Environmental Innovation and Environmental Policy: An Empirical Test of Bi-Directional Effects

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Abstract

In this paper, we study the empirical strength of bi-directional linkages between environmental standards and performance, on the one hand, and environmental innovation, on the other. To do so, we examine a panel of 127 manufacturing industries over the period 1989 – 2002 using pollutant emissions to measure policy stringency. Our empirical results reveal a negative and significant relationship between emissions and environmental patents, in both directions. Thus, environmental R&D both spurs the tightening of government environmental standards and is spurred by the anticipation of such tightening, suggesting that U.S. environmental policy (at least in the context of the manufacturing industries that we study) has been responsive to innovation and effective in inducing innovation.

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1. Introduction

Innovation in environmental technologies has long been considered the driving force behind pollution reduction (Kneese and Schultze, 1975; Jaffe, et al., 2002). Like research and development (R&D) in other areas, environmental research and development is driven by the prospective economic gains that new technologies can deliver in cost savings or revenue generation. Unlike many other realms of innovative investment, however, the economic gains from new environmental technologies are largely determined by government environmental policy. For example, if government standards for allowable pollutant emissions are tightened, costs of meeting these standards rise (ceteris paribus) and the prospective cost savings from new environmental technologies rise in tandem, spurring new innovation.

In a growing literature, economists have studied the links between different environmental policy instruments and innovation incentives on a theoretical level, comparing emission taxes, marketable permits, technology mandates and performance standards, with and without technology spillovers and patent protections (see Requate, 2005a). In this literature, the government is typically modeled as a first-mover, committing to a given setting of a given regulatory instrument and allowing innovation to respond accordingly. The government may consider the effect of its policy standard on innovation; for example, it may set a seemingly ambitious pollutant standard in order to spur environmental R&D. When faced with new environmental regulations, firms may develop new methods for complying with higher standards. Alternately, there is considerable anecdotal evidence that government environmental policy *responds* to environmental innovation, often with requirements for adoption of the "best available control technology" (Jaffe, et al., 2002). Such responsive policies also provide strong incentives for environmental innovation, as they offer successful innovators a "ready market" for their products (Jaffe, et al., 2002). Innes and Bial (2002) study such responsive policies in an imperfectly competitive market setting, showing how flexible emission taxes and standards can be combined to elicit both optimal pollution levels and optimal environmental R&D (see also Requate, 2005b).

With responsive policies, there are bi-directional links between environmental standards and performance, on the one hand, and environmental innovation, on the other. Pollutant emissions and environmental R&D are jointly determined as successful R&D prompts policy change and attendant pollution reductions, and as anticipated policy change (and attendant tightening of pollution standards) spurs new R&D.

The purpose of this paper is to study the empirical strength of these bi-directional linkages and, hence, the role of policy in spurring environmental R&D and, in turn, ultimate environmental performance. Specifically, we examine 127 manufacturing industries over the fourteen-year period 1989 – 2002. Changes in environmental technologies, as measured by the number of environmental patents, can lead to changes in effective environmental standards, which in turn drive observed emissions. Emissions in turn proxy for the changes in standards that drive environmental R&D and, hence, resulting patents. In view of the joint determination of research and pollution outcomes, we estimate two simultaneous equations, using appropriate instruments to identify each endogenous variable. Our empirical results reveal that there is a negative and significant relationship between emissions and environmental patents, in both directions. Thus, environmental R&D both spurs the tightening of government environmental standards and is spurred by the anticipation of such tightening, suggesting that U.S. environmental policy (at least in the context of the manufacturing industries that we study) has been responsive to innovation and effective in inducing innovation.

This paper contributes to a surprisingly small empirical literature on environmental innovation. This literature focuses on the effects of pollution abatement expenditures (PAE) on innovative activity. In doing so, scholars have sought to test the "induced innovation" hypothesis. The latter hypothesis posits that higher pollution abatement costs, costs that can be reduced by innovative success, spur more innovative activity (ceteris paribus). Jaffe and Palmer (1997) find evidence for this hypothesis in U.S. industry-level panel data on total (environmental and non-environmental) R&D expenditures and patent counts. Lanjouw and Mody (1993) also find informal evidence that environmental innovation is induced by higher PAE, presenting tabular data on environmental patents and control costs from the U.S., Germany and Japan. Brunnermeir and Cohen (2003) are the first to estimate a model that links PAE to U.S. *environmental* patent counts, again finding evidence in support of the induced innovation hypothesis.

Our work differs from previous studies primarily because we study a model of *bi-directional* links between environmental policy and environmental R&D that explicitly accounts for the joint determination of these outcomes.[2] In doing so, we use what we consider to be a more direct measure of policy stringency, emissions as opposed to PAE. This focus permits us to infer interactions between policy, innovation, and pollution that are not possible in the existing uni-directional studies of PAE effects on patent counts.

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[2] Like us, Managi et al., (2005) are interested in bi-directional links between technology change and environmental policy stringency, in their case in the context of the offshore oil and gas industry. However, their approach is quite different than ours, examining distributed lag models of the effect of policy

The balance of the paper is organized as follows. Section 2 presents our empirical model. Section 3 describes the sample we use to analyze the link between emissions and environmental innovation. Here, we define the variables used in our empirical analysis and explain in detail our identification strategy and associated choice of instruments. In section 4 we discuss the econometric methods that we employ. Section 5 presents our empirical findings. Section 6 concludes by highlighting the contributions of this paper and offering suggestions for future research.

2. Empirical Model

We envision an underlying structural model that determines four outcomes, our two observable variables (emissions and patents) and two unobservable variables (effective environmental standards and environmental R&D). Let us suppose that this model takes the following simple form:

$$P_{it} = a_{pit} + b_p\, RD_{it-1} + c_p\, X_{pit} + \varepsilon_{pit} \tag{1}$$

$$Q_{it} = a_{qit} + b_q\, S_{it} + \varepsilon_{qit} \tag{2}$$

$$S_{it} = a_{sit} + b_s\, P_{it} + c_s X_{sit} + d_s\, S_{it-1} + \varepsilon_{sit} \tag{3}$$

$$RD_{it} = a_{rit} + b_r\, \mathrm{E}_t\,(S_{it+1}) + c_r X_{rit} + d_r\, S_{it} + \varepsilon_{rit}, \tag{4}$$

where P_{it} is time t environmental patents in industry i, RD_{it-1} is lagged environmental R&D in industry i, Q_{it} is the volume of emissions in industry i, S_{it} are emission standards for industry i, the vectors X_{it} represent exogenous observable variables, the ε_{it}'s represent random errors, and E is an expectation operator. Equation (1) indicates that patent numbers are determined by lagged industry R&D (among other variables). Equation (2)

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stringency on technology and factor productivity. We instead focus on a model of joint endogeneity in a panel of industries, building more closely upon earlier work on the induced innovation hypothesis.

indicates that emissions respond to changes in environmental standards. Because they are costly to firms, emission reductions beyond those required by government regulations are likely to be limited and anchored to the government's requirements; emissions are thus driven by government standards as described by equation (2).[3] Equation (3) indicates that environmental standards are determined (in part) by improvements in environmental technology as measured by the number of environmental patents. Finally, Equation (4) indicates that R&D expenditures are determined (in part) by anticipated changes in environmental standards.

Lagging (2), substituting into (3) (for S_{it-1}) and then substituting (3) into (2), gives the following structural form for emissions:

$$(5) \qquad Q_{it} = a^*_{qit} + b^*_q Q_{it-1} + c^*_q P_{it} + d^*_q X_{sit} + \varepsilon^*_{qit}$$

Intuitively, the change in environmental technology, as measured by the number of patents, drives changes in effective environmental standards, which in turn drive observed emissions. The key parameter of interest in the resulting Equation (5) is c_q^*, which incorporates the effects of patents on standards (b_s).

Similarly, solving (1), (2) and (4) gives the structural form for the determination of patents:

$$(6) \qquad P_{it} = a^*_{pit} + b^*_p E_{t-1}(Q_{it}) + c^*_p Q_{it-1} + d^*_p X_{rit-1} + f^*_p X_{pit} + \varepsilon^*_{pit}$$

Intuitively, emissions proxy for the changes in standards that drive environmental R&D and, hence, resulting patents. The key parameter of interest in equation (6) is b_p^*, which incorporates the effects of policy changes (S_{it}) on environmental R&D (b_r).

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[3] For simplicity, other exogenous (observable) determinants of emissions are assumed to operate through standards (and the associated Xsit variables) At the cost of expositional simplicity, all that follows extends to the presence of other exogenous emission regressors, Xqit.

In sum, estimating Equation (5) tests for effects of R&D on environmental policy, and estimating Equation (6) tests for effects of environmental policy on environmental R&D. Note that Equation (5) is identified by X_{sit}, which incorporates determinants of changes in "effective standards," S_{it}. As discussed below, key among such determinants are government enforcement activity that increases the stringency of environmental regulations. Equation (6), in turn, is identified by X_{pit} and $X_{ri(t-1)}$, those variables that drive research and patent outcomes.

Before turning to the econometric issues relevant to the estimation of equations (5) and (6), note that equation (6) contains an expectation on the right hand side. The simplest (but perhaps unpalatable) way to treat this expectation is to assume that agents have perfect foresight, so that we can simply substitute the realized value Q_{it}. Then (5)-(6) give us a standard simultaneous equation framework (albeit with some complicating econometric issues that we turn to momentarily).

Now let us suppose instead that agents do not have perfect foresight. Then from (5)-(6), we have the following relationship between observable emissions and the "true regressor," $E_{t-1}(Q_{it})$:

$$Q_{it} = E_{t-1}(Q_{it}) + u_{it} \tag{7}$$

where

$$u_{it} = c^*_q f^*_p (X_{pit} - E_{t-1}(X_{pit})) + d^*_q (X_{sit} - E_{t-1}(X_{sit})) + \varepsilon_{uit}, \quad \varepsilon_{uit} = c^*_q \varepsilon^*_{pit} + \varepsilon^*_{qit}\,. \tag{8}$$

For our observable regressor Q_{it}, equations (7)-(8) imply two econometric problems: (1) our "true" regressor is measured with error, and (2) our observable regressor is jointly endogenous in the sense that it is correlated with the equation (6) error ε^*_{pit}. To obtain consistent equation (6) parameter estimates – addressing both of these problems – requires instruments that are uncorrelated with both the equation (7) "measurement error" u_{it} and the equation (6) error ε^{*}_{pit} as well. Our exogenous data, { X_{pit} , $X_{ri(t-1)}$, X_{sit} }, satisfies the second criterion, but unless it is all lagged, not necessarily the first. However, under the following innocuous assumption, lagged counterparts to our exogenous data satisfy both criteria:

> *Assumption 1.* The prediction errors, $X_{pit} - E_{t-1}(X_{pit})$ and $X_{sit} - E_{t-1}(X_{sit})$, are uncorrelated with information available at time (t-1).

In what follows, we estimate equation (6) under both the perfect foresight premise (using contemporaneous exogenous variables and lagged instruments) and the rational expectations premise (Assumption 1, using lagged exogenous variables and instruments).

3. Data

Our sample is a balanced industry-level panel of 127 manufacturing industries (SIC codes 200-399) over the period 1989 – 2002. Because we focus on toxic emissions, we restrict attention to manufacturing industries that are the principle sources of such pollutants. Table 1 and 2 present variable definitions and descriptive statistics for our sample.

[TABLE 1 HERE]

[TABLE 2 HERE]

Using the EPA's Toxic Release Inventory (TRI), we construct industry level total toxic releases (***Emissions***) by aggregated weight by year. Facility releases reported in the TRI are assigned to the primary industry of the parent company. Following previous studies (c.f., Jaffe and Palmer, 1997; Brunnermeier and Cohen, 2003 and Popp, 2002), we use successful environmental patent applications as a proxy for environmental innovation. Using data from the U.S. Patent and Trademark Office, we construct successful patent application counts by year, by industry, environmental and non-environmental, obtained by U.S. companies.[4] Environmental patents are determined by patent classifications that relate to air or water pollution, hazardous waste prevention, disposal and control, recycling and alternative energy (***EnvPatents***). As in prior research (c.f., Jaffe and Palmer, 1997; Brunnermeier and Cohen, 2003), we determine the SIC industry to which each of these patents belongs using the primary line of business of the organization that is named first on the patent application. Table AI in the Appendix indicates the patent utility classes that we designate as environmental in our analysis. In an endeavor to include all environment-related patents in our *EnvPatents* measure, we use a broad definition of utility classes that may contain environment-related innovations. Non-environmental patents are those in all other patent utility classes (***NonEnvPatents***).

In our patent equation, we measure innovative outcomes (our dependent variable) using annual patent counts, reflecting the latest innovative responses to environmental policy. In our emission equation, however, we expect environmental standards to be revised in response to the recent history of environmental patents, not solely the last year's set of patent applications. Hence, we use a moving average of patent application counts over the preceding five years as our jointly endogenous innovation regressor; as a robustness check, we consider two alternatives as well: one and two year lagged patent

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[4] The literature suggests that it is preferable to count patents by date of application rather than by date of grant, because application dates better reflect the timing of discovery (uncontaminated by variability in regulatory delays). The average lag between patent applications and grants is approximately two years. All of our patent measures are for U.S. companies. U.S. companies are likely to be the most sensitive to U.S. environmental policy. Moreover, U.S. (vs. foreign) environmental innovation is more likely to be associated with an improved ability of U.S. firms to comply (at lower cost) with tightened U.S. environmental standards, and hence, to spur revisions in U.S. regulation.

counts.[5]

Our exogenous data can be broken into three categories: (1) Variables that we believe may drive both emissions and patents – that is, variables common to both X_{sit} and X_{pit}/X_{rit-1}; (2) instruments that identify emissions in the patent equation, namely, variables that are only elements of X_{sit} and not X_{pit}/X_{rit-1}; and (3) instruments that identify patents in our emission equation because they are only contained in X_{pit}/X_{rit-1} and not X_{sit}. Table 2 gives summary statistics for the variables that we use in our analysis. We now describe the sources and logic for our three categories of exogenous data.

Beginning with the first category (of common variables), we use a number of relevant financial indicators that we obtain from Standard & Poor's Compustat Services and the U.S. Department of Commerce. Deflators are obtained using producer price indexes reported in the Economic Report of the President (2004).

First, we include (deflated) industry sales volume (***Real Sales***) in order to account for potential effects of industry size on emissions and patents. Larger industries (ceteris paribus) are expected to produce more emissions. Expected effects on patent outcomes are less clear, as larger industries may or may not be more innovative in their environmental technologies.

Second, because market structure is a potentially important determinant of both innovative activity and environmental performance (Jaffe and Stavins, 2000; Innes and Bial, 2002), we include the four-firm Herfindahl index (***Concentration***) as an indicator of

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[5] The moving average is calculated to weight more recent counts more heavily. Specifically, we use a declining balance five-year average, calculated as follows:

$$ENVPATENTSMA = \sum_{t=1}^{5} [(6\text{-z})/15]\, P_{t\text{-}z},$$

where $P_{t\text{-}z}$ is environmental patent application counts z years prior to year t.

industry concentration.[6] Expected effects of concentration on innovative activity are unclear. On one hand, more concentrated industries are more likely to be subject to the "raising rivals' costs" motives for innovative effort (Innes and Bial, 2002). On the other hand, however, firms in more concentrated industries are more likely to recognize the cost of their innovative success in prompting regulators to tighten environmental standards, thus raising their costs of environmental compliance. For example, a monopoly may avoid innovation in order to avoid higher costs of regulation. Theory also offers no clear *a priori* prediction of how concentration affects emissions. The government might regulate more concentrated industries more heavily because they are perceived to be more facile in adapting to revised standards; on the other hand, concentrated industries may be more effective at lobbying for more lax regulation.

Third, more capital intensive industries may be more polluting and have more scope for cost-reducing environmental innovation. We therefore include a measure of capital intensity (***Capital Intensity***), namely, the level of new capital and equipment expenditures divided by sales volume.

Fourth, we include each industry's total lagged level of research and development expenditures per-unit-sales (***R&D Intensity***) in order to capture effects of overall industry research activity on both environmental innovation and tightening of emission standards. Regulators may be more prone to tighten standards for more research-intensive industries that are better able to adapt (at lower cost) to regulatory changes; we therefore expect a negative coefficient on *R&D Intensity* in the emissions equation. Conversely, more research intensive industries are likely to produce environmental innovations as research

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[6] Other indicators such as the 4-firm concentration ratio and the number of small firms in the industry were also considered.

byproducts (as opposed to research outcomes targeted to environmental objectives); hence, we expect a positive coefficient on *R&D Intensity* in the patent equation.[7]

Fifth, industries with older assets (ceteris paribus) may have more scope to reduce emissions and improve their environmental technology with innovation; to control for these effects, we include a measure of asset age (***Age)***, obtained by dividing total assets of an industry by its gross assets (as in Khanna and Damon, 1999). Total assets are defined as current assets plus net property, plant and equipment and other non-current assets. Gross assets are defined as total assets plus accumulated depreciation on property plant, plant and equipment. *Age* is between zero and one; ratios closer to one indicate newer plant and equipment with more current assets and less depreciation.

Sixth and last, both innovation and environmental policy may be affected by the rates of growth, and hence the modernity, of the different industries. We therefore include a sales growth measure (***Salesgrowth)***.[8]

Turning next to instruments that identify emissions (in the patent equation); we note that environmental enforcement activity is widely cited as a stimulus to pollution abatement (e.g., see Magat and Viscusi (1990), Gray and Deily (1996), Deily and Gray (2007), Decker and Pope (2006)). However, there is no evidence, in theory or empirical work, that enforcement activity affects innovative activity; indeed, in testing for such effects, Brunnermeier and Cohen (2003) find none of significance. We therefore propose

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[7] In principle, environmental R&D may be a component of the research intensity measure, raising the potential prospect of joint endogeneity. However, targeted environmental R&D is a very small component of overall R&D. For example, in our sample, the average annual industry-level environmental patent count calculated using the more focused measure of Brunnermeier and Cohen (2003) is 7.59, compared to over 40 for overall patent counts. Hence, if there is any bias, we expect it to be small and to bias against our hypothesized negative effect of environmental patents on emissions. Nevertheless, in view of this issue, we have estimated our models both with and without *R&D Intensity*, finding that our central qualitative results are robust.

to use various measures of U.S. environmental enforcement activity to identify emissions. Specifically, environmental compliance and enforcement histories are obtained from the EPA's IDEA database. IDEA contains facility level data from the Aerometric Information Retrieval System (AIRS) and the Air Facility Subsystem (AFS). AFS contains compliance and enforcement data on stationary sources of air pollution. Regulated sources range from large industrial facilities to relatively small operations. We use counts of enforcement actions (***Actions***), numbers of facilities out of compliance with clean air laws (***Outcomp***), and the number of reported self-inspections (***Selfinspect***) as indicators of environmental enforcement stringency.[9] In all cases, we lag these instruments by three years in order to avoid any potential for endogeneity. For robustness purposes, we consider a variety of different instrument combinations; we report results using two combinations but have obtained similar results using other instrument menus. In addition, we estimate patent models that include an enforcement variable on the right-hand-side (*Actions*) to ensure that there is no (uncontrolled) direct enforcement effect on innovation to which our excluded instruments may relate.

To identify environmental patent counts in our emission equation, we use corresponding (moving average or lagged) non-environmental patent counts. Intuitively, trends in overall innovative output are reflected in a high correlation between these two patent measures; for example, environmental and non-environmental patents by U.S. companies have a correlation coefficient equal to .75 in our sample. However, to our

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8 Initially, we also included an exogenous variable measuring each industry's export intensity (ratio of exports to total sales). However, as this variable was not statistically significant in any estimated equation (regardless of the model), and its inclusion compromised model performance, we do not include it in our reported model estimations.

9 We also considered a fourth instrument -- counts of government environmental inspections (Federal and State) -- and a variety of different enforcement lags, to explain emissions performance. We use lags in our enforcement variables to avoid endogeneity issues when using contemporaneous emissions and enforcement variables. We found that three-year lags in our three other enforcement variables performed the best as determinants of emissions.

knowledge, the only possible reason to expect non-environmental innovation to drive U.S. environmental standards and performance, controlling for the relevant (environmental) innovative output, is due to potential effects of overall research proficiency on the economic adaptability of different industries to regulatory changes; we control for such effects by including lagged *R&D Intensity* as a regressor.[10]

As always, two key criteria underpin our instrument choices. First, the instruments should be highly correlated with the jointly endogenous variable that they identify. In linear simultaneous systems, a common statistical test for this property is obtained from first stage regressions of the endogenous variables on all exogenous data (Bound, et al., 1995). In our emissions equation, however, we have a lagged dependant variable (and evidence of serial correlation when treating the lag as exogenous); hence, we perform both a standard first-stage regression (on purely exogenous data) and a dynamic panel analog to the "first-stage" regression (following Arellano and Bover, 1995, and Blundell and Bond, 1998, as discussed in detail in the next section). Table 3 reports estimates for the pure and pseudo (dynamic) first stage models for our emission equation. In all cases, note that our identifying instruments, *Selfinspect*, *Outcomp* and *Actions*, are jointly significant. We expect (from prior work and intuitive logic) that lagged enforcement scrutiny, as measured by enforcement actions and compliance status, will spur reductions in emissions. In contrast, we expect that self-inspections may substitute for government scrutiny and, hence, favor laxity in emissions performance. The "first stage" estimations in Table 3 are consistent with these expectations.

[TABLE 3 HERE]

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[10] A potential concern with use of non-environmental patents as an identifying instrument is that we may have improperly classified some "environmental" patents as "non-environmental." For this reason, we have sought to make

Similarly, Table 4 provides statistical evidence of the "first stage" relationship between environmental patent counts and non-environmental patent counts. Again, we find that our identifying instrument (non-environmental patents) is a significant predictor of environmental patent measures, with the predicted positive sign.

[TABLE 4 HERE]

Second, the instruments for emissions (patents) should be uncorrelated with the errors in the patent (emission) equation. The best we can do to test for this property is to test the validity of our over-identifying restrictions Corresponding (Hansen / Sargan) test statistics are constructed for each estimated equation and reported in the tabular results of Section 5 below. Note that, in all cases, we do not reject our maintained (null) hypothesis of no correlation (with p-values above twenty percent in almost all cases, for example).

4. Econometric Methods

We have two simultaneous equations which we estimate equation-by-equation.[11] In doing so, a variety of econometric issues arise. First, we have a panel data structure and, hence, need to account for individual effects. Second, we have endogenous regressors. Third, our emission equation has a dynamic structure. And fourth, our observed patent measure takes a count form for which we must account in our estimation strategy. In what follows, we describe how we address these issues in each of the two equations.

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our definition of "environmental" utility classes as broad as possible.

[11] In principle, one can gain some efficiency if the two equations are estimated as a system. However, we prefer to estimate equation by equation for simplicity (given that we have a distinct set of estimation issues for each equation) and in order to avoid any potential bias due to any cross-equation misspecification.

4.1. Emission Equation

Our econometric analysis of the emission equation is based on equation (5), with industry fixed effects.[12] The equation error, ε^{*}_{qit}, is assumed to be independently distributed across industries with zero mean. However, no restrictions are placed on heteroskedasticity across industries and time.[13]

Because we have a dynamic linear panel model, standard estimators that ignore the lagged dependant variable, or fail to account for its potential endogeneity, are biased and inconsistent (Baltagi, 1995). Arellano and Bond (1991) are the first (to our knowledge) to propose a Generalized Method of Moments (GMM) estimator for a dynamic panel data model with endogenous regressors that is consistent (in the number of cross-section units) for a fixed time horizon. Arellano and Bover (1995) and Blundell and Bond (1998) subsequently recommend more efficient estimators. In particular, Blundell and Bond (1998) develop a system GMM estimator with a two-step finite sample correction (see also Windmeijer, 2000). We use the system GMM variant mainly because the two-step estimator uses a weighting matrix which is (asymptotically) efficient and heteroskedasticity consistent.[14]

Because most estimates of emission equations in the literature are based on static models, we also want to compare our estimates to those obtained with traditional static methods (i.e., a model without lagged emissions on the right hand side). Therefore, we

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[12] Formally, we assume that $a^{*}_{qit} = \lambda_{qt}+\mu_{qi}$. Because the time dummies are found to be jointly insignificant, they are dropped from the estimation for the sake of efficiency.

[13] In estimating (5), we considered a variety of alternative lag structures for both Q and the exogenous data. In all cases, we could not rejct the null hypothesis that additional lags of Q and X are equal to zero; p-values for these hypotheses range from 0.2384 to 0.6145

[14] This matrix is calculated using the estimated residuals from the one-step estimation; see Arellano and Bond (1991).

also present a non-dynamic (fixed effects) IV estimation.

4.2. Patent Equation

So far, in deriving our patent equation (6), we have implicitly assumed a linear process that generates a continuous variable. However, measured patent outcomes take a count form, with no negative values, a substantial number of zeroes (roughly one third in our sample), and integer positive values that range from one to 153 (with half of the positive values less than 40). Conceptually, we interpret patent outcomes as the observable consequence of our continuous (and unobservable) index of technology change P_{it} (of equation (6)). Specifically, let us suppose that patent counts P^*_{it} are distributed Poisson with

$$\mathrm{E}_{\mathrm{t}}(P^*_{it}) = \exp(P_{\mathrm{it}}),$$

where P_{it} is determined by equation (6) with industry fixed effects.[15] This gives us the multiplicative error Poisson panel model, with endogenous regressors, of Windmeijer and Santos Silva (1996), which we use to estimate our patent equation.[16] A well-known drawback of the fixed effects Poisson is the potential for over-dispersion. Hence, we test for over-dispersion and, in all cases, do not find evidence of misspecification (not rejecting the mean-equal-variance null).

5. Empirical Findings

5.1 Emission Equation

Table 5 presents estimation results for the dynamic panel model of the emission

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[15] As in the emission equation, we allow for both time and industry fixed effects. However, the time dummies are again jointly insignificant; hence, for efficiency, we estimate with industry fixed effects only.

equation (5). Four dynamic panel estimations are presented, with two alternate sets of enforcement measures, and three alternative measures of lagged environmental patent counts: Lagged five year moving average of environmental patents (which we view as our best measure), one-year lagged counts, and two-year lagged counts. Note that test statistics for serial correlation (m_1 and m_2) and overidentifying restrictions (Hansen) do not indicate misspecification in any of the models.[17] The coefficient for the lagged dependent variable is 0.7174 using Model 3, and is statistically significant.[18] Performing the unit root test developed by Levin, et al. (2002), we reject the null hypothesis that the emissions series contains a unit root, thus indicating that the series is stationary.[19]

[TABLE 5 HERE]

Qualitative implications of Table 5 can be summarized as follows.

1) *Technological innovation spurs a tightening of emission standards*. In all specifications – and with all three alternative measures of technological progress / patent counts – we find negative and significant effects of environmental innovation on emissions. We interpret such costly intra-industry emission reductions to imply a corresponding tightening of toxic emission standards, as firms will surely not engage in

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[16] Mullahy (1997) proposes an additive cross-section Poisson panel model that accounts for endogeneity. We prefer the multiplicative model here because, consonant with our theoretical model, it treats unobservable and observable explanators symmetrically.

[17] The test statistics m_1 and m_2 test for the presence of serial correlation in the first differenced residuals of first and second order, respectively, asymptotically distributed as a N(0,1) under the null hypothesis of no serial correlation (see Arellano and Bond, 1991). As expected, there is significant negative first order autocorrelation, but no significant second order autocorrelation, a crucial property for the validity of our instruments. Moreover, the Hansen (1982) test statistic of overidentifying restrictions is $\chi 2$ –distributed with degrees of freedom (shown in parenthesis) equal to the number of instruments minus the number of estimated parameters. This misspecification test does not indicate correlation between the instruments and the error term. We report the Hansen test statistic rather than the Sargan (1958) test statistic because it is robust to heteroskedasticity and autocorrelation. For a more detailed discussion, see Hansen (1982), Hansen and Singleton (1982), and Newey and West (1987).

[18] This estimated coefficient lies in the interval between the within group and OLS estimates (of 0.5665 and 0.893, respectively), as expected.

[19] The Levin statistic for Model 3 is -0.5452 with a t-value of -33.17.

costly emission abatement that is not otherwise required.[20] Assessing the quantitative importance of these effects is not particularly easy. For example, Model 3 implies that the estimated long-run effect of one patent (approximately 5.4 percent of the sample mean) is to reduce associated industry emissions by .2 percent (of sample mean).[21] Although this effect seems small on one level, it is indeed significant when taken cumulatively. It implies, for instance, that one year of innovative success (evaluated at the sample mean of the moving average of environmental patents) is estimated to spur a 3.8 percent long-run reduction in emissions.

2) *Emission standards tend to be tighter for industries that are more concentrated, have newer assets, and are growing more rapidly*, with significant negative coefficients on our measures of concentration, asset age, and sales growth. All of these effects are consistent with the hypothesis that regulators impose tighter standards in industries that are deemed to be more facile (i.e., better able at lower cost) to adapt to stronger regulation.

5.2 Patent Equation

Tables 6A and 6B present estimation results for our patent equation. Table 6A presents results under a perfect foresight premise that next period emission standards are foreseen by industry participants; hence, regressors can be contemporaneous (see Section 2 above). Table 6B presents results under the alternative rational expectations

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[20] In principle, if cross-plant emissions trading were possible, there could be an alternative interpretation of our results: Improved industry-level environmental technology (as measured by a higher patent count) may spur emission permit sales from the innovating industry to other industries. However, for the hazardous pollutants that are reported in the TRI, U.S. regulation does not allow cross-plant trading of emission rights (see, for example, U.S. Code, Title 42, Section 7412). Hence, emission reductions are net (i.e., not offset in other industries) and thus represent tightening of industry-level emission standards.

[21] This percentage is obtained by converting Model 3 into difference form (subtracting lagged emissions from both sides) and solving for the long-run marginal effect of a patent on the change in emissions (with the sum of emissions and its change substituted for lagged emissions).

(Assumption 1) premise, requiring that exogenous variables be lagged. We use a two-year lag as the conjectured time between R&D investments and patent outcomes in our equation (1). From both Tables, note that test statistics for serial correlation (m_1 and m_2) and over-identifying restrictions (Sargan) do not indicate misspecification.

In each Table, we present three models, two with alternative instrument sets to identify emissions, and one that includes a key enforcement measure (*Actions*) as a regressor. The purpose of the third model is to ensure that we control for any potential direct effects of enforcement activity on innovative outcomes and thus avoid any potential correlation between our identifying enforcement instruments and the error in the patent equation. Note that, in doing so, we find (consistent with prior work) that enforcement activity has no significant direct effect on patent outcomes, with statistically insignificant coefficients on our *Actions* regressor. However, enforcement activity has a significant *indirect* effect on patent outcomes due to its impact on emission performance.

[TABLE 6A HERE]

[TABLE 6B HERE]

Key qualitative implications of our results can be summarized as follows.

1) *Environmental innovation is spurred by the anticipated tightening of emission standards*. In all models, the estimated coefficient on emissions is negative and significant; hence, lower industry-level emissions increase successful patent applications. In quantitative terms, these estimated effects are also significant. For example, based on the Rational Expectations (Table 6B) Model 1, a one percent (of sample mean) reduction in anticipated emissions is estimated to increase successful environmental patent applications by 1.65 percent (of sample mean).

2) *Environmental innovation tends to be greater in more research intensive, more capital intensive, more rapidly growing, smaller, and less concentrated industries*. Intuitively, more capital intensive industries with older assets may have more scope and incentive for emission-reducing innovation; notably, this result is consistent with prior work that finds innovation incentives to rise with capital intensity and pollution abatement expenditures that are higher when assets are older. Larger and more concentrated industries may better internalize prospective costs of innovation in leading regulators to tighten environmental standards, costs that can deter innovation. Potentially, smaller and less concentrated industries may also be more innovative by nature, and be able to distinguish themselves in "green markets" as environmentally proactive corporate citizens (Arora and Cason, 1996). More rapidly growing and more research intensive industries, as expected, are more active in environmental patenting.

6. Conclusion

In this paper, we present empirical evidence of bi-directional linkages between environmental standards and environmental performance, on the one hand, and environmental innovation, on the other. Pollutant emissions and environmental R&D are jointly determined as successful R&D prompts policy change and attendant pollution reductions, and as anticipated policy change (and attendant tightening of pollution standards) spurs new R&D. Specifically, we examine 127 manufacturing industries over the fourteen-year period 1989 – 2002, accounting for the joint determination of research and pollution outcomes.

Our empirical results reveal a negative and significant relationship between emissions and environmental patents, in both directions. Thus, environmental R&D both spurs the tightening of government environmental standards and is spurred by the anticipation of such tightening, suggesting that U.S. environmental policy (at least in the context of the manufacturing industries that we study) has been responsive to innovation and effective in inducing innovation. Empirical results also suggest that a linear feedback model is appropriate in order to capture the dynamic nature of the links between environmental policy and environmental innovation.

These results suggest that there is a salutary process by which the promise of tightened standards stimulates environmental research, and environmental research, by lowering costs of abatement, stimulates tighter standards. However, they say nothing about the efficiency of this process. Indeed, these results are consistent with (but don't imply) a regulator who chooses standards that are ex-post efficient – that is, efficient for any given state of technology – but not chosen with ex-ante commitments that account for impacts on research incentives (see Requate, 2005b; Innes and Bial, 2002). Hence, there is no evidence per se that regulators set tighter standards – vis-à-vis those that are ex-post efficient – in order to spur more innovation, as one might interpret Michael Porter's (1995) famous conjecture to imply.

This observation, as well as the aggregations we make in this study, suggest natural avenues for further inquiry. For example, how do different forms of regulation – tighter standards vs. voluntary pollution reduction programs vs. updated technological regulations – affect innovative effort? And how do different types of innovative effort (more exploratory vs. more derivative) influence and get influenced by environmental standards and regulation? Finally, is there any sense in which regulatory strategy is optimal in inducing and responding to environmental innovation? All of these issues, we believe, merit further study.

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Table 1. Variable Definitions	
REAL SALES	Industry Sales Volume
REAL SALES GROWTH	Real Industry Sales Growth Measure
CONCENTRATION	Herfindahl Index for firm’s two digit class
CAPITAL INTENSITY	Level of new capital and equipment expenditures per-unit-sales
R&D EXPENDITURES	Level of research and development expenditures per-unit-sales
AGE OF CAPITAL	Total assets of an industry divided by Gross Assets
ENVPATENTS	Number of Environmental Patents
NONENVPATENTS	Number of Non-environmental Patents
ENVPATENTSMA(5)	Moving Average of Environmental Patents over the last five years
NONENVPATENTSMA(5)	Moving Average of Non-environmental Patents over the last five years
SELFINSPECT	Number of on-site tests conducted by the firm
ACTIONS	Number of Enforcement actions against firms
OUTCOMPLIANCE	Number of times the firm was reported as out of compliance
EMISSIONS	Total air emissions for each industry (TRI Releases)

Table 2. Summary Statistics

Regression Sample, N= 1778 T=14

Variables	Measurement	Mean	Std. Dev
		t	
REAL SALES	MILLION DLLS	31112	103547
REAL SALES GROWTH	RATIO	-0.0348	0.2649
CONCENTRATION	RATIO	0.0958	0.2197
CAPITAL INTENSITY	PERCENT	0.0833	0.0522
R&D EXPENDITURES	PERCENT	0.6267	0.2920
AGE OF CAPITAL	RATIO	0.7045	0.1429
ENVPATENTS	NUMBER	19.69	17.45
NONENVPATENTS	NUMBER	21.12	22.89
ENVPATENTSMA(5)	AVERAGE	18.47	16.19
NONENVPATENTSMA(5)	AVERAGE	20.74	23.83
SELFINSPECT $_{t-3}$	NUMBER	5.17	13.43
ACTIONS $_{t-3}$	NUMBER	86.34	169.63
OUTCOMPLIANCE $_{t-3}$	AVERAGE	112.81	178.34
EMISSIONS	NUMBER	39.473	145.073

Table 3. “First Stage” Emissions Estimation Results

	Model 1: Fixed Effects		Model 2:Fixed Effects		Model 3: Dynamic Model		Model 4: Dynamic Model	
Dependent Variable	***Emissions***							
Variable Instrumented	***None***				***Emissions $_{t-1}$***			
Exogenous Variables	Coefficient (Robust SE)	z-ratio	Coefficient (Robust SE)	z-ratio	Coefficient (Robust SE)	z-ratio	Coefficient (Robust SE)	z-ratio
SELFINSPECT $_{t-3}$	17.14 (4.98)	3.44	18.74 (5.00)	3.74	18.34 (4.71)	3.89	16.47 (4.48)	3.67
OUTCOMP $_{t-3}$	-197.21 (85.78)	-2.30	-191.43 (86.27)	-2.22	-23.93 (5.70)	-4.20	-19.87 (7.152)	-2.78
ACTIONS $_{t-3}$	-56.56 (9.115)	-6.20	-47.55 (9.16)	-5.19	*	*	-21.825 (7.748)	-2.81
R&D EXPENDITURES $_{t-1}$	-0.0205 (0.3231)	-0.06	-0.0708 (0.3246)	-0.22	-0.1009 (0.2990)	-0.34	-0.0619 (0.2754)	-0.22
CAPITAL INTENSITY	126.62 (79.39)	1.59	126.15 (79.81)	1.58	95.78 (99.95)	0.96	65.38 (85.54)	0.76
CONCENTRATION	102.02 (176.41)	0.06	105.10 (177.35)	0.59	-10.92 (159.29)	-0.07	-27.41 (147.72)	-0.02
AGE	50.39 (39.00)	1.29	52.65 (39.20)	1.34	-32.88 (52.13)	-0.63	15.64 (44.17)	0.35
SALES	0.0733 (0.1931)	0.38	0.0746 (0.1942)	0.38	0.1241 (0.1782)	0.70	0.1479 (0.1643)	0.90
SALES GROWTH	-3.73 (11.71)	-0.32	-5.67 (11.77)	-0.48	-5.57 (10.53)	-0.53	-5.54 (9.76)	-0.57
USNONAPP $_{t-2}$	*	*	-0.1986 (0.0475)	-4.17	*	*	*	*
USNONAPPMA5	*	*	*	*	-0.3381 (0.9293)	-3.64	-0.3239 (0.0848)	-3.82
EMISSIONS $_{t-1}$	*	*	*	*	0.4017 (0.3307)	1.22	0.3188 (0.2581)	1.24
CONSTANT	8.405 (3.4195)	2.45	15.862 (34.354)	0.46	27.169 (35.749)	0.76	36.671 (31.982)	1.15
	F-Statistic	p-value	F-Statistic	p-value	Chi-Statistic	p-value	Chi-Statistic	p-value
Instrument Tests	7.10	0.0001	7.23	0.0001	9.91	0.0071	12.36	0.0062
Time Dummy Tests	0.64	0.8058	0.77	0.6838	13.11	0.2654	14.16	0.2747
Hansen Tests	*	*	*	*	30.89	0.875	40.67	0.573

R^2(adj)	0.945	*	0.969	*	*	*	*	*
DW	1.75	*	1.70	*	*	*	*	*
Hausman Test	5.05	0.4095	7.88	0.1631	*	*	*	*

Table 4. “First Stage” Patent Estimation Results

	Model 1: Fixed Effects		Model 2: Fixed Effects		Model 3: Poisson FE		Model 4: Poisson FE	
Dependent Variable	***USENVPATMA5***				***USENVAPP*** $_{t-1}$		***USENVAPP*** $_{t-2}$	
Variable Instrumented	***None***							
Exogenous Variables	Coefficient (Robust SE)	Coefficient (Robust SE)	z-ratio	z-ratio	Coefficient (Robust SE)	z-ratio	Coefficient (Robust SE)	z-ratio
USNONPATMA5	0.0614 (0.0056)	10.89	0.0768 (0.0071)	10.68	*	*	*	*
USNONAPP$_{t-1}$	*	*	*	*	0.0317 (0.0058)	5.40	*	*
USNONAPP$_{t-2}$	*	*	*	*	*	*	0.020 (0.0073)	2.73
R&D EXPENDITURES $_{t-1}$	0.0005 (0.0002)	2.45	0.0004 (0.0002)	1.96	0.0001 (0.0004)	4.19	0.0017 (0.0004)	4.20
CAPITAL INTENSITY	18.29 (47.13)	0.39	28.88 (58.52)	0.49	26.60 (58.32)	0.45	23.69 (49.57)	0.47
CONCENTRATION	-39.43 (80.55)	-0.49	-41.61 (80.52)	-0.51	-37.46 (81.50)	-0.45	-32.42 (81.05)	-0.40
AGE	8.89 (20.02)	0.44	18.29 (28.74)	0.64	14.45 (28.32)	0.51	13.64 (28.88)	0.47
SALES	0.0002 (0.0001)	1.91	0.0002 (0.0001)	1.67	0.0003 (0.0002)	1.5	0.0002 (0.0001)	1.98
SALES GROWTH	-1.70 (6.19)	-0.27	-1.70 (6.19)	-0.27	-1.45 (7.52)	-0.19	-1.25 (7.70)	-0.16
SELFINSPECT $_{t-3}$	-0.3700 (0.9048)	-0.40	-0.1734 (0.3672)	-0.47	-0.4921 (0.5942)	-0.82	-0.4393 (0.6011)	-0.73
OUTCOMP $_{t-3}$	0.0509 (0.3860)	0.13	0.0143 (0.0632)	0.23	0.1185 (0.1055)	1.12	0.1104 (0.1062)	1.03
ACTIONS $_{t-3}$	*	*	0.0394 (0.0671)	0.59	*	*	*	*
	F-Stat	p-value	F-Stat	p-value	Chi-Statistic	p-value	Chi-Statistic	p-value
Instrument Tests	118.68	0.0000	114.01	0.0000	29.82	0.0000	26.82	0.0000
Time Dummy Tests	0.59	0.8616	0.46	0.9372	0.54	0.4605	0.24	0.6270
R^2(adj)	0.927	*	0.930	*	*	*	*	*

Table 5. Emission Equation Estimation Results										
	Model 1: IV Fixed Effects		Model 2: Dynamic Model		Model 3: Dynamic Model		Model 4: Dynamic Model		Model 5: Dynamic Model	
Dependent Variable	***Emissions***									
Variable Instrumented	***USENVPATMA***		***Emissions $_{t-1}$ and USENVPATMA***				***Emissions $_{t-1}$ and Env. Patent Count $_{t-1}$***		***Emissions $_{t-1}$ and Env. Patent Count $_{t-2}$***	
Exogenous Variables	Coefficient (Robust SE)	t-ratio	Coefficient (Robust SE)	t-ratio	Coefficient (Robust SE)	t-ratio	Coefficient (Robust SE)	t-ratio	Coefficient (Robust SE)	t-ratio
SELFINSPECT $_{t-3}$	18.29	3.60	13.66 (2.70)	5.05	16.40 (3.53)	4.64	19.05 (4.34)	4.38	10.29 (3.65)	2.81
OUTCOMP $_{t-3}$	-22.21	-3.27	-40.44 (20.01)	-2.02	-52.47 (25.78)	-2.03	-52.50 (25.80)	-2.03	-52.63 (25.75)	-2.04
ACTIONS $_{t-3}$	*	*	*	*	-24.70 (12.70)	-1.89	*	*	*	*
USENVAPPMA5	-0.4609	-3.43	-0.1077 (0.048)	-2.20	-0.1034 (0.0470)	-2.20	*	*	*	*
USENVAPP$_{t-1}$	*	*	*	*	*	*	-0.1383 (0.0576)	-2.40	*	*
USENVAPP$_{t-2}$	*	*	*	*	*	*	*	*	-0.0676 (0.0295)	-2.29
EMISSION $_{t-1}$	*	*	0.7166 (0.0588)	12.18	0.7174 (0.0582)	12.32	0.7175 (0.0582)	12.32	0.7173 (0.0583)	12.30
R&D EXPENDITURES $_{t-1}$	-0.3510	-1.00	-0.1119 (0.0372)	-3.00	-0.1204 (0.0379)	-3.18	-0.1214 (0.0372)	-3.26	-0.1218 (0.0377)	-3.23
CAPITAL INTENSITY	11.783	1.40	93.80 (65.09)	1.44	87.81 (63.21)	1.37	84.35 (63.58)	1.32	85.67 (63.36)	1.35
CONCENTRATION	-12.92	0.07	-10.19 (3.98)	-2.56	-8.39 (3.89)	-2.15	-8.58 (3.89)	-2.20	-8.67 (3.36)	2.58
AGE	6.15	1.49	-6.38 (2.76)	-2.31	-5.30 (2.61)	-2.03	-5.78 (2.97)	-1.94	-6.28 (2.97)	-2.11
SALES	0.2138	1.03	0.0411 (0.0149)	2.75	0.0409 (0.0148)	2.76	0.0411 (0.0142)	2.89	0.0410 (0.0145)	2.82
SALES GROWTH	-7.645	-0.62	-12.59 (4.43)	-2.84	-13.52 (5.38)	-2.55	-13.26 (2.45)	-5.41	-14.26 (2.46)	-5.79
CONSTANT	37.81	1.03	47.29 (62.39)	0.76	53.07 (57.46)	0.92	56.77 (57.44)	0.98	53.50 (57.53)	0.92
			Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
HANSEN TEST			41.90	0.431	45.58	0.365	45.44	0.412	43.81	0.437
SERIAL CORR M1			-1.74	0.082	-1.74	0.082	-1.74	0.082	-1.74	0.082
M2			0.44	0.658	0.43	0.665	0.44	0.663	0.43	0.664

Table 6A. Patent Equation Estimation Results
Perfect Foresight

	Model 1: Wooldridge Moment Conditions		Model 2: Wooldridge Moment Conditions		Model 3: Wooldridge Moment Conditions	
Dependent Variable	***Environmental Patent Count***					
Variable Instrumented	***Emissions and Emissions $_{t-1}$***					
Exogenous Variables	Coefficient (Robust SE)	t-ratio	Coefficient (Robust SE)	t-ratio	Coefficient (Robust SE)	t-ratio
EMISSION	-0.9428 (0.1608)	-5.86	-0.9682 (0.1459)	-6.63	-0.9832 (0.3127)	-
EMISSION $_{t-1}$	0.4242 (0.0222)	19.09	0.3123 (0.0256)	12.18	0.2172 (0.1355)	1.60
R&D EXPENDITURES $_{t-1}$	8.866 (1.345)	6.58	8.245 (5.388)	1.53	8.492 (1.2144)	
CAPITAL INTENSITY	8.341 (0.7149)	11.66	9.115 (2.476)	3.68	11.21 (6.0189)	1.86
CONCENTRATION	-13.833 (1.323)	-10.45	-13.298 (5.20)	-2.55	-13.981 (3.178)	-4.39
AGE	-0.4970 (0.2460)	-2.02	-0.5401 (4.06)	-0.13	-0.6170 (0.6005)	-
SALES	-19.62 (3.99)	-4.91	-18.498 (17.11)	-1.08	-20.299 (2.822)	-7.19
USNONAPP	0.0051 (0.0004)	13.09	0.0051 (0.0027)	1.88	0.0040 (0.0008)	5.18
SALES GROWTH	0.1314 (0.0428)	3.06	0.0678 (0.0618)	1.09	0.6598 (0.1208)	-5.46
ACTIONS $_{t-2}$	*	*	*	*	0.0027 (0.0040)	0.675
Instruments Used						
SELFINSPECT $_{t-3}$	YES		YES		YES	
OUTCOMP $_{t-3}$	YES		YES		YES	
ACTIONS $_{t-3}$	NO		YES		NO	
	Statistic	p-value	Statistic	Statistic	Statistic	p-value
SARGAN TEST	24.37	0.2262	26.35	0.1545	21.4895	0.2052
SERIAL CORR M1	-1.56	0.1180	0.1088	0.1180	-1.0033	0.3157
M2	-0.7659	0.4438	0.5863	0.4438	-0.5009	0.6165

Table 6B. Patent Equation Estimation Results **Rational Expectations**						
	Model 1: Wooldridge Moment Conditions		Model 2: Wooldridge Moment Conditions		Model 3: Wooldridge Moment Conditions	
Dependent Variable	***Environmental Patent Count***					
Variable Instrumented	***Emissions and Emissions $_{t-2}$***					
Exogenous Variables	Coefficient (Robust SE)	t-ratio	Coefficient (Robust SE)	t-ratio	Coefficient (Robust SE)	t-ratio
EMISSION	-0.8340 (0.1114)	-7.48	-1.2428 (0.1608)	-7.72	-0.0057 (0.0024)	-7.48
EMISSION $_{t-2}$	0.2130 (0.0271)	7.87	0.4242 (0.022)	19.02	0.0155 (0.0068)	7.87
R&D EXPENDITURES $_{t-2}$	6.662 (0.5108)	13.04	8.866 (1.3458)	6.58	-0.1272 (0.0786)	-1.61
CAPITAL INTENSITY $_{t-2}$	4.122 (0.7321)	5.63	8.341 (0.7149)	11.66	3.3945 (0.2431)	13.96
CONCENTRATION $_{t-2}$	-12.79 (0.7379)	-17.34	-13.83 (1.323)	-10.45	-4.4770 (0.4550)	-9.83
AGE $_{t-2}$	-0.5038 (0.5685)	-0.88	-0.4970 (0.246)	-2.02	-0.5382 (0.1395)	-3.85
SALES $_{t-2}$	-11.59 (1.362)	-8.5	-19.62 (3.993)	-4.91	-11.0076 (2.002)	-5.49
USNONAPP $_{t-2}$	0.0049 (0.0020)	2.45	0.0052 (0.0026)	1.99	0.0117 (0.0022)	5.85
SALES GROWTH $_{t-2}$	0.0139 (0.0852)	0.16	0.1314 (0.0428)	3.06	0.4277 (0.0269)	15.90
ACTIONS $_{t-2}$	*	*	*	*	-0.0002 (0.0003)	0.5095
Instruments Used						
SELFINSPECT $_{t-3}$	YES		YES		YES	
OUTCOMP $_{t-3}$	YES		YES		YES	
ACTIONS $_{t-3}$	NO		YES		NO	
	Statistic	p-value	Statistic	Statistic	Statistic	p-value
SARGAN TEST	25.35	0.1881	24.37	0.2262	31.0889	0.2675
SERIAL CORR M1	-1.1377	0.2552	0.1180	0.2552	0.4271	0.6693
M2	-0.8027	0.4221	0.4438	0.4221	-1.5822	0.1136

Appendix

Table A1. Environmental Patent Classifications

	Patent Utility Classes according to the US Patent Classification System
1. Wind Energy	**242**, 073, 180, 440, 340, 343, **422**, 280, 104, 374
2. Solid Waste Prevention	**137**, **435**, **165**, **119**, **210**, **205**, **405**, **065**
3. Water Pollution	**405**, **203**, **210**
4. Recycling	**264**, **201**, 229, 460, **526**, **106**, **205, 425**, **060**, **075**, **099**, 100, **162**, 164, 198, **210**, 216, **266**, **422**, **431**, **432**, 502, **523**, **525**, 902
5. Alternative Energy	204, **062**, 228, 248, **425**, 049, 428, **242**, **222**, 708, **976**
6. Alternative Energy Sources	**062**, **425**, **222**
7. Geothermal Energy	**060**, 436
8. Air Pollution Control	**123**, **060**, **110**, **422**, **015**, **044**, **423**
9. Solid Waste Disposal	**241**, **239**, **523**, **588**, **137**, **122**, **976**, **405**
10. Solid Waste Control	**060**, **137**, **976**, **239**, **165**, **241**, **075**, **422**, **266**, 118, **119**, **435**, **210**, **405**, 034, **122**, **423**, **205**, 209, **065**, **099**, **162**, **106**, **203**, **431**