Adoption of Pollution Prevention Techniques: The Role of Management Systems, Demand-Side Factors and Complementary Assets

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This paper investigates the extent to which firm level technological change that reduces unregulated emissions is driven by demand-side factors, technological and organizational capabilities of firms and anticipated regulatory pressures. 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. Information disclosure is found to create positive but weakly significant external pressures towards the worst performers in an industry to undertake pollution prevention. Moreover, we find that the presence of 'complementary assets' within a firm is important for creating an internal capacity to undertake incremental adoption of such techniques.

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1. Introduction

The increasing complexity and costs of command and control environmental regulations that seek to control pollution after it has been generated have shifted the attention of environmental regulators and firms towards flexible environmental strategies that target the reduction of pollution at source and prevent its generation. 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. The adoption of technologies that prevent pollution is not mandatory; instead the USEPA has sought to induce voluntary adoption of such technologies through mechanisms, such as the promotion of environmental management systems and the disclosure of information (to the public) about the environmental performance and pollution prevention activities of firms (Crow, 2000; USEPA, 1997, 1998; USGAO, 1994). This paper investigates the efficacy of these two strategies in motivating the adoption of pollution prevention techniques to reduce toxic releases. It also explores the extent to which the internal technological capabilities of firms can explain their adoption behavior.

Underlying the USEPA's strategy of encouraging adoption of environmental management systems is the premise that such systems advocate 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. The application of these principles to environmental management, referred to as total quality environmental management (TQEM)[1], 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. 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. This is also suggested by surveys of firms which show that the firms that adopted pollution prevention practices were more likely to be those practicing TQEM.[2] However, there has been no systematic empirical determination of a link between TQEM and pollution prevention. 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).[3]

The impetus for information provision, the second prong of the USEPA strategy to encourage pollution prevention, is that it can broaden public participation in the efforts to protect the environment. An important instrument for information dissemination is the Toxics Release Inventory (TRI) which provides detailed information to the public about the toxic chemicals emitted by facilities.[4] There are numerous examples of TRI information spurring community, environmental and labor groups, and investors to take action against the worst polluters. Such actions are often successful in persuading firms to reduce pollution at source because firms seek a reputation as a clean corporate citizen (USEPA, 2003; Fung and O'Rourke, 2000).

In addition to exploring the role of management systems and of information driven external pressures on firms to undertake pollution prevention, we also consider the possibility that the internal resources and capabilities of firms influence their adoption decisions as well. 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 which influence the firm's learning costs and capability to adopt new pollution prevention techniques.

While exploring the extent to which these three factors are inducing the voluntary adoption of pollution prevention techniques to reduce toxic releases, we control for other factors that could also explain the adoption of such techniques. These include the pressures that firms might face from consumers and environmental groups that care about "green" products (Reinhardt, 1999). Firms might also adopt pollution prevention practices to reduce toxic releases and preempt stricter legislation. We also seek to examine whether these factors are leading firms to simply pick the 'low hanging fruit' or instead leading them to make more fundamental and costly changes in processes and products. We, therefore, distinguish between two types of pollution prevention techniques: the first consists of those that require low technical skills and low costs; the second consists of technologically sophisticated modifications to raw materials, processes and products. We conduct this analysis using a 3-year unbalanced panel of 169 firms from the S&P 500 list which reported to the TRI and responded to the survey on adoption of environmental management practices conducted by the Investor Research Responsibility Center, over the period 1994-96.

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 and the type of pollution prevention practices they are more likely to induce. It also shows the role that information disclosure policies can play in influencing the environmental behavior of firms. The results obtained here also highlight the importance of providing technical assistance to firms that may not have had prior experience with related technologies, to improve their capacity to undertake innovative environmental 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.

This paper makes a contribution to the literature on the determinants of environmental innovations. Previous studies have examined the relationship between environmental regulation and innovation (Lanjouw and Mody, 1996; Jaffe and Palmer, 1997; Gray and Shadbegian, 1998; Brunnermeier and Cohen, 2003; Pickman, 1998). Proxies for innovation used by the former three studies include annual investment spending, industry expenditures on R&D, and number of all patents obtained, while the latter two studies focus specifically on explaining environmental patents. A more closely related study, by Cleff and Rennings (1999), examines the extent to which the adoption of various pollution control methods depends on the nature of environmental policy instruments. They found that firms perceived voluntary programs (eco-labels and voluntary commitments) to be important in encouraging both product and process innovations and end-of-pipe emissions control while civil regulations (taxes, subsidies) were important in creating incentives for end-of pipe abatement and disposal only.

This paper also adds to the literature on the incentives for voluntary measures taken by firms to improve their environmental performance (see survey in Khanna, 2001). A number of studies 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 compliance status (Dasgupta et al. 2000). However, this is the first study that investigates the implications of environmental management systems for environmental innovation while recognizing the heterogeneity among firms in their technological capabilities and in the stakeholder pressures they face. This study also contributes to the literature on environmental information disclosure by examining its role in influencing the adoption of environmentally friendly innovations. Previous studies show that information disclosure can affect environmental performance directly by influencing firms to improve their rates of environmental compliance (Foulon, et al. 2002) or indirectly by first affecting a firm's stock market value which then motivates firms to reduce toxic releases (Khanna et al 1997). Finally, this paper uses a very rich dataset on environmental innovation and allows us to more precisely examine firms' incentives to undertake such innovation.

2. Conceptual Framework

We consider profit maximizing firms that are emitting pollutants 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. Motivations of both types became stronger after 1990. Firms began to increasingly adopt environmental management systems centered around the philosophy of total quality management. This is an integrated management philosophy that emphasizes continuous progress in improving quality by preventing defects, reducing waste and increasing efficiency through process management (Powell, 1995). Additionally, external stakeholders have also become more environmentally conscious as environmental information about firms has become more publicly available. These stakeholders have the potential to take actions that affect the market share, stock prices, 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 methods for controlling such releases.

Interest in pollution prevention has grown among firms with the passage of the Pollution Prevention Act raised and the 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, 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 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 and the specific factors that can explain higher levels of adoption by some firms as compared to others.

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 any of 8 different activities to prevent pollution they adopted for each toxic chemical reported by them to TRI in a given year.[7] These activities consist of: (1) changes in operating practices, (2) materials and inventory control, (3) spill and leak prevention (4) raw material modifications (5) equipment and process modifications (6) rinsing and draining equipment design and maintenance (7) cleaning and finishing practices and (8) product modifications. We aggregate the number of such practices adopted in a year across chemicals and across the 8 practices for each facility and then across all facilities belonging to a parent company to obtain *New P2* at the firm-level for that year. In some of the models we estimate, we distinguish between the number of low-tech activities to prevent pollution and the number of high-tech activities adopted. We define *Low-Tech P2* as consisting of activities 1 and 2 which are mainly procedural changes and require lower technical skills and low costs and *High-Tech P2* as consisting of activities 3 to 8 that involve more complex and costly changes in techniques and operations.

We expect that firms that have adopted TQEM would be more likely to identify profitable pollution prevention techniques and more likely to adopt them in larger numbers. The managerial literature suggests that organizational systems are critical to the innovativeness of firms because they condition how firms respond to challenges (Teece and Pisano, 1994). 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. Within this framework, employees are empowered to work in cross functional, multi-disciplinary teams to find innovative firm-specific solutions to environmental quality problems (President's Commission on Environmental Quality, 1993). This system-based approach and the proactive involvement of larger numbers of employees, is crucial for focusing attention on the causes of environmental problems and for accounting for any hidden costs of regulatory compliance. It may also enable firms 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. This may lead firms 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 1a: 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 1, 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.

TQEM could lead firms to adopt *Low-Tech P2* and also *High-Tech P2*. However, we expect that since the former represents low cost and easily identifiable opportunities for waste reduction, the impact of *TQEM* on its adoption may be less pronounced. In contrast, the presence of *TQEM* is expected to be more critical for the adoption of *High-Tech P2* techniques as these involve greater effort at identifying appropriate modifications to products and production systems, require significant customization of available technologies and impose higher costs. We, therefore, hypothesize that:

Hypothesis 1b: Firms which adopt TQEM will adopt relatively more High-Tech than Low-Tech pollution prevention techniques.

We examine if this is so by estimating some specifications with *High-Tech P2* and *Low-Tech P2* as dependent variables.

The next two hypotheses are based on the premise that *New P2* is driven, in large part, by non-regulatory, market-based, forces external to the firm. A key element in generating these external forces is publicly available information through the TRI which can lead to adverse publicity and loss in reputation for firms that are poor environmental performers. TRI based blacklisting of these poor performers has led to public agency actions, mass media focus, stock market reactions, development of new environmental legislation, and corporate public relations campaigns (Fung and O'Rourke, 2000). Each year since the initial release of the TRI in 1989, hundreds of articles singling out a small number of firms as the top polluters have appeared in local and national media (see for example, New York Times, 1991). Fung and O'Rourke (2000) refer to the TRI as "populist maxi-min regulation" because the public spends the maximum effort targeting the worst environmental performers. They also provide anecdotal examples of firm pledges and efforts to make environmental improvements following such public pressure. We hypothesize that:

Hypothesis 2: The poorer the publicly disclosed environmental performance of a firm the greater its incentives to adopt more pollution prevention practices.

We may measure environmental performance in either absolute terms using the volume of a firm's *Toxic Releases* reported to the TRI or in relative terms by comparing a firm's performance to that of its peers within the same industry group. As a proxy for absolute performance we include the five-year lagged value of releases as an explanatory variable because the TRI is only available to the public with a lag. It also avoids the problem of endogeneity bias since contemporaneous toxic releases may be simultaneously determined together with the count of *New P2*. We expect *Toxic Releases* to have a positive impact on the incentives to adopt pollution prevention practices. It is also possible that the public and regulators may care about the toxicity of the releases generated by a firm and not simply the volume of releases. We, therefore, also include the *Toxicity-Weighted Releases* as an explanatory variable in one model.

We proxy relative performance by the ratio of a firm's toxic releases relative to the average toxic releases of all other firms within the same 2-digit SIC code. We refer to this variable as *Relative Releases*. We expect this variable to be a stronger proxy for external pressures for pollution prevention as compared to the level of *Toxic Releases* of a firm. This is because the latter is also a proxy for the scale of the pollution problem to be addressed by the firm.[8] 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 emissions. If larger toxic polluters face larger costs of abatement using pollution prevention methods, then one might observe a negative sign for the *Toxic Releases* variable. In that case, if the cost effect represented by *Toxic Releases* dominates the information-related external pressure effect, current *Toxic Releases* may be a better proxy for the costs of pollution prevention as compared to lagged releases; we, therefore, include current instead of lagged *Toxic Releases* as an explanatory variable in some specifications. We recognize that current releases might be determined jointly with *New P2* and describe how we address this in the next section.

In addition to public pressure faced by large toxic polluters, firms that sell directly to consumers may be more exposed to demand-side pressures for pollution prevention from consumers and environmental organizations than producers of intermediate products.[9] 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; Deltas et al., 2004). 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 postulate that firms that are located in areas where environmental groups and communities are more active are more likely to adopt pollution prevention practices.[10] This suggests:

Hypothesis 3: The greater the external pressure from consumers, public and environmental groups, the larger the number of P2 techniques adopted.

We test Hypothesis 3 using a number of variables. 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.[11] We measure *Environmental Activism* by 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.[12] Higher values of this variable indicate that a firm has its facilities in states with relatively high per capita membership in environmental organizations. We proxy community activism by the percentage of white population in a county. The environmental justice literature suggests that industrial pollution tends to follow the path of least resistance. This is supported by Brooks and Sethi (1997) and Grant (1997) who show that areas dominated by black population were more likely to be exposed to toxic releases, suggesting that firms in such areas were less likely to undertake pollution control activities. For this reason we include *White* defined for each parent company as the average of the percentage of population that is white in the counties where its facilities are located.

Demand side pressures to undertake pollution prevention may also be generated by environmental regulators. Compliance with mandatory regulations is enforced through inspections of facilities and civil penalties for noncompliance. Frequent inspections and penalties are not only costly for firms but they can also have a negative impact on a firm's reputation. Several authors have 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). Empirical studies show that firms with larger toxic releases were more likely to be subject to frequent inspection activity and stricter enforcement and to delays in obtaining environmental permits (Decker, 2003; 2004). We, therefore, hypothesize that firms with frequent inspections and a larger number of penalties have greater incentives to be innovative and adopt pollution prevention techniques, 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.

Future regulations form a second channel through which regulators can impact adoption of pollution prevention techniques. 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).[13] 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.[14] 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 4: The higher the costs of compliance with existing and anticipated regulations the greater the incentives to adopt more 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.[15] 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.

We include 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 the 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 are to be regulated under New Emissions Standards for HAP starting in 2000. We expect that firms with a larger *HAP* face a greater threat of anticipated HAP regulations and are more likely to adopt pollution prevention technologies to obtain strategic advantages over competitors by reducing these emissions ahead of time.

Finally, as a measure of the stringency of the 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, and 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.

Adoption of pollution prevention technologies may also be influenced by a firm's technological capabilities. Cohen and Levinthal (1994) refer to these as "complementary internal expertise" or "absorptive capacity" while Teece (1986) refers to it as "complementary assets". These capabilities can arise either from the level of in-house technical sophistication or from prior experience in developing and adopting pollution prevention practices.[16] Previous experience with technologies which embody constituent elements of the same technological paradigm can lower the costs of learning and enable firms to realize a competitive advantage through incremental adoption earlier than competitors (Nelson and Winter, 1982). 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).[17] Based on this literature we hypothesize that:

Hypothesis 5a: Firms that have larger technical capabilities and cumulative learning 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.

A possible measure of cumulative learning in year *t*, is the cumulative number of pollution prevention techniques that have been adopted between 1991 (when firms first began reporting this information to the TRI) and year *t-1*. We refer to this as *Cumulative P2* and expect that it will be associated with a firm's *New P2* adoption in three ways. First, it is an indicator of the experience that firms have had with pollution prevention techniques which might lower their current costs of adoption of *New P2*. Second, *Cumulative P2* might also pick up long lasting firm characteristics that capture a firm's unobserved propensity to adopt pollution prevention techniques. Such characteristics would have led the firm to adopt more pollution prevention practices in the past and would continue to lead to more adoption of such practices in the present. To the extent that *Cumulative P2* is a proxy for these unobserved effects, its coefficient would tend to be positive. Third, a firm could experience diminishing returns to pollution prevention, thus *ceteris paribus*, higher level of *Cumulative P2* would lead to lower level of *New P2* adoption. The coefficient of *Cumulative P2*, therefore, has an indeterminate sign.

In order to identify the existence of learning effects, as hypothesized in Hypothesis 5a, we distinguish between the cumulative adoption of High-Tech P2 techniques (*Cumulative High-Tech*) and the cumulative adoption of Low-Tech P2 (*Cumulative Low-Tech*) techniques. We would expect, for example, that the learning effect of cumulative pollution prevention of a particular type will be larger on *New P2* of its own type than on *New P2* of the other type. Moreover, we would expect that the adoption of *New P2* of a particular type will be affected more strongly by prior cumulative adoption of pollution prevention practices of the same type than of the other type. This suggests the following:

Hypothesis 5b: New High-Tech P2 adoption is likely to be affected more strongly by Cumulative High-Tech P2 than by Cumulative Low-Tech P2 (and conversely for New Low-Tech P2). Moreover, Cumulative High-Tech P2 is expected to have a larger impact on New High-Tech P2 adoption than on New Low-Tech P2 adoption (and conversely for Cumulative Low-Tech P2).

While testing the above seven hypotheses we need to control for other factors that could also influence the adoption rates of pollution prevention practices. We control for the number of pollution reduction opportunities a firms has by including the *Number of Chemicals* emitted. 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.

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 a firm's equipment is, the more costly it would be to replace, 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*.[18]

We include the *Market Share* of a firm in terms of industry sales to control for any effects of market 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.[19] 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.[20]

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}.

$$Y_{it} = \alpha X_{it} + \beta T_{it} + \varepsilon_{1it} \tag{1}$$

Contemporaneous values of explanatory variables are used to explain *New P2* in equation (1), except for five-year lagged values of toxic releases 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, we include the square roots of these variables as explanatory variables to reduce the effects of the right tail. 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. A fixed effects model could not be estimated because we have several regressors that are time-invariant.

To examine if the explanatory variables have a differential impact on different types of pollution prevention techniques, we disaggregate the total count of *New P2* techniques adopted into those that are high technology type, Y_{it}^{H}, and those that are low technology type, Y_{it}^{L}, and estimate separate equations for each type of adoption decision.

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 and negative if it is less likely to be adopted by such firms (possibly because firms with an inherently higher propensity to do pollution prevention may find the adoption cost of *TQEM* not worthwhile). 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} (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.

$$T_{it}* = \gamma W_{it} + \varepsilon_{2it} \tag{2}$$

The indicator variable for *TQEM* is $T_{it} = 1$ if $T_{it}* > 0$ and 0 otherwise. Some of the variables included in W_{it} 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 σ_{ε}^2. We estimate the probit model using pooled data. 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 in estimating equation (2) are chosen based on the existing literature (see Khanna, 2001). This literature suggests that the incentives for firms to adopt environmental management systems include regulatory pressures and market pressures which determine the benefits from adoption. They also depend on the costs of adoption.[21] We include *Civil Penalties*, *Inspections, Superfund sites* and *HAP* as proxies for regulatory pressures. We include *Final Good* as a measure of consumer pressure and *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 *Toxic Releases* and reporting to the TRI as a measure of the scale of the environmental problem. Additionally, *R&D Intensity*, *Age of Assets* and *Number of Facilities* could influence the net benefits of adopting TQEM. *R&D Intensity* is a proxy for the technical capacity of firms while *Age of Assets* is a proxy for the costs of replacement of assets that might need to be incurred with the adoption of an environmentally friendly management system. 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 and TQEM adoption in the past could have in turn influenced some of the variables listed above. *Number of facilities* which is included to explain *TQEM* adoption is not expected to influence *New P2* adoption. This together with several other variables (such as, *Age of Assets*, *R&D Intensity*, *Civil Penalties*, *Inspections, Superfund sites)* whose lagged values are included in the TQEM equation while current values are included in the *New P2* equation, ensures identification of the parameters in equation (1).

We estimated several alternative probit models, some of which include concave transformations (square root of the variable or the log of the variable plus one) of these explanatory variables because we expect many of these variables to have diminishing effects on the adoption of TQEM. These transformations also reduce the effects of the right tails for some of these variables. These models are consistent in showing that firms that have larger R&D intensity are more likely to adopt TQEM. The effect of toxic releases and sales is also positive and statistically significant. Other consumer pressure and regulatory pressure variables are not found to have any effect on TQEM adoption. The model with the square root of all the variables had the highest likelihood as compared to the others. We use this model to generate the predicted probability of *TQEM* adoption which is used as an instrument in the estimation of the determinants of *New P2*. The conclusions of our paper regarding the determinants of *New P2* techniques do not depend materially on the specification of the probit model. They also do not depend on the use of these variables directly as instruments while estimating equation (1). Since the parameter vector γ is not of direct interest in this study, we omit reporting the estimation results of equation (2) in this paper.[22] These results are reported in Harrington et al. (2005).

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.[23] 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*.[24] 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.[25] 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 169 firms for which at least two years of TRI and TQEM data were available led to 474 observations. Some of these observations had to be dropped from the regressions because of missing data resulting in 398 usable observations for most specifications. Summary statistics for the variables used here are presented in Table 1.

The number of environmental *Penalties* and the number of *Inspections* are derived from the USEPA 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 originally 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 is 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.

Data on *White* are obtained at the county level from the 1990 Census by the Bureau of Census[26]. The *Non-attainment* status of counties is obtained from the USEPA Greenbook.[27] 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).[28]

5. Results

We estimate several different models to examine the determinants of *New P2* adoption. All models recognize the panel nature of the data and 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. Models I, II and III (Table 2) examine the impact of *TQEM* and the stakeholder demand side factors on *New P2* without controlling for differences in *Cumulative P2* across firms. Models IV and V include *Cumulative P2* as an explanatory variable (Table 3). Models VI and VII distinguish between *High-Tech P2* and *Low-Tech P2*, and examine if *Cumulative P2* of different types has differential effects on *New P2* of each of the two types (Table 4).[29]

Model IA which is estimated without correcting for the endogeneity of *TQEM* shows that the effect of *TQEM* on *New P2* is positive but statistically insignificant. A test for the endogeneity of *TQEM* (Woodridge, 2001) rejects the null hypothesis that it is an exogenous variable at the 1% significance level. Models 1B and 1C in Table 2 are estimated using different instruments for *TQEM*. Model II is similar to Model IC but uses lagged releases as an instrument for current *Toxic Releases*. Model III is similar to Model II with the toxicity-weighted releases included as an explanatory variable. Unlike Model IA, these models consistently support Hypothesis 1 and show that *TQEM* has a positive and statistically significant impact on *New P2*. The effect of TQEM is positive even in Models IV and V, after the addition of *Cumulative P2* as a regressor. However, even in the presence of learning effects due to cumulative pollution prevention, *TQEM* continues to have a statistically significant impact on *High-Tech* P2 as expected from Hypothesis I (see Table 4). On the other hand, *TQEM* has an insignificant impact on the adoption of *Low-Tech P2*.

We find weak support for Hypothesis 2 with Model IC which shows that firms with large *Relative Releases* were more likely to adopt a larger number of *New P2* practices, and with Model VI which shows that this effect was significant only on *High-Tech P2*. In other models, the effect of this variable is positive but insignificant. This suggests that public pressure may be only weakly effective in promoting pollution prevention by firms. Similarly, the effect of toxicity-weighted releases in Model III is positive but not significant. The effects of other external pressures, from environmental groups, communities or consumers, on adoption of pollution prevention techniques, as suggested by Hypothesis 3 and proxied by *White*, *Environmental Activism* and *Final Good* is not statistically significant. This could be because proxies such as *White* and *Environmental Activism* capture external pressures on facilities at a local or state level rather than on the parent company at a national level.

Our results consistently support Hypothesis 4 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* adoption. Surprisingly, we find that the effect of *Superfund Sites* is negative and statistically significant, suggesting that firms that were responsible for fewer *Superfund Sites* were more likely to adopt *New 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 techniques.

We find that firms with smaller *Toxic Releases* (whether lagged or current) were likely to adopt more pollution prevention techniques. This is consistent with the premise that firms with larger *Toxic Releases* would incur higher net costs of reducing them using pollution prevention. The effects of other firm characteristics, such as *Sales, Age of Assets* and *Market Share*, are not robustly significant across all the models. *Number of Chemicals*, on the other hand, does have a significant positive impact on *New P2* techniques adopted. As expected, the more opportunities a firm has to adopt pollution prevention techniques the more such techniques it will adopt.

Models I, II and III provide support for the positive effects of technological capabilities, as proxied by *R&D Intensity*. However, this variable becomes statistically insignificant after the addition of *Cumulative P2* as an explanatory variable in Models III, IV and V. This suggests that the latter may be a more appropriate proxy for the internal capabilities that affect the adoption of pollution prevention techniques. Our results show that there is indeed a positive association between *Cumulative P2* and *New P2* adoption. This finding demonstrates that the learning and proxy effects of *Cumulative P2* which spur *New P2* offset any diminishing marginal effects that might reduce incentives for *New P2*. Model VI supports Hypothesis 5a, while Model VII strongly supports Hypotheses 5a and 5b. It shows that *Cumulative High-Tech P2* has a statistically significant positive impact on the adoption of *High-Tech P2* and this effect is larger than its effect on the adoption of *Low-Tech P2*. We also find that on any particular type of pollution prevention techniques, the effect of cumulative adoption of the same type is significantly larger than the effect of the other type of practices. In other words, a comparison of the magnitudes of the coefficients shows that the effect of *Cumulative High-Tech P2* on new adoption of *High-Tech P2* techniques is larger than the effect of *Cumulative Low-Tech P2* techniques. This suggests that learning is most effective through prior adoption of closely related technologies.

6. Conclusions

The objective of this paper is to study the factors influencing the voluntary adoption of techniques 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 pressures stimulated by information disclosure on the adoption of pollution prevention practices. In addition, we investigate the role played by internal capabilities, developed through prior experience with similar techniques, in influencing incremental adoption of these techniques. More generally, our study makes a contribution to the literature that studies the impact of a firm's management philosophy and its interactions with external stakeholders on its environmental management techniques.

Our main econometric findings are as follows. First, adoption of total quality management systems does indeed motivate the adoption of more pollution prevention techniques, particularly those that involve modifications to products, processes and raw materials. Thus, managerial innovations, such as adoption of TQEM, lead firms to be innovative in their approaches towards environmental management. Second, information disclosure creates positive but only weakly significant external pressures towards the worst performers in an industry to adopt pollution prevention techniques. Third, technological interdependencies and more importantly cumulative learning are important determinants of a firm's adoption of pollution prevention techniques. Fourth, regulatory pressure from current and anticipated regulations plays an important role in motivating voluntary behavior. In contrast, market pressures are found to have an insignificant effect on firm behavior.

These results suggest that firms' claims of adopting TQEM are not simply a 'greenwash' nor are they simply 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 us towards those goals.

Table 1. Descriptive Statistics (1994-96).

Variables	Mean	Std Deviation	Minimum	Maximum	No. of observations
Count of All P2 Techniques Adopted (Types 1-8)	21.28	35.58	0.00	284.00	475
Count of High-Tech P2 Adopted (Types 3-8)	14.41	24.64	0.00	206.00	475
Count of Low-Tech P2 Adopted (Types 1 and 2)	6.87	12.50	0.00	95.00	475
Cumulative P2 (Types 1-8)	116.90	191.73	0.00	1374.00	475
Cumulative High-Tech P2 (Types 3-8)	81.17	135.42	0.00	420.00	475
Cumulative Low-Tech P2 (Types 1 and 2)	35.74	62.46	0.00	1024.00	475
TQEM	0.68	0.47	0.00	1.00	474
Current Toxic Releases (Millions of pounds)	29.20	66.91	0.00	519.18	475
Lagged Toxic Releases (Millions of pounds)	13.89	41.54	0.00	382.88	475
Lagged Hazardous Air Pollutants (Million of pounds)	2.72	6.53	0.00	57.97	475
Lagged Relative Toxic Releases	2.61	10.13	0.00	153.78	462
Lagged Toxicity-Weighted Releases	29.15	173.66	0	3077.7	475
Number of chemicals	73.09	109.48	0.00	625.00	475
Age of Assets	0.75	0.10	0.46	0.93	449
Net Sales ($ Billion)	13.37	22.37	0.18	165.37	452
Final good	0.59	0.49	0.00	1.00	475
Inspections	46.41	79.14	0.00	491.00	475
Penalties	1.38	3.29	0.00	33.00	475
Superfund sites	63.50	164.69	0.00	1376.00	475
Non-attainment	1.86	1.63	0.00	6.00	475
Market share	0.25	0.22	0.00	0.98	441
Environmental Activism	0.19	0.03	0.09	0.31	456
White	0.82	0.08	0.43	0.99	456
R&D Intensity	0.03	0.04	0.00	0.24	452

Summary statistics are based on non-missing observations for each variable.

Table 2. Impact of TQEM on Adoption of Pollution Prevention Techniques

Variables	MODEL IA OLS	MODEL IB (Predicted probability as instrument)	MODEL IC (Lagged values as instruments)	MODEL II[a] (Predicted probability and Lagged Releases as instruments)	Model III (Predicted probability as instrument)
Constant	2.94	-10.23	-16.02	-1.24	-11.67
	(13.74)	(15.60)	(15.01)	(15.44)	(15.68)
Internal Managerial and Innovative Capabilities					
TQEM	1.74	17.24 **	24.44***	20.89 **	16.78**
	(2.30)	(8.72)	(7.55)	(9.26)	(8.7)
R&D Intensity	77.46 ***	68.52 **	63.42**	62.48 **	68.36**
	(21.48)	(30.89)	(30.21)	(31.07)	(30.84)
Market and Information-Related Pressure					
Final good	1.08	-0.76	-1.27	-1.59	-0.23
	(2.49)	(2.65)	(2.57)	(2.70)	(2.66)
White	10.63	11.95	12.23	11.05	12.57
	(13.26)	(13.53)	(13.45)	(13.59)	(13.53)
Environmental Activism	0.61	2.17	3.0	-0.06	-2.39
	(3.62)	(3.78)	(3.74)	(3.80)	(3.78)
Toxic Releases	-1.03 **	-1.54 ***	-1.83 ***	-3.58 ***	-1.95***
	(0.41)	(0.48)	(0.48)	(1.13)	(0.58)
Relative Releases	0.04	0.14	0.21*	0.05	0.15
	(0.11)	(0.12)	(0.12)	(0.11)	(0.12)
Toxicity-Weighted Releases	---	---	---	---	0.33
					(0.25)
Regulatory Pressure					
Superfund	-0.02 ***	-0.03 ***	-0.03 ***	-0.02 ***	-0.028***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
HAP	4.57 ***	3.94 ***	3.26	5.89***	4.40***
	(1.51)	(1.56)	(1.56)	(1.69)	(1.58)
Penalties	0.59 *	0.79 **	0.77 **	1.40 ***	0.74**
	(0.35)	(0.37)	(0.36)	(0.43)	(0.37)
Inspections	0.04 **	0.05 **	0.05 **	0.07 ***	0.05**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Non-attainment	0.43 ***	0.44 ***	0.41 ***	0.43 ***	0.46***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
Other Firm-Characteristics					
Market share	11.53 **	6.94	4.51	2.60	6.06
	(5.28)	(6.06)	(5.84)	(6.43)	(6.13)
Net Sales	-0.02	-0.02	-0.03	-0.10	0.02
	(0.08)	(0.08)	(0.08)	(0.10)	(0.08)
Age of Assets	-27.17 **	-22.23 *	-19.7	-31.04 **	-21.4*
	(12.62)	(13.31)	(13.0)	(13.23)	(13.34)
Number of chemicals	0.18 ***	0.18 ***	0.19 ***	0.23 ***	0.18***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
ρ_1	0.60 ***	0.57 ***	0.55***	0.55 ***	0.58***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.41)
N	405	398	398	39 8	398

Values in parentheses are standard errors. * Significant at 10%, ** Significant at 5%, *** Significant at 1%. Models which include 1 digit SIC code dummies yield similar results as above.

[a] Model II has current toxic releases as an explanatory variable with lagged releases as an instrument.

Table 3. Impact of Cumulative Learning on Adoption of Pollution Prevention Techniques

Variables	MODEL IV (Predicted probability as instrument)	MODEL V[a] (Predicted probability and lagged Releases as instruments)
Constant	-1.78 (13.49)	-13.64 (13.41)
Internal Managerial and Innovative Capabilities		
TQEM	11.13 (7.66)	16.81 ** (8.17)
R&D Intensity	17.114 (25.93)	12.98 (26.00)
Cumulative P2	0.12 *** (0.01)	0.11 *** (0.01)
Market and Information-Related Pressure		
Final good	-0.36 (2.21)	-1.55 (2.26)
White	8.93 (11.79)	8.00 (11.79)
Environmental Activism	0.58 (3.32)	-3.31 (3.34)
Toxic Releases	-2.22 *** (0.44)	-5.00 *** (0.99)
Relative Releases	0.11 (0.11)	-0.01 (0.11)
Regulatory Pressure		
Superfund	-0.02 *** (0.01)	-0.02 ** (0.01)
HAP	4.78 *** (1.31)	7.47 *** (1.46)
Penalties	1.02 *** (0.33)	1.84 *** (0.38)
Inspections	0.004 (0.02)	0.04 * (0.02)
Non-attainment	0.48 *** (0.07)	0.47 *** (0.07)
Other Firm Characteristics		
Market share	0.23 (5.09)	-5.26 (5.39)
Net Sales	-0.05 (0.06)	-0.2 *** (0.1)
Age of Assets	-17.07 (11.04)	-30.12 *** (11.06)
Number of chemicals	0.02 (0.03)	0.10 *** (0.03)
P_1	0.33 *** (0.05)	0.33 *** (0.05)

Values in parentheses are standard errors. * Significant at 10%, ** Significant at 5%, *** Significant at 1%. Models which include 1 digit SIC code dummies yield similar results as above. N=398 in both models.

[a] Model V has current toxic releases as an explanatory variable with lagged releases as an instrument.

Table 4. Impact of Technique Specific Learning on High & Low-Tech Pollution Prevention

Variables	MODEL VI		MODEL VII	
	High-Tech	Low-Tech	High-Tech	Low-Tech
Constant	-17.38 (10.57)	6.01 (7.14)	-0.03 (8.98)	6.88 (6.05)
Internal Managerial and Innovative Capabilities				
TQEM	20.71 *** (5.91)	-3.14 (3.99)	10.27 ** (4.95)	-5.40 (3.33)
R&D Intensity	41.67 ** (20.94)	26.74 * (14.00)	14.00 (17.59)	8.46 (11.60)
Cumulative High-Tech P2	---	---	0.15 *** (0.01)	0.03 *** (0.01)
Cumulative Low-Tech P2	---	---	-0.07 *** (0.02)	0.08 *** (0.01)
Market and Information-Related Pressure				
Final good	-0.43 (1.80)	-0.47 (1.19)	-0.25 (1.51)	0.01 (0.99)
White	7.36 (9.16)	5.10 (6.25)	0.51 (7.95)	4.77 (5.40)
Environmental Activism	1.34 (2.56)	0.87 (1.75)	-1.48 (2.23)	-0.36 (1.52)
Toxic Releases	-1.16*** (0.32)	-0.36 (0.23)	-1.51 *** (0.29)	-0.62 *** (0.21)
Relative Releases	0.17 ** (0.08)	-0.03 (0.06)	0.10 (0.07)	-0.05 (0.05)
Regulatory Pressure				
Superfund	-0.02 *** (0.01)	-0.004 (0.004)	-0.02 *** (0.01)	-0.002 (0.003)
HAP	2.11 ** (1.06)	1.78 ** (0.71)	3.21 *** (0.89)	2.17 *** (0.59)
Penalties	0.34 (0.25)	0.43 ** (0.17)	0.17 (0.22)	0.61 *** (0.15)
Inspections	0.04 *** (0.01)	0.01 (0.01)	0.01 (0.01)	-0.01 (0.01)
Non-attainment	0.32 *** (0.06)	0.13 *** (0.04)	0.35 *** (0.05)	0.15 *** (0.03)
Other Firm Characteristics				
Market share	2.61 (4.11)	4.53 * (2.76)	-0.60 (3.42)	2.41 (2.26)
Net Sales	-0.06 (0.05)	0.04 (0.03)	-0.1 ** (0.04)	-0.02 (0.03)
Age of Assets	-7.54 (9.03)	-14.14 ** (6.01)	-8.05 (7.48)	-10.69 ** (4.92)
Number of chemicals	0.14 *** (0.02)	0.04 *** (0.01)	0.02 (0.02)	-0.02 (0.01)
P_1	0.58 *** (0.04)	0.45 *** (0.04)	0.41 *** (0.05)	0.23 *** (0.05)

Values in parentheses are standard errors. * Significant at 10%, ** Significant at 5%, *** Significant at 1%. For all models, the instrument used for TQEM is the predicted probability of TQEM adoption. Models which include 1 digit SIC code dummies yield similar results as above. N =398 in both models.

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

[2] A survey of U.S. manufacturing firms in 1995 by Florida (1996) found that 60% of respondents considered P2 to be very important to corporate performance and two-thirds of these had also adopted TQEM. Of the 40% of firms that considered P2 to be only moderately important, only 25% had adopted TQEM. A survey of U.S. manufacturing plants in 1998 found that among the P2 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).

[3] 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. Staw 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.

[4] TRI was established under Section 313 of the Emergency Planning and Community Right to Know Act (EPCRA) in 1986. It requires all manufacturing facilities operating under SIC codes 20-39, with 10 or more employees, and which produce or use toxic chemicals above threshold levels to submit a report of their annual releases to the USEPA. Since 1991, reporting of all P2 activities adopted in that year to reduce the TRI chemicals is mandatory under the National Pollution Prevention Act of 1990. The TRI is then made widely available to the public with a lag of two years.

[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] Each facility reports up to four different P2 activities they might have adopted for controlling levels of each chemical. 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] We also use toxicity weighted releases to examine if firms that were generating emissions that were more toxic faced greater pressure to adopt P2 techniques. Arora and Cason (1995) find that firms with larger toxicity weighted releases of 33/50 chemicals in the past were more likely to participate the voluntary 33/50 program.

[9] 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).

[10] The Coastal Rainforest Coalition, a network of environmental organizations successfully persuaded 20 US companies including Nike, Hewlett-Packard, Mitsubishi Electric of America, and Kinko's to stop using products from old growth rainforests. Environmental organizations

pressured a Dow Chemicals facility to find ways to prevent pollution and cut wastes by 35% (NY Times, 1999; South-North Development Monitor, 1998).

[11] 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)..

[12] 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 the reduction in intensity of use of certain toxic chemicals (Maxwell et al., 2000). Using this measure of environmental activism, Welch et al. (1999) finds that firms headquartered in states with greater environmentalism were more likely to participate in the voluntary Climate Challenge program.

[13] 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.

[14] This is also suggested by surveys which 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).

[15] 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.

[16] These capabilities or specialized assets are firm-specific. They acquired over time, are non-substitutable and imperfectly imitable, such as firm-specific human capital, R&D capability, brand loyalty. They can influence the extent to which a firm is able to capture the profits associated with a technology or innovation (Dierickx and Cool, 1989).

[17] Blundell et. al. (1995) and Crepon and Duguet (1997) find that the stock of innovations and patents accumulated in the past, respectively, were significant in explaining current innovations and patents applications. Gourlay and Pentecost (2002) and Colombo and Mosconi (1995) show that prior experience in using technologies that embody characteristics of same technological paradigm plays an important role in explaining current technology adoption. 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.

[18] 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).

[19] 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.

[20] 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).

[21] 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, 2002 a) They also find that external pressures on firms that were larger toxic polluters and likely to face greater public scrutiny, in closer contact with consumers and more visible to the public also motivated firms 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 33/50 program (Arora and Cason, 1996) and 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, respectively.

[22] For an in-depth analysis of this see Harrington et al. (2005).

[23] In the estimation of the TQEM equation we also include those firms that reported to TRI in the 1989-91 period.

[24] 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.

[25] To match the facilities with their parent companies, the Dun and Bradstreet number is used, in addition, to facility name, location, and SIC code. The ticker symbol, which identifies the parent companies in the Research Insight database is 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.

[26] Can be found at http://www.census.gov/

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

[28] 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, Sea Shepherd Conservation Society.

[29] We also estimated all these models while including dummies for the 1-digit SIC codes in our sample to control for any industry level differences that could affect P2 adoption. The signs and significances of all explanatory variables remained unchanged and the SIC dummies were often statistically insignificant.

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