GREEN MANAGEMENT AND THE NATURE OF TECHNICAL INNOVATION

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Abstract

The types and nature of a firm's innovative activities are influenced by a firm's organizational structure. We develop an empirical framework to examine the effect of Total Quality Environmental Management (TQEM) on the adoption of 43 types of innovative pollution prevention activities over the period 1992-1996, and to determine whether it differs systematically across innovation types. We differentiate innovations according to (i) their functional characteristics: whether they involve procedural changes, equipment modifications, material modifications or other unclassified/customized changes; (ii) their visibility to consumers and, (iii) their ability to enhance efficiency. We find that the effect of TQEM on pollution prevention is non-uniform and stronger for the adoption of practices that involve procedural changes or have unclassified/customized attributes. We also find that the visibility to consumers or efficiency enhancement does not incrementally contribute to the effect of TQEM on the adoption of pollution prevention practices. These findings are robust to controlling for the timing of TQEM adoption and any type-specific trends in pollution prevention activities. Because the pollution prevention activities most strongly affected by TQEM are generally more prevalent in the petroleum refining and chemical manufacturing, these sectors experience the largest impact from the adoption of TQEM on pollution prevention innovation.

Key words: pollution prevention, TQEM, technical innovation, organizational structure
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1. INTRODUCTION

Innovation is a key component of a firm's strategy to improve market competitiveness and operational efficiency as well as to respond effectively to changing consumer preferences and regulations. Innovations differ in the extent to which they involve changes in products, processes or practices and lead to gains in efficiency or brand image. We postulate that the extent and nature of innovation undertaken by a firm depends on its management system which influences the firm's organizational structure, the extent of employee involvement in decision making and the internal communication channels for information sharing. The management system, therefore, has an impact on the incentives and ability to improve a firm's technology. We develop an empirical framework to examine how the effect of a management system differs across different types of innovations and draw implications from the nature of this differential impact on the channels through which a management system affects a firm's operations. Our framework can also be used to evaluate the effect of adoption of the management system on firms with different pre-adoption innovation profiles.

We apply this framework to investigate the effect of total quality management (TQM), one of the single most influential managerial systems developed in the last twenty five years, on technical innovations that reduce the generation of pollution. TQM is an integrated management philosophy that 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). 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, has led firms to apply the systems-based approach of TQM to the management of their environmental impacts. This is referred to as Total Quality

Environmental Management (TQEM).[1] It involves changing the organizational culture of the firm and using quality management tools to encourage prevention of pollution upstream (at source) as a way to increase efficiency rather than controlling pollution after it is generated (DiPeso, 2000; Klassen and MaLaughlin, 1993). Pollution can be reduced at source through a variety of different practices. We examine the types of pollution prevention activities that are more responsive to TQEM systems, and the implications of such differential response on the channels through which TQEM in particular influences innovation and technology adoption.

We use a very detailed dataset that catalogues the rate of technical innovation in pollution prevention to reduce toxic releases by a sample of S&P 500 firms over the five year period 1992-1996. This dataset is a particularly well suited one to demonstrate our approach for a number of reasons. First, it forms a rich five year panel of pollution prevention innovations that firms have undertaken in 43 different categories. Second, a number of firms have chosen to apply TQM for environmental management during this period. Third, the description of adopted pollution prevention practices is very detailed and allows us to classify them on the basis of their functional characteristics, their potential for improving production efficiency and possibly yielding auxiliary cost benefits, and their visibility to consumers. In particular, we partition the practices according to four mutually exclusive functional characteristics: whether the practice requires physical change in equipment, a change in materials usage, a change in operating procedures, or other modifications. This last category includes practices that the firms have been unable to assign to one of the established types of pollution prevention categories as defined by the EPA. Some of these unclassified/customized practices are likely to be newly innovated practices that modify the firm's operations and, therefore, cannot be classified generically. In

[1] The Global Environmental Management Initiative is recognized as the creator of *TQEM* which embodies four key principles: customer identification, continuous improvement, doing the job right first time, and a systems approach

addition to this multinomial classification of practices on the basis of their functional characteristics, we also include binary attributes that reflect the presence of efficiency gains and visibility to consumers.

The waste prevention-oriented philosophy of TQEM suggests an inherent complementarity between TQEM systems and pollution prevention. One would expect the adoption of all types of pollution prevention practices to be higher among TQEM firms than among otherwise identical firms that are not practicing TQEM. However, the TQEM tools used for identifying and evaluating opportunities for waste reduction and the measures for assessing performance may be more conducive to the adoption of some types of practices than others. We use count models to examine how the effect of TQEM adoption differs across practices of different types and to what extent any such differences may lead the pollution prevention activities of some industries to be more sensitive to TQEM than those of other industries. In addition to the role of organizational structure and practice attributes, our analysis recognizes 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/effectiveness of those 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 associated with incremental adoption, and other unobserved slowly evolving factors.[2]

In particular, our analysis can be summarized as follows. We first define a set of binary variables that take the value of 1 if the pollution prevention activity possesses a particular attribute and 0 otherwise. We use their interaction with TQEM to investigate whether the effect

(http://www.bsdglobal.com/tools/ systems_tqem.asp).

of TQEM on pollution prevention is non-uniform, and if so, which types of activities (attributes) are associated with stronger TQEM effects. Firm fixed effects and a number of suitable controls to capture some effects discussed above are also included in the analysis. Our base estimates are complemented with a number of internal consistency checks that test the validity of our framework and some alternative explanations for the pattern of observed pollution prevention activities. Finally, we combine our estimates of the effect of TQEM on the pollution prevention activities of different types with the systematic differences in the prevalence of these activity types across industries to ascertain the degree to which TQEM impacts the rate of pollution prevention innovation differentially across industries.

Several studies have shown that organizational characteristics are important determinants of innovation by firms (see reviews by Hage, 1999; Damanpour, 1991; Sciulli, 1998). A survey of the vast literature on quality management and its key practices suggests that TQEM has many pro-innovation attributes, such as its emphasis on continuous improvement through the application of scientific information and a non-hierarchical organizational structure that enables the efficient creation and utilization of valuable specific knowledge at all levels of the organization (Sousa and Voss, 2002; Wruck and Jensen, 1998).[3] A few studies have focused specifically on the relationship between TQEM and innovation. Curkovic et al. (2000) use scaled responses on various aspects of total quality management systems and environmentally responsible manufacturing practices to construct measures of each and examine synergies between the two. They find that firms with advanced total quality management systems also have more advanced environmentally responsible manufacturing practices because the two concepts

[2] The resource based view of the firm suggests that heterogeneity in this expertise across firms lead to differences in the firm's ability to capture the profits associated with a new technology (see survey in Christmann, 2000).

share a similar focus, rely on similar tools and practices. Khanna et al. (2007) undertake a systematic empirical investigation of the linkage between an objectively measured aggregate count of pollution prevention techniques adopted and TQEM. They focus on explaining pollution prevention adoption rates as a function of the TQEM adoption decision, regulatory factors, and many other firm and industry characteristics that proxy for market pressures faced by firms and other relevant effects. Unlike that study, this paper analyzes the type (attributes) of pollution prevention activities adopted by firms and its variation across TQEM adopters and non-adopters using a more disaggregated and longer data series and employing fixed effects model to control for firm heterogeneity.[4]

Our findings demonstrate that the effect of TQEM on pollution prevention is non-uniform. TQEM supports the adoption of practices that involve procedural changes or that are customized or otherwise do not fall neatly into well established standard categories. In contrast, the adoption of practices that involve material or equipment modifications is not statistically significantly responsive to TQEM adoption. We also find that the visibility to consumers or efficiency enhancement attribute of the practice does not incrementally contribute to the effect of TQEM on the adoption of pollution prevention practices. The stimulus provided by TQEM to the adoption of such practices is essentially determined by their functional attributes. Lastly, we demonstrate that these effects are not driven by secular trends that favor one type of pollution prevention activity over another, but are subject to diminishing returns and inertia.

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[3] TQM is "science-based" because individuals at all levels of the organization are trained to use scientific method in everyday decision making. It is non-hierarchical in that it provides a process for allocating decision rights in ways that do not correspond to the traditional corporate hierarchy.

[4] Technology characteristics have been shown to be significant drivers for the adoption and diffusion of specific technologies in other areas. Innovations that are costly and require a considerable investment were found to diffuse at a slower rate in manufacturing industries (Romeo 1975, 1977, Stoneman and Karshenas, 1993). Similarly, Karlson (1986) found that new innovations that are expected to yield higher cost savings and improve profitability tend to be adopted faster in the steel industry. In the agriculture sector, new innovations that were less risky, less complex and expected to increase yield and quality were adopted much faster than other (Batz et al 1999; Adesina

We show the usefulness of our framework through simulations. In these simulations, we find that on the average, 16% of the count of pollution prevention activities adopted by firms can be attributed to the organizational structure inherent in TQEM. This effect is not uniform across firms but depends on their pollution prevention profile. In particular, firms in petroleum refining and chemical manufacturing industries are more strongly affected because their pollution prevention profile includes procedures and customized modifications.

The rest of the paper is organized as follows. Section 2 of the paper describes the conceptual framework while Section 3 describes our empirical implementation of this framework. Data is described in Sections 4, and we present and discuss our results in Section 5, followed by the conclusions in Section 6.

2. CONCEPTUAL FRAMEWORK

The TQEM philosophy has three strategic goals: (i) continuous improvement in quality, (ii) defect (waste) prevention while enhancing value added activities and (iii) meeting or exceeding customer requirements. To achieve these goals, quality management requires management commitment, long range planning, and close relationships with customers that allow anticipation of customer needs sometimes even before customers are aware of them. At the operational level, TQEM involves the adoption of certain management "tools" or processes. In TQEM firms, cross functional teams undertake research projects to develop or identify pollution prevention practices, managers do benchmarking visits to other organizations to learn about alternative ways of performing the work, and front-line employees are expected to search continuously for improved and simplified work practices (Hackman and Wageman, 1995). By allocating decision-making authority to problem-solving teams, enabling a high level of

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and Baidu-Forson 1995, Adesina and Zinnah 1993).

employee involvement in quality improvement, facilitating better communication and information sharing among all hierarchical levels in the organization and offering employee training and team-based rewards, Total Quality Management enables the efficient creation and utilization of valuable firm-specific knowledge at all levels of the organization. These system based changes are driven by identified consumer needs and aim to achieve quality improvements while lowering costs (Cole, 1998).

Growing concerns for environmental quality from consumers, the public, and regulators has led firms to expand their notion of product quality and apply TQEM to reduce the environmental impact of their production systems and products. This together with the belief that efficiency can be enhanced by minimizing pollution provides a rationale for firms to proactively integrate environmental considerations in product and process design.[5] The upstream prevention focus of TQM, together with the view that pollution is a defect and an indicator of waste in production, creates an explicit focus on source-reduction of pollution as opposed to end-of-pipe control (Curkovic et al. 2000). Case studies indicate that quality management tools such as affinity diagrams, Pareto analysis, cause-and-effect diagrams and cost of quality analysis help the teams responsible for environmental management to focus on the causes of their difficult environmental problems (PCEQ, 1993).[6] Moreover, TQM performance measures tend to be function- or task-specific, thus allowing isolation of the contribution of particular activities to performance. This helps employees understand what actions they can take to improve overall

[5] Studies examining the relationship between TQM and innovative approaches to environmentally conscious manufacturing find that TQM goals and methods align well with those of environmental management and promote environmental excellence (Klassen and McLaughlin, 1993).

[6] Pareto analysis is used to identify the major factors that contribute to a problem and to distinguish the vital few from the trivial many causes. Cost of quality analysis is used to highlight the cost-savings that can be achieved by doing the work right the first time (Hackman and Wageman, 1995). See Ploch and Wlodarczyk (2000) and relevant references therein for an illustration of the successful application of these and related tools.

performance (Wruck et al.).[7] This suggests that firms that adopt TQEM are more likely to be able to identify opportunities for waste reduction and select cost-effective pollution prevention practices. Indications of an inherent complementarity between the concepts of pollution prevention and TQEM can be found in case studies and surveys of firms which indicate that TQEM adopters are indeed more likely to adopt pollution prevention practices (Florida, 1996; Atlas, 1997; Klassen and McLaughlin, 1993; see survey in Curkovic et al., 2000).[8]

Pollution can be prevented using a variety of different practices that differ in their characteristics and in the degree to which their adoption is amenable to TQEM. The list of pollution prevention practices used in our analysis is included in Table 1. We distinguish three key characteristics of these practices. The first is functional or technical attributes, the second is whether they yield auxiliary efficiency-enhancing or cost saving benefits and the third is whether they are visible to consumers. The functional characteristic involves the partitioning of practices into four groups depending on whether they are likely to require physical modifications to

[7] For example, employees under quality management are likely to readily understand how their actions affect cycle time or how they can reduce waste or scrap rates. The case Polaroid's application of TQEM through their Environmental Accounting and Reporting System (EARS) is a good example. The EARS allows the tracking of all 1400 materials at the chemical level at several stages (the input stage, end of process line before abatement, during abatement, and after abatement). It promotes accountability of all employees for each unit of chemical and encourages employees to devise new equipment or processes to use inputs more effective. For example, through the EARS, Polaroid employees have identified substitutes for toxic materials and adopted aqueous based coating systems in place of solvent-based coating systems which led to a 10% reduction of toxic emissions. Polaroid employees also had the incentive to develop a devise to scrape reactor vessels of every unit of chemical, which would have gone untraced and unused had the EARS system not been in place. Furthermore, the EARS also encouraged communication across various specialized units and encouraged multi-faceted types of innovations. The chemical-level reporting and accountability allowed the manufacturing division to put pressure on the R&D division to develop less toxic chemicals that the manufacturing divisions would be willing to use. As a result, these chemical substitutions further required changes in the manufacturing process and in the design of products as well. In 1990, two years after its introduction, the EARS allowed Polaroid to successfully achieve a 20% reduction of toxic chemicals from 1988 levels through input substitution, process changes and more environmentally-sound products (Nash et al., 1992).

[8] A survey of U.S. manufacturing firms in 1995 by Florida (1996) found that 60% of respondents considered P2 to be very important to corporate performance and two-thirds of these had also adopted TQM. Of the 40% of firms that considered P2 to be only moderately important, only 25% had adopted TQM. A survey of U.S. manufacturing plants in 1998 found that among the P2 adopters, the percentage of firms practicing TQM was twice that for other plants (Florida, 2001). A survey of Japanese manufacturing firms found that plants adopting a green design were more likely to be involved in TQM than other plants (Florida and Jenkins, 1996).

equipment; changes in raw materials; changes in operating procedures for employees; or involve other hard to categorize/multiple changes. Practices 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 labeling procedures, which involve changes in the way that operations are organized and managed, are classified as *Procedural* modifications. Practices that are hard to categorize because they do not belong in any of the EPA's well defined practice categories form the fourth group, henceforth denoted as *Unclassified/Customized* practices; this forms the omitted category in the econometric analysis.

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 (Hackman and Wageman, 1995; Wruck and Jensen, 2000). TQEM emphasizes cross-functional teamwork, allocation of decision-making authorities to employees and improved flow of information among employees; it is therefore more likely to promote "grass-roots" efforts at waste reduction using the full spectrum of information and expertise to bear on decisions about system wide problems. On the other hand, practices that involve technical 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/training of a firm's employees or a firm's management system. We, therefore, test whether TQEM firms experience a larger increase in the adoption rate of pollution prevention practices that require procedural changes as compared to the adoption rate of practices that require physical or material modifications. In other words, we test whether practices with *Equipment* or *Material* modifications attribute get a smaller boost from TQEM systems as compared to those with a *Procedural* modification.

The fourth *Unclassified/Customized* attribute is assigned to practices whose definitions in the dataset do not provide enough information to allow us to discern their attributes. This category includes some practices that do not belong to standard categories or approaches of preventing pollution and are individually tailored to a firm's production operations. For example, in the category Process Modifications, practices such as, 'instituting a re-circulation system' or 'modifying layout or piping' and 'changing the process catalyst', may be standard approaches to reduce pollution while practices included in 'other process modifications' may be those that are custom-designed and hence cannot be easily labeled. Such practices are likely to be based on in-depth understanding of the source of the problem to be fixed. We, therefore, expect that firms that adopt TQEM, and thus have a high level of cross-disciplinary employee involvement, a system for facilitating flow of information across departments and the tools needed to generate innovative ideas, are likely to adopt customized practices.

In addition to these technical considerations, the adoption of a practice may be influenced by attributes that affect the economic benefits from its adoption. One such attribute of a practice is its visibility to *Consumers*. A second such attribute is the ability of that practice to lead to improvements in production efficiency, reduction in costs and savings in time and resource use, enabling firms to gain a competitive advantage. We consider such practices to be production *Efficiency* enhancing.

Practices that involve changing the raw materials used 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. Firms that adopt TQEM are likely have closer relationships with customers and the tools (such as, life-cycle analysis to evaluate the environmental impacts of alternative product specifications) to identify the environmentally-friendly product modifications that customers' value. We, therefore, test whether TQEM adopters adopt more practices which are visible to *Consumers*. If this is the case, the results would reveal the extent to which TQEM is being implemented to increase the appeal of a firm's products to environmentally conscious consumers.

Pollution prevention practices that could enhance production-efficiency and provide cost-savings include improved recordkeeping, inventory control, installation of overflow alarms or automatic shut-off valves and better inspection, and monitoring and labeling procedures. Wruck et al. (1998) find that although TQEM is grounded in a concern for product quality, it reaches beyond these issues to emphasize efficiency throughout the organization on issues that may have little or no direct relation to product quality, such as equipment maintenance. We, therefore, test whether the count of practices which are *Efficiency* enhancing is higher in TQEM firms. Empirical evidence of this would provide support for the contention that "lean and green" go hand in hand as firms seek to become more productive by pursuing strategies that enhance business and environmental performance (Florida, 1996). This would suggest that TQEM adopters consider pollution prevention as part of the broader corporate effort to improve quality and implement leaner management systems.

While the focus of this work is the identification of within-firm differential effects of

TQEM on the adoption of pollution prevention practices, we also control for the effects of other factors on adoption rates. Ideally, we would adopt a purely treatment effects count data model which would include an exhaustive set of firm-cross-practice fixed-effects which would control for the baseline propensity of firms to adopt a particular pollution prevention practice. We depart from this ideal estimation strategy in that we use firm-fixed-effects and practice-fixed-effects. Including an exhaustive set of firm-cross-practice fixed effects is not feasible for our data as most firms have zero adoption rates for most practices. Instead, we use firm dummies to account for unobserved firm-specific characteristics such as technological knowledge and capacity or inherent propensity of the firm to undertake pollution prevention activities, and we use pollution-prevention dummies to control for the differential baseline adoption rates of these practices. Finally, we control for secular changes in adoption rates through year fixed effects, which in some specifications are interacted with the attributes to control for attribute specific trends, and also include some potentially important time varying firm specific factors that are relevant for the adoption of pollution prevention techniques.

3. ECONOMETRIC FRAMEWORK

3.1. Specification and Estimation

We consider a general framework that relates the count of adoption of pollution prevention practices with the presence of TQEM and the level of other time varying firm characteristics. The expected number of pollution prevention practices of type *j* adopted by firm *i* in year *t*, denoted as $P2_{ijt}$, is given by

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

where the variables and the parameters are defined as follows.[9] 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.[10] 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 in the text 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 (which arise from experience with all types of pollution prevention practices but which are expected to decay over time), changes in managerial interest in pollution prevention (which is expected to revert to some steady state over time), transient changes in firm expertise through staff turnover, and other factors. We would expect the parameter β to be positive but smaller than 1, reflecting the non-permanence of the above factors. The variable $CUMP2_{it-1}$ is the cumulative number of pollution prevention techniques of any type adopted by firm *i* from 1991 until before the start of year *t* (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 in case it would tend to vary positively with *P2* adoption counts. For single facility firms, the variable $CHEM_{it}$ is the *Number of Chemicals* a firm uses in period *t*, while for

[9] The description of the source data and the construction of the variables are deferred to the next section.

[10] We do not include attribute fixed effects because these would not be identified given our inclusion of practice fixed effects. Moreover, if we had included attribute fixed effects instead of practice fixed effects, the coefficients would not have been interpretable because they are not independent of artificial aggregation or subdivision of P2 categories. In contrast, the interactions of attributes times TQEM are identified because they reflect percentage changes from the baseline.

multi-facility firms $CHEM_{it}$ aggregates this number over all facilities of that firm. The 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.

The primary parameters of interest, α_j, are assumed to relate to characteristics of pollution prevention practices *j* through the linear equation

$$\alpha_j = \alpha + \alpha_e EQUIP_j + \alpha_m MAT_j + \alpha_p PROC_j + \alpha_f EFF_j + \alpha_c CONS_j \tag{2}$$

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 unclassified/customized attribute being the omitted category as described in the previous section. EFF_j is a dummy variable that indicates whether practice *j* is *Efficiency* enhancing, while $CONS_j$ 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 not uniform for reasons discussed in the conceptual framework, then the α_j's will be statistically significantly different from α and they will vary across practices. Since the functional attributes are mutually exclusive, the adoption of TQEM on the adoption of these practices would therefore depend on which of the four functional attributes characterize the particular practice and whether the practice is visible to consumers and/or is efficiency-enhancing.

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 independent variables are exogenous, i.e., independent of the equation disturbance term. Our estimation and inference follow the Quasi-Maximum Likelihood (QML) estimation approach: while point estimates are obtained from Poisson regression which is the QML estimator (see Wooldridge 1997 and references therein), standard errors are obtained from the Huber-White robust covariance matrix constructed from the regression residuals.[11]

Estimation of the model specification given in equation (1) is complicated by a number of factors. First, though *Number of Chemicals* is always positive, *Cumulative P2* and *Lagged Total P2* are occasionally zero (albeit rarely: *Cumulative P2* is zero in 2.63% of the sample, while *Lagged Total P2* is zero in only 8.5% of the sample). 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. Second, 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 only adopted some of the remaining 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.

[11] Implementation is through STATA 8 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. However, Maximum Likelihood Poisson standard errors are smaller than either of the above by a factor of 2, consistent with the presence of substantial over-dispersion in the P2 count.

The parameter vector α_j is interpreted structurally. That is, we posit that if a firm were to adopt TQEM, the effect on the rate of adoption of pollution prevention activities would be given by the values of the parameters α_j. It is possible that the estimated values of α_j could differ from the true structural effect of TQEM due to endogeneity of $TQEM_{it}$, i.e. if $TQEM_{it}$ is correlated with 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 period of TQEM adoption and the periods thereafter, but not the periods before TQEM adoption. 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 and ramps up both the pollution prevention innovation and adopts TQEM. If the manager stays for the remainder duration of our sample, then his arrival is a permanent 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. One approach to address the possibility of endogeneity due to time varying factors that are correlated with TQEM adoption and P2 adoption would be to have time varying instruments. In a cross-section setting one can use variables that explain the incidence of TQEM adoption across different types of firms (such as a predicted probability of TQEM adoption estimated using first stage models, as in Khanna et al. (2007)), but in a time-series analysis one needs instruments that are correlated with the systematic component of the timing of TQEM adoption decision. These instruments need to vary meaningfully and substantially over time and not simply due to random fluctuations. In the absence of such an instrument (since an instrument such as a predicted probability of TQEM adoption from a first stage regression would vary only slightly over time) we cannot directly eliminate the possibility of such endogeneity. However, we emphasize that its source cannot arise from the correlation of permanent firm characteristics with the application of TQEM (given the incorporation of firm fixed effects) or the correlation of economy wide shocks with the application of TQEM (given the incorporation of year fixed effects) or the presence of slow build-up of firm level factors that simultaneously lead to increases in pollution prevention innovation and to the application of TQEM (given the incorporation of *Lagged Total P2* in the regression). We thus posit that the likelihood that such endogeneity would lead to substantial bias is remote, an assumption made by the bulk of the panel data literature using short panels with fixed effects.

3.2. Counterfactual Simulation and Policy Analysis

In this section we describe our use of the model to quantify the impact of delaying the adoption TQEM for each firm who adopted TQEM for the first-time within our sample period. Let τ denote the year in which the firm has adopted TQEM for the first time i.e., the year that *TQEM* takes the value of 1 for that firm following a zero for that same firm. For these firms the simulated counterfactual number of pollution prevention practices of type *j* would be the actual value of $P2_{ij\tau}$ in year τ multiplied by the percent change due to TQEM de-adoption predicted by our model. Or simply:

$$P2^{S}_{ij\tau} = P2^{A}_{ij\tau}\left\{\exp\left(-\left(\alpha + \alpha_e EQUIP_j + \alpha_m MAT_j + \alpha_p PROC_j + \alpha_f EFF_j + \alpha_c CONS_j\right)\right)TQEM_{i\tau}\right\} \quad (3)$$

where $P2^{S}_{ij\tau}$ is the projected level and $P2^{A}_{ij\tau}$ is the actual baseline level for firm *i*'s type *j* pollution prevention activities at year τ. We aggregate the predicted *P2* count at the firm level to obtain $P2_{i\tau}^{S}$. The percent contribution of *TQEM* adoption on a firm's actual count of *P2* practices is measured by $(P2_{i\tau}^{A} - P2_{i\tau}^{S}) / P2_{i\tau}^{A}$. Note that this simulation is looking only at the first year effects of *TQEM* adoption because in subsequent years the P2 count is also affected by dynamic factors such as *Cumulative P2* and *Lagged Total P2*. Given that firms have different "baseline" rates of employing each of these pollution prevention types, and given that *TQEM* turns out to have a differential impact on the adoption rate of different types of pollution prevention practices, the *TQEM* treatment effect varies by firm even when measured in percentage terms. We then group firms on the basis of SIC codes to investigate if the percentage effects of *TQEM* on pollution prevention counts varies systematically across industries.

4. DATA DESCRIPTION AND VARIABLE CONSTRUCTION

The sample in this study consists of S&P 500 firms which responded to the Investor Research Responsibility Center (IRRC) survey on the adoption of corporate environmental management practices and whose facilities reported to the Toxics Release Inventory (TRI) over the period 1992-96. The IRRC surveys firms annually about their environmental management practices, one of which is the application of total quality management 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.[12] Chemicals which have been added or deleted over the period 1991-1996 were dropped due to changes in the reporting requirements by the USEPA. This ensures that the change in pollution prevention activities in our sample over time is not due to differences in the chemicals that were required to be reported. Since all S&P 500 companies that reported to the TRI did not respond to the survey by the IRRC, observations with missing data were deleted. Our final sample consists of a five year unbalanced panel of 160 parent companies for a total of 34,400 observations. Of these 160 firms, 66 firms had adopted TQEM by the start of our sample period and 35 firms adopted it during our sample period. The remaining 59 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.[13] 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.

Our dependent variable is the count of new pollution prevention techniques of each of

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

[13] This has two implications for our data. To avoid dropping the observations for which *TQEM* adoption data was not available for some years, we assume that if the firm did not report to the IRRC survey in a particular year, but reported to the IRRC and adopted *TQEM* in the immediately preceding and succeeding years, then that the firm also adopted in that year with missing data and filled in the blank year with "1". In addition, if the first time a firm responds to the IRRC survey it states that it has not adopted *TQEM* we assume that it has never adopted in the past and we fill in earlier years with missing data to be "0". For the (fewer) observations that have a zero preceded and followed by a 1 for *TQEM*, we convert the zero to a 1 for the reasons stated above.

these 43 specific activities adopted by a firm during a year. We call this variable *P2*. It is derived from information mandatorily reported by each facility to the USEPA on the source reduction activities newly implemented by it for each chemical in that reporting year.[14] We aggregated the number of P2 such 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 (from all categories) of pollution prevention activities undertaken in the previous year and labeled this as *Lagged Total P2*. 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 greater scope for the adoption of such practices.

[14] We verified if facilities do indeed report new P2 activities. We look at the USEPA Form R which is used to collect data for P2. Section 8.10 of Form R allows for 4 new source reduction activities, and 3 methods used to identify the activity (internal auditing, external auditing, government assistance, industry assistance). Section 8.10 specifically asks "Did your facility engage in any source reduction activities for this chemical during the reporting year?" The instructions/guide for filling out Form R specifies that Section 8.10 "must be completed only if a source reduction activity was newly implemented specifically (in whole or in part) for the reported EPCRA section 313 chemical during the reporting year." (EPA, 2004) We verified if firms do indeed report only new source reduction activities by examining the annually reported P2 counts by each facility belonging to S&P 500 firms and reporting to TRI, for each chemical for the period 1992-1996 and compared it with their reports for the previous period (1991-1995). We then derived the change in the reported *New P2* count for a total of 74,780 instances at the chemical-facility level. If firms were inadvertently reporting all P2 activities adopted instead of New P2 activities, we would expect that the annual count of P2 reported would be increasing or stay constant over time for all years. Our investigation focused at the facility level on the premise that any misinterpretation of the instructions in the TRI would be at the facility rather than chemical level. In particular, we have calculated the number of facilities for which the reported P2 counts were non-decreasing for all chemicals. We found that this was the case for only 236 facilities (5.68% of all 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.

To develop the attributes for the *P2s*, the authors started with brainstorming and developed a list of all 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 vs. lower managerial levels, technological sophistication, and practices that will alter the production process. The characterization of the *P2s* according to different attributes was done by each of the authors separately. Characterizations of *P2s* by three other experts in the field of business and environmental strategy were also solicited. We then looked at the correlations among the attributes and found that some 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 relatively low and merging together those with high correlations with each other.[15] This final classification was arrived at through discussion among the authors. Note that the *Unclassified*/*Customized* category is the omitted functional category (the category for which *Equipment*, *Procedural*, and *Materials* are all zero) (See Table 1).[16] Correlation between the

[15] Our initial set of attributes include (1) visibility to consumers, (2) visibility to shareholders, (3) visibility to regulator, (4) technological sophistication, (5) level of management decision involved, (6) frequency of activity, (7) time and cost savings, (8) production effects, and (9) final product functionality effects. Because the level of technological sophistication (4) is hard to determine, we instead used procedural changes as an attribute, i.e., whether it is involves changes in operations or procedures. These are distinguished from practices that involve physical changes in materials in equipment. We dropped visibility to shareholders and to regulators, as these are difficult to ascertain for each P2. We merged consumer visibility (1) and final product functionality effects (9) into one attribute. We also dropped the level of management decision-making involved in implementing each P2 (5) since this attributes is very difficult to determine. We also dropped production effects as these are not easily separable from the consumer visibility attribute

[16] We were able to provide a likely attribute to two of these practices based on the set of attributes that the rest of the pollution prevention activities in that same category possess. If all of pollution prevention activities in a category had a particular attribute, the "Other" pollution prevention activities were assigned the same attribute. For example, since all practices, 21, 22,23, 24 and 25, in the category Inventory Control, had the feature that they were efficiency

characteristics is low. Positive correlation of 0.42 is observed between *Procedural* and *Efficiency* attributes and of 0.35 between *Consumers* and *Materials* attributes.

The summary statistics in Table 1 show that highest adoption rates for both TQEM and non-adopters 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 categories (e.g., practice 19 and 58). Generally, the rate of adoption of P2 is higher among TQEM firms than among firms that are non-adopters of TQEM.[17] These practices also differ considerably in their attributes. In Table 2, we summarize adoption rates of pollution prevention activities according to whether they possess a particular attribute. As shown there, the most widely undertaken pollution prevention activities for both adopters and non-adopters are those which are *Efficiency* enhancing or require *Procedural* changes.

5. RESULTS

5.1. Estimation of Count Models

We estimate a number of models that explain the count of each of the 43 different pollution prevention activities practices undertaken by firms, Our results, discussed in detail below, show that in all models, the firm-specific dummies and the practice-specific dummies are

enhancing, we expect that practice 29 (Other changes made in inventory control) would also have that attribute and assign it a 1 for *Efficiency*. Due to lack of definitive information on the functional attributes of practices included in categories 23,25,29,39,54,58,71,78 and 89 we assign a value of "0" for all their functional attributes and include them in the *Unclassified/Customized* category. These include practices that may involve combinations of changes in equipment, material or procedures as well as practices that cannot be labeled generically because they involve modifications designed specifically for a firm.

[17] With the exception of elimination of shelf-life requirements for stable materials (practice 23), improved procedures for loading and unloading and transfer operations (32), institution of recirculation within a process (51), change from small to big bulk containers (55), and to a lesser extent, modification of spray systems or equipment (72), substitution of coating materials (73), change from spray to other techniques (75) and modification of packaging (83).

always jointly significant, indicating that there are indeed unobservable firm and practice-specific effects that need to be accounted for.

Table 3 presents our primary results, which consist of models I and II, and their variants. Model I examines the effects of only the functional attributes on the effects of *TQEM* on the adoption rates while Model II includes the full set of practice attributes. The base variant (Variant A) of these models includes no other controls except the *Number of Chemicals*, year fixed effects, firm fixed effects, and practice fixed effects, while Variant B includes *Lagged Total P2* and *Cumulative P2* as additional control variables in logs. We have also estimated variants of this and other specifications in which the latter two variables are in levels, with generally 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. All of the regressions show that TQEM adopters have higher adoption rates for pollution prevention practices that involve *Procedural* changes or are *Unclassified/Other*, but not for those that involve *Equipment* or *Material* modifications. This is supported by the positive statistically significant coefficients of *TQEM+TQEM*Procedural* (except Model II-B), the positive and statistically significant coefficient for *TQEM* (no interactions), and the statistically insignificant coefficients of *TQEM+TQEM*Equipment* and *TQEM+TQEM*Materials*.[18]

These results suggest that TQEM enables firms to identify specific areas that require changes in operational practices and procedures that might not be identified by non-adopters of TQEM, 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 *Unclassified/Other* 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. This further indicates that the bottom-up nature of TQEM stimulates the development of customized pollution prevention practices. However, *TQEM* may not have a similar positive effect on pollution prevention activities that require *Equipment* or *Material* modifications: the negative coefficients on *TQEM*Equipment* and *TQEM*Materials* offset the positive coefficient of *TQEM,* making the impact of *TQEM* on the adoption of practices with these attributes statistically insignificant. This suggests that identification and implementation of the equipment and material modifications needed to prevent pollution do not necessarily require an organizational structure such as TQEM.

Model II shows that the *Consumer* visibility and *Efficiency* enhancing characteristics of pollution prevention practices by themselves do not have a statistically significant incremental effect on the count of practices adopted by TQEM adopters as compared to TQEM non-adopters. The effect of *TQEM* on a practice with the *Consumer* or *Efficiency* attribute is determined by the functional characteristic of that practice. Given the discussion above, this effect will be positive and statistically significant for practices that have *Customized* or *Procedural* attributes, and not significant for other combinations of functional attributes with the *Consumer* and/or *Efficiency* attributes (joint test statistics are not shown).

In addition to the attributes of pollution prevention practices, we find that experience with pollution prevention activities in the past has two distinct effects on *P2* adoption. In particular, we find that while *Lagged Total P2* is associated with higher levels of *P2*, the count of *Cumulative P2* adopted has a negative effect on incremental adoption rates. The first finding

[18] Note that our standard errors are not the maximum likelihood Poisson standard errors that tend to be biased downwards due to over-dispersion in the data. Rather our reference is based on GLM standard errors that allow for

implies that adoption of more pollution prevention activities in the recent past (previous year) is associated with higher adoption counts in the current period, likely arising 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 in the past is high. In other words, a firm that has already reaped the "low hanging fruit" will find it more difficult to identify additional worthwhile pollution prevention practices.

All models also consistently show that the *Number of Chemicals,* the number of opportunities to undertake pollution prevention activities increases the count of *P2s* adopted. 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-B and II-B after controlling for the past adoption levels of pollution prevention activities (*Lagged Total P2* and *Cumulative P2*). However, the negative significant signs of the time dummies in models I-A and II-A indicate that, in those models, diminishing returns are being captured by the time dummies because the dynamic effects from past pollution prevention activities, both *Lagged Total P2* and *Cumulative P2*, are not accounted for.

We investigate the robustness and internal consistency of our findings using a number of specification variants. We first consider the effect of combining the physical attribute categories *Equipment* modifications and *Material* modifications into a single *Physical* modifications category. The results, reported in Table 4 Models III-A and III-B, show that firms do not develop

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arbitrary correlations between the disturbance terms for observations within a firm.

more physical modification *P2* techniques following their adoption of TQEM. However, *Procedural* changes and practices that have *Unclassified/Customized* attributes continue to be key attributes associated with higher adoption of pollution prevention practices by TQEM firms.

We conduct a second robustness of our classification strategy driven by the observation that most of the pollution prevention activities that are *Efficiency* enhancing also involve *Procedural* changes (see Table 1). In particular, we drop *Efficiency* from the regressions in order to see if our conclusions with regard to *Procedural* modifications remain valid (Models IV-A and IV-B). We find results that are similar to those described above: TQEM promotes the adoption of *Procedural* changes and *Unclassified*/*Customized* practices. We continue to find that practices that involve either *Equipment* or *Material* modifications do not respond significantly to TQEM adoption.

Our third robustness check is 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 favor the adoption of some pollution prevention activities over others we added interactions between each attribute with each year dummy for a total of 20 interaction terms as explanatory variables in Model II-B yielding Model V. 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 the attribute are very similar to those in Model II-B.

A careful examination of fixed effects identification strategy reveals that the coefficient of *TQEM* is identified from the mean change in pollution prevention practices by the 35 firms whose TQEM status changed during our sample period. Firms for which the *TQEM* variable takes the same value for all five years in our sample, do not contribute to the identification of the baseline TQEM treatment effect, since we employ a fixed effects model. In contrast, the coefficients of interactions between *TQEM* and pollution prevention attributes are identified not only by the change in adoption patters by the 35 new TQEM adopters but also by comparison of the 66 existing TQEM adopters with the 59 TQEM non-adopters.

As an indication of the validity of applying the *TQEM* coefficient to all firms we would like to show that firms that changed TQEM status during our sample period ("recent adopters") do not differ significantly from firms that had adopted TQEM prior to the start of our sample ("early adopters") in the pattern of pollution prevention practices they employ (i.e., that the effect of TQEM on the *mix* of practices does not vary across the two types of firms). We, therefore, construct a *New TQEM* dummy variable to indicate a recent adopter as a firm that adopted TQEM for the first time within our sample, with *New TQEM* taking the value of 1 on the year a firm started adopting *TQEM* and thereafter, and 0 before it adopted TQEM. Those who never adopted or had adopted TQEM before the start of our sample (early adopters) are also given a value of 0.[19] Note that we include only the interaction of *New TQEM* with each of the attributes; inclusion of New TQEM itself would lead to co-linearity with the TQEM variable given that we have a fixed effects model.

[19] We do not have data on how early they adopted *TQEM* prior to 1992. In any case, 1992, is the arbitrary cut-off year for early versus recent adopters.

As shown in Table 5, Model VI, we test for the difference in the pattern of pollution prevention practices adopted by early and recent adopters by examining the significance of the coefficients of each attribute interacted with *New TQEM*. We find that there is no systematic difference in the sign of these interaction terms between recent and early adopters. With the exception of the negative statistically significant coefficient of *New TQEM**Equipment*, all other coefficients of these interaction terms are not statistically significant.[20] Moreover, when we combine *Equipment* and *Material* modifications together as *Physical* modifications (results are not shown in the Table 5), we find that *New TQEM**Physical* is no longer statistically significant. Furthermore, we find that the signs and significance of all coefficients of *TQEM*, its interactions with each attribute, and of *Lagged Total P2*, *Cumulative P2*, and *Number of Chemicals* are similar to those in Model II-B. We also find that these results are robust to dropping *Efficiency* from these regression variants (results are not shown). We, therefore, conclude that identifying the *TQEM* coefficient from the recent adopters and projecting it to all adopters is a reasonable approach.

To further investigate this issue, we adopt an estimation approach that is similar in spirit to a difference-in-difference type estimator at the firm-cross-practice-characteristic level for the new adopters, which allows us to investigate whether the treatment effect as identified from the new adopters differs from the treatment effect as identified from the comparison of the always adopters to the never adopters. To do so, we construct for the new adopters a variable *Pre-TQEM* which is equal to 1 for the years prior to their TQEM adoption, and 0 thereafter (this variable also takes the value of 0 if the firms are always adopting TQEM or never adopt TQEM within our sample). Note that we include only the interaction of *Pre-TQEM* with each of the attributes since including the variable as a regressor would lead to co-linearity with *TQEM* given that we

[20] The interactions of *New TQEM * Attribute* are also jointly significant.

have a fixed-effects model. Results of estimating this model are reported in Model VII in Table 5. We find that the coefficient of *Pre-TQEM*Equipment* is negative and statistically significant, suggesting that the recent adopters of TQEM were developing fewer practices with the *Equipment* attribute prior to the adoption of TQEM as compared to other non-adopters. However, the treatment effect of TQEM on practices with different attributes is the same for the new adopters as it is for the entire sample since the difference between *Pre-TQEM*Attribute* coefficient and the *New TQEM* Attribute* is not statistically significant for any attribute and varies as to the sign. Thus, once the differences in baseline rates of practices with the *Equipment* attribute between recent adopters and non-adopters of TQEM is taken into consideration, the effect of *TQEM* on adoption count of equipment related practices is not statistically significantly different across recent and early adopters. This finding provides additional support for the validity of the identification strategy.

5.2. Simulations

We use the results of Model II-B to simulate the impact of TQEM adoption on the count of pollution prevention practices at the industry level for the firms that adopted TQEM during our sample period.[21] In order for our results to represent effects of TQEM on annual counts, we conduct this simulation by computing the counterfactual count of practices that a firm would have adopted had it delayed the adoption of TQEM by a year. The method used to construct these simulated counts is described in section 3.2 and the results are reported in Table 6.[22]

The simulation results can be used to investigate the implications of the adoption of TQEM for pollution prevention by different industries, despite the absence of SIC fixed effects

[21] Using Model II-A for the simulation yields similar results.
[22] There are 35 firms that changed their *TQEM* status from 0 to 1: 16 in 1993, 7 in 1994, 8 in 1995 and 4 in 1996.

and their interaction with TQEM in the regression analysis. This is because firms differ in the distribution of pollution prevention practices of different types they tend to adopt, i.e. in their baseline adoption rates. Moreover, these differences are higher across industries since there is some commonality of production processes within an industry. Thus, even though the same parameter estimates govern the responsiveness of every practice to the adoption of TQEM by every firm, the aggregate effect of pollution prevention activities at the firm level (and hence also at the industry level) would differ even in percentage terms. As a measure of the effect of TQEM adoption at the industry level, in the last column of Table 6, we report the unweighted average of the percentage effects of TQEM adoption on pollution prevention counts of firms in each industry, treating each firm as an equally informative signal of the industry's propensity to adopt pollution prevention practices in response to TQEM. We find that Petroleum Refining and Related Industries (SIC 29) and Chemical and Allied Products (SIC 28) would have experienced the highest mean percent reduction in the number of activities had they delayed TQEM. In both these industries, practices with *Procedural* and *Unclassified/Customized* attributes are very heavily represented in the pre-*TQEM* baseline of pollution prevention practices adopted. Industries that gained less from TQEM adoption include SICs 34 and 35 that tend to be sectors involved in the manufacturing of metals, machinery and computer equipment, likely because of the equipment and materials oriented nature of the pollution prevention practices employed in these industries.

6. FURTHER DISCUSSION AND CONCLUDING REMARKS

Organizational structure plays a large role in dictating the number and type 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 and unclassified/customized modifications. We also find that the adoption of practices that enhance efficiency or are visible to consumers is not being driven by TQEM more than practices without these characteristics. Moreover, we find that TQEM does not appear to promote the adoption of practices that involve physical changes in equipment and materials.

The variations in the adoption rates of various practices based on their attributes in response to TQEM is useful for better understanding how TQEM works in practice, and possibly for inferring the strategic motivations that underlie TQEM adoption and the type of outcomes that TQEM is designed as an instrument to achieve. We find that TQEM systems seem to be more amenable to using specifically generated knowledge to search for, identify and implement improvements in recurrent operations that are tailored to a firm's processes and/or involve non-standard modifications. Finally, the fact that TQEM adoption does not yield disproportionately high increase in pollution prevention activities that have efficiency enhancing or consumer visibility attributes, suggests that TQEM adoption is not driven primarily by the economic or strategic outcomes that might be achieved.

Our findings provide insight on the extent to which policymakers can rely upon corporate environmental management for inducing voluntary pollution prevention and the types of practices that are likely to be adopted by firms. To the extent that other 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, our results show that the benefits in the form of technological innovation from promoting TQEM differ across industries, suggesting the usefulness of targeting policy efforts to promote TQEM adoption to firms in particular industries. In particular, we find that firms in the petroleum refining and chemical products industries would gain the most in their count of pollution prevention practices from the adoption of TQEM while firms in the manufacturing of metals, machinery and computer equipment industries gain less from TQEM adoption. Finally, our analysis shows that firms do experience diminishing returns to pollution prevention. While there exists some “low hanging fruit,” further adoption of pollution prevention practices of any type is likely to be increasingly costly, and thus diminish over time in the absence of any regulatory stimulus.

Table 1. Types of P2, their Attributes and Mean and Standard Deviations of P2 Adoption Rates.

P2 Activities and Codes	Consumers	Efficiency	Equipment	Material	Procedural	Customized Functional Attributes	Remarks	*TQEM* Adopters	Non-*TQEM* Adopters	Total Sample
13 Improved maintenance scheduling, record keeping, or procedures		X			X		This activity involves changes in procedures for basic upkeep and for documentation of activities which provides firms with time savings.	2.990 (6.202)	2.165 (4.293)	2.685 (5.584)
14 Changed production schedule to minimize equipment and feedstock changeovers		X			X		Similar to Category 13, for procedural changes associated with planning of operating activities.	0.970 (3.186)	0.716 (2.493)	0.876 (2.949)
19 Other changes made in operating practices		X			X		Similar to Category 13 and Category 14.	3.519 (17.244)	2.426 (4.381)	3.115 (6.356)
21 Instituted procedures to ensure that materials do not stay in inventory beyond shelf-life		X			X		It is a procedural change as it involves modifications in the cataloging of and accounting of stocks and materials. As such, it saves inventory costs and reduces disposal of expired materials.	0.633 (2.163)	0.436 (1.222)	0.560 (1.872)
22 Began to test outdated material — continue to use if still effective		X			X		Similar to Category 21.	0.175 (1.246)	0.155 (0.656)	0.168 (1.066)
23 Eliminated shelf-life requirements for stable materials		X				X	This activity saves inventory costs by improving management of inputs and materials. It may or may not be a procedural change.	0.006 (0.077)	0.024 (0.152)	0.012 (0.111)
24 Instituted better labeling procedures		X			X		This improves procedures for the classification of supplies and in effect provides time savings.	0.127 (0.834)	0.139 (0.574)	0.131 (0.748)
25 Instituted clearinghouse to exchange materials that would otherwise be discarded		X				X	Similar to Category 23.	0.181 (0.791)	0.047 (0.242)	0.131 (0.648)
29 Other changes made in inventory control		X				X	Characterization of these activities depends on Categories 23 and 25.	0.700 (2.486)	0.341 (1.364)	0.568 (2.146)
31 Improved storage or stacking procedures		X			X		This activity involves changing the system for organization of materials and equipment and can save time and space.	0.359 (1.400)	0.236 (0.916)	0.314 (1.244)
32 Improved procedures for loading, unloading, and transfer operations		X			X		Similar to Category 31, except it is a procedural change for transporting materials and equipment.	0.552 (1.746)	0.669 (1.715)	0.595 (1.734)
33 Installed overflow alarms or automatic shut-off valves		X	X				Installation of such fixtures can save costs of cleanup as it can prevent leaks and spills.	0.194 (0.904)	0.128 (0.591)	0.170 (0.803)
35 Installed vapor recovery systems		X	X				This equipment change can serve to save of clean up costs associated with residue from vapors and can also conserve material.	0.401 (1.339)	0.091 (0.438)	0.286 (1.106)
36 Implemented inspection or monitoring program of potential spill or leak sources		X			X		This is a procedural change which can save firms cost of clean-up.	1.998 (6.562)	0.733 (2.171)	1.530 (5.406)

Table 1. *(continued)*

P2 Activities and Codes	Consumers	Efficiency	Equipment	Material	Procedural	Customized Functional Attributes	Remarks	*TQEM* Adopters	Non-*TQEM* Adopters	Total Sample
39 Other changes made in spill and leak prevention		X				X	Other Category 3 *P2s* are presumed to provide savings like all other Category 3 *P2s*. However, we cannot characterize them according to other attributes,	1.450 (4.078)	0.540 (1.600)	1.114 (3.407)
41 Increased purity of raw materials				X			This activity involves a physical change in materials and inputs Raw material modifications may or may not bring about savings.	0.169 (0.695)	0.115 (0.451)	0.149 (0.616)
42 Substituted raw materials	X			X			Similar to Category 41.	2.268 (4.160)	1.622 (3.525)	2.029 (3.947)
49 Other raw material modifications made				X			Similar to Category 41 and Category 42.	0.891 (3.439)	0.324 (0.857)	0.681 (2.791)
51 Instituted re-circulation within a process		X	X				This activity involves installation of new equipment It may provide savings.	0.609 (1.446)	0.794 (2.663)	0.677 (1.986)
52 Modified equipment, layout, or piping			X				It involves physical equipment changes. It may or may not bring about savings.	2.313 (5.183)	2.051 (3.960)	2.216 (4.766)
53 Used a different process catalyst				X			The use of a new catalyst is a change in materials used. It may or may not bring about savings.	0.077 (0.399)	0.101 (0.416)	0.086 (0.405)
54 Instituted better controls on operating bulk containers to minimize discarding of empty containers		X			X		This is a procedural activity that needs to be done regularly as part of periodic checks in operations. This can also provide firms savings in clean up costs from possible spills that may result from operation of bulk containers.	0.357 (1.414)	0.166 (0.752)	0.286 (1.215)
55 Changed from small volume containers to bulk containers to minimize discarding of empty containers		X	X				These involve physical changes and can provide savings in packaging and waste disposal.	0.212 (0.946)	0.348 (1.537)	0.262 (1.200)
58 Other process modifications made						X	It is difficult to characterize “other” Category 5 *P2s* due to differences among *P2s* in this Category.	3.304 (7.168)	1.753 (3.606)	2.730 (6.141)
59 Modified stripping/cleaning equipment			X				Similar to Category 52.	0.226 (0.931)	0.115 (0.553)	0.185 (0.813)
60 Changed to mechanical stripping/cleaning devices (from solvents or other materials)			X				Because this activity involved a shift from material inputs to a physical equipment it is characterized by both equipment and material modifications.	0.058 (0.382)	0.071 (0.366)	0.062 (0.376)
61 Changed to aqueous cleaners (from solvents or other materials)				X			This is a change in materials.	0.811 (2.343)	0.682 (1.952)	0.764 (2.206)
63 Modified containment procedures for cleaning units					X		This is a procedural change.	0.067 (0.372)	0.034 (0.215)	0.055 (0.323)

Table 1. *(continued)*

P2 Activities and Codes	Consumers	Efficiency	Equipment	Material	Procedural	Customized Functional Attributes	Remarks	*TQEM* Adopters	Non-*TQEM* Adopters	Total Sample
64 Improved draining procedures					X		Similar to Category 63.	0.097 (0.437)	0.010 (0.100)	0.065 (0.355)
65 Redesigned parts racks to reduce drag out			X				This is a physical equipment change.	0.026 (0.193)	0.020 (0.163)	0.024 (0.182)
66 Modified or installed rinse systems			X				Similar to Category 65 except that it does not involve material modification	0.029 (0.192)	0.020 (0.183)	0.026 (0.189)
67 Improved rinse equipment design			X				Similar to Category 65 and Category 66.	0.083 (0.543)	0.024 (0.192)	0.061 (0.447)
68 Improved rinse equipment operation					X		Similar to Category 63 and Category 64.	0.153 (1.010)	0.024 (0.152)	0.105 (0.809)
71 Other cleaning and degreasing modifications made						X	It is difficult to characterize "other" Category 7 *P2s* due to differences among *P2s* in this Category.	0.514 (1.303)	0.358 (1.144)	0.456 (1.248)
72 Modified spray systems or equipment			X				Similar to Category 65, Category 66 and Category 67.	0.308 (1.429)	0.324 (1.488)	0.314 (1.450)
73 Substituted coating materials used				X			This involves a physical change in materials.	0.621 (1.810)	0.834 (2.354)	0.700 (2.029)
74 Improved application techniques					X		This may only be a procedural change since the physical changes are covered by Category 72 and Category 73.	0.549 (3.291)	0.294 (1.469)	0.455 (2.762)
75 Changed from spray to other system			X				Similar to Category 72.	0.046 (0.413)	0.064 (0.507)	0.052 (0.449)
78 Other surface preparation and finishing modifications made						X	It is difficult to characterize "other" Category 7 *P2s* due to differences among *P2s* in this Category.	0.117 (0.535)	0.071 (0.337)	0.100 (0.472)
81 Changed product specifications	X					X	This activity is visible to consumers but may not require changes in physical equipment or materials.	0.401 (1.392)	0.311 (1.311)	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.	0.556 (1.836)	0.297 (0.867)	0.460 (1.554)
83 Modified packaging	X			X			Packaging is definitely visible to consumers and usually involves physical change in material.	0.014 (0.117)	0.027 (0.259)	0.019 (0.183)
89 Other product modifications made	X					X	Other product modifications would definitely visible to consumers. However, other attributes may or may not be present.	0.442 (1.912)	0.206 (0.756)	0.355 (1.5389)
Total P2								29.58 (46.38)	19.91 (28.67)	26.00 (41.00)

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

Table 2. Descriptive Statistics.

Explanatory Variables	All Firms	TQEM Non-Adopters	TQEM Adopters		
			All TQEM Adopters	New TQEM Adopters	Existing TQEM Adopters
Different Types of P2 According to Attributes					
Consumers	0.073 (0.261)	0.071 (0.26)	0.075 (0.26)	0.069 (0.25)	0.074 (0.26)
Efficiency	0.32 (0.47)	0.29 (0.45)	0.34 (0.47)	0.32 (0.47)	0.32 (0.47)
Material	0.14 (0.34)	0.13 (0.34)	0.14 (0.34)	0.13 (0.33)	0.14 (0.34)
Equipment	0.20 (0.40)	0.20 (0.40)	0.20 (0.40)	0.18 (0.38)	0.20 (0.40)
Procedural	0.24 (0.43)	0.22 (0.42)	0.25 (0.44)	0.25 (0.43)	0.24 (0.43)
Other Functional Attributes	0.065 (0.25)	0.04 (0.20)	0.079 (0.27)	0.075 (0.26)	0.063 (0.24)
All Types of P2	0.60 (2.57)	0.46 (1.85)	0.69 (2.91)	0.79 (3.32)	0.58 (2.44)
Other Explanatory Variables					
Total Cumulative P2	94.73 (160.34)	57.74 (75.56)	116.46 (190.19)	93.50 (147.28)	87.17 (135.93)
Total Lagged P2	29.20 (45.94)	21.98 (34.37)	33.44 (51.06)	36.81 (65.43)	28.05 (42.10)
Number of Chemicals	75.69 (107.55)	55.71 (71.79)	87.42 (122.32)	93.50 (147.28)	73.00 (99.92)
Number of Firms	160	59	101	35	66

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 (pre-adoption observations are included in the non-adopters column). Existing TQEM adopters are firms that have adopted TQEM prior to our sample period. The values for all TQEM adopters reflect the observations of the existing TQEM adopters and the post-adoption observations of the new TQEM adopters.

Table 3. The Role of Practice Characteristics on the Effects on TQEM on Pollution Prevention.

Variables	Model I-A	Model I-B	Model II-A	Model II-B [a/]
TQEM	0.488*** (0.105)	0.444*** (0.102)	0.484*** (0.115)	0.440*** (0.112)
TQEM * Equipment	-0.560*** (0.109)	-0.560*** (0.109)	-0.554*** (0.110)	-0.554*** (0.110)
TQEM * Material	-0.366*** (0.102)	-0.366*** (0.101)	-0.390*** (0.123)	-0.390*** (0.122)
TQEM * Procedural	-0.242*** (0.092)	-0.242*** (0.091)	-0.231** (0.114)	-0.231** (0.114)
TQEM * Consumers			0.05 (0.123)	0.05 (0.122)
TQEM * Efficiency			-0.007 (0.108)	-0.007 (0.108)
ln(Lagged Total P2)		0.645*** (0.102)		0.645*** (0.102)
ln(Cumulative Total P2)		-0.704*** (0.248)		-0.704*** (0.248)
Number of Chemicals	0.870*** (0.159)	0.696*** (0.158)	0.870*** (0.159)	0.696*** (0.158)
Year 2	-0.116** (0.053)	0.403** (0.175)	-0.116** (0.053)	0.403** (0.175)
Year 3	-0.227*** (0.056)	0.588** (0.267)	-0.227*** (0.056)	0.588** (0.267)
Year 4	-0.406*** (0.059)	0.668** (0.336)	-0.406*** (0.059)	0.668** (0.336)
Year 5	-0.539*** (0.060)	0.743* (0.386)	-0.539*** (0.060)	0.743* (0.386)
Constant	-4.548*** (1.037)	-4.572*** (1.037)	-4.547*** (1.037)	-4.572*** (1.037)
Joint Tests of Significance				
TQEM+TQEM*Equipment	-0.073 (0.108)	-0.117 (0.106)	-0.071 (0.115)	-0.114 (0.113)
TQEM+TQEM*Material	0.121 (0.105)	0.077 (0.102)	0.094 (0.132)	0.050 (0.128)
TQEM+TQEM*Procedural	0.246 *** (0.094)	0.202 ** (0.091)	0.252 * (0.145)	0.208 (0.142)
Firm dummies (χ^2)	1872.95***	5246.96***	1843.44***	275.24***
P2 dummies (χ^2)	5218.30***	275.24***	5219.76***	52248.82***
Residual squared	98.0	77.76	98.04	77.76
Number of Observations	34400	34400	34400	34400

[a/] Total *P2* and Cumulative *P2* are in logs. Standard errors are in parentheses: *** Significant at 1%, ** significant at 5%, * significant at 10%.

Table 4. Robustness Checks

Variables	Model III-A	Model III-B	Model IV-A	Model IV-B
TQEM	0.483*** (0.115)	0.439*** (0.112)	0.481*** (0.106)	0.438*** (0.103)
TQEM * Equipment			-0.554*** (0.110)	-0.554*** (0.110)
TQEM * Material			-0.388*** (0.119)	-0.388*** (0.118)
TQEM * Physical	-0.486*** (0.095)	-0.486*** (0.095)		
TQEM * Procedural	-0.205* (0.112)	-0.205* (0.112)	-0.236** (0.093)	-0.236** (0.093)
TQEM * Efficiency	-0.034 (0.107)	-0.034 (0.107)		
TQEM * Consumers	0.130 (0.103)	0.130 (0.103)	0.051 (0.122)	0.051 (0.121)
ln(Lagged Total P2)		0.645*** (0.102)		0.645*** (0.102)
ln(Cumulative Total P2)		-0.704*** (0.248)		-0.704*** (0.248)
Number of Chemicals	0.870*** (0.159)	0.696*** (0.158)	0.870*** (0.159)	0.696*** (0.158)
Year 2	-0.116** (0.053)	0.403** (0.175)	-0.116** (0.053)	0.403** (0.175)
Year 3	-0.227*** (0.056)	0.588** (0.267)	-0.227*** (0.056)	0.588** (0.267)
Year 4	-0.406*** (0.059)	0.668** (0.336)	-0.406*** (0.059)	0.668** (0.336)
Year 5	-0.539*** (0.060)	0.743* (0.386)	-0.539*** (0.060)	0.743* (0.386)
Constant	-4.546*** (1.037)	-4.571*** (1.037)	-4.548*** (1.037)	-4.572*** (1.037)
Joint Tests of Significance				
TQEM +TQEM * Equipment			-0.073 (0.108)	-0.117 (0.106)
TQEM +TQEM * Material			0.094 (0.131)	0.049 (0.128)
TQEM +TQEM * Physical	-0.003 (0.102)	0.047 (0.099)		
TQEM +TQEM * Procedural	0.278 * (0.144)	0.234 * (0.141)	0.246 *** (0.094)	0.202 ** (0.091)
Firm dummies (χ^2)	1874.35***	275.31***	1873.41***	275.23***
P2 dummies (χ^2)	5238.45***	5267.74***	5215.95***	5244.79***
Residual squared	98.04	77.76	98.04	77.76

Standard errors are in parentheses: *** Significant at 1%, ** significant at 5%, * significant at 10%.. Number of observations is 34400.

Table 5. Specification Tests and Further Robustness Checks.

Variables	Model V	Model VI	Model VII
TQEM	0.449*** (0.113)	0.526*** (0.131)	0.313** (0.139)
TQEM * Equipment	-0.540*** (0.114)	-0.478*** (0.114)	-0.624*** (0.125)
TQEM * Material	-0.411*** (0.125)	-0.454*** (0.124)	-0.488*** (0.142)
TQEM * Procedural	-0.264** (0.117)	-0.255** (0.115)	-0.304** (0.121)
TQEM * Efficiency	0.005 (0.110)	0.062 (0.107)	0.021 (0.116)
TQEM * Consumers	0.051 (0.126)	0.044 (0.127)	0.114 (0.145)
New TQEM * Equipment		-0.357** (0.145)	-0.358** (0.145)
New TQEM * Material		0.22 (0.180)	0.219 (0.180)
New TQEM * Procedural		0.123 (0.214)	0.122 (0.214)
New TQEM * Efficiency		-0.319 (0.211)	-0.320 (0.210)
New TQEM * Consumers		0.018 (0.171)	0.018 (0.172)
Pre-TQEM * Equipment			-0.667*** (0.209)
Pre-TQEM * Material			-0.136 (0.191)
Pre-TQEM * Procedural			-0.224 (0.243)
Pre-TQEM * Efficiency			-0.14 (0.218)
Pre-TQEM * Consumers			0.224 (0.189)
Joint Tests of Significance			
Year dummy * Attribute jointly zero χ^2 stat (p-value)	12.560 (0.8956)		
(New TQEM * Equipment) – (Pre TQEM * Equipment)			0.309 (0.252)
(New TQEM * Material) – (Pre TQEM * Material)			0.356 (0.261)
(New TQEM * Procedure) – (Pre TQEM * Procedure)			0.347 (0.321)
(New TQEM * Efficiency) – (Pre TQEM * Efficiency)			-0.179 (0.303)
(New TQEM * Consumers) – (Pre TQEM * Consumers)			-0.206 (0.254)

Standard errors are in parentheses, except for the χ-square test statistics for which p-value are reported: /*** Significant at 1%, ** significant at 5%, * significant at 10%.. For brevity, the coefficient for each *Attribute*Year dummy*$_i$ for all *i=1993, 1994, 1995 and 1996*, and all coefficients and standard errors of the other variables are suppressed. Lagged *P2* and Cumulative *P2* are in logs for all models in this table. Lagged P2 is positive significant and Cumulative p2 is negative significant. *Year dummies*, *Number of chemicals*, and *Constant* are similar to previous models. The chi-square statistic for the joint test of significance of all New TQEM*Attribute for Model VI is 28.9 which is statistically significant,

Table 6. Contribution of TQEM on Total Pollution Prevention Counts of New TQEM Adopters, by 2-Digit SIC Code

SIC Code and Industry Name		Number of New TQEM Adopters	Total Actual P2 by New TQEM Adopters (with TQEM)		Total Projected P2 by New TQEM Adopters (without TQEM)		% of Pollution Prevention Counts due to TQEM
			Mean	(Min, Max)	Mean	(Min, Max)	Mean
13	Oil & Gas Extraction	3	9.0	(2,17)	7.35	(1.93,13.68)	14.17
20	Food & Kindred Products	4	33.0	(0.0,106)	28.00	(0.0,90.18)	13.58
21	Tobacco Products	1	8.0	(8, 8)	6.88	(6.88, 6.88)	14.00
26	Paper & Allied Products	4	9.25	(1,17)	7.85	(0.95, 14.41)	12.01
28	Chemicals & Allied Products	5	11.8	(3,18)	9.68	(2.09, 15.75)	20.08
29	Petroleum Refining & Related Industries	1	2.0	(2, 2)	1.45	(1.45, 1.45)	27.71
32	Stone, Clay, Glass, & Concrete Products	1	42	(42, 42)	34.45	(34.45,34.45)	17.98
33	Primary Metal Industries	4	27.75	(1, 90)	23.70	(0.64,77.44)	19.23
34	Fabricated Metal Products	1	19	(19.19)	16.94	(16.94, 16.94)	10.85
35	Industrial & Commercial Machinery & Computer Equipment	4	5.5	(0,16)	5.00	(0.0,14.72)	10.03
36	Electronic & Other Electrical Equipment	3	96.33	(0, 269)	78.52	(0.0, 219.48)	18.97
37	Transport Equipment	2	190	(149, 231)	161.33	(122.84,199.82)	15.53
38	Measuring, Analyzing, Controlling Instruments	1	0	(0, 0)	0	(0, 0)	---
48	Communication	1	2	(2, 2)	1.61	(1.61,1.61)	19.39
All Industries		35	32.29	(0, 269)	27.09	(0.0, 219.48)	16.05

The columns under Total Actual P2 report the mean (and min and max) of the count of all P2 practices adopted by new adopters of TQEM, by industry, in the first year of TQEM adoption. The columns under Total Projected P2 report the mean (and min and max) of the simulated counterfactual count of all P2 practices by the same firms in the same year, assuming they had not adopted TQEM. The last column represents the average of the percentage P2 count due to the TQEM adoption, by industry (each firm's percentage change is weighted equal in computing the average). See notes of Table 6 and text for details on the construction of this table.

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