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. Additionally, more pollution prevention activities are adopted by firms facing greater regulatory pressures and having relatively large toxic releases; the latter effect, however, is only weakly statistically significant. 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

[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).

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 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).[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,

[2] 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 these had also adopted TQEM. Of the 40% of 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).

[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

environmental and labor groups, and empirical work demonstrating that investors are using the TRI 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). However, the effect of information disclosure on the adoption of specific P2 activities has not yet been investigated.

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.

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 conduct this analysis using a 3-year unbalanced panel of 161 firms from the S&P 500 list which reported to the TRI and responded to the survey on adoption

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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).

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. 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 through a negative effect on the stock market value of polluting firms (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. Additionally, external stakeholders have also become more environmentally conscious as environmental information about firms has become more

[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)).

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 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, 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 new adoption of any of 43 different activities to prevent pollution for each toxic chemical to TRI in a given year. These activities can be 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 they might have adopted for controlling levels of each chemical.

We use several different methods for aggregating the number of P2 practices across practices and across facilities belonging to the same parent company. First we simply aggregate the number of all P2 practices adopted in a year across 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*. Finally, we also use the fraction of facilities of a firm that adopt any P2 activity as a dependent variable, *Fraction of New P2 Facilities*. 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 measures of adoption of P2 techniques discussed above.

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 (Powell, 1995). It may also enable firms

[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.

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 1: 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.

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 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 emissions. If larger toxic polluters face larger costs of abatement using pollution prevention

methods, and if this cost effect dominates the information-related external pressure effect discussed above, then one would observe a negative association between the emissions reported to the TRI and pollution prevention activities. The ideal identification strategy to disentangle these two effects would be based on the utilization of an important institutional detail. The TRI information is released to the public with a two year lag. Therefore, after controlling for lagged emissions, current emissions should not be correlated with the external pressure effect and should thus be negatively associated with pollution prevention adoptions. Conversely, after controlling for current emissions, lagged emissions should not be correlated with the adoption costs but only with the external-pressure effect, and thus be positively correlated with pollution prevention. Unfortunately, current emissions are endogenous, as they are affected by the level of pollution prevention activities, and cannot be easily instrumented for when lagged emissions are also included in the regression. Thus, we either use lagged emissions (choosing a five year lag to ensure that endogeneity is not an issue even in the presence of serial correlation) or current emissions instrumented by lagged emissions. The relative value and sign of the point estimates shed's light on the above issues.

Therefore, 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.

To test the above hypothesis subject to the caveats above we include the five year lagged value of toxic releases as an explanatory variable. We expect it to have a positive impact on the incentives to adopt pollution prevention practices, unless the cost effect discussed above dominates. 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 lagged *Toxicity-Weighted Releases* as an explanatory variable in one model. Finally, one may measure environmental performance in relative terms by comparing a firm's performance to that of its peers within the same industry group. 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*. [8]

To test the presence of possible confounding cost effects of higher emissions, as discussed above, we also replace lagged *Toxic Releases* by current *Toxic Releases* as an explanatory variable in some specifications of which we report one. We recognize that current releases might be determined jointly with *New P2* and describe in the next section our instrumentation strategy on how to address this endogeneity issue.

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 are 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 located in areas where environmental groups and communities are more active are more likely to adopt pollution prevention practices.[10] This suggests:

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[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

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

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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.

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. 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.[13] We hypothesize that facilities located in states with mandatory P2 programs are more likely to adopt *New P2* activities.

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).[14] By taking actions to control

[13] 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.

[14] 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

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.[15] 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 mandatory 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.[16] 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 anticipated costs of compliance, we include the volume of *Hazardous Air Pollutants* (*HAP*) consisting of 189 toxic chemicals listed in Title III

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environmental management practices, but their direct effect on environmental technology adoption has not been examined.

[15] 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).

[16] 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.

of the 1990 Clean Air Act Amendments. These were expected to regulated under New Emissions Standards for HAP starting in 2000. 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.

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. 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.

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.[17] Previous experience with technologies which embody constituent elements of the same technological paradigm can lower the costs of adoption 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).[18] Based on this literature we hypothesize that:

Hypothesis 5: Firms that have larger technical capabilities and cumulative experience 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 experience 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

[17] 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).

[18] Blundell et. al. (1995) and Crepon and Duguet (1997) find that the stock of innovations and patents accumulated in the past 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.

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. Since there might be some non-transient factors, such as the type of operations/products that make a firm more amenable to undertaking P2, *Cumulative P2* could be correlated with the error term. We use the Hausman test (Maddala, 2001) to investigate if this is the case and discuss our approach for addressing this issue in the next section.

While testing the above five 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 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 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*.[19]

We include the *Market Share* of a firm in terms of industry sales 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.[20] 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.[21]

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 ith firm at time t to a vector of observed exogenous variables, X_{it}; the *TQEM* adoption decision, T_{it}; *Cumulative P2*, $CP2_{it-1}$ and unobserved factors ε_{1it}.

[19] 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).

[20] 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.

[21] 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).

$$Y_{it} = \alpha X_{it} + \beta T_{it} + \gamma CP2_{it-1} + \varepsilon_{1it} \qquad (1)$$

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 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. 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.

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 $\sigma_{\varepsilon 2}^2$. 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 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.[22] 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 also expect that firms with stronger internal organizational capabilities and ability to establish leadership in the product market by growing at the expense of their rivals, as proxied by their *Market Share,* to be more likely to adopt TQEM. We include *Toxic Releases* reported 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. However, adoption may have occurred during or after

[22] 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 were large toxic polluters and likely to face greater public scrutiny, that were 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 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.

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. To the extent that the errors in (1) are serially correlated it is possible that *Cumulative P2*, $CP2_{it-1}$, could be influenced by some of the same unobservables as *New P2*$_{it}$. We test for the endogeneity of $CP2_{t-1}$, knowing that *TQEM* is endogeneous, using the Hausman test presented in Maddala (2001, p: 499). The test is unable to reject the null hypothesis that $CP2_{t-1}$ is an exogenous variable.

Nevertheless, to test the robustness of our results to possible endogeneity of $CP2_{t-1}$, we estimate a reduced form regression to explain *Cumulative P2* levels using only exogenous explanatory variables and use its predicted value as an instrument in the regression explaining *New P2* in one of the specifications. We hypothesize that a suitable reduced form expression for *Cumulative P2* is given by:

$$CP2_{it-1}^{*} = \gamma_2 W_{it-5} + \varepsilon_{3it} \qquad (2)$$

The *i.i.d.* error component ε_{3it} is assumed to be normally distributed with mean zero and variance $\sigma_{\varepsilon 3}^2$. The variables included in W_{it-5} are the same as those used to explain TQEM adoption decision. An exception is that we now include the *Number of Chemicals in 1991* instead of *Number of Facilities* as an explanatory variable. The number of chemicals reported by the firm in 1991 represents the baseline number of opportunities for adopting P2 activities and is expected to be correlated with the count of P2 activities adopted over time. Five-year lagged value of explanatory variables (other than *Number of Chemicals in 1991*) are used to explain *Cumulative P2* in 1993-1995. This is because *Cumulative P2* is composed of P2 practices adopted since 1991 and the use of explanatory variables measured for the period 1989-91, avoids any possible correlations between the dependent and the independent variables. This is the case for all other variables included except for *Number of Chemicals*, which does not exist prior to 1991. We also include a *Time* variable to control for the increasing trend inherent in cumulative

P2.[23] The signs and the effect of the lagged values of these variables on *Cumulative P2* are expected to be similar to those of their contemporaneous values on *New P2* discussed above. We estimate equation (3) using OLS with pooled data. The purpose of equation (2) is simply to obtain an instrument(s) that is correlated with *Cumulative P2* but uncorrelated with *New P2* and not to develop a comprehensive model to explain *Cumulative P2* which is given by the sum over time of the New P2 as given by equation (1). The standard errors reported allow for correlation in the disturbance of the latent variable across time for the same firm.

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.[24] 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*.[25] 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

[23] For the same reason, we also incorporated interactions of the time trend with various explanatory variables to allow for the possibility that, due to the accumulative nature of the dependent variable, the effect of these explanatory variables could become stronger over time. However, we found that these interaction terms were not statistically significant and hence those regressions are not reported.

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

[25] 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.

facility level data to obtain parent company level data.[26] 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 161 firms for which complete data for estimating equations (1)-(3) was available resulted in 392 observations. 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

[26] 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 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.

this was the case for only 236 facilities (5.68% of all facilities examined) 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. [27]

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.[28] The *Non-attainment* status of counties is obtained from the USEPA Greenbook.[29]

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[27] 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.

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

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

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).[30] Data on state P2 policies is obtained from the National Pollution Prevention Roundtable.[31]

5. Results

We estimated three alternative first-stage probit models to explain TQEM adoption (results reported in the first three columns of Table 2). The first model includes all explanatory variables measured in levels. We also estimate a model using all explanatory variables measured in square roots (except for *Age of Assets*). The Schwarz Information Criterion statistic indicates that explanatory variables measured in square-roots provide a better fit to the data on *TQEM*. We then estimate a parsimonious model using only the square roots of variables that have a statistically significant effect on *TQEM*. We estimate two OLS regressions to examine the factors associated with *Cumulative P2*, the first using all explanatory variables measured in levels and the second one including a parsimonious set of variables (in levels) found to be statistically significant. The model with all explanatory variables measured in square roots was found to have a smaller adjusted R^2 than the model with explanatory variables in levels and hence is not reported. Focusing on the results of the parsimonous models we find that firms that have larger *R&D intensity*, larger *Sales*, larger *Market share*, larger *Toxic releases* and a fewer *Number of Facilities* are more likely to adopt TQEM. Consumer pressure and regulatory pressure variables are not found to have any effect on TQEM adoption. These results are consistent with those reported in Harrington et al. (forthcoming). Firms that have a larger *R&D intensity*, larger *Sales*, larger *Market share*, higher *Inspections* and emitted a larger *Number of Chemicals in 1991* had a higher *Cumulative P2* than other firms. There was also a statistically

[30] 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.
[31] http://www.p2.org/inforesources/nppr_leg.html.

significant time trend in the cumulative P2 adoption levels.

We employ the parsimonious model to generate the predicted probability of *TQEM* adoption which is used as an instrument in the estimation of the *New P2* equation. We also investigated the possibility of using the explanatory variables included in the parsimonious model for TQEM directly as instruments while estimating equation (1). Since we have more instruments than endogenous variables and hence more instruments than are needed to identify equation (1) we test for the validity of these instruments by examining if they are uncorrelated with the error term in equation (1) using the method in Wooldridge (2002).[32] We find that we fail to reject the null hypotheses that all the instruments for *TQEM* are uncorrelated with the error term in (1) at the 1% significance level. We, therefore, estimate some specifications of (1) using lagged variables in the parsimonious model for TQEM as instruments. *Number of facilities* which is included to explain *TQEM* is not expected to influence *New P2*. Moreover, the use of the lagged values of variables included in the first stage regressions and current values of those variables included in the *New P2* equation, ensures identification of the parameters in equation (1). In one specification that includes *Cumulative P2* as a regressor, we include the predicted value of *Cumulative P2* generated from the parsimonious model as an instrument and obtained generally similar results 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.

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

[32] The test for the validity of the overidentification restrictions is obtained by first estimating equation (1) (without including $CP2_{t-1}$) using two stage least squares and all the variables in the parsimonious model for TQEM and exogenous variables, X_{it}, as instruments. The residual from this equation is then regressed on all these instruments and on X_{it}; N times the R^2 of this regression is a chi-squared statistic with degrees of freedom being the number of overidentifying restrictions. We then repeated this test by including $CP2_{t-1}$ in (1) and estimating it using the predicted probability of TQEM and the variables in the parsimonious model of $CP2_{t-1}$ as instruments.

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 1A-1D and Model 2 (Table 3) examine the impact of *TQEM* and the stakeholder demand side factors on *New P2* using different instruments and different specifications, while Models 1E-1J (Table 4) examine these impacts on alternative measures of pollution prevention. Following the suggestions of the referees we estimate Model 1D, which is similar to Model 1B, but uses a two-step Poisson model. Model 2 includes current toxic releases as an explanatory variable and lagged toxic releases as an instrument. None of these models control for differences in *Cumulative P2* across firms. The instruments used for TQEM differ across these models and are reported in the Tables 3 and 4. Model 3A-3C and 4 include *Cumulative P2* as an explanatory variable (Table 5).[33] In Model 3C we measure *Environmental Activism* and *White* for the state in which the corporate headquarters of the firm are located rather than for the state in which each facility is located, as in the other regressions. This allows us to examine if external pressures on the corporate headquarters had a different effect than on individual facilities. Model 3D includes the predicted value of *Cumulative P2* as an instrument. Model 4 includes the five-year lagged square root of toxicity-weighted releases as an explanatory variable.

Model 1A 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. Unlike Model 1A, the other Models 1B, 1C and 2 consistently support Hypothesis 1 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 1A, indicating the presence of a negative selection bias in its estimation. The two-step Poisson in Model 1D 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. They also account for

[33] 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.

correlation in the disturbance of *New P2* across time for the same firm. The explanatory variables are all in logarithms (with the exception of the binary variables and *Year*) and parameter estimates can be interpreted as elasticities.[34] Though the linear and Poisson specifications are not directly comparable, the Poisson analysis allows us to test for the robustness of our results when the non-negative and integer nature of the dependent variable is incorporated in the estimation model (at the cost of not taking account the serial correlation from the parameter estimates). In the Poisson model, *TQEM* marginally fails to attain significance (it is significant at the 11% level). The effect of *TQEM* is statistically significant and positive even on all the alternative measures of pollution prevention considered here in Models 1E to 1J and in Models 3 and 4, after the addition of *Cumulative P2* as a regressor (with the exception of Model 3B).

The magnitude of the TQEM coefficient in the base models suggests that the average effect of TQEM adoption on the annual count of Pollution Prevention practices is equal to approximately 20 practices. In most of the sensitivity analyses that includes *Cumulative P2* as a regressor, this number drops to about 13 practices. In our sample, the average annual count of pollution prevention practices by adopters of TQEM is equal to 26.5. This suggests that if these firms had not adopted TQEM, their average annual count would be only about 6.5 if using the base models and 13.5 if using many of the variant models that include *Cumulative P2* as a regressor (the Poisson estimates of 100% TQEM effects on the P2 count are consistent with the variant rather than base model specifications). Non-adopters of TQEM average about 18 P2 practices per year. 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. Notice, however, that there is considerably uncertainty surrounding the magnitude of these point estimates across the different versions of the model, and the true magnitude may be lower.

We find support for Hypothesis 2 with Models 1B to 1F which show that firms with large

[34] Including the explanatory variables in a Poisson model in logarithmic form is equivalent to estimating a linear model in which both the dependent and independent variables are in logs.

Relative Releases were more likely to adopt a larger number of *New P2* and *Chem-Count P2* practices. However, this effect on *New P2* is positive but weaker with the inclusion of *Cumulative P2* as an explanatory variable; moreover its effect on the *Weighted Sum of New P2* and on the *Fraction of P2* facilities is positive but not statistically significant. Similarly, the effect of toxicity-weighted releases in Model 5 is positive but not significant. Moreover, *Total Releases* (whether lagged or not) have a negative rather than positive sign. The fact that the point estimate is smaller when current rather than lagged releases are used as a regressor suggests that the negative sign is due to the cost effect dominating the external pressure effect in the former case, as discussed in section 2.

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 irrespective of whether they are measured based on facility location or corporate headquarter location. Therefore, we find no support for Hypothesis 3.

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* and *Chem-Count 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* 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 techniques.

We find some support for the first part of Hypotheses 5 in Models 1A-1C and 1E-1H about the positive effects of technological capabilities, as proxied by *R&D Intensity* on *New P2*.

However, this variable becomes statistically insignificant after the addition of *Cumulative P2* as an explanatory variable in Models 3 and 4. This suggests that the latter might be a more appropriate proxy for the internal capabilities that affect the adoption of pollution prevention techniques. However, note that R&D is strongly and positively correlated with *Cumulative P2* as shown in Table 2, so the effect of R&D is still present, though indirect. We find strong support for the hypotheses about the positive association between *Cumulative P2* and *New P2* adoption in models 3-5. This finding demonstrates that the experience and proxy effects of *Cumulative P2* offset any diminishing marginal effects that might reduce incentives for *New P2*.

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* and *Chem-Count P2* techniques adopted. As expected, the more opportunities a firm has to adopt pollution prevention techniques the more such techniques it will adopt.

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 in influencing incremental adoption of these techniques. More generally, our study makes a contribution to the broader literature that studies the impact of a firm's management system on its environmental related activities.

Our main econometric findings are as follows. First, adoption of total quality management systems does indeed motivate the adoption of more pollution prevention techniques. Thus, managerial innovations, such as adoption of TQEM, lead firms to be

innovative in their approaches towards environmental management. Second, firms with relatively larger toxic releases are likely to adopt more pollution prevention activities, although this effect is only weakly statistically significant. To the extent that firms with larger relative toxic releases face greater public pressure to improve environmental performance, this finding suggests that 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 possibly cumulative experience 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' 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 us towards those goals.

Table 1. Descriptive Statistics (1994-96).

Variable	Mean	Std.Dev.	Minimum	Maximum
TQEM	0.70	0.46	0.00	1.00
New P2	23.97	36.90	0.00	284.00
Chem-Count P2	15.02	23.32	0.00	173.00
Weighted Sum of New P2	2.55	4.23	0.00	28.93
Fraction of P2 Facilities	0.31	0.23	0.00	1.00
Cumulative P2	132.44	202.60	0.00	1374.00
R&D Intensity	0.03	0.04	0.00	0.24
Final Good	0.55	0.50	0.00	1.00
White	0.82	0.08	0.43	0.99
Environmental Activism	0.91	0.28	0.26	1.95
Lagged Toxic Releases (Millions of pounds)	15.30	43.38	0.00	382.88
Current Toxic Releases (Millions of pounds)	32.52	70.02	0.00	519.18
Lagged Toxicity-Weighted Releases	38.80	208.89	0.00	3077.75
Lagged Relative Toxic Releases	3.02	11.10	0.00	153.78
Superfund Sites	70.22	179.08	0.00	1376.00
Lagged HAP (Million of pounds)	2.92	6.15	0.00	49.19
Penalties	1.56	3.52	0.00	33.00
Inspections	52.20	83.53	0.00	491.00
Non-attainment	12.64	17.18	0.00	96.00
Mandatory P2 Policy	1.74	2.90	0.00	18.00
Market share of Sales	0.25	0.22	0.00	0.93
Net Sales ($ Billion)	12.99	22.64	0.22	165.37
Age of Assets	0.75	0.10	0.46	0.93
Number of chemicals	83.08	113.91	1.00	625.00

Table 2: Determinants of TQEM Adoption

Dependent Variable	TQEM	TQEM	TQEM	Cumulative P2	Cumulative P2
Constant	0.658 (0.835)	-0.073 (0.851)	-0.363 (0.310)	-31.935 (58.165)	-41.317*** (12.541)
R&D Intensity	2.974 (2.643)	2.005** (0.999)	2.006** (0.989)	287.833** (130.482)	277.291* (149.064)
Final Good	0.137 (0.244)	0.114 (0.257)		-1.643 (16.339)	
Toxic Releases	0.004 (0.002)	0.057 (0.040)	0.112*** (0.043)	0.158 (0.173)	
Superfund	0.001 (0.001)	0.012 (0.028)		-0.146* (0.077)	
HAP	0.018 (0.024)	0.045 (0.131)		3.757 (2.636)	
Penalties	0.052 (0.062)	0.113 (0.132)		-1.126 (5.835)	
Inspections	0.002 (0.002)	0.040 (0.041)		1.090*** (0.235)	1.270*** (0.233)
Market Share	1.394** (0.552)	1.354*** (0.504)	1.154** (0.498)	41.572 (28.938)	64.763* (33.282)
Sales	0.000 (0.000)	0.004 (0.003)	0.006** (0.002)	0.001* (0.0006)	0.0009 (0.0007)
Age of Assets	-0.750 (1.175)	-0.411 (1.189)		-13.137 (78.820)	
Number of Facilities	-0.022*** (0.006)	-0.223*** (0.072)	-0.160*** (0.056)		
Number of Chemicals in 1991				0.624*** (0.208)	0.501*** (0.189)
Year				16.115*** (4.081)	14.841*** (3.899)
Schwarz I.C.	504.62	492.198	462.374		

N= 392 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 column 1 with TQEM as dependent variable are in linear terms. All variables in columns 2 and 3 with TQEM as dependent variable are in square root with the exception of Age of Assets. All variables in columns 4 and 5 with Cumulative P2 as dependent variable are in linear terms.

Table 3: Impact of TQEM on Adoption of Pollution Prevention Techniques

Variables	MODEL 1A OLS	MODEL 1B (Predicted probability as instrument)	MODEL 1C (Lagged values as instruments)	Model 1D (Poisson Two-Step Model; Predicted probability and logged explanatory variables)	MODEL 2[a] (Predicted probability and lagged releases as instruments)
Constant	7.278 (14.666)	-6.490 (15.392)	-9.160 (15.573)	-0.461 (0.594)	2.844 (15.417)
Internal Managerial and Innovative Capabilities					
TQEM	1.126 (2.325)	19.294*** (7.105)	21.789*** (7.476)	1.072^{+} (0.675)	23.711*** (7.812)
R&D Intensity	72.623** (30.082)	55.449* (30.466)	57.040* (30.219)	1.512 (1.966)	48.587^{+} (30.682)
Market and Information Related Pressure					
Final good	-0.191 (2.536)	-1.439 (2.551)	-1.462 (2.543)	-0.145 (0.144)	-2.295 (2.586)
White	6.145 (14.267)	4.722 (14.193)	5.612 (14.169)	0.575 (0.858)	4.216 (14.245)
Environmental Activism	2.355 (4.023)	3.490 (4.026)	3.415 (4.018)	0.136 (0.308)	1.976 (4.065)
Toxic Releases	-0.935** (0.463)	-1.384*** (0.493)	-1.479*** (0.502)	-0.075 (0.079)	-2.725*** (0.979)
Relative Releases	0.054 (0.106)	0.198* (0.117)	0.222* (0.119)	0.143** (0.054)	0.156 (0.113)
Regulatory Pressures					
Superfund	-0.025*** (0.009)	-0.029*** (0.009)	-0.030*** (0.009)	-0.118*** (0.038)	-0.026*** (0.009)
HAP	3.697** (1.696)	2.436 (1.741)	2.119 (1.761)	-0.057 (0.114)	3.361* (1.798)
Penalties	0.662* (0.374)	0.740** (0.374)	0.740** (0.374)	-0.025 (0.059)	1.184*** (0.412)
Inspections	0.046** (0.022)	0.051** (0.022)	0.053** (0.022)	0.087 (0.077)	0.068*** (0.024)
Non-attainment	0.397*** (0.096)	0.413*** (0.095)	0.411*** (0.095)	0.256*** (0.088)	0.399*** (0.097)
Mandatory P2 Policy	-0.346 (0.590)	-0.041 (0.594)	0.006 (0.594)	0.028 (0.091)	-0.047 (0.592)
Other Firm-Characteristics					
Market share	16.004*** (5.585)	10.672* (5.864)	9.585 (5.940)	-0.017 (0.070)	7.361 (6.125)
Net Sales	-0.009 (0.081)	-0.016 (0.079)	-0.021 (0.079)	0.014 (0.098)	-0.115 (0.089)
Age of Assets	-25.622* (13.136)	-20.378 (13.126)	-19.653 (13.124)	-0.512 (0.479)	-25.800*** (13.176)
Number of Chemicals	0.186*** (0.029)	0.186*** (0.029)	0.189*** (0.029)	0.596*** (0.139)	0.224 (0.035)
Year	-1.008 (1.054)	-0.363 (1.086)	-0.245 (1.093)	-0.055 (0.055)	-1.639 (1.013)
ρ_1	0.590*** (0.041)	0.559*** (0.042)	0.553*** (0.042)		0.538*** (0.043)

Values in parentheses are standard errors. * Significant at 10%, ** Significant at 5%, *** Significant at 1%. $^{+}$ Significant at the 15% level. [a] Model II has current toxic releases as an explanatory variable with lagged releases as an instrument.

Table 4: Impact of TQEM on Alternative Measures of Pollution Prevention Adoption

Variables	Model 1E Chem-Count P2	Model 1F Chem-Count P2	Model 1G Weighted Sum of New P2	Model 1H Weighted Sum of New P2	Model 1I Fraction of P2 Facilities	Model 1J Fraction of P2 Facilities
Constant	-10.521	-11.786	1.483	-0.672	0.158	0.115
	(8.812)	(8.916)	2.690	(2.685)	(0.178)	(0.180)
Internal Managerial and Innovative Capabilities						
TQEM	13.236***	14.275***	2.401*	4.987***	0.203**	0.257***
	(4.084)	(4.288)	1.245	(1.294)	(0.086)	(0.088
R&D Intensity	35.213**	36.743**	12.901**	11.347**	0.103	0.0723
	(17.420)	(17.291)	5.319	(5.204)	(0.344)	(0.343
Market and Information-Related Pressure						
Final good	-1.183	-1.156	0.371	0.258	-0.031	-0.034
	(1.459)	(1.455)	(0.445)	(0.438)	(0.029)	(0.029)
White	7.507	8.106	1.714	1.660	-0.123	-0.124
	(8.138)	(8.127)	(2.483)	(2.452)	(0.166)	(0.166)
Environmental Activism	-0.378	-0.455	2.629***	2.735***	-0.025	-0.025
	(2.310)	(2.305)	(0.705)	(0.696)	(0.047)	(0.047)
Toxic Releases	-0.781***	-0.829***	0.019	-0.052	-0.001	-0.003
	(0.284)	(0.289)	(0.087)	(0.087)	(0.006)	(0.006)
Relative Releases	0.117*	0.128*	0.009	0.030	0.001	0.002
	(0.067)	(0.068)	(0.021)	(0.020)	(0.001)	(0.001)
Regulatory Pressure						
Superfund	-0.012**	-0.012**	-0.002	-0.002	0.000	-0.0001
	(0.005)	(0.005)	(0.002)	(0.001)	(0.001)	(0.0001)
HAP	0.511	0.350	0.965***	0.778**	0.051**	0.046**
	(0.996)	(1.007)	(0.304)	(0.303)	(0.019)	(0.020)
Penalties	0.673***	0.672***	0.083	0.092	0.002	0.002
	(0.215)	(0.214)	(0.066)	(0.065)	(0.004)	(0.005)
Inspections	0.030**	0.031**	0.003	0.003	0.000	0.0004*
	(0.012)	(0.012)	(0.004)	(0.003)	(0.001)	(0.0003)
Non-attainment	0.179***	0.177***	0.031*	0.033**	0.000	0.0000
	(0.054)	(0.054)	(0.017)	(0.016)	(0.001)	(0.001)
Mandatory P2 Policy	0.435	0.456	-0.156	-0.140	-0.003	-0.033**
	(0.338)	(0.339)	(0.191)	(0.101)	(0.006)	(0.014)
Other Firm-Characteristics						
Market share	3.681	3.163	0.104	0.402	0.014	0.007
	(3.361)	(3.404)		(1.026)	(0.068)	
Net Sales	0.035	0.032	1.286	0.024*	0.001	-0.004
	(0.045)	(0.045)	(1.026)	(0.013)	(0.001)	0.069
Age of Assets	-6.861	-6.584	0.026*	-7.379***	0.270*	0.001
	(7.500)	(7.502)	(0.014)	(2.255)	(0.147)	0.001
Number of chemicals	0.126***	0.128***	-8.225***	-0.007	-0.001**	0.288**
	(0.016)	(0.016)	(2.291)	(0.004)	(0.000)	0.148
Year	-0.268	-0.212	-0.008	-0.053	-0.036**	-0.001**
	(0.627)	(0.631)	(0.005)	(0.192)	(0.014)	0.0003
ρ_1	0.535***	0.532***	0.541***	0.507***	0.289***	0.299***
	(0.042)	(0.428)	(0.043)	(0.043)	(0.048)	0.048

Values in parentheses are standard errors. * Significant at 10%, ** Significant at 5%, *** Significant at 1%. Models 1E, 1G and 1I have the predicted probability of TQEM as an instrument. Models 1F, 1H and 1J have lagged variables as instruments.

Table 5: Relationship between Cumulative and Current Adoption of Pollution Prevention Techniques

Variables	Model 3A	Model 3B	Model 3C	Model 3D	Model 4
Constant	3.231 (12.864)	7.149 (12.938)	12.101 (10.990)	1.006 (15.714)	2.910 (12.933)
Internal Managerial and Innovative Capabilities					
TQEM	12.191* (6.223)	7.015 (6.353)	15.474** (6.648)	12.733 + (8.052)	12.184* (6.228)
R&D Intensity	10.606 (24.962)	15.170 (24.777)	16.368 (23.678)	34.962 (30.310)	11.259 (24.963)
Cumulative P2	0.129*** (0.009)	0.131*** (0.0094)	0.136** (0.009)	0.068** *(0.022)	0.129*** (0.009)
Market and Information-Related Pressure					
Final good	-1.079 (2.089)	-0.754 (2.080)	-0.766 (2.026)	-0.914 (2.541)	-0.886 (2.105)
White	7.584 (11.923)	8.384 (11.910)	-3.001 (6.909)	3.337 (14.138)	7.609 (11.944)
Environmental Activism	-0.591 (3.413)	-0.971 (3.418)	-3.930* (2.113)	1.828 (4.063)	-0.518 (3.423)
Toxic Releases	-1.685*** (0.446)	-1.563*** (0.452)	-1.938*** (0.451)	-1.692*** (0.509)	-1.859*** (0.544)
Relative Releases	0.140 (0.101)	0.097 (0.101)	0.160 (0.100)	0.156 (0.122)	0.122 (0.210)
Toxicity-Wtd. Releases					0.137 (0.101)
Regulatory Pressure					
Superfund	-0.024*** (0.007)	-0.0234 *** (0.007)	-0.026*** (0.007)	-0.026*** (0.009)	-0.024*** (0.007)
HAP	2.331* (1.431)	2.632* (1.436)	2.544* (1.358)	2.838 (1.736)	2.539* (1.453)
Penalties	0.962*** (0.325)	-0.0017*** (0.009)	0.917** (0.319)	0.907** (0.380)	0.951*** (0.327)
Inspections	0.003 (0.020)	0.0024 (0.020)	0.011 (0.019)	0.031 (0.024)	0.003 (0.020)
Non-attainment	0.399*** (0.077)	0.393*** (0.077)	0.347*** (0.074)	0.371*** (0.096)	0.400*** (0.078)
Mandatory P2 Policy	0.314 (0.475)	0.234 (0.474)	0.667 (0.462)	-0.034 (0.579)	0.347 (0.482)
Other Firm Characteristics					
Market share	2.217 (4.928)	3.530 (4.952)	1.347 (4.764)	7.958 (5.821)	1.939 (4.995)
Net Sales	-0.025 (0.063)	-0.018 (0.062)	-0.006 (0.059)	-0.030 (0.077)	-0.025 (0.063)
Age of Assets	-12.661 (10.630)	-14.134 (10.600)	-11.406 (10.111)	-14.775 (12.934)	-12.540 (10.660)
Number of chemicals	0.014 (0.026)	0.009 (0.026)	-0.003 (0.024)	0.099 *** (0.038)	0.014 (0.026)
Year	-3.258*** (1.045)	-3.507*** (1.058)	-3.353*** (1.057)	-2.085*** (1.275)	-3.268*** (1.046)
ρ_1	0.314*** (0.048)	0.296*** (0.048)	0.232*** (0.050)	0.463*** (0.045)	0.316*** (0.048)

N=392 in all models except Model 3C where it is 385.Values in parentheses are standard errors. * Significant at 10%, ** Significant at 5%, *** Significant at 1%. +Significant at 15% level. Models 3A, 3C 3D and 4 include the probability of TQEM as an instrument while Model 3B includes lagged variables as instruments for TQEM. Model 3D also includes the predicted value of Cumulative P2 as an instrument. .Model 3C measures environmental activism and White for the state in which the corporate headquarters of the firm are located.

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