

Green management and the nature of pollution prevention innovation

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Management systems have a strong impact on the level of innovation and on production operations. Understanding this impact sheds light on how firms function. This article examines the relationship between a firm's approach to environmental management and the nature of the pollution prevention activities or practices that it undertakes. We differentiate pollution prevention activities according to (i) four functional characteristics and (ii) visibility to consumers. We find that the application of the total quality management (TQM) approaches on pollution prevention has a stronger effect for practices that involve procedural changes or are of a customized nature. These are indeed the type of practices where one would expect TQM to have a disproportionate impact in decision-making effectiveness. There seems to be no corresponding effect on the adoption of practices that are visible to consumers. Our results corroborate the notion that a well-designed management system can help stimulate innovation, but only for specific types. They also help identify the types of firms that are more likely to benefit from adoption of TQM principles.

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JEL Classification: L23; Q55

I. Introduction

Technical change and production routines depend on many factors. A substantial body of literature investigates linkages between technical change, firm size, market structure and trade opportunities; examines spillovers from technical advances by geographically proximate firms; investigates dynamic aspects of innovation (e.g.

the effect that prior innovation has on future innovation); or considers other factors.¹ The literature linking management systems and internal organization with technical change is relatively less developed as compared to that investigating other sources of technical change.² A large part of this existing work adopts an indirect approach to measuring technical change and quantifies it through changes in productivity (see the survey by Bartelsman

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¹ A summary of this literature is impractical. In addition to papers cited elsewhere, it is worth mentioning Henderson and Cockburn (1996), Power (1998) and Cohen and Klepper (1996) on firm/plant size and technical change; Clerides *et al.* (1998) and Pavcnik (2002) on trade and productivity; Almeida and Kogut (1999), Jaffe *et al.* (1993) and Peri (2005) on spatial spillovers; Bernstein *et al.* (2004) on efficiency and productivity growth; and Chavas *et al.* (1997) on agricultural productivity.

² See Black and Lynch (2001) on workplace practices; Baily and Solow (2001) on retailing formats; Kessler and McClellan (2002) on ownership structure; Sciulli (1998) on banking; and Acemoglu *et al.* (2007); Zoghi *et al.* (2007), Laursen and Foss (2003) and Hage (1999) on some broader aspects.

and Doms (2000)), while another part of the literature uses patents as a proxy.

This article contributes to the literature on management systems and innovation, and specifically on the linkage between total quality environmental management (TQEM) and pollution prevention. Our utilization of panel data on the adoption of techniques of different types provides a direct (rather than indirect) measure of technical change.³ This is important since technical change may not be reflected in productivity, especially if a relevant 'output' (e.g. pollution) is omitted, or even in patent counts if the associated R&D expenditures are devoted to meeting regulations.⁴ Our identification strategy moves beyond the standard battery of fixed effects employed in panel data analysis. It is partially based on the observation that, by its very nature, TQEM is expected to have a differential impact on techniques of different types. This differential impact, which we verify empirically, suggests that the estimated effects are indeed largely driven by changes in the managerial system.

The adoption of innovative methods of production and waste management are key components of a firm's strategy to improve market competitiveness and operational efficiency, and to respond effectively to changing consumer preferences and regulations. A firm's management system influences the extent and nature of technologies it adopts through its effect on internal incentives, the degree of employee involvement in decision-making and the internal communication channels for information sharing. Total quality management (TQM), one of the most influential managerial systems, emphasizes customer satisfaction through continuous progress in preventing defects and seeks to achieve gains in efficiency using a systems-wide approach to process management (Powell, 1995; Cole, 1998; Black and Lynch, 2001; Sousa and Voss, 2002). This approach is based on a nonhierarchical and decentralized organizational structure that enables the creation and utilization of valuable knowledge on production inefficiencies from employees at all levels. It encourages information sharing across organizational levels which facilitates dissemination and implementation of ideas and diffusion of innovation. Expansion of the notion of product quality to include the environmental impact of production systems and products, and the belief that pollution is equivalent to a waste of resources, led firms to apply the TQM approach to the management of their environmental impact. This is referred to as TQEM and involves using quality management tools to prevent pollution at source

rather than controlling it after it is generated (Klassen and McLaughlin, 1993; Wruck and Jensen, 1998; Khanna *et al.*, 2009).

The waste prevention-oriented philosophy of TQEM suggests an inherent complementarity with pollution prevention. One would expect the adoption of all types of pollution prevention practices to be higher among firms that use TQEM than among otherwise identical firms that do not. Indeed, a survey of US manufacturing firms in 1995 by Florida (1996) finds that 60% of respondents considered pollution prevention to be very important to corporate performance and two-thirds of these had also adopted TQM. Of the 40% of firms that considered pollution prevention to be only moderately important, only 25% had adopted TQM. A later survey of US manufacturing plants (in 1998) finds that among the pollution prevention adopters, the percentage of firms practising TQM was twice that for other plants. Finally, a survey of Japanese manufacturing firms finds that plants adopting a green design were more likely to be involved in TQM than other plants (Florida and Jenkins, 1996).

However, the TQEM approach for identifying and evaluating opportunities for waste reduction is likely to be more conducive to the adoption of practices that are of organizational nature or of higher complexity, or are otherwise less standardized. We examine how the effect of TQEM adoption differs across practices of different types, recognizing that the net benefits of adopting pollution prevention practices are also likely to be influenced by firm-specific technical and economic factors. These include the suitability of practices for a firm's production system (or the inherent propensity of a firm to adopt certain types of pollution prevention practices), the costs of learning about new technologies, the potential for diminishing returns in pollution prevention and others.

We use a detailed data set that catalogues the pollution prevention practices adopted by a sample of S&P 500 firms over the 1992–1996 period to reduce their toxic releases. This data set is constructed by merging the Toxic Release Inventory (TRI) that is managed by the US Environmental Protection Agency (EPA), the Compustat database, and the Investor Responsibility Research Center (IRRC) survey. The data set provides a rich five year panel of pollution prevention activities that firms have undertaken in each of 43 types of practices. The EPA provides a detailed description of each of these types of practices, which allows us to categorize them based on a set of

³ Hannan and McDowell (1984) and Karlson (1986), among others, also study the adoption of specific technologies.

⁴ See Jaffe and Palmer (1997) for a negative and Brunnermeier and Cohen (2003) for a positive assessment. In fact, environmental regulation which may stimulate technical change may be perceived as a drag on productivity (see Bernman and Bui, 2001 and references therein).

attributes that we define. The first attribute, on the basis of which we classify pollution prevention activities, is their functional characteristic, while the second attribute is their visibility to consumers. In particular, we partition the practices according to four functional characteristics: whether the practice requires a change in equipment, a change in materials usage, a change in operating procedures, or other customized modifications. This last category includes practices that firms have been unable to assign to one of the pollution prevention activity codes with specific descriptions, as defined by the EPA, or which are organization specific. We define a set of binary variables that take the value of 1 if the practice possesses a particular attribute and 0 otherwise. Another binary variable reflects visibility of the practices to consumers. We then investigate whether the effect of TQEM on pollution prevention is nonuniform, and if so, which types of activities are associated with stronger TQEM effects. Firm fixed effects and suitable controls to capture the effects discussed above are also included. Our base estimates are complemented with a number of internal consistency checks that test the validity of our framework.

Our results show that the effect of TQEM on pollution prevention adoption is nonuniform, with stronger effects for practices that involve procedural changes or that are customized or do not fall neatly into well-established standard activity types. In contrast, there is no statistically significant response for practices that involve material or equipment modifications. We also find that the visibility of the practices to consumers does not incrementally contribute to the effect of TQEM on practice adoption. Lastly, we demonstrate that these effects are not driven by secular trends that favour some types of pollution prevention activity, but that these effects are subject to diminishing returns and inertia. To ensure that disaggregation plays no role in artificially establishing a positive relationship between TQEM and pollution prevention, we aggregate the number of pollution prevention practices to the firm level and employ the same estimation procedure on the aggregated data. We find that the positive and statistically significant effect of TQEM on the count of pollution prevention practices persists.

A few other studies have focused specifically on the relationship between TQEM and innovation. Curkovic *et al.* (2000) find that firms with advanced TQM systems also have more advanced environmentally responsible manufacturing practices. Khanna *et al.* (2009) investigate the linkage between the aggregate count of pollution prevention techniques adopted and a number of factors, including TQEM. Unlike that study, this article focuses on the effect of TQEM on the adoption of pollution prevention of different types using a more disaggregated and longer data series and controlling for unobserved firm heterogeneity.

II. Framework

Hypotheses and empirical model

The belief that pollution is a defect and an indicator of waste in production provides a rationale for firms that adopt TQEM to integrate environmental considerations in product and process design by focusing on reducing pollution at source rather than at end of pipe. TQEM emphasizes continuous improvement in waste prevention and enhancing customer satisfaction. It seeks to achieve these goals largely through the use of cross functional teams of employees to undertake projects to identify and develop pollution prevention practices that also improve and simplify work practices (in addition to the use of other TQM tools described earlier). This decentralized approach to decision-making enables high level of employee involvement, communication and information sharing, and aims to achieve quality improvements while lowering costs (Hackman and Wageman, 1995; Wruck and Jensen, 1998). Thus firms that practise TQEM are more likely to be able to identify opportunities for waste reduction and select cost-effective pollution prevention practices, and we expect them to adopt more such practices compared to non-TQEM firms.

We also posit pollution prevention practices differ in the degree to which their adoption is facilitated by TQEM on the basis of their functional or technical attributes and whether they are visible to consumers. We partition the practices on the basis of their function into four categories depending on whether they are likely to involve changes in operating procedures of employees (*Procedures*), require physical modifications to equipment (*Equipment*), require changes in raw materials (*Materials*), or involve other customized changes (*Customized*). Among these, we expect that TQEM firms experience a larger increase in the adoption rate of pollution prevention practices that require procedural changes or are customized (relative to the increases of practices involving equipment or material modifications), for reasons that we explain in the next paragraph. Firms that adopt TQEM are also likely to make efforts to identify environmentally friendly product modifications that customers' value, a possibility that we investigate by testing whether TQEM adoption is associated with a disproportionately large increase of practices which are visible to *Consumers*.

Procedural changes require specific and detailed knowledge about work processes that is likely to reside with employees on the factory floor rather than with upper management. Customized practices are those that do not belong to standard activity codes with descriptive practice titles or that are individually tailored to a firm's production operations and organizational structure. Because TQEM emphasizes cross-functional teamwork,

decentralized decision-making and better flow of information among employees, it is more likely to promote 'grass-roots' efforts at waste reduction through changes in a firm's operating routines and procedures. Similarly, TQEM emphasis on cross-disciplinary employee involvement, increased information flow across departments and the use of innovation inducing tools (such as flow charts) are likely to result in the adoption of customized practices or practices that are specific to a firm's organizational structure. On the other hand, practices that involve changes in equipment and materials may be relatively easy to identify even by firms that are not practicing TQEM. Such modifications may be more process-specific rather than firm-specific and their benefits are more likely to be standard knowledge among firms. Their adoption may thus be less responsive to specific knowledge of a firm's employees or its management system.

The expected number of pollution prevention practices of type j adopted by firm i in year t , denoted as $P2_{ijt}$, depends not only on the technical attributes described above but also on other firm characteristics. We employ a number of different specification, but a base specification that can be used as a point of departure for the all the others is as follows:

$$E[P2_{ijt}] = \exp\{\alpha_0 + \alpha_j TQEM_{it} + \beta \log[TOTP2_{it-1}] + \gamma \log[CUMP2_{it-1}] + \delta \log[CHEM_{it}] + \theta \log[NUMFACS_{it}] + w_t + e_{ij}\}$$

where $\exp$ is the exponentiation function, $\log$ is the natural log, α_0 is the constant (baseline effect) and α_j is the treatment effect, which differs by practice type j and is given by $\alpha_j = \alpha + \alpha_e EQUIP_j + \alpha_m MAT_j + \alpha_p PROC_j + \alpha_c CONS_j$. All the remaining variables and parameters are defined as follows. The indicator variable $TQEM_{it}$ takes the value of 1 if firm i applied TQM to the environmental aspects of its production in year t . The effect of $TQEM_{it}$ on the adoption rate of pollution prevention practices of type j , α_j , is the parameter vector of primary interest in our study. These parameters relate to the characteristics of pollution prevention practices j through the linear expression defined above, where $EQUIP_j$, MAT_j and $PROC_j$ are mutually exclusive dummy variables that indicate whether practice j has *Equipment*, *Material* or *Procedural* attributes, with the customized attribute being the omitted category.⁵ $CONS_j$ is a dummy variable that indicates whether practice j is visible to the *Consumers* of the product. If $TQEM$ affects the adoption rate of all types of practices equally, then the parameters α_e through α_c would

all be zero and the effect of $TQEM$ on pollution prevention would not be systematically related to the composition of pollution prevention practices employed by firms. However, if the effect of $TQEM$ on pollution prevention practices is nonuniform, α_j s will differ (statistically significantly) from α and will vary across practices.

The variable $TOTP2_{it-1}$ is the total number of pollution prevention activities of all types adopted by firm i in the preceding year (hereafter also referred to as *Lagged Total P2*), and it proxies for slowly evolving (or transient) unobserved factors that affect the adoption of pollution prevention techniques. These would include effects of learning (arising from experience with all types of pollution prevention practices but which are expected to slowly decay), changes in managerial interest in pollution prevention (which is expected to slowly revert to some steady state), transient changes in firm expertise through staff turnover and others. We would expect the parameter β to be positive but less than 1, reflecting the nonpermanence of these factors. The variable $CUMP2_{it-1}$ is the cumulative number of pollution prevention techniques of any type adopted by firm i from 1991 until the end of year $t - 1$ (henceforth referred to in the text as *Cumulative P2*), and it reflects the possible presence of diminishing returns to pollution prevention: the more techniques have been introduced by a firm, the fewer remaining pollution prevention opportunities may be left to exploit. It may also measure cumulative permanent learning in which case its coefficient would be positive. For single facility firms, the variable $CHEM_{it}$ is the *Number of Chemicals* a firm uses in period t , while for multi-facility firms $CHEM_{it}$ aggregates this number over all facilities of that firm. This is a natural control variable, since the number of pollution prevention practices reported by each firm is the sum of practices adopted for each of the chemicals emitted by each facility of each firm. The bigger the *Number of Chemicals*, the greater is the scope for the adoption of pollution prevention techniques. The variable $NUMFACS_{it}$ is the *Number of Facilities* of firm i reporting in year t . This is a plausible control variable for two reasons: (i) a pollution prevention practice adopted by one facility of the firm might be easily transmitted to the other facilities of the firm that have similar production processes, and (ii) a firm that emits fewer chemicals per facility might be a bigger emitter of these chemicals, and thus find that their control is more worthwhile. Both the *Number of Chemicals* and the *Number of Facilities* exhibit meaningful variation over time. The natural log specification for these variables allows the model parameters to be interpreted as elasticities. Finally, w_t and e_{ij} are year and firm-cross-practice fixed effects, respectively.

⁵ There is one exception to the exclusive assignment of practices to functional attributes. Practice 60 explicitly involves a switch between materials and equipment and thus is classified under both. However, the results do not depend on the classification of this one practice to either of the two categories.

Estimation strategy

We now turn to the estimation of Equation 1. We make no assumptions on the distribution of $P2_{ijt}$ other than that each realization is conditionally independent of each other. Thus, we not only relax the Poisson assumption of equality of mean and variance, but we also relax the weaker assumption of proportionality of mean and variance. We also assume that all regressors are exogenous, i.e. independent of the equation disturbance term. Point estimates are obtained from the Poisson regression, which is the quasi-maximum-likelihood estimator, and standard errors are obtained from the Huber–White robust covariance matrix constructed from the regression residuals (see Wooldridge, 2002).⁶ With regards to asymptotics, we note that there is no incidental parameters problem for the Poisson regression (See Cameron and Trivedi, 1998, pp. 280–282). Thus, the parameter estimates other than the fixed effects themselves (which are nuisance parameters) are consistently estimated when the number of firms goes to infinity, holding the time horizon constant. In the alternative conditional fixed effects Poisson approach to estimating a model with firm effects, the fixed effects are conditioned on the sum of the event counts within the panel and then concentrated out of the likelihood. This approach relies on the fact that observations across units are independent and yields identical point estimates and standard errors to a regression in which the fixed effects are estimated.⁷

Estimation of the model specification given in Equation 1 is complicated by a number of factors. First, *Cumulative P2* and *Lagged Total P2* are zero in 2.63% and 8.5% of the observations, respectively. To prevent the loss of any observations, we add 1 to these two variables prior to taking the log, a rather small change in the transformation given the scale of the variables. For robustness, we have also re-estimated the model using these two variables in levels rather than in logs, though in this latter specification the model parameters can no longer be interpreted as elasticities. The results, which we do not report, are qualitatively similar.

Second, the parameter vector α_j is interpreted structurally. That is, we posit that if a firm were to adopt TQEM, its effect on the rate of adoption of pollution prevention activities would be given by α_j . It is possible that the estimated values of α_j differ from the true structural effect of TQEM due to endogeneity of $TQEM_{it}$, i.e. due to

correlation between $TQEM_{it}$ and the equation disturbance term. Given the presence of firm and year fixed effects, and the inclusion of *Lagged Total P2* as an independent variable, such correlation must be with the idiosyncratic disturbance terms for the year of TQEM adoption and the years thereafter. In other words, such endogeneity cannot arise from some omitted permanent firm characteristic, but can arise from some characteristic that changes during our sample period and is correlated with the implementation of TQEM. For example, consider a ‘green’ manager who arrives at the firm, ramps up pollution prevention innovation and independently also adopts TQEM. The manager’s arrival is a shock that is positively correlated with the adoption of TQEM. Under this example, the estimates of α_j will be upwardly biased estimates of the true structural parameters. We posit that the likelihood such endogeneity leads to substantial bias is remote, an assumption made by the bulk of the panel data literature using short panels with fixed effects.

Third, while our focus is the identification of within-firm differential effects of TQEM on the adoption of $P2$, we also control for the effects of other factors. Ideally, we would adopt a purely treatment effects count data model which includes an exhaustive set of firm-cross-practice fixed-effects, controlling for the propensity of firms to adopt each practice. However, identification of the firm-cross-practice fixed effects e_{ij} is not possible as the typical firm has not adopted most of the practices over our 5-year period (and has adopted some practices only once). Therefore, we assume that e_{ij} has the additive structure, $e_{ij} = u_i + v_j$, which prevents the loss of any observations (and the information they contain) and also eliminates any possible concerns about censoring, albeit by imposing a parametric assumption. The firm dummies account for unobserved firm-specific characteristics such as technological knowledge or inherent propensity of the firm to adopt pollution prevention activities, while the practice dummies control for the differential baseline adoption rates of these practices.⁸ Finally, we control for secular changes in adoption rates through year fixed effects, w_t , which in some specifications are interacted with the attributes to control for attribute specific trends, and also include *Cumulative P2* and *Lagged P2* in the set of regressors. In estimating all equations, one element from each of the three fixed effects, w_t , u_i and v_j , is dropped to preclude collinearity with the constant.

⁶ Implementation is through STATA, using the cluster option in the GLM Poisson command. The robust standard errors are similar to those obtained under the assumption that the variance of $P2$ is proportional to its mean, using the (normalized) Pearson residuals. Maximum-likelihood Poisson standard errors are smaller by a factor of 2.

⁷ Liang and Zeger (1986) and Zeger *et al.* (1988) suggest an alternative random effects type approach, but it requires assumptions about the correlation structure. We have also considered the zero-inflated Poisson process as a robustness check. This approach is more efficient if the number of zeros is larger than expected, but it imposes the Poisson assumption on the number of events, when those exceed zero. In other words, it sacrifices robustness for the benefit of higher efficiency if the model is correctly specified. However, this model failed to converge, likely due to the large number of incidental parameters in a short panel.

⁸ We do not include attribute fixed effects since they are subsumed by our inclusion of practice fixed effects.

III. Data Description and Variable Construction

Sample and data description

The sample consists of S&P 500 firms which responded to the IRRC survey on the adoption of corporate environmental management practices and whose facilities reported to the TRI over the period 1992 to 1996. The IRRC surveys firms annually about their environmental management practices, one of which is the application of TQM principles to environmental management. 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. Reporting of all pollution prevention activities adopted in a year to reduce the TRI chemicals became mandatory in 1991 following the National Pollution Prevention Act of 1990. Each facility of a firm is required to report the adoption of any of 43 different pollution prevention activities for each toxic chemical mandated in the TRI in a given year (see Table 1 for a list).

To match the facility level TRI data with the parent company level IRRC information on TQEM adoption, we constructed unique parent company identifiers for each facility in the TRI database.⁹ We dropped chemicals which have been added or deleted over the period 1991 to 1996 due to changes in the EPA reporting requirements. This ensures that the change in *P2* activities in our sample over time is not due to differences in the chemicals that were required to be reported. Since not all S&P 500 firms that report to the TRI responded to the IRRC survey, observations with missing data were deleted. There are 561 firms in the S&P 500 for at least one year during our sample period (this number exceeds 500 because the set of firms in the S&P 500 changes as some firms grow and other shrink). Of these 561 firms, 168 are in the sample, yielding a 5-year unbalanced panel of 168 parent

companies for a total of 34 400 observations. The remaining 393 firms are not in the sample because of missing data or because they reported zero pollution prevention counts for all years.¹⁰ Of these, 221 firms had no TRI emissions data but had EMS data from IRRC, 13 firms had no EMS data but had TRI data, 86 had neither TRI or EMS data, 60 had both EMS and TRI data but no pollution prevention data and 13 had TRI, EMS and pollution prevention data, but reported zero pollution prevention activities on every year in our sample.¹¹ It is worth emphasizing that all findings in this article pertain to firms with a high enough level of toxic emissions to mandate reporting to the TRI, and which also reported their pollution prevention activities. Even though these are the firms of highest interest, that is, those where TQEM could have a substantial impact on pollution prevention, it is not the universe of polluting firms.

Of the 168 firms in our sample, 86 firms had adopted TQEM by the start of our sample period and 35 firms adopted it during our sample period. The remaining 47 firms had not adopted TQEM by the end of our sample period. Since the decision to adopt TQEM is not likely to be made year to year and even if a firm were to de-adopt TQEM, the culture and organizational practices are likely to persist, we assume that there is no de-adoption of TQEM during our sample period. This allows us to ‘fill-in’ missing values for *TQEM* for 15% of the sample and affects an additional 4% of the observations for which transient ‘de-adoption’ of TQEM was reported.¹² The coefficients of interactions between *TQEM* and *P2* attributes are identified not only by the change in adoption patterns by the 35 new TQEM adopters but also by comparison of the 86 existing TQEM adopters with the 47 TQEM nonadopters. We employ a robustness check to test the validity of applying the *TQEM* coefficient to all firms.

Variable construction

Our dependent variable is the count of new pollution prevention techniques of each of the 43 specific activities adopted by a firm during a year as reported by each facility

⁹ To match the facilities with their parent companies, the Dun and Bradstreet number is used, in addition to facility name, location and SIC code.

¹⁰ Given our estimation strategy, firms with zero pollution prevention counts are automatically dropped, as the value of the corresponding fixed effect is not identified. They do not contribute any information pertinent to the estimation of the parameters of interest.

¹¹ To check for any possible systematic biases from nonresponse to the IRRC, we compared the 17 firms which responded to the TRI, but which do not report to the IRRC. For these firms, we do not know their environmental management practices, but we do have financial, emissions and pollution prevention information. The firms that did make into our sample are larger (using various measures of size) by a factor of 2 or 3 than the firms that did not. However, on measures that are scale-free (Tobin's *q*, Return on Assets, Return on Investment, Book Value, Debt over Asset ratios and Price–Earnings ratios), the two sets of firms are comparable.

¹² In particular, we assume that if the firm did not report to the IRRC survey in a particular year, but reported to the IRRC and employed TQEM in the immediately preceding and succeeding years, then that firm also employed TQEM in the year with missing data. In addition, if the firm states that it has not adopted TQEM at the first time it responded to the IRRC survey, then we assume that it had not adopted TQEM in any prior year. For the few observations that a 0 is preceded and followed by 1 for *TQEM*, we convert the 0 to 1 for the reasons stated above. Moreover, we assumed that the firm would not fail to report a change in status. Thus, if a missing value is preceded by 0 and followed by 1, then it was converted to 0. In practice, no missing values were converted to 1.

Table 1. Types of pollution prevention, their attributes, and the mean and SDs of their adoption rates

Pollution prevention activities and codes	Consumers	Equipment	Material	Procedural	Customized attributes	Remarks	Mean (SD)
13 Improved maintenance scheduling, record keeping or procedures				x		This activity involves changes in procedures for basic upkeep and for documentation of activities	2.685 (5.584)
14 Changed production schedule to minimize equipment and feedstock changeovers				x		Similar to activity 13, for procedural changes associated with planning of operating activities	0.876 (2.949)
19 Other changes made in operating practices				x		Similar to activities 13 and 14	3.115 (6.356)
21 Instituted procedures to ensure that materials do not stay in inventory beyond shelf life				x		It is a procedural change as it involves modifications in the cataloguing and accounting of stocks and materials	0.560 (1.872)
22 Began to test outdated material – continue to use if still effective				x		Similar to activity 21	0.168 (1.066)
23 Eliminated shelf life requirements for stable materials					x	This activity involves improvement of management of inputs and materials. It may or may not be a procedural change so it is classified as a customized activity	0.012 (0.111)
24 Instituted better labelling procedures				x		This improves procedures for the classification of supplies	0.131 (0.748)
25 Instituted clearing house to exchange materials that would otherwise be discarded					x	Similar to activity 23. This seems to be a firm-specific organizational change	0.131 (0.648)
29 Other changes made in inventory control					x	EPA descriptor for this activity is nonspecific (the activity title is not descriptive). Moreover, characterization of these activities should be the same as that of activities 23 and 25	0.568 (2.146)
31 Improved storage or stacking procedures				x		This activity involves changing the procedures for arranging materials (and possibly equipment)	0.314 (1.244)
32 Improved procedures for loading, unloading and transfer operations				x		Similar to activity 31, except it is a procedural change for transporting materials and equipment	0.595 (1.734)
33 Installed overflow alarms or automatic shut-off valves		x				This is clearly an equipment modification for avoiding leaks and spills	0.170 (0.803)
35 Installed vapour recovery systems		x				This is an equipment modification	0.286 (1.106)
36 Implemented inspection or monitoring programme of potential spill or leak sources				x		This is a procedural change	1.530 (5.406)
39 Other changes made in spill and leak prevention					x	EPA descriptor for this activity is nonspecific (the activity title is not descriptive)	1.114 (3.407)

(continued)

Table 1. Continued

Pollution prevention activities and codes	Consumers	Equipment	Material	Procedural	Customized attributes	Remarks	Mean (SD)
41 Increased purity of raw materials			x			This activity involves a physical change in materials and inputs	0.149 (0.616)
42 Substituted raw materials	x		x			Similar to activity 41	2.029 (3.947)
49 Other raw material modifications made			x			Similar to activities 41 and 42	0.681 (2.791)
51 Instituted re-circulation within a process		x				This activity involves installation of new equipment	0.677 (1.986)
52 Modified equipment, layout or piping		x				It involves physical equipment changes	2.216 (4.766)
53 Used a different process catalyst			x			The use of a new catalyst is a change in materials used	0.086 (0.405)
54 Instituted better controls on operating bulk containers to minimize discarding of empty containers				x		This is a procedural activity that needs to be done regularly as part of periodic checks in operations	0.286 (1.215)
55 Changed from small volume containers to bulk containers to minimize discarding of empty containers		x				These involve physical changes	0.262 (1.200)
58 Other process modifications made					x	EPA descriptor for this activity is nonspecific (the activity title is not descriptive)	2.730 (6.141)
59 Modified stripping/cleaning equipment		x				Similar to activity type 52	0.185 (0.813)
60 Changed to mechanical stripping/cleaning devices (from solvents or other materials)		x	x			Because this activity involves a shift from material inputs to the use of physical equipment, it is characterized by both equipment and material modifications. It is the only one that belongs to two functional categories simultaneously	0.062 (0.376)
61 Changed to aqueous cleaners (from solvents or other materials)			x			This is a change in materials	0.764 (2.206)
63 Modified containment procedures for cleaning units				x		This is a procedural change	0.055 (0.323)
64 Improved draining procedures				x		Similar to activity 63	0.065 (0.355)
65 Redesigned parts racks to reduce drag out		x				This is a physical equipment change	0.024 (0.182)
66 Modified or installed rinse systems		x				Similar to activity 64	0.026 (0.189)
67 Improved rinse equipment design		x				Similar to activities 65 and 66	0.061 (0.447)
68 Improved rinse equipment operation				x		Similar to activities 63 and 64	0.105 (0.809)
71 Other cleaning and degreasing modifications made					x	EPA descriptor for this activity is nonspecific (the activity title is not descriptive)	0.456 (1.248)

(continued)

Table 1. Continued

Pollution prevention activities and codes	Consumers	Equipment	Material	Procedural	Customized attributes	Remarks	Mean (SD)
72 Modified spray systems or equipment		x				Similar to activities 65, 66 and 67	0.314 (1.450)
73 Substituted coating materials used			x			This involves a physical change in materials	0.700 (2.029)
74 Improved application techniques				x		This may only be a procedural change since the physical changes are covered by activity 72 and activity 73	0.455 (2.762)
75 Changed from spray to other system		x				Similar to activity 72	0.052 (0.449)
78 Other surface preparation and finishing modifications made					x	EPA descriptor for this activity is nonspecific (the activity title is not descriptive)	0.100 (0.472)
81 Changed product specifications	x				x	This activity is visible to consumers, but it is unclear whether any changes in physical equipment or materials would be needed, or if they did, what they would be	0.367 (1.363)
82 Modified design or composition of product	x		x			This is also visible to consumers, but may or may not involve equipment modification. However, change in composition implies changes in materials	0.460 (1.554)
83 Modified packaging	x		x			Packaging is definitely visible to consumers and usually involves physical change in material	0.019 (0.183)
89 Other product modifications made	x				x	EPA descriptor for this activity is nonspecific (the activity title is not descriptive). However, these product modifications would definitely be visible to consumers	0.355 (1.539)

Notes: The SD of counts is given in parentheses below the mean count. See text for sources and details on the construction of this table.

to the EPA.¹³ We aggregated the number of pollution prevention practices adopted in a year across chemicals for each facility and then across all facilities belonging to a parent company to obtain *P2* at the firm level for that year. We construct *Cumulative P2* as the cumulative number of pollution prevention techniques of all types

that have been adopted between 1991 (when firms first began reporting this information to the TRI) and year $t - 1$. We also constructed the total count of all types of pollution prevention activities undertaken in the previous year and labelled this as *Lagged Total P2*. The variable *Number of Chemicals* is obtained by summing up the

¹³ We verified if facilities do indeed report new pollution prevention activities by examining the annually reported counts by each facility belonging to S&P 500 firms and reporting to TRI, for each chemical for the period 1992 to 1996, and compared it with their reports for the preceding year. We calculated the number of facilities for which the reported pollution prevention counts were nondecreasing for all chemicals. This was the case for only 236 facilities (5.68% of all facilities) and represents only 0.67% of the chemical–facility pairs (these facilities have a lower than average chemical count). Therefore, even if there was any misinterpretation of the survey question, it impacted a tiny fraction of the data.

number of chemicals reported by each facility over all facilities of that firm in a particular year.¹⁴ The variable *Number of Facilities* is the count of all the facilities of each firm, by year.

To assign attributes for the *P2s*, the authors developed a list of possible attributes of these practices. In addition to the five attributes described above, the original expanded list included others such as visibility to stakeholders and regulators, practices requiring decision-making at the upper versus lower managerial levels, technological sophistication, practices that will alter the production process and potential for cost-savings. Using our independent characterizations and the characterizations of three other experts in the field of business and environmental strategy, we found that some attributes were very closely related to each other (for example, practices that were visible to consumers were also likely to be visible to other stakeholders), while for some attributes our confidence in assigning them to practices based on information available in the TRI was not high. We therefore narrowed the list to the attributes described in Table 1 by dropping those for which agreement in assigning them to the pollution prevention practices was not high and merging together those with high correlations with each other. This final classification was arrived at through discussion among the authors.

The practices that were classified as requiring *Equipment* modifications include changes in container design, cleaning devices, rinse and spray equipment and overflow alarm systems. Practices requiring *Material* modifications involve substitutions of raw materials, new solvents, coating materials or process catalysts. Practices, such as improved maintenance scheduling, improved storage and stacking procedures, better labelling procedures, which involve changes in the way that operations are organized and managed, are classified as *Procedural* modifications. Practices that do not belong in any of the EPA's defined practice types with descriptive titles form the fourth category denoted as *Customized* practices. This category is expected to include practices that do not belong to standard pollution prevention approaches and are individually tailored to a firm's production operations. For example, in the EPA-defined practice group Process Modifications, practices, such as 'instituting a re-circulation system' or 'modifying layout or piping' and 'changing the process catalyst', correspond to standard approaches to reduce pollution while practices included in 'other process modifications' are custom-designed or otherwise unusual. Such practices are likely to be specifically developed or adapted to the operations of the

adopting firm. A very few practices with descriptive titles are by their nature tailored to a firm's organizational structure (e.g. instituting a clearing house to exchange materials that would otherwise have been discarded), and these practices are also assigned to the *Customized* category.

We also characterized practices according to their visibility to consumers. Practices that involve changing raw materials or the specifications or composition of the product and affect its functionality, appearance or disposal after use could be considered visible to *Consumers*. Firms may include such information in product labels or advertisements to make consumers aware of the environmental friendliness of that product. Such practices can allow firms to appeal to environmentally conscious consumers and charge price premiums or increase market share. The highest correlation between the *Consumers* attribute and one of the functional attributes is 0.45, and is the correlation between *Consumers* and *Materials*.

The summary statistics in Table 1 show that highest adoption rates for both adopters and nonadopters of TQEM are for 'maintenance scheduling and record-keeping procedures' (practice 13), 'modification of equipment, lay-out or piping' (practice 52), 'substitution of raw materials' (practice 42) and practices that fall under miscellaneous or other activity codes. In Table 2, we summarize the adoption rates of pollution prevention activities according to whether they possess a particular attribute. As shown there, the most widely undertaken activities for both adopters and nonadopters are those which require *Procedural* changes, followed by *Equipment* modifications. For most pollution prevention categories, the rate of adoption is higher among TQEM firms than among firms that are nonadopters of TQEM.

IV. Results

We estimate a number of models that explain the count of each of the 43 different pollution prevention activities practices undertaken by firms. The firm and practice dummies are always jointly significant in all models; in what follows we discuss the other parameters. The values presented in the tables with regard to the functional or technical attributes are the effects of TQEM on the adoption of *P2* that has that particular attribute, i.e. for every *P2* that has functional attribute k , (k refers to *Equipment*, *Materials*, *Procedural* and *Customized*), we report $\alpha + \alpha_k$, where α and α_k are the regression coefficients from the Poisson model. Similarly, the reported standard

¹⁴ Chemicals emitted by more than one facility are counted multiple times. For example, if a firm has two facilities, one emitting chemicals A, B and C, while the second emitting chemicals B and D, the *Number of Chemicals* for that firm is 5. We do this because a pollution prevention activity applied to, say, chemical B for each of the two plants would be counted by the EPA as two distinct pollution prevention activities.

Table 2. Firm level descriptive statistics

Explanatory variables	All firms	TQEM nonadopters	TQEM adopters	
			All TQEM adopters	New TQEM adopters
Different types of pollution prevention according to attributes				
Material	0.14 (0.34)	0.13 (0.34)	0.14 (0.34)	0.13 (0.33)
Equipment	0.20 (0.40)	0.20 (0.40)	0.20 (0.40)	0.18 (0.38)
Procedural	0.24 (0.43)	0.22 (0.42)	0.25 (0.44)	0.25 (0.43)
Other customized functional attributes	0.065 (0.25)	0.04 (0.20)	0.079 (0.27)	0.075 (0.26)
Consumers	0.073 (0.261)	0.071 (0.26)	0.075 (0.26)	0.069 (0.25)
All types of <i>P2</i>	0.60 (2.57)	0.46 (1.85)	0.69 (2.91)	0.79 (3.32)
Other explanatory variables				
<i>Total Cumulative P2</i>	94.73 (160.34)	57.74 (75.56)	116.46 (190.19)	93.50 (147.28)
<i>Total Lagged P2</i>	29.20 (45.94)	21.98 (34.37)	33.44 (51.06)	36.81 (65.43)
<i>Number of Chemicals</i>	75.69 (107.55)	55.71 (71.79)	87.42 (122.32)	93.50 (147.28)
<i>Number of Facilities</i>	16.82 (19.34)	16.36 (18.88)	17.09 (19.60)	20.14 (27.00)
Number of observations	34 400	12 728	21 672	4515

Notes: See text for sources. New TQEM adopters are the firms that have adopted TQEM within our sample period; the reported values correspond to their activity level following adoption. The values for all TQEM adopters reflect the observations of the firm that have adopted TQEM from the start of our sample and the post-adoption observations of the new TQEM adopters.

errors in all tables are those of the sum, i.e. we report $se(\alpha + \alpha_k)$ and take into account the covariance between α and α_k . Note that for *Customized*, the omitted category, this effect is measured by α . The value reported for *Consumers* is simply the coefficient of *Consumers*, i.e. the incremental effect of the *Consumers* attribute over and beyond the impact of any of the functional characteristics. The values reported for the rest of the variables are the regression coefficients of the Poisson regression.

Table 3 presents the six models that form our primary results. Model I is our base model which corresponds to the specification described in Section II, except that it omits the *Number of Facilities* variable. Model II uses the one year lag value of *Number of Chemicals* rather than the current value of this variable, motivated by the possibility that the *Number of Chemicals* variable might potentially be endogenous: firms that do unusually high P2 in a particular year might also reduce the number of

chemicals they emit in that year. Model III excludes the number of chemicals and yields coefficients that are very similar to those of Model I. Models IV and V provide robustness checks for the specifications of Models I, II and III. Finally, Model VI, which corresponds exactly to the specification described in Section II, investigates any adoption spillovers in multi-facility firms, and whether accounting for these affects our results. We have also estimated variants of these (and other specifications) in which we use the level rather than the log of the independent variables, with generally a poorer fit. In these variants, variables of interest maintain their signs and significance, and therefore, we do not report or further discuss these results for brevity.

The first three models (Models I, II and III) show that TQEM adopters have higher adoption rates for pollution prevention practices that involve *Procedural* changes or are *Customized*, but not for those that

Table 3. Main results

Variables, effects of TQEM	Model I	Model II	Model III	Model IV	Model V	Model VI
TQEM on equipment	−0.117 (0.106)	−0.285* (0.157)	−0.116 (0.106)		−0.117 (0.106)	−0.125 (0.106)
TQEM on material	0.050 (0.128)	−0.020 (0.180)	0.050 (0.128)		0.077 (0.102)	0.042 (0.128)
TQEM on physical				−0.055 (0.095)		
TQEM on procedural	0.202** (0.091)	0.071 (0.142)	0.202** (0.091)	0.202** (0.090)	0.202** (0.091)	0.194** (0.090)
TQEM on customized	0.438*** (0.103)	0.388** (0.157)	0.438*** (0.103)	0.427*** (0.102)	0.444*** (0.102)	0.430*** (0.103)
TQEM on consumers	0.051 (0.121)	0.133 (0.152)	0.051 (0.121)	0.138 (0.100)		0.051 (0.121)
log(Lagged Total P2)	0.645*** (0.102)	0.402*** (0.107)	0.679*** (0.101)	0.645*** (0.102)	0.645*** (0.102)	0.638*** (0.102)
log(Cumulative Total P2)	−0.704*** (0.248)	−0.429 (0.356)	−0.721*** (0.250)	−0.704*** (0.248)	−0.704*** (0.248)	−0.712*** (0.249)
log(Current Num. of Chemicals)	0.696*** (0.158)			0.696*** (0.158)	0.696*** (0.158)	0.424** (0.214)
log(Current Num. of Facilities)						0.542** (0.244)
log(Lagged Num. of Chemicals)		0.182 (0.205)				
Year 2	0.403** (0.175)	−0.032 (0.311)	0.407** (0.177)	0.403** (0.175)	0.403** (0.175)	0.397** (0.176)
Year 3	0.588** (0.267)	0.029 (0.179)	0.584** (0.270)	0.588** (0.267)	0.588** (0.267)	0.568** (0.268)
Year 4	0.668** (0.336)	0.030 (0.095)	0.688** (0.339)	0.668** (0.336)	0.668** (0.336)	0.659* (0.337)
Year 5	0.743* (0.386)		0.755* (0.390)	0.743* (0.386)	0.743* (0.386)	0.737* (0.388)
Tests of significance						
Firm dummies (χ^2)	275.23***	7071.81***	289.87***	275.28***	275.24***	5248.82***
P2 dummies (χ^2)	5244.79***	4169.86***	5246.21***	5262.37***	5246.96***	275.23***

Notes: Standard errors are heteroscedasticity robust and clustered on firm-year pairs, and reported in parentheses: *** significant at 1%, ** significant at 5% and * significant at 10%. Log is the natural log. All models also contain a constant, the value of which is not meaningful given the inclusion of fixed effects, and is suppressed. The χ^2 statistics are for the test of joint significance of the firm and P2 dummies. The number of observations is 34 400 except for Model II, which has 26 445 observations.

involve *Equipment* or *Material* modifications (with the exception of Model II which uses lagged *Number of Chemicals* as a regressor). These results suggest (or, alternatively, corroborate the notion) that TQEM enables firms to identify specific areas that require changes in operational practices and procedures that might be missed by other firms, possibly because the latter do not benefit from the expertise and knowledge sharing among various ‘grass-roots’ employees. This explanation is particular apt for explaining the strong

positive effect of TQEM on the adoption of practices in the *Customized* category. These practices may comprise the less typical types of source reduction methods not classified by the regulator and, instead, may be composed of activities that firms develop themselves to address firm-specific operations and environmental goals. The bottom-up nature of TQEM could be responsible for the identification and implementation of such customized pollution prevention practices. However, TQEM may not have a similar positive

effect on pollution prevention activities that require *Equipment* or *Material* modifications, which are ‘off-the-shelf’ solutions, often relying on products of third-party vendors. These models also show that the *Consumer* visibility characteristic of pollution prevention practices by itself does not have a statistically significant incremental effect on the count of practices adopted by TQEM adopters as compared to TQEM nonadopters.

In addition to the attributes of pollution prevention practices, we find that *Lagged Total P2* is associated with higher levels of *P2*, while the count of *Cumulative P2* adopted has a negative effect on incremental adoption rates. The first finding likely arises from the presence of slowly evolving unobserved factors (notice that we do not assign a causal interpretation to this variable). These could include complementary knowledge and expertise available to a firm, short-term learning and management attitudes. The second finding suggests diminishing returns to the adoption of pollution prevention activities, possibly because of reduced opportunities to develop and undertake new pollution prevention practices when the number of environmental innovations already adopted is high: a firm that has already reaped the ‘low hanging fruit’ will find it more difficult to identify additional worthwhile pollution prevention practices. We also find evidence of secular trends in technical change, as evidenced by the positive and significant signs of the year dummies in Models I and III, after controlling for past levels of *P2*.

Model I shows that the *Number of Chemicals*, i.e. the number of opportunities to undertake pollution prevention activities, increases the count of *P2s* adopted. Model II, which uses the lagged values of chemicals, tends to yield similar but smaller parameter estimates for most coefficients than those which use the current values. The coefficient on the lagged number of number of chemicals is not statistically significant, indicating that this variable is not a good control for the exposure of firms to more opportunities for pollution prevention adoption. Moreover, excluding the number of chemicals variable altogether (Model III) has only a tiny effect on the parameter estimates. These findings together suggest that endogeneity concerns are not quantitatively important, and that using the current values of the *Number of Chemicals* is more appropriate. Finally, using the lagged number of chemicals results in a loss of 23% of our sample and some loss in

precision. We henceforth report results that use the current value of chemicals.¹⁵

In Models IV and V, we investigate the robustness and internal consistency of our findings using two specification variants. First, we conduct a robustness check of our classification strategy and consider the effect of combining the physical attribute categories *Equipment* modifications and *Material* modifications into a single *Physical* modifications category (Model IV). The results show that TQEM firms are not more likely to adopt pollution prevention practices that involve physical modifications. However, *Procedural* changes and practices that have *Customized* attributes continue to be the pollution prevention practices disproportionately adopted by TQEM firms. We conduct a second robustness check of our classification strategy by dropping *Consumers* from the regressions in order to see if our conclusions with regard to *Procedural* modifications remain valid (Model V). This variation yields results that are essentially indistinguishable from those of Model I.

Finally, Model VI augments Model I by adding the *Number of Facilities* as an independent variable. An increase in the number of facilities is positively associated with the pollution prevention count, even when controlling for the aggregated number of chemicals emitted by the firm’s facilities. An explanation for this is that firms with an expanding number of facilities (recall, the associated parameter is identified from variation of the number of facilities over time) can easily port a pollution prevention practice to its other facilities. A shrinking firm does not have that advantage. An alternative interpretation is that firms that emit fewer chemicals per facility are more intensive emitters of those chemicals and thus more likely to adopt pollution prevention to reduce their emissions. The TQEM effects are only very marginally affected by the inclusion of this variable. The only coefficient that is materially affected is the *Number of Chemicals*, which is reduced but still significant. It is noteworthy that the sum of the coefficients of *Number of Chemicals* and *Number of Facilities* is very close to unity (0.966), implying that the doubling of a firm by replicating its existing facilities leads to a doubling of the firm’s expected count of adopted pollution prevention techniques. This provides support for the second of the two explanations discussed above and also some additional validation of our framework.¹⁶

¹⁵ A complete set of results using lagged number of chemicals is available upon request. Our conclusions do not depend on whether the current or lagged values are used, though standard errors are higher with lagged values.

¹⁶ There is another technical issue with regards to the changing number of facilities operated by a firm. Any such change, due either to a merger or a large change in firm size, would formally invalidate the use of fixed effects and may cause biases in the TQEM coefficient and its interactions. We have identified 36 firms (almost one-fifth of our sample) that experienced a change in the number of facilities by more than 2 during our period. Since the average number of facilities operated by a firm is 14, a change of 2 or fewer facilities during the 5-year period of our sample can be considered as nonsalient. We re-estimated our main specification, Model I, excluding this set of 36 firms and we find that parameter estimates are similar for the two samples (results are available upon request).

Table 4 reports a number of robustness checks. Model VII is a variation of Model VI, in which the *Number of Chemicals* variable is dropped. Not surprisingly, the coefficient of the *Number of Facilities* increases, and is now not statistically different from unity. It is also, in fact, larger than the coefficient of *Number of Chemicals* when the latter is the only proxy for the scope of firm's

potential pollution prevention activities. Nonetheless, all parameters of interest are unaffected. The remaining robustness checks are addressing temporal issues. Model VIII excludes the lag structure (*Lagged Total P2* and *Cumulative P2*) from Model I and yields similar coefficients. However, exclusion of these lagged variables make the time dummies negative and significant which indicates

Table 4. Robustness checks

	Model VII	Model VIII	Model IX	Model X	Model XI	Model XII
Variables, effects of TQEM	Facilities instead of chemicals	No dynamics	No dynamics; physical P2	Attribute* year dummies	New TQEM* attribute	New TQEM* attribute; physical P2
TQEM on equipment	-0.128 (0.106)	-0.073 (0.108)		-0.089 (0.108)	-0.030 (0.140)	
TQEM on material	0.038 (0.128)	0.094 (0.131)		0.038 (0.130)	-0.021 (0.150)	
TQEM on physical			0.011 (0.098)			-0.070 (0.128)
TQEM on procedural	0.190** (0.090)	0.246*** (0.094)	0.246*** (0.094)	0.190** (0.092)	0.231* (0.129)	0.191 (0.128)
TQEM on customized	0.426*** (0.103)	0.481*** (0.106)	0.471*** (0.105)	0.450*** (0.105)	0.449*** (0.120)	0.407*** (0.120)
TQEM on consumers	0.051 (0.121)	0.051 (0.122)	0.138 (0.100)	0.05 (0.125)	0.035 (0.126)	0.047 (0.107)
New TQEM on equipment, (incr. effect for new adopters)					-0.385*** (0.133)	
New TQEM on material, (incr. effect for new adopters)					0.277 (0.186)	
New TQEM on physical, (incr. effect for new adopters)						-0.090 (0.120)
New TQEM on procedural, (incr. effect for new adopters)					0.154 (0.106)	0.154 (0.106)
log(<i>Lagged Total P2</i>)	0.647*** (0.102)			0.646*** (0.102)	0.645*** (0.102)	0.645*** (0.102)
log(<i>Cumulative Total P2</i>)	-0.721*** (0.250)			-0.704*** (0.248)	-0.704*** (0.248)	-0.704*** (0.249)
log(<i>Current Num. of Chemicals</i>)		0.870*** (0.159)	0.870*** (0.159)	0.697*** (0.158)	0.696*** (0.158)	0.696*** (0.158)
log(<i>Current Num. of Facilities</i>)	0.820*** (0.182)					
Year 2	0.394** (0.177)	-0.116** (0.053)	-0.116** (0.053)	0.271 (0.200)	0.403** (0.175)	0.403** (0.176)
Year 3	0.554** (0.271)	-0.227*** (0.056)	-0.227*** (0.056)	0.511* (0.283)	0.588** (0.267)	0.589** (0.268)
Year 4	0.661* (0.339)	-0.406*** (0.059)	-0.406*** (0.059)	0.561 (0.353)	0.668** (0.336)	0.668** (0.337)

(continued)

Table 4. Continued

	Model VII	Model VIII	Model IX	Model X	Model XI	Model XII
Variables, effects of TQEM	Facilities instead of chemicals	No dynamics	No dynamics; physical <i>P2</i>	Attribute* year dummies	New TQEM* attribute	New TQEM* attribute; physical <i>P2</i>
Year 5	0.738* (0.390)	−0.539*** (0.060)	−0.539*** (0.060)	0.690* (0.403)	0.743* (0.386)	0.743* (0.387)
Tests of significance						
<i>Year dummy*Attribute</i> (χ^2)				9.690		
Firm dummies (χ^2)	5250.51***	1873.41***	1874.33***	275.15***	275.72***	274.80***
<i>P2</i> dummies (χ^2)	280.57***	5215.95***	5233.42***	5181.82***	5282.84***	5283.41***

Notes: The *Year dummy*Attribute* parameter estimates (Model VIII) are not reported for brevity. Standard errors are heteroscedasticity robust and clustered on firm-year pairs, and reported in parentheses: *** Significant at 1%, ** significant at 5% and * significant at 10%. Log is the natural log. All models also contain a constant, the value of which is not meaningful given the inclusion of fixed effects, and is suppressed. The χ^2 statistics are for the test of joint significance of the firm and *P2* dummies, and the joint significance of the year dummy cross attribute indicator variables. The number of observations is 34 400 for all models.

that, in this model, diminishing returns are captured by the time dummies. The next robustness check, Model IX, is a variant of Model VIII and combines *Equipment* and *Materials* into *Physical* and yields similar results. The next three robustness checks, Models X, XI and XII are motivated by the possible concern that our findings are driven by a temporal correlation between TQEM adoption and secular trends in the popularity of pollution prevention practices with particular attributes. Suppose that procedure-based and customized modifications were becoming popular over time for reasons unrelated to TQEM adoption. Then, these trends would result in a spurious positive coefficient of the interaction terms between TQEM and these two practice attributes, given that the propensity to adopt TQEM also increases over time. To investigate if indeed there are time-specific factors that may favour the adoption of some pollution prevention activities over others, we added to Model I interactions between each attribute with each year dummy for a total of 16 interaction terms as explanatory variables (Model X). We find that the joint test statistic for all *Year dummy*Attributes* interactions is not significant and the magnitude and significance of the coefficients of TQEM and its interactions with each attribute are similar to those in Model I.

To test the validity of applying the TQEM coefficient α to all adopters even though it is identified only from firms that changed TQEM status during our sample period ('recent or new adopters'), we check whether these firms differ significantly from firms that had adopted TQEM prior to the start of our sample ('early or old adopters') in the pattern of pollution prevention practices they employ (i.e. whether the effect of TQEM on the mix of practices varies across the two types of firms). We construct a *New TQEM* dummy variable that takes the

value of 1 on the year a firm adopted TQEM and thereafter, and 0 before it adopted TQEM. Firms that never adopted or had adopted TQEM before the start of our sample (early adopters) are also given a value of 0. Note that we include in the regression only the interactions of *New TQEM* with each of the attributes; inclusion of *New TQEM* itself would lead to collinearity with the TQEM variable given the firm fixed effects. These interactions yield the incremental effect of TQEM adoption for new adopters (for practices of each attribute), relative to its effect on old adopters. Note that the effect for customized practices cannot differ across the two types of firms since the difference is not identified. We find that there is no systematic difference in the effect of TQEM between early and recent adopters, except for a negative difference for the adoption of *Equipment* practices. When *Equipment* and *Materials* are combined into one attribute (Model XII), this difference disappears. The signs and significance of all other variables are similar to those in Model I. Therefore, we conclude that our identification approach is reasonable.

The analysis so far has presumed that the effect of TQEM on the rate of adoption of pollution prevention techniques is positive, but differs along the various types of techniques. The pattern of variation was intended to provide support for the notion that TQEM is indeed the driver of the increase in the adoption rates, based on the manner through which TQEM is expected to impact a firm's operations. Though some prior literature has investigated the effect of TQEM on pollution prevention, as discussed in the introduction, we have not yet corroborated these findings in our own data set. One might argue that this is not necessary, since in our disaggregated analysis, the effects of TQEM are either positive and

significant or close to zero (equipment modifications have a negative effect, but it is not large and almost never significant). However, because the 43 practice types are not equally prevalent, it is theoretically possible (though unlikely) that TQEM has a positive effect when evaluated at a disaggregated level, but a negative effect when evaluated at the aggregate level. To ensure that this is not case, we summed up the count of pollution prevention practices of all types to the firm level, yielding a sample of 800 observations. We then re-estimated most of the models of Table 3 at this aggregate level to estimate the effect of TQEM on the firm-level adoption rate of pollution prevention practices of any type (some of the disaggregated models estimated in Table 3 collapse to the same model when we aggregate at the firm level, and these duplicate models are not reported). We complemented these models with a ‘bare bones’ model with no covariates. In all other respects, the estimation proceeds in the same manner as the specifications discussed earlier. The results are reported in Table 5. The effect of TQEM on the adoption rate of pollution prevention practices ranges, for the most part, from around 17% to over 22%. This figure is,

reassuringly, within the range that one would expect by an examination of our disaggregated results.

V. Further Discussion and Concluding Remarks

Organizational structure plays a large role in determining the number and nature of innovative activities that firms undertake. The impact of a management structure such as TQEM on different pollution prevention activities is not uniform because some practices are more complementary to the philosophy of quality management than others or more easily identified and designed given the tools embodied in TQEM. Our analysis shows that TQEM is conducive to the greater adoption of pollution prevention practices that involve procedural changes or customized modifications (or are specific to the organizational structure of the firm), but not to the adoption of other practices. This variation in the adoption rates of practices of various attributes in response to TQEM is useful for better

Table 5. Firm level aggregate analysis

Variables	Model 0	Model I-F	Model II-F	Model III-F	Model VI-F
TQEM	0.223** (0.091)	0.173** (0.069)	0.073 (0.088)	0.173** (0.070)	0.165** (0.067)
log(Lagged Total P2)		0.645*** (0.085)	0.402*** (0.090)	0.679*** (0.084)	0.638*** (0.085)
log(Lagged Cumulative P2)		-0.704*** (0.176)	-0.429*** (0.166)	-0.721*** (0.185)	-0.712*** (0.178)
log(Current Num. of Chemicals)		0.696*** (0.125)			0.424** (0.175)
log(Current Num. of Facilities)					0.542*** (0.200)
log(Lagged Num. of Chemicals)			0.182 (0.149)		
Year 2	-0.131*** (0.040)	0.403*** (0.123)	-0.033 (0.162)	0.407*** (0.128)	0.397*** (0.124)
Year 3	-0.260*** (0.043)	0.588*** (0.190)	0.029 (0.096)	0.584*** (0.199)	0.568*** (0.194)
Year 4	-0.419*** (0.048)	0.668*** (0.247)	0.029 (0.051)	0.688*** (0.257)	0.659*** (0.251)
Year 5	-0.571*** (0.053)	0.743*** (0.283)		0.755** (0.294)	0.737*** (0.285)
Firm dummies (χ^2 test stat.)	1 200 000***	44 425.38***	10 153.34***	34 183.44***	38 898.35***

Notes: Standard errors are heteroscedasticity robust and clustered on firm-year pairs, and reported in parentheses: *** Significant at 1%, ** significant at 5% and * significant at 10%. Log is the natural log. All models also contain a constant, the value of which is not meaningful given the inclusion of fixed effects, and is suppressed. The χ^2 statistics are for the test of joint significance of the firm dummies. The number of observations is 800 except for Model II-F, which has 615 observations.

understanding how TQEM works in practice, and possibly for inferring the motivations for TQEM adoption and the type of outcomes that TQEM is designed as an instrument to achieve. Alternatively, this variation pattern can be viewed as increasing our confidence that the empirical regularity that TQEM increases pollution prevention is indeed driven by the adoption of TQEM, since it is the variation pattern that is expected on the basis of how this management system operates in practice. Finally, the fact that TQEM adoption does not yield a disproportionate increase in pollution prevention activities that are visible to consumers suggests that it is not driven primarily by market-driven considerations.

Our findings provide insight on the extent to which policy-makers can rely upon corporate environmental management for inducing voluntary pollution prevention. To the extent that some types of practices such as those requiring changes in equipment or materials are considered necessary to improve environmental quality, policy-makers may need to rely on mandatory regulations rather than on promoting the adoption of TQEM by firms. Moreover, the current profile of pollution prevention activities of different types that a firm is adopting can be used to infer which firms are likely to experience a bigger effect from TQEM adoption, permitting the targeting of efforts to promote TQEM adoption to firms with a given mix of operations. Finally, our analysis suggests the presence of diminishing returns to pollution prevention. While there exist some 'low hanging fruit', further adoption of pollution prevention practices is likely to be increasingly costly and diminish over time in the absence of any regulatory stimulus.

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