory variable with lagged releases as an instrument. All other models use lagged toxic releases.

Table 5: Determinants of Adoption of Alternative Measures of Pollution Prevention

Variables	Model VIII-A Chem-Count P2 2SLS: Predicted probability as IV	Model VIII-B Chem-Count P2 2SLS: Variables as IV	Model VIII-C Weighted P2: 2SLS: Predicted probability as IV	Model VIII-D Weighted P2: 2SLS: Variables as IV
Constant	-3.946 (6.368)	-3.039 (6.334)	2.578 (1.949)	1.170 (1.912)
Internal Managerial and Innovative Capabilities				
TQEM	11.362*** (3.834)	10.451*** (3.801)	2.908** (1.175)	4.573*** (1.148)
R&D Intensity	30.069* (16.773)	31.758* (16.732)	12.673** (5.128)	11.025** (5.038)
Regulatory Pressure				
Superfund	-0.012** (0.005)	-0.012** (0.005)	-0.002 (0.001)	-0.002 (0.001)
HAP	1.334^{+} (0.871)	1.286^{+} (0.875)	1.113*** (0.266)	1.054*** (0.264)
Penalties	0.659*** (0.208)	0.642*** (0.207)	0.092 (0.064)	0.100 (0.063)
Inspections	0.032*** (0.012)	0.031** (0.012)	0.004 (0.004)	0.004 (0.004)
Non-attainment	0.176*** (0.053)	0.164*** (0.053)	0.034** (0.016)	0.033** (0.016)
Mandatory P2 Policy	0.187 (0.321)	0.199 (0.323)	-0.214** (0.098)	-0.186* (0.097)
Other Firm Characteristics				
Final good	-0.842 (1.362)	-0.650 (1.358)	0.288 (0.417)	0.280 (0.410)
Environmental Activism	0.089 (2.014)	-0.014 (2.014)	2.329*** (0.618)	2.401*** (0.612)
Toxic Releases	-0.634** (0.258)	-0.645** (0.261)	0.006 (0.080)	-0.038 (0.080)
Market share	4.430 (3.086)	4.651 (3.095)	1.048 (0.944)	0.486 (0.933)
Net Sales	0.022 (0.042)	0.021 (0.042)	0.023* (0.013)	0.020 (0.013)
Age of Assets	-5.822 (6.963)	-6.139 (6.970)	-7.745*** (2.130)	-7.124*** (2.102)
Number of chemicals	0.123*** (0.016)	0.125*** (0.016)	-0.010** (0.005)	-0.009** (0.005)
Year	-0.444 (0.576)	-0.501 (0.574)	-0.140 (0.178)	-0.089 (0.177)
Log Likelihood	-1700.81	-1706.43	-1172.63	-1221.88
ρ_1	0.554*** (0.0406)	0.556*** (0.405)	0.534*** (0.0411)	0.512*** (0.0419)

N=422. Values in parentheses are standard errors. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.
$^{+}$ Significant at 15% level.

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