Does Induced Innovation Create an Environmental Policy Multiplier? A Simultaneous Equation Model of Pollution Policy and Patenting

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December 2007

Abstract

By estimating a simultaneous panel data model of environmental innovation and policy, this paper identifies bi-directional causal links between the two. We study a panel of 127 manufacturing industries over the period 1989 – 2002. Pollutant emissions are used to measure policy stringency and environmental patent counts to measure environmental innovation. After accounting for the joint endogeneity, we find that environmental innovation is an important driver of U.S. environmental policy and attendant reductions in toxic emissions over time. Conversely, we find that environmental policy induces innovation. However, our estimates indicate that the "environmental policy multiplier" – the proportionate contribution of induced innovation to long-run emission reduction – is small.

Keywords: Environmental Innovation; Pollution Standards; Dynamic and Count Panel Data Models
JEL Classification: Q55, Q20, O30, L51

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1. Introduction

Does environmental policy spur innovation in environmental technology? Alternately, does environmental innovation lead to a tightening of environmental standards, reflecting the lower pollution abatement costs associated with better technologies? Recent empirical work focuses on the first question, finding evidence of induced innovation. In particular, higher pollution abatement expenditures (PAE) – attributable to tighter environmental policy – are estimated to increase rates of environmental patenting (Jaffe and Palmer, 1997; Brunnermeier and Cohen, 2003). However, in principle, causal effects may go in both directions: environmental policy may spur innovation, and innovation may spur tightening of environmental policy.

This observation is important for at least three reasons. First, not only does one want to understand whether and how environmental policy can yield derivative benefits in environmental innovation, but it is also of interest to understand whether regulators tighten environmental standards in response to innovation, as would be an efficient response to lowered costs of environmental compliance and would imply some sharing of the benefits of innovation with the general public. Second, even if one is only interested in "induced innovation" – how policy affects research outcomes – one needs to account for the other direction of causal effect. That is, innovation and policy are, at least in principle, jointly determined.[2] Hence, estimates of induced innovation effects that fail to

[2] In a growing literature, economists study 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; Montero, 2002; Biglaiser and Horowitz, 1995). In this literature, the government typically commits to a given setting of a given regulatory instrument and allows innovation to respond accordingly. However, there is considerable anecdotal evidence that government environmental policy also *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,

account for the joint endogeneity of innovation and policy are likely to be biased. Third, ultimately one would like to understand whether, and to what extent, tightened environmental policy can stimulate innovation and thereby yield additional long-run environmental dividends – long-run pollution reductions beyond those required by the initial tightening of standards. Because these additional pollution reduction effects multiply the initial pollution reduction, they represent what we call an environmental policy multiplier. To identify such benefits requires studying both directions of causal effect between policy and research outcomes.

The purpose of this paper is to study these bi-directional effects. 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.

This paper contributes to a surprisingly small empirical literature on environmental innovation.[3] This literature focuses on the effects of pollution abatement expenditures (PAE) on innovative activity. Jaffe and Palmer (1997) find evidence for the

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, 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.

[3] There is of course an extensive empirical literature on generic R&D and R&D spillovers (e.g., see Pakes and Grilliches, 1984; Jaffe, et al., 1993; Adams and Jaffe, 1996; Klette, 1996; Lerner, 1997; Orlando, 2004).

induced innovation 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. Brunnermeier 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. [4]

Our work differs from previous studies primarily because we study a model of *bi-directional* links that explicitly accounts for the joint determination of environmental policy and environmental R&D. In doing so, we use a more direct measure of policy stringency, emissions as opposed to PAE. PAE costs are problematic when one is interested in bidirectional effects. The reason is that innovation can be expected to lower PAE costs directly, but indirectly raise them due to a stimulated tightening in emission standards. Our more direct measure of regulatory stringency enables us to identify the latter link between innovation and policy.

Because the two directions of causal effect are expected to be reinforcing – both negative, with higher emissions lowering research incentives, and greater research output lowering environmental standards – one expects that our accounting for joint endogeneity will dampen estimated impacts in both directions. We nevertheless find policy-induced innovation and innovation-induced policy effects that have the predicted negative sign,

[4] See also related work by Popp (2002), who studies induced innovation in energy production. In addition, Newell, Jaffe and Stavins (1999) assess the effects of energy prices and energy efficiency standards on innovation. Finally, 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 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.

and are statistically significant.

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:

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

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

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

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

where P_{it} is time t environmental patents in industry i, RD_{it-1} is lagged environmental R&D, Q_{it} is the volume of emissions, S_{it} is the emission standard, the vectors X_{it} represent exogenous observable variables that we describe in Section 3 below, the ε_{it}'s represent random disturbances, and E is an expectation operator. Equation (1) indicates that patent numbers (P_{it}) are determined by lagged industry R&D (RD_{it-1}), among other variables. Equation (2) indicates that emissions (Q_{it}) respond to changes in environmental standards (S_{it}). 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).[5] Equation (3) indicates that environmental standards (S_{it}) are determined (in part) by improvements in environmental technology as measured by the number of

[5] For simplicity, other exogenous (observable) determinants of emissions are assumed to operate through standards (and the associated X_{sit} variables) At the cost of expositional simplicity, all that follows extends to the presence of other exogenous emission regressors, X_{qit}.

environmental patents (P_{it}). Finally, Equation (4) indicates that R&D expenditures are determined (in part) by anticipated environmental standards (E_t (S_{it+1})). The impact of standards on R&D can be decomposed into two relevant effects that will be important in what follows: the impact of the anticipated *change* in environmental standards (b_r) and the impact of the initial *level* of standards (d_r+b_r). We expect the first effect to be negative and the second effect to be non-positive, as tightened (lower) emission standards promote R&D investment.

We do not have good measures of either environmental standards or environmental R&D expenditures. However, we can use relationships (1)-(4) to derive equations that indicate the relationship between environmental patents and pollutants, which we do measure. Specifically, by lagging (2), solving for S_{it-1} and substituting into (3), then substituting (3) into (2), we obtain the following structural form for emissions:

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

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): $c_q^* = b_s\ b_q$, where b_q>0 from equation (2).

Similarly, lagging (4) to substitute for RD_{it-1} in (1), and using (2) to substitute for E_{t-1}(S_{it}) and S_{it-1}, gives the structural form for the determination of patents:

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

Intuitively, emissions proxy for the changes in standards that drive environmental R&D and, hence, resulting patents. The key parameters of interest in equation (6) are b^*_p, which incorporates the effects of anticipated policy *changes* (S_{it}-S_{it-1}) on environmental R&D (b_r), and c^*_p, which incorporates the effect of the initial *level* of standards (S_{it-1}) on R&D (d_r): $b^*_p = b_r b_p/b_q$, and $c^*_p = d_r b_p/b_q$, where b_p>0 from equation (1) and b_q>0 from equation (2). From our above discussion of equation (4), note that the *level* effect of standards on R&D is (d_r+b_r), and is proportional to the sum of the two equation (6) coefficients, $b^*_p + c^*_p$.

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 emissions (from equation (5)) are identified by elements of X_{sit} that are not contained in the equation (6) set of regressors (X_{pit} and $X_{ri(t-1)}$). X_{sit} 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. Likewise, patents (from equation (6)) are identified by elements of X_{pit} and $X_{ri(t-1)}$ that are not contained in X_{sit}. X_{pit} and $X_{ri(t-1)}$ contain variables that drive research and patent outcomes, including general trends in non-environmental research that are not relevant per se in the determination of environmental standards.

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," $E_{t-1}(Q_{it})$:

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

where[6]

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

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) disturbance 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

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[6] Equation (8) follows from equation (5),

$$Q_{it} -E_{t-1}(Q_{it}) = c^*_q\ (P_{it} – E_{t-1}(P_{it})) + d^*_q\ (X_{sit} – E_{t-1}\ (X_{sit})) + \varepsilon^*_{qit}$$

and substitution from equation (6),

$$P_{it} - E_{t-1}(P_{it})= f^*_p\ (X_{pit} – E_{t-1}(X_{pit})) + \varepsilon^*_{pit}$$

instruments).[7]

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.[8] 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

[7] Our lags here need not be one year. In this model, units of time reflect lags between R&D and patent outcomes. In the empirical analysis of the rational expectations model, for example, we posit that this lag length is two years.

[8] 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.

(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 A1 in the Appendix indicates the patent utility classes that we designate as environmental in our analysis. Non-environmental patents are those in all other patent utility classes (***NonEnvPatents***). 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. From Table 2, we note that our broad definition of environmental patents gives us a mean count that is almost as large as that for non-environmental patents. For robustness purposes, we also construct a narrower measure of environmental patent counts based on the categorization of Brunnermeier and Cohen (2003); we denote this measure ***EnvPatentsBC***, and note that its sample mean is much smaller as a proportion of total patent counts (Table 2).

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 counts.[9]

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

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 (***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, Newell, and Stavins, 2002, 2003; Innes and Bial, 2002), we include the four-firm Herfindahl index (***Concentration***) as an indicator of industry concentration. Expected effects of concentration on innovative activity are unclear. On one hand, more concentrated industries are more

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

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

likely to be subject to the "raising rivals' costs" motives for innovative effort (Innes and Bial, 2002), with imperfectly competitive firms investing in environmental R&D in order to gain a profit-enhancing cost advantage over rival firms. 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 byproducts (as opposed to research outcomes targeted to environmental objectives);

hence, we expect a positive coefficient on *R&D Intensity* in the patent equation.[10]

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 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***).

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 other than due to its effects on "effective" environmental standards and, hence, emissions.[11] We therefore use various

[10] 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 *EnvPatentsBC* is 7.5, 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.

[11] Brunnermeier and Cohen (2003) include a measure of government environmental inspections as an explanatory variable in their patent equation. In doing so, they rightfully argue (p. 284) that "to the extent that stricter government monitoring or enforcement induces firms to comply, they might now seek less costly methods of complying." In our model, in contrast, compliance efforts (that may spur innovation) are

thrice-lagged 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. Because enforcement effects on emission performance occur with a substantial delay, we lag all of our instruments by three years.[12] 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.

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. On the other side of

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captured by our emissions measure; that is, compliance efforts will reduce emissions, which in turn will potentially fuel environmental R&D incentives. In sum, in our paper, enforcement effects operate via emissions, even though they need not operate via PAE, the policy proxy in Brunnermeier and Cohen's (2003) analysis.

[12] A potential worry about our enforcement instruments is that government enforcement policy may be jointly determined with technological change and emission performance. To avoid the potential for endogeneity, -- and because enforcement is expected to affect emissions with a substantial lag – we use three-year-lagged enforcement instruments. Even with the lags, serial correlation could conceivably cause endogeneity. However, in all of our models, we test for AR(1) and AR(2) serial correlation and find no evidence of either. We also perform (and pass) standard tests of the over-identifying restrictions. In all cases, our statistical evidence thus validates our maintained premise of instrument exogeneity.

the coin, is there any reason to expect non-environmental patents to be relevant to the determination of emissions (other than via effects on environmental patenting)? In principle, there may be two reasons (that we can think of), and we control for both. First, perhaps there are effects of overall research proficiency on the economic adaptability of different industries to regulatory changes, which in turn influence regulatory standard setting; we control for such effects by including lagged *R&D Intensity* as a regressor. Second, perhaps non-environmental innovation increases overall industry productivity, and hence output, thus raising emissions; we control for such effects by including an industry output measure (*Sales*) as a regressor.[13]

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 dependent 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

[13] A potential concern with use of non-environmental patents as an identifying instrument is that we may improperly classified some "environmental" patents as "non-environmental." For this reason, we make our definition of "environmental" utility classes broad, incorporating all classes that have potential environmental relevance (see Appendix). As a result, our *EnvPatents* variable has a mean almost three times that of the more narrow measure of Brunnermeier and Cohen (2003) (see Table 2).

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]

Similarly, Table 4 provides statistical evidence of the "first stage" relationship between environmental patent counts and non-environmental patent counts. Here, we present both linear and Poisson fixed effects estimations of "first stage" patent equations. 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. Beyond our intuitive arguments that there is no correlation, the best we can do to test for this property is to examine 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).

4. Econometric Methods

We have two simultaneous equations which we estimate equation-by-equation.[14] A number of econometric issues arise. First, we have a panel data structure and, hence,

[14] 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.

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.

4.1. Emission Equation

Our econometric analysis of the emission equation is based on equation (5), with industry fixed effects.[15] The disturbance term, ε^{*}_{qit}, is assumed to be independently distributed across industries with zero conditional mean. However, no restrictions are placed on heteroskedasticity across industries and time.[16]

Because we have a dynamic linear panel model, standard estimators that ignore the lagged dependent 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)

[15] 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.

[16] In estimating (5), we considered a variety of alternative lag structures for both Q and the exogenous data. In all cases, we could not reject 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.

efficient and heteroskedasticity consistent.[17]

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 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

$$E(P^*_{it} \mid \varepsilon^*_{pit}) = \exp(P_{it}),$$

where P_{it} is determined by equation (6) with industry fixed effects.[18] This gives us the multiplicative error Poisson panel model, with endogenous regressors, of Blundell, Griffith and Windmeijer (2002) (see also Windmeijer (2002) and Windmeijer and Santos Silva (1997)). This is the model we use to estimate our patent equation.[19]

[17] This matrix is calculated using the estimated residuals from the one-step estimation; see Arellano and Bond (1991).
[18] 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.
[19] Because we have a mixture Poisson with multiplicative error, our estimation allows for over-dispersion (see Cameron and Trivedi, 1998, p. 98) and thus avoids the main criticism of a standard fixed effects Poisson. To our knowledge, there is no known Negative Binomial counterpart to the Poisson estimator of

5. Empirical Findings

Before turning to our two equations, we note that a key issue motivating our work is the prospective joint endogeneity of emissions and patent outcomes. Given endogeneity tests available to us, we are able to provide some preliminary evidence that we indeed have simultaneity in our sample. In particular, for our IV fixed effects emissions equation, we can test for the endogeneity of patents (*ENVPATENTSMA*) with a standard Hausman statistic; the resulting (Chi-square (1)) statistic is 15.91 with a p-value of 0.0002, clearly rejecting the null of exogeneity in the patent variable. In the patent equation, we can also construct a Hausman statistic provided we restrict the model to have only contemporaneous emission effects (see Grogger, 1990; and Windmeijer and Santos Silva, 1997); doing so for one of our main patent models (our Rational Expectations Model 2 of Table 6B below) yields a test statistic equal to 5.49 with a p-value of 0.001.[20] Again, we clearly reject the null of exogeneity in the emission variable.[21] Both statistics indicate a need to account for endogeneity of emissions and patents in both equations.

5.1 Emission Equation

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

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Blundell, et al. (2002) and Windmeijer and Santos-Silva (1997) that accounts for our case of an endogenous regressor with a nonlinear (dynamic) generating process.

[20] Corresponding Hausman statistics / p-values for our other models are 5.23 / .001 (Model 1, Table 6A), 4.92 / .002 (Model 2, Table 6A), and 5.71 / .001 (Model 1, Table 6B).

[21] These tests are clearly only illustrative as they fail to account for the dynamic (lagged) effects of emissions in either equation.

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.[22] The coefficient for the lagged dependent variable is 0.7174 using Model 3, and is statistically significant.[23] 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.[24]

[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 costly emission abatement that is not otherwise required.[25] 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

[22] 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 for overidentifying restrictions is $\chi 2$ –distributed with degrees of freedom 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).

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

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

[25] 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.

mean) is to reduce associated industry emissions by .2 percent (of sample mean).[26] Although the marginal effects of patents on emissions are small, the total effects of patents, when taken cumulatively, are indeed significant. Our Model 3 estimates imply, for instance, that one year of innovative success (evaluated at the sample mean of the moving average of environmental patents) spurs 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 (Assumption 1) premise, requiring that exogenous variables be lagged. We use a two-year lag, assuming that R&D investments (in equation (4)) are driven by a two-year-ahead policy forecast. 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 four models, two each using our broad environmental

[26] 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.

patent measure *EnvPatents* and our more focused measure *EnvPatentsBC*, respectively. In each case, we report models with two alternative instrument sets to identify emissions. Moreover, note that in both cases we measure non-environmental patent counts using our broad measure of environment-related patents; we do this to ensure that the non-environmental patent regressor is uncontaminated by any potential environment-related research outcomes.

[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*. As noted in Section 2, we are interested in two effects of emissions standards on R&D. The first is the impact of the anticipated *change* in standards and is measured by the coefficient on contemporaneous emissions. The second is the effect of the initial *level* of standards and is measured by the sum of the coefficients on contemporaneous and lagged emissions.

Turning to the first effect, we see that, in all models, the estimated coefficient on emissions is negative and significant; hence, anticipated reductions in industry-level emissions standards lead to increases in successful patent applications. In quantitative terms, these estimated effects are of roughly similar magnitudes across the different models and different environmental patent measures. Similar estimated coefficients across the two environmental patent measures imply that proportional impacts of changes in environmental standards are similar for the two measures. Hence, environmental patents included in our "broad" measure (*EnvPatents*), but not included in our "narrow"

(Brunnermeier and Cohen, 2003) measure (*EnvPatentsBC*), have similar sensitivity to environmental policy as do those in the "narrow" category. To assess the magnitude (and economic importance) of these effects, consider our Rational Expectations (Table 6B) Model 2; in this Model, a one percent (of sample mean) reduction in anticipated emissions is estimated to increase successful environmental patent applications by roughly one-half of one percent (.49).

With regard to the second (level) effects of standards, we again see estimated effects of roughly similar magnitudes across the different models, again implying similar proportional impacts for our two environmental patent measures. In all cases, as expected, initial emission standards have significant negative effects on R&D / patent outcomes, implying that tighter initial standards spur environmental R&D. To assess the magnitude of the estimated effects, let us again use our Rational Expectations Model 2 (of Table 6B) to illustrate; in this Model, a one percent reduction in the initial level of emissions (based on the sample mean of emissions) is estimated to increase subsequent environmental patenting by roughly one-third of one percent (.32, based on the sum of the two emissions coefficients).

The magnitudes of our "induced innovation" effects are large by comparison to earlier work. Brunnermeier and Cohen (2003), for example, find that a one percent increase in pollution abatement costs spurs an increase in successful environmental patent applications of approximately four-one-hundredths of one percent. The larger impacts that we find are likely due to our different (emission-based) measure of policy stringency. However, our estimated effects are nonetheless rather small in the following sense.

2) *The "multiplier effect" of induced innovation on long-run emissions – what we*

have termed the "environmental policy multiplier" – is proportionately small. Consider the impact of an exogenous one percent (of sample mean) permanent tightening in emission standards. Simulating resulting changes in emissions and patents over time using Model 3 of Table 5 and Model 2 of Table 6B, we estimate an additional long-run emission reduction of 2.74 percent and a long-run increase in annual environmental patenting of 1.2 percent (as shares of sample average emissions and patents, respectively). A key question here is: How much of the additional emission reduction is attributable to the additional patenting? The answer (obtained by comparing to simulated outcomes with no induced innovation) is .08182, which is 7.55 percent of the additional (2.74 percent) emission reduction and 20.7 percent of the initial (one percent) emission reduction.[27] While this impact is not inconsequential, it is also not particularly large.

This observation, however, should be qualified. Our analysis relates to emissions, and not pollution abatement costs. Cost savings from induced innovation (e.g., from a 1.2 percent rise in annual patenting, due to a one-percent shock to environmental standards and a corresponding 2.74 percent long-run emission reduction) may potentially be economically important in the sense that they offset a large share of cost increases that otherwise result from the emission reduction.

In sum, we find that tightened emission standards spur environmental innovations that in turn fuel greater emission reductions. However, the proportionate contribution of *induced* innovation to long-run emission reduction appears to be modest. On the other hand, the contribution of *overall* innovation to long-run emission reductions is estimated to be substantial (Table 5). It would thus appear that environmental innovation, stimulated in part by environmental policy but predominantly by overall technological

[27] The remainder is attributable to the dynamic multiplier.

advancement, is a very important driver of progress in ultimate pollution reduction.

3) *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. 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, the ultimate benefits of tightened pollution standards, due to the resulting stimulus to environmental innovation, appear to be modest. While environmental innovation is found to be a very important driver of long-run pollution reduction, environmental policy plays a role in stimulating environmental research that is statistically significant and not inconsequential, but proportionately not very large. This stimulus may nonetheless be important in offsetting costs (to firms) of meeting new emission reduction targets, a subject that we do not address in this paper.

Our results also say nothing about the efficiency of environmental policy in stimulating research. Indeed, these results are consistent with (but do not 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 (1990) 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	
SALES	Real industry sales ($ millions)
SALES GROWTH	Real industry sales growth rate
CONCENTRATION	Herfindahl index for each industry
CAPITAL INTENSITY	New capital and equipment expenditures per-unit-sales
R&D INTENSITY	Research and development expenditures per-unit-sales
AGE OF CAPITAL	Net industry assets divided by gross assets
ENVPATENTS	Number of environmental patents, “broad” measure (Table A1)
ENVPATENTSBC	Number of environmental patents, “narrow” measure (BC, 2003)
NONENVPATENTS	Number of non-environmental patents
ENVPATENTSMA	Moving average of environmental patents over the last five years
NONENVPATENTSMA	Moving average of non-environmental patents over the last five years
SELFINSPECT	Number of on-site tests conducted by firms
ACTIONS	Number of enforcement actions against firms
OUTCOMP	Number of firms’ citations for out of compliance with clean air laws
EMISSIONS	Total air emissions for each industry (TRI Releases, thousands of pounds)

Table 2. Summary Statistics		
Regression Sample, N= 1778 T=14		
Variables	Mean	Std. Dev
SALES	31112	103547
SALES GROWTH	-0.0348	0.2649
CONCENTRATION	0.0958	0.2197
CAPITAL INTENSITY	0.0833	0.0522
R&D INTENSITY	0.6267	0.292
AGE OF CAPITAL	0.7045	0.1429
ENVPATENTS	19.69	17.45
ENVPATENTSBC	7.507	14.761
NONENVPATENTS	21.12	22.89
ENVPATENTSMA	18.47	16.19
NONENVPATENTSMA	20.74	23.83
SELFINSPECT $_{t-3}$	5.17	13.43
ACTIONS $_{t-3}$	86.34	169.63
OUTCOMP $_{t-3}$	112.81	178.34
EMISSIONS	39.473	145.073

Table 3. "First Stage" Estimation Results

Dependent Variable	Emissions							
Variable Instrumented	None				Emissions t-1			
	Model 1: Fixed Effects		Model 2: Fixed Effects		Model 3: Dynamic Model		Model 4: Dynamic Model	
Exogenous Variables	Coefficient (Robust SE)	t	Coefficient (Robust SE)	t	Coefficient (Robust SE)	z	Coefficient (Robust SE)	z
SELFINSPECT $_{t-3}$	17.987*** (4.7929)	3.75	17.143*** (4.9841)	3.44	8.633*** (2.789)	3.10	15.551*** (3.512)	4.43
OUTCOMP $_{t-3}$	-234.50*** (60.296)	-3.89	-196.90*** (85.6117)	-2.30	-43.892*** (19.491)	-2.25	-61.037** (27.2356)	-2.24
ACTIONS $_{t-3}$	*	*	-56.344* (30.0557)	-1.87	*	*	-36.576* (18.856)	-1.94
R&D INTENSITY	-0.0358 (0.1119)	-0.32	-0.0762 (0.3268)	-0.23	-0.0025 (0.0057)	-0.44	-0.0017 (0.0033)	-0.52
CAPITAL INTENSITY	127.889 (79.240)	1.61	126.865 (79.277)	1.60	85.892** (53.412)	1.61	63.241 (61.3990)	1.03
CONCENTRATION	154.136 (1760.97)	0.09	102.949 (176.335)	0.06	56.561* (30.908)	-1.83	51.913** (26.486)	1.96
AGE OF CAPITAL	51.086 (38.518)	1.33	50.026 (38.5662)	1.30	-44.427 (83.825)	-0.53	-38.273 (60.750)	-0.63
SALES	0.0722 (0.1602)	0.45	0.0802 (0.1607)	0.50	0.0190** (0.0096)	1.98	0.0242* (0.013)	1.86
SALES GROWTH	-3.6020 (11.6060)	-0.31	-3.64 (11.609)	-0.31	-3.299 (2.750)	-1.20	-3.406 (2.805)	-1.21
NONENVPATENTS	-0.8378* (0.4429)	-1.89	-0.8476* (0.4429)	-1.91	-0.5191*** (0.2579)	-2.01	-0.6019** (0.2487)	-2.42
EMISSIONS $_{t-1}$	*	*	*	*	0.3473 (0.2381)	1.46	0.3804* (0.1957)	1.94
CONSTANT	7.1342 (33.6860)	0.21	8.732 (33.794)	0.26	8.643 (7.463)	1.16	9.732 (8.145)	1.19
R-sq (with instruments)	0.3476		0.3479		*		*	
R-sq (without instruments)	0.1192		0.1219		*		*	
					Statistic	p-value	Statistic	p-value
Hansen Test	*		*		7.07	0.422	7.23	0.3
AR(1)	*		*		-1.34	0.179	-1.34	0.179
AR(2)	*		*		0.88	0.378	0.88	0.381

Table 4. "First Stage" Estimation Results.								
	Model 1: Fixed Effects		Model 2: Fixed Effects		Poisson FE		Poisson FE	
Dependent Variable	**USENVPATMA5**				**USENVPAT $_{t-1}$**		**USENVPAT $_{t-2}$**	
Exogenous Variables	Coefficient (Robust SE)	t	Coefficient (Robust SE)	t	Coefficient (Robust SE)	z	Coefficient (Robust SE)	z
NONENVPATENTSMA	0.0614*** (0.0056)	10.89	0.0768*** (0.0071)	10.68	*	*	*	*
NONENVPATENTS $_{t-1}$	*	*	*	*	0.0317*** (0.0058)	5.47	*	*
NONENVPATENTS $_{t-2}$	*	*	*	*	*	*	0.0273*** (0.0073)	3.74
R&D INTENSITY	0.0005** (0.0002)	2.45	0.0004** (0.0002)	1.96	0.0001** (0.00004)	2.5	0.0017*** (0.0004)	4.25
CAPITAL INTENSITY	18.29 (47.13)	0.39	28.88 (58.52)	0.49	26.6038 (58.3284)	0.46	23.694 (49.573)	0.48
CONCENTRATION	-39.43 (80.55)	-0.49	-41.61 (80.52)	-0.51	-37.46 (81.538)	-0.46	-32.428 (81.05)	-0.40
AGE	8.89 (20.02)	0.44	18.29 (28.74)	0.64	14.4584 (28.3294)	0.51	13.648 (28.8827)	0.47
SALES	0.0002* (0.0001)	1.91	0.0002* (0.0001)	1.67	0.0003 (0.0002)	1.5	0.0002* (0.00014)	1.63
SALES GROWTH	-1.7839 (6.1945)	0.29	-1.7539 (6.1972)	-0.28	-1.4527 (7.5284)	-0.19	-1.2547 (7.7365)	-0.16
SELFINSPECT $_{t-3}$	-0.37 (0.9048)	-0.4	-0.1734 (0.3672)	-0.47	-0.4921 (0.5942)	-0.83	-0.4393 (0.6011)	-0.73
OUTCOMP $_{t-3}$	0.0509 (0.386)	0.13	0.0143 (0.0632)	0.23	0.1185 (0.1055)	1.12	0.1104 (0.1062)	1.04
ACTIONS $_{t-3}$	*	*	0.0394 (0.0671)	0.59	*	*	*	*
CONSTANT	45.4319** (18.1277)	2.51	44.69023** (18.4239)	2.43	*	*	*	*
R-sq (with instruments)	0.1786		0.1798		*		*	
R-sq (without instruments)	0.1276		0.1127		*		*	
Log-Likelihood	*		*		-22615.561		-23788.412	

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	**EMISSIONS $_{t-1}$ and ENVPATENTSMA(5)**						**EMISSIONS $_{t-1}$ and ENVPATENTS $_{t-1}$**		**EMISSIONS $_{t-1}$ and ENVPATENTS $_{t-2}$**	
Exogenous Variables	Coefficient (Robust SE)	t	Coefficient (Robust SE)	t	Coefficient (Robust SE)	t	Coefficient (Robust SE)	t	Coefficient (Robust SE)	t
SELFINSPECT $_{t-3}$	18.29*** (5.0806)	3.60	13.66*** (2.7)	5.05	16.4*** (3.53)	4.64	19.05*** (4.34)	4.38	10.29*** (3.65)	2.81
OUTCOMP $_{t-3}$	-22.21*** (6.7920)	-3.27	-40.44*** (20.01)	-2.02	-52.47*** (25.78)	-2.03	-52.50*** (25.8)	-2.03	-52.63*** (25.75)	-2.04
ACTIONS $_{t-3}$	*	*	*	*	-24.7** (12.7)	-1.89	*	*	*	*
ENVPATENTSMA	-0.4609*** (0.1344)	-3.43	-0.1077*** (0.048)	-2.20	-0.1034*** (0.047)	-2.20	*	*	*	*
ENVPATENTS $_{t-1}$	*	*	*	*	*	*	-0.1383*** (0.0576)	-2.4	*	*
ENVPATENTS $_{t-2}$	*	*	*	*	*	*	*	*	-0.0676*** (0.0295)	-2.29
EMISSIONS $_{t-1}$	*	*	0.7166*** (0.0588)	12.18	0.7174*** (0.0582)	12.32	0.7175*** (0.0582)	12.32	0.7173*** (0.0583)	12.3
R&D INTENSITY	-0.351 (0.3529)	-0.99	-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 (8.4164)	1.40	93.8 (65.09)	1.44	87.81 (63.21)	1.37	84.35 (63.58)	1.32	85.67 (63.36)	1.35
CONCENTRATION	-12.927 (184.671)	-0.07	-10.19*** (3.98)	-2.56	-8.39*** (3.89)	-2.15	-8.58*** (3.89)	-2.2	-8.67*** (3.36)	2.58
AGE OF CAPITAL	6.1543 (4.1304)	1.49	-6.38*** (2.76)	-2.31	-5.3*** (2.61)	-2.03	-5.78** (2.97)	-1.94	-6.28*** (2.97)	-2.11
SALES	0.2138 (0.2076)	1.03	0.0411*** (0.0149)	2.75	0.0409*** (0.0148)	2.76	0.0411*** (0.0142)	2.89	0.041*** (0.0145)	2.82
SALES GROWTH	-7.645 (12.3306)	-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	37.814 (36.713)	1.03	47.29 (62.39)	0.76	53.07 (57.46)	0.92	56.77 (57.44)	0.98	53.5 (57.53)	0.92
	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
Hansen Test	*	*	41.9	0.431	45.58	0.365	45.44	0.412	43.81	0.437
AR(1)	*	*	-1.74	0.082	-1.74	0.082	-1.74	0.082	-1.74	0.082
AR(2)	*	*	0.44	0.658	0.43	0.665	0.44	0.663	0.43	0.664

Table 6A. Patent Equation Estimations Results								
PERFECT FORESIGHT								
	Model 1		Model 2		Model 3		Model 4	
Dependent Variable	**ENVPATENTS**				**ENVPATENTSBC**			
Variable Instrumented	**Emissions and Emissions $_{t-2}$**							
Exogenous Variables	Coefficient (Robust SE)	t	Coefficient (Robust SE)	t	Coefficient (Robust SE)	t	Coefficient (Robust SE)	t
EMISSIONS	-0.00943*** (0.001608)	-5.86	-0.00968*** (0.001459)	-6.63	-.01024* (0.0057714)	-1.77	-.01122** (0.005062)	-2.22
EMISSIONS $_{t-1}$	0.004242*** (0.00022)	19.09	0.003123*** (0.000256)	12.18	0.003994** (0.00201)	1.98	0.003918** (0.001656)	2.37
R&D INTENSITY $_{t-1}$	8.8660*** (1.3450)	6.58	8.245 (5.388)	1.53	6.3870* (3.8546)	1.66	6.3821* (3.7216)	1.71
CAPITAL INTENSITY	8.341*** (0.715)	11.66	9.115*** (2.476)	3.68	8.860*** (2.902)	3.05	9.0343*** (2.9008)	3.11
CONCENTRATION	-13.833*** (1.32)	-10.45	-13.298** (5.2)	-2.55	-14.184*** (4.43)	-3.20	-14.0392*** (4.3647)	-3.20
AGE OF CAPITAL	-0.497** (0.246)	-2.02	-0.5401 (4.06)	-0.13	-2.272 (4.536)	-0.50	-2.2667 (4.5698)	-0.50
SALES	-19.6200*** (3.9900)	-4.91	-18.498 (17.11)	-1.08	-13.8492 (8.9194)	-1.55	-13.1132 (8.5812)	-1.53
SALES GROWTH	0.1314*** (0.0428)	3.06	0.0678 (0.0618)	1.09	0.2437 (0.6418)	0.37	0.2138 (0.6485)	0.32
NONENVPATENTS	0.0051*** (0.0004)	13.09	0.0051* (0.0027)	1.88	0.0051** (0.0023)	2.18	0.0050** (0.0023)	2.20
Instruments used								
SELFINSPECT $_{t-3}$	YES		YES		YES		YES	
OUTCOMP $_{t-3}$	YES		YES		YES		YES	
ACTIONS $_{t-3}$	NO		YES		NO		YES	
					Statistic	p-value	Statistic	p-value
Hansen Test	24.37	0.2262	26.35	0.1545	23.8025	0.2511	23.7915	0.2043
AR(1)	-1.56	0.118	0.1088	0.1180	-1.6214	0.1049	-1.5546	0.1200
AR(2)	-0.7659	0.4438	0.5863	0.4438	-0.6284	0.5297	-0.8118	0.4169

Table 6B. Patent Equation Estimations Results

RATIONAL EXPECTATIONS

	Model 1		Model 2		Model 3		Model 4	
Dependent Variable	**ENVPATENTS**				**ENVPATENTSBC**			
Variable Instrumented	**Emissions and Emissions $_{t-2}$**							
Exogenous Variables	Coefficient (Robust SE)	t	Coefficient (Robust SE)	t	Coefficient (Robust SE)	t	Coefficient (Robust SE)	t
EMISSIONS	-0.00834*** (0.001114)	-7.48	-.01243*** (0.001608)	-7.72	-.010041 (0.006747)	-1.49	-.010844* (0.006056)	-1.79
EMISSIONS $_{t-2}$	0.002130*** (0.00027)	7.87	0.004242*** (0.00022)	19.02	0.003804*** (0.001298)	2.93	0.003663*** (0.001382)	2.65
R&D INTENSITY $_{t-2}$	6.6620*** (0.5108)	13.04	8.866*** (1.3458)	6.58	6.6854** (3.1837)	2.10	6.2484 (4.0028)	1.56
CAPITAL INTENSITY $_{t-2}$	4.122*** (0.732)	5.63	8.341*** (0.7149)	11.66	8.806*** (2.342)	3.76	8.8979*** (2.4823)	3.58
CONCENTRATION $_{t-2}$	-12.790*** (0.74)	-17.34	-13.83*** (1.323)	-10.45	-13.656** (6.923)	-1.97	-13.2261* (7.086)	-1.87
AGE OF CAPITAL $_{t-2}$	-0.504 (0.569)	-0.88	-0.497** (0.246)	-2.02	-1.902** (0.7543)	-2.52	-1.746*** (0.673)	-2.60
SALES $_{t-2}$	-11.5900*** (1.3620)	-8.50	-19.62*** (3.993)	-4.91	13.0183* (7.2394)	1.80	11.6192 (7.301)	1.59
SALES GROWTH $_{t-2}$	0.0139 (0.0852)	0.16	0.1314*** (0.0428)	3.06	0.2332 (0.1629)	1.43	0.2056*** (0.0642)	3.20
NONENVPATENTS $_{t-2}$	0.0049** (0.0020)	2.45	0.0052** (0.0026)	1.99	0.0047 (0.0029)	1.62	0.0045* (0.0026)	1.73
Instruments used								
SELFINSPECT $_{t-3}$	YES		YES		YES		YES	
OUTCOMPT $_{t-3}$	YES		YES		YES		YES	
ACTIONS $_{t-3}$	NO		YES		NO		YES	
	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
Hansen Test	25.35	0.1881	24.37	0.2262	24.28	0.2215	23.8956	0.2319
AR(1)	-1.1377	0.2552	0.118	0.2552	-1.3294	0.2561	-1.3554	0.2554
AR(2)	-0.8027	0.4221	0.4438	0.4221	-0.8513	0.4829	-0.8437	0.4365

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