# Environmental Innovation and Environmental Performance

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**Abstract**

By estimating a simultaneous panel data model of environmental innovation and toxic air pollution, this paper identifies bi-directional causal links between the two. We study a panel of 127 manufacturing industries over the period 1989 – 2004. Pollutant emissions are an implicit measure of policy stringency and environmental patent counts are used to measure environmental innovation. After accounting for the joint endogeneity, we find that environmental innovation is an important driver of reductions in U.S. toxic emissions. Conversely, we find that tightened pollution targets induce environmental innovation. However, our estimates indicate that the "environmental policy multiplier" – the proportionate contribution of induced innovation to long-run emission reduction – is small.

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## 1. Introduction

Does environmental policy spur innovation in environmental technology? conversely, 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. From both positive and normative perspectives, we want to understand the effects of environmental innovation on environmental performance. The most likely channel for effect is due to innovation-induced tightening of government standards. However, innovation may also spur at least temporary over-compliance with government pollution standards by lowering costs of meeting demands of environmental NGO's and green consumers (e.g., Baron, 2001; Innes, 2006; Arora and Gangopadhyay, 1995). Identifying the qualitative and quantitative impact of innovation sheds light on the potential benefit of promoting environmental research in order to reduce toxic pollution.

Second, regardless of which direction of effect one wishes to study – how policy affects research or how innovation affects policy-driven environmental performance – one needs to account for the other direction of causal effect. That is, innovation and policy are, at least in principle, jointly determined.[1] Hence, estimates of induced innovation effects that fail to 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 object of our study.

In this paper, we examine 127 manufacturing industries over the sixteen-year period 1989 – 2004. Changes in environmental technologies, as measured by the number of environmental patents, can lead to changes in producing firms' pollution targets, which in turn drive their observed emissions. Emissions in turn proxy for the changes in pollution targets 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.

[1] 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, 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

This paper contributes to a surprisingly small empirical literature on environmental innovation.[2] This literature focuses on the effects of pollution abatement expenditures (PAE) on innovative activity. Jaffe and Palmer (1997) find evidence for the 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. 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.[3]

Our work differs from previous studies in a number of respects. To our knowledge, this is the first paper to directly estimate the impact of environmental innovation on pollution. Relative to the induced innovation literature, we study a model of *bi-directional* links that explicitly accounts for the joint determination of policy-induced pollution outcomes and environmental R&D, and we use a more direct measure of policy stringency, emissions as opposed to PAE.[4] PAE costs are problematic when

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pollution reductions, and as anticipated policy change (and attendant tightening of pollution standards) spurs new R&D.

[2] 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).

[3] 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.

[4] Referees have rightly pointed out that emission reductions may be driven by both regulatory policy and firms' voluntary over-compliance with government standards (as discussed above). Hence, emissions are not an exact measure of policy stringency per se. However, we note that the same is true for PAE. Just as emissions may be lower due to firms' over-compliance efforts, so may PAE be higher for the same reason.

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 leading to tighter environmental targets – one expects that our accounting for joint endogeneity will dampen estimated impacts in both directions. We nevertheless find policy-induced innovation and innovation-induced pollution effects that have the predicted negative sign, and are statistically significant. In quantitative terms, our estimates of policy effects on innovation are small, but much larger than suggested by prior work (Brunnermeier and Cohen, 2003). However, our estimated effects of patent counts on environmental performance are large by any measure, revealing the central role of innovation in achieving reductions in toxic pollution.

**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 industry pollution targets and environmental R&D). We assume that this model takes the following simple form, reflecting intuitive dynamics and causal relationships that we describe below:

(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 aggregated pollution target of firms in industry i (more below), the vectors $X_{it}$ represent exogenous observable variables that we describe in Section 3 below, the $\varepsilon_{it}$'s represent random disturbances (assumed independently distributed across industry, time, and equation), 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, where the unit of time in the lag reflects the average distance between project R&D and patent application and is likely to be more than one year (more later).

Equation (2) indicates that emissions ($Q_{it}$) respond to changes in environmental standards ($S_{it}$).[5] We interpret $S_{it}$ as governmental standards because costly emission reductions, beyond those required by the government, are likely to be limited and anchored to government requirements. However, $S_{it}$ broadly represents firms' target emissions and, therefore, also captures potential effects of private political pressures (such as boycott threats of NGO's), "green marketing" incentives, and voluntary government pollution reduction programs such as the EPA's 33/50 program (Khanna and Damon, 1999). For example, environmental innovation can lower firms' costs of over-compliance with environmental regulations in order to appease environmental NGO's and green consumers (Arora and Gangopadhyay, 1995; Innes, 2006); if so, innovation will lead to changes in target emissions ($S_{it}$) even absent changes in government standards. As evidence for such effects is limited and mixed (Gamper-Rabindran, 2006; Vidovic and Khanna, 2008; Innes and Sam, 2008; Lyon and Maxwell, 2007)[6] and a number of proposed mechanisms for such effects ultimately operate through changes in government standards,[7] we refer to the $S_{it}$ of equation (2) as regulatory standards for expositional simplicity, but caution the reader that other interpretations are possible.

Equation (3) indicates that environmental standards ($S_{it}$) are determined (in part) by improvements in environmental technology as measured by the number of environmental patents ($P_{it}$).

Finally, Equation (4) indicates that R&D expenditures are determined (in part) by anticipated environmental standards ($E_t$ ($S_{it+1}$)), where again (as in equation (1)) the unit of time forecast length reflects the average R&D – patent lag. 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 pollution targets ($S_{it}$) or environmental R&D expenditures. However, we can use relationships (1)-(4) to derive equations that

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[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, $X_{qit}$.

[6] Gamper-Rabindran (2006) and Vidovic and Khanna (2008) call into question Khanna and Damon's (1999) initial finding that 33/50 program participation resulted in reduced toxic emissions. While Innes and Sam (2008) find new evidence for 33/50 program impacts on emissions, they identify a significant (and persistent) impact only in the first year of program operation and conclude that "green consumerism" played no role in promoting either 33/50 participation or pollutant reductions.

[7] For example, environmental over-compliance to raise rivals' costs (Innes and Bial, 2002) or deter environmental lobbying (Maxwell, et al., 2000) is generally codified in government standards. This is the

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:

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

Intuitively, the change in environmental technology, as measured by the number of patents, drives changes in effective environmental standards ($S_{it}$), 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). Note that, as (5) is obtained only from equations (2)-(3), we will operationalize this equation with a one-year length of lag.

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:

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

Intuitively, emissions proxy for the changes in standards that drive environmental R&D and, hence, resulting patents. In contrast to equation (5), (6) embeds a lag length that reflects average delays between R&D and patent applications, which are generally more than one year.

The key parameters of interest in equation (6) are $b^*_p$, which incorporates the effects of anticipated *changes* in pollution targets ($S_{it}$-$S_{it-1}$) on environmental R&D ($b_r$), and $c^*_p$, which incorporates the effect of the initial *level* of pollution targets ($S_{it-1}$) 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

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explicit objective in firm endeavors to raise rivals' costs and is likely the proximate mechanism for the 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 targets (broadly defined, as described above), and estimating equation (6) tests for effects of environmental policy – and attendant pollution targets – 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 pollution targets.

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

industry collusion posited in Maxwell, et al. (2000).

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

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

where[8]

(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 $\varepsilon^*_{pit}$. 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 $\varepsilon^*_{pit}$ 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). Recall that our lags here are not one year. In equation (6), units of time reflect lags

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[8] 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),

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

between R&D and patent outcomes. In the empirical analysis, we posit that this lag length is two years.

## 3. Data

Our sample is a balanced industry-level panel of 127 manufacturing industries (SIC codes 200-399) over the period 1989 – 2004. 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 measure of regulated toxic air releases (***Emissions***) by aggregated weight by year. Chemicals included in our measure are those that are (i) regulated under the Clean Air Act's National Emissions Standards for Hazardous Air Pollutants (NESHAPS, CAA section 112(b), 40 CFR Part 61), and (ii) contained in the TRI's 1988 Core Chemical list. This gives us a common set of 165 toxic air pollutants reported in the TRI throughout our study period. As all of these chemicals are subject to emission standards, monitoring requirements (under the CAA) and reporting requirements under the Emergency Planning and Community Right to Know Act (EPCRA), they provide an excellent proxy for regulatory stringency. Facility releases of these chemicals are assigned to the primary industry of the parent company.

Following previous studies (c.f., Jaffe and Palmer, 1997; Brunnermeier and Cohen, 2003; 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.[9] 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 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

[9] 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.

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.[10]

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 $X_{pit}$ or $X_{rit-1}$; and (3) instruments that identify patents in our emission equation because they are only contained in $X_{pit}$ or $X_{rit-1}$ 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***) and number of employees (***Employees***) in order to account for potential effects of industry size on emissions and patents. Larger industries (ceteris paribus) are expected to produce more

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

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

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

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 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. Note that this R&D measure reflects *overall* research expenditures, not environmental R&D.[11] 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.

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 of Capital)***, 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 of Capital*** is between zero and one; ratios closer to one indicate newer plant and equipment with more current assets and less depreciation.

Sixth, 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

[11] 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 7.3, compared to over 55 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.

growth measure (***Salesgrowth***).

Finally, industries more sensitive to exports may also be more sensitive to pro-environment pressures from abroad; including export sales per-unit-sales (***Export Intensity***) controls for such effects on environmental performance.

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.[12] We therefore use various 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

[12] 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 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

four years.[13] For robustness purposes, we consider a variety of 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 .74 in our sample. On the other side of 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.[14]

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emissions, even though they need not operate via PAE, the policy proxy in Brunnermeier and Cohen's (2003) analysis.

[13] Using lagged enforcement measures as exogenous explanatory variables in emission equations is standard in the literature (dating back to the classic work of Magat and Viscusi, 1990; see, for example, Innes and Sam, 2008, and Earnhart, 2004). However, a potential concern about using these measures as identifying instruments is as follows: Conceivably, government enforcement policy may be jointly determined with technological change (with improved technology spurring enforcement, for example). Absent serial correlation in patenting, our use of four-year-lagged enforcement instruments avoids this potential for endogeneity. Moreover, in all of our models, we test for AR(1) and AR(2) serial correlation in our patent measures and find no evidence of either (Table 6). We also perform (and pass) standard tests of the over-identifying restrictions implicit in the identification of emissions. Statistical evidence thus supports the use of the enforcement variables as identifying instruments.

[14] A potential concern with use of non-environmental patents as an identifying instrument is that we may improperly classify some "environmental" patents as "non-environmental." For this reason, we make our

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 (using a robust IV-GMM estimation, as discussed 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]

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.

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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

[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) 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 all above fifteen percent and much higher in most cases).

## 4. Econometric Methods

We have two simultaneous equations which we estimate equation-by-equation.[15] A number 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 our theoretical model implies serial correlation in the disturbance term.[16] 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 the dynamic panel

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times that of the more narrow measure of Brunnermeier and Cohen (2003) (see Table 2).

[15] 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.

[16] In the emission equation (5), we have $\varepsilon^*_{qit} = b_q\varepsilon_{sit} + \varepsilon_{qit} - d_s\varepsilon_{qit-1}$, which is clearly serially correlated. In the patent equation (6), however, we have $\varepsilon^*_{pit} = b_p\varepsilon_{rit-1} + \varepsilon_{pit} - c^*_p\varepsilon_{qit-1}$, which (by our independence assumptions) is serially uncorrelated.

model of equation (5), with fixed industry and time effects.[17] 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). Recent dynamic panel Generalized Method of Moment (GMM) estimators (e.g., Arellano and Bond, 1991; Blundell and Bond, 1998) are based on a maintained assumption of no serial correlation in the error, which permits the use of lags in the dependent variable as instruments for identification of the parameter on the (endogenous) lagged dependent variable. In our case, serial correlation in the error of equation (5) rules out these estimators, and the attendant use of lags in emissions for identification. We instead use a standard robust IV-GMM estimator (see, for example, Arellano and Honore, 2001; Arellano, 2003) with differences in lagged exogenous data and our non-environmental patent measure jointly used to identify our lagged dependent variable (***Emissions***$_{t-1}$) and our endogenous regressor (***EnvPatents***). No restrictions are placed on heteroskedasticity across industries and time.[18]

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*

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[17] Formally, we assume that $a^*_{qit} = \lambda_{qt} + \mu_{qi}$.

[18] 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 0.1832 to 0.5840. For each observation in our GMM estimation of equation (5), we have 38 moment conditions for the model with all three enforcement variables, one each for the 11 regressors, 11 lagged instruments, the NONENVPATENT instrument, and 15 constant / time effects (for 16 years, less one lag). In our models with two enforcement variables, there are 36 moment conditions.

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 23 percent of our sample), and integer positive values that range from one to 157 (with 41 percent 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 $P_{\mathrm{it}}$ (of equation (6)). Specifically, let us suppose that patent counts $P^*_{it}$ are distributed Poisson with

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

where $P_{\mathrm{it}}$ is determined by equation (6) with fixed industry and time effects. 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]

## 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 14.67 with a p-

[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

value of 0.0001, 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 6.03 with a p-value of 0.001.[20] Again, we clearly reject the null of exogeneity in the emission variable. 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 our best measure), one-year lagged counts, and two-year lagged counts. We report test statistics for serial correlation ($m_1$ and $m_2$) and validity of the overidentifying restrictions (Hansen), and do not find evidence of correlation between our instruments and the disturbance term.[21] The coefficient for the lagged dependent variable is 0.5809 using

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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 5.42 / .001 (Model 1, Table 6A), 4.33 / .002 (Model 2, Table 6A), and 5.28 / .001 (Model 1, Table 6B). Note that these tests are only illustrative as they fail to account for the dynamic (lagged) effects of emissions in either equation.

[21] 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). The Hansen (1982) test statistic for overidentifying restrictions is $\chi2$ –distributed with degrees of freedom equal to the number of instruments minus the number of estimated parameters. 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).

Model 3, and is statistically significant.[22] 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.[23]

[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 producing firms' toxic emission targets. Tightened emission targets are most likely due to strengthening of government standards, but may also reflect increased voluntary emission reduction in response to pressure by NGO's or green consumers (see discussion in Section 2).[24] 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 3.9 percent of the sample mean) is to reduce associated industry emissions by 2.4 percent (of sample mean).[25] A doubling of innovative output (evaluated at the sample mean of the moving average of environmental patents) is thus estimated to spur over a 60 percent long-run reduction in emissions.

[22] This estimated coefficient lies in the interval between the within group and OLS estimates (of 0.4604 and 0.7953, respectively), as expected.
[23] The Levin statistic for Model 3 is -0.7092 with a t-value of -28.64.
[24] 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 / targets.

2) *Emission targets tend to be tighter for industries that have newer assets, are less capital intensive, and are growing more rapidly*, with significant negative coefficients on our measures of asset age and sales growth, and significant positive coefficients on capital intensity. 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) in adapting to stronger regulation.[26] The other models imply even larger impacts of innovation. Arguably, by any standard, these are big effects that suggest a vital role for environmental R&D promotion in society's pursuit of toxic pollution reductions.

*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 (Hansen) do not indicate misspecification.

In each Table, we present four models, two each using our broad environmental patent measure ***EnvPatents*** and our more focused measure ***EnvPatentsBC***, respectively.

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[25] From equation (5), the cumulative long-run reduction in emissions, due to a one-time increase of one in patents, is $\Delta Q = c^*_q/(1- b^*_q)$. This change can also be interpreted as the annual long-run reduction in emissions due to a permanent increase in patents, annually, of one.

[26] The sometimes-significant negative coefficient on R&D intensity is also consistent with this hypothesis. In some models, export intensity has a weakly significant negative coefficient, providing some loose

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, but somewhat smaller for the narrower BC measure of environmental patents. Similar estimated coefficients across the two environmental patent measures would imply that proportional impacts of changes in environmental standards are similar for the two measures. Hence, environmental patents included in our "broad" measure (***EnvPatents***),

support for the conjecture that environmental pressure from abroad has a positive impact on domestic environmental performance.

but not included in our "narrow" (Brunnermeier and Cohen, 2003) measure (***EnvPatentsBC***), are at least as sensitive to environmental policy as are 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-quarter of one percent (.256).

With regard to the second (level) effects of standards, we again see estimated effects of roughly similar magnitudes across the different models, but substantially smaller proportional impacts for the narrow BC patent measure than for our broader patent count. 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.[27] 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-sixth of one percent (.161, 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 three differences: (i) our different (emission-based)

[27] t-statistics for the level effect of emissions (the sum of the two emissions coefficients in Table 6) are, for Table 6A, -3.58 (Model 1), -3.82 (Model 2), -2.65 (Model 3), and -2.61 (Model 4). For Table 6B, corresponding t-statistics are -4.06 (Model 1), -4.31 (Model 2), -2.53 (Model 3), and -2.24 (Model 4). All

indicator of policy stringency; (ii) our broader environmental patent measure; and (iii) the potential for endogeneity of abatement costs in BC, which would lead to an understatement of their impact on innovation. 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 1.64 percent and a long-run increase in annual environmental patenting of .43 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 .06399, which is 15.6 percent of the additional (1.64 percent) emission reduction and 25.7 percent of the initial (one percent) emission reduction.[28] 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 .43 percent rise in annual patenting, due to a one-percent shock to environmental standards and a corresponding 2.64 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.

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of these statistics are significant at the one percent level except for the last one (Model 4, Table 6B), which is significant at the five percent level.

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 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, more labor intensive, smaller, less concentrated and less export-intensive 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. Finally, more export-intensive industries are likely to be less subject to raising rivals' cost motives for research (Innes and Bial, 2002), which may explain their estimated tendency to invest less in environmental R&D.

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

## 6. Conclusion

In this paper, we present empirical evidence of bi-directional linkages between toxic pollutant emissions, on the one hand, and environmental innovation, on the other. Emissions and environmental R&D are jointly determined as successful R&D prompts pollution reduction, and as the anticipated tightening of pollution targets spurs new R&D. Specifically, we examine 127 manufacturing industries over the sixteen-year period 1989 – 2004, 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. This feedback may reflect effects of both government policy and "private politics" (Gupta and Innes, 2009). In either case, innovation can lower firms' costs of meeting tighter government or consumer or NGO pollution targets, spurring successful demands for improved environmental performance, whether by government or private political agents. Conversely, tightened pollution targets elevate the potential cost-saving benefits of environmental R&D, and thereby spur more innovation. Our empirical results also suggest that a linear feedback model is appropriate in order to capture the dynamic links between environmental policy and innovation.

Arguably the most important message from our estimation results is that innovation plays an important role in reducing toxic pollution, potentially motivating a policy focus on strategies to promote environmental R&D. Our results also 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 improved environmental performance. However, the ultimate benefits of tightened pollution standards, due to the resulting stimulus to environmental innovation, appear to be modest. 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 $100 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 |
| EMPLOYEES | Number of Emloyees |
| EXPORT INTENSITY | Real industry export sales per-unit-sales |
| 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 toxic air emissions of CAA 112(B) chemicals on the 1988 TRI Core Chemical List (thousands of pounds) |

**Table 2. Descriptive Statistics**
**Regression Sample N= 2032**

| Variables | Mean | Std. Dev |
|---|---|---|
| SALES | 64280.08 | 226227.2 |
| SALES GROWTH | 0.0411 | 0.1024 |
| EMPLOYEES | 177.12 | 426.58 |
| CONCENTRATION | 0.0783 | 0.2317 |
| CAPITAL INTENSITY | 0.0954 | 0.0256 |
| R&D INTENSITY | 0.5148 | 0.2238 |
| AGE OF CAPITAL | 0.5572 | 0.1274 |
| EXPORT INTENSITY | 0.0483 | 0.0317 |
| ENVPATENTS | 24.786 | 22.459 |
| ENVPATENTSBC | 7.293 | 16.813 |
| NONENVPATENTS | 30.784 | 38.391 |
| ENVPATENTSMA | 25.368 | 27.914 |
| NONENVPATENTSMA | 34.097 | 38.246 |
| SELFINSPECT $_{t-4}$ | 6.257 | 19.115 |
| ACTIONS $_{t-4}$ | 93.695 | 194.36 |
| OUTCOMP $_{t-4}$ | 108.127 | 178.90 |
| EMISSIONS | 24.919 | 126.07 |

**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 |
| $SELFINSPECT_{t-4}$ | 29.924 *** | 3.46 | 30.417 | 3.71 | 8.472 *** | 3.24 | 9.148 *** | 3.67 |
| | (8.6486) | | (8.1987) | | (2.6148) | | (2.4926) | |
| $OUTCOMP_{t-4}$ | -254.233 *** | -3.67 | -200.438 ** | -2.17 | -55.48 *** | -2.83 | -61.475 ** | -2.25 |
| | (69.2733) | | (92.3677) | | (19.6042) | | (27.3222) | |
| $ACTIONS_{t-4}$ | * | * | -67.202 | -1.56 | * | * | -42.53 ** | -1.99 |
| | | | (43.0782) | | | | (21.3719) | |
| R&D INTENSITY | -0.0732 | -1.10 | -0.1039 | -1.17 | -0.0636 | -0.55 | -0.0024 | -0.59 |
| | (0.0665) | | (0.0888) | | (0.1156) | | (0.0041) | |
| CAPITAL INTENSITY | 114.845 ** | 2.10 | 128.21 ** | 2.04 | 62.495 *** | 2.67 | 63.582 ** | 2.40 |
| | (54.6881) | | (62.8480) | | (23.4064) | | (26.4925) | |
| CONCENTRATION | 167.344 | 0.99 | 153.291 | 0.89 | -55.13 ** | -1.96 | -51.438 * | -1.88 |
| | (169.0343) | | (172.2371) | | (28.1276) | | (27.3606) | |
| AGE OF CAPITAL | 67.304 | 1.43 | 58.135 * | 1.67 | -50.284 | -1.23 | -52.446 | -1.36 |
| | (47.0657) | | (34.8114) | | (40.8813) | | (38.5632) | |
| SALES | 0.2042 * | 1.90 | 0.1842 * | 1.83 | 0.1549 ** | 2.04 | 0.146 ** | 2.01 |
| | (0.1075) | | (0.1007) | | (0.0759) | | (0.0726) | |
| SALES GROWTH | -5.294 | -0.59 | -3.193 | -0.51 | -3.204 | -1.42 | -3.084 | -1.57 |
| | (8.9729) | | (6.2608) | | (2.2563) | | (1.9643) | |
| EMPLOYEES | 0.2984 * | 1.95 | 0.3471 ** | 1.97 | 0.0081 ** | 2.11 | 0.0076 ** | 2.05 |
| | (0.1530) | | (0.1762) | | (0.0038) | | (0.0037) | |
| EXPORT INTENSITY | -0.0613 | -1.48 | -0.0819 | -1.33 | -0.0283 * | -1.67 | -0.0275 * | -1.74 |
| | (0.0414) | | (0.0616) | | (0.0169) | | (0.0158) | |
| NONENVPATENTS | -0.9403 ** | -1.98 | -0.8048 * | -1.95 | -0.9184 ** | -2.06 | -0.984 ** | -2.08 |
| | (0.4749) | | (0.4127) | | (0.4458) | | (0.4731) | |
| $EMISSIONS_{t-1}$ | * | * | * | * | 0.5263 * | 1.93 | 0.5593 ** | 1.98 |
| | | | | | (0.2727) | | (0.2825) | |
| CONSTANT | 10.391 | 1.29 | 8.13 | 1.33 | 9.429 | 1.26 | 9.402 | 1.30 |
| | (8.0550) | | (6.1128) | | (7.4833) | | (7.2323) | |
| R-sq (with instruments) | 0.542 | | 0.546 | | * | | * | |
| R-sq (without instruments) | 0.3194 | | 0.3261 | | * | | * | |

| | Model 1 | Model 2 | Model 3 Statistic | DoF | p-value | Model 4 Statistic | DoF | p-value |
|---|---|---|---|---|---|---|---|---|
| Hansen Test | * | * | 7.11 | 9 | 0.382 | 7.26 | 10 | 0.320 |
| AR(1) | * | * | -1.32 | | 0.182 | -1.34 | | 0.178 |
| AR(2) | * | * | 0.89 | | 0.36 | 0.88 | | 0.361 |

*Notes.*

1. Year dummies are included in all specifications
2. Asymptotic standard errors, asymptotically robust to heteroskedasticity, are reported in parenthesis.
3. AR are tests for first order and second ordern serial correlationin the first differenced residuals, asymptotically distributed as N(0,1) under the null of no serial correlation.
4. Hansen is a test of over-identifying restrictions, asymptotically distributed as chi-square under the null of instrument validity

**Table 4. "First Stage" Estimation Results.**

| Dependent Variable | ENVPATENTSMA | | | | $ENVPATENTS_{t-1}$ | | $ENVPATENTS_{t-2}$ | |
|---|---|---|---|---|---|---|---|---|
| | Model 1: Fixed Effects | | Model 2: Fixed Effects | | Model 3: Poisson FE | | Model 4: Poisson FE | |
| Exogenous Variables | Coefficient (Robust SE) | t | Coefficient (Robust SE) | t | Coefficient (Robust SE) | z | Coefficient (Robust SE) | z |
| NONENVPATENTSMA | 0.0528 *** (0.0084) | 6.28 | 0.0622 *** (0.0095) | 6.53 | * | * | * | * |
| $NONENVPATENTS_{t-1}$ | * | * | * | * | 0.0741 *** (0.0174) | 4.25 | * | * |
| $NONENVPATENTS_{t-2}$ | * | * | * | * | * | * | 0.0371 *** (0.0093) | 4.01 |
| R&D INTENSITY | 0.0004 *** (0.0001) | 3.56 | 0.0004 *** (0.0001) | 3.28 | 0.0001 ** (0.0001) | 2.20 | 0.0001 ** (0.0000) | 2.25 |
| CAPITAL INTENSITY | 54.57 (82.6818) | 0.66 | 59.51 (100.8644) | 0.59 | 26.83 (58.3261) | 0.46 | 23.554 (49.0708) | 0.48 |
| CONCENTRATION | -55.157 * (29.3388) | -1.88 | -52.129 * (29.9592) | -1.74 | -35.194 (22.8532) | -1.54 | -38.201 (25.1322) | -1.52 |
| AGE OF CAPITAL | 10.298 (6.6439) | 1.55 | 11.298 (7.1057) | 1.59 | 17.853 * (10.6268) | 1.68 | 14.297 (8.6648) | 1.65 |
| SALES | 0.0001 (0.0001) | 1.57 | 0.0001 (0.0001) | 1.58 | 0.0002 * (0.0001) | 1.95 | 0.0002 * (0.0001) | 1.67 |
| EMPLOYEES | 0.0854 ** (0.0436) | 1.96 | 0.0847 ** (0.0428) | 1.98 | 0.1359 ** (0.0669) | 2.03 | 0.1473 ** (0.0719) | 2.05 |
| EXPORT INTENSITY | 44.275 * (24.4613) | 1.81 | 43.298 * (23.7901) | 1.82 | 40.394 * (23.7612) | 1.70 | 38.1852 * (22.0724) | 1.73 |
| SALES GROWTH | -2.6541 (3.5388) | -0.75 | -2.7466 (3.6139) | -0.76 | -1.462 (1.5891) | -0.92 | -1.502 (1.5172) | -0.99 |
| $SELFINSPECT_{t-4}$ | -0.5913 (1.7391) | -0.34 | -0.5573 (1.6888) | -0.33 | -0.4652 (1.0113) | -0.46 | -0.4318 (0.9596) | -0.45 |
| $OUTCOMP_{t-4}$ | 0.0548 (0.1075) | 0.51 | 0.0699 (0.1271) | 0.55 | 0.0917 (0.1554) | 0.59 | 0.1048 (0.1690) | 0.62 |
| $ACTIONS_{t-4}$ | * | * | 0.5217 (0.8281) | 0.63 | * | * | * | * |
| CONSTANT | 30.172 *** (9.1154) | 3.31 | 32.185 *** (10.0265) | 3.21 | * | * | * | * |
| R-sq (with instruments) | 0.2196 | | 0.2099 | | * | | * | |
| R-sq (without instruments) | 0.1601 | | 0.1547 | | * | | * | |
| Log-Likelihood | * | | * | | -25173.16 | | -241631.46 | |

*Notes.*

1. Year dummies are included in all specifications

2. Asymptotic standard errors, asymptotically robust to heteroskedasticity, are reported in parenthesis.

**Table 5. Emission Equation Estimation Results**

| Dependent Variable | EMISSIONS | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variable Instrumented | $EMISSIONS_{t-1}$ and ENVPATENTSMA | | | | | | $EMISSIONS_{t-1}$ and $ENVPATENTS_{t-1}$ | | $EMISSIONS_{t-1}$ and $ENVPATENTS_{t-2}$ | |
| | Model 1: IV Fixed Effects | | Model 2: Dynamic Model | | Model 3: Dynamic Model | | Model 4: Dynamic Model | | Model 5: Dynamic Model | |
| Exogenous Variables | Coefficient (Robust SE) | t | Coefficient (Robust SE) | t | Coefficient (Robust SE) | t | Coefficient (Robust SE) | t | Coefficient (Robust SE) | t |
| $SELFINSPECT_{t-4}$ | 22.519 ** | 2.55 | 20.156 ** | 2.05 | 18.247 *** | 3.66 | 14.398 *** | 3.42 | 12.095 *** | 3.44 |
| | (8.8310) | | (9.8322) | | (4.9855) | | (4.2099) | | (3.5160) | |
| $OUTCOMP_{t-4}$ | -30.478 *** | -3.12 | -26.174 *** | -3.07 | -23.719 *** | -3.24 | -44.355 *** | -3.32 | -42.464 *** | -3.23 |
| | (9.7686) | | (8.5257) | | (7.3207) | | (13.3599) | | (13.1467) | |
| $ACTIONS_{t-4}$ | * | * | * | * | -27.196 ** | -2.21 | * | * | * | * |
| | | | | | (12.3059) | | | | | |
| ENVPATENTSMA | -0.5529 *** | -4.01 | -0.2814 *** | -3.57 | -0.2481 *** | -3.20 | * | * | * | * |
| | (0.1379) | | (0.0788) | | (0.0775) | | | | | |
| $ENVPATENTS_{t-1}$ | * | * | * | * | * | * | -0.5134 *** | -5.19 | * | * |
| | | | | | | | (0.0989) | | | |
| $ENVPATENTS_{t-2}$ | * | * | * | * | * | * | * | * | -0.3146 *** | -3.61 |
| | | | | | | | | | (0.0871) | |
| $EMISSIONS_{t-1}$ | * | * | 0.5517 *** | 4.02 | 0.5809 *** | 3.91 | 0.773 *** | 4.92 | 0.7923 *** | 4.80 |
| | | | (0.1372) | | (0.1486) | | (0.1571) | | (0.1651) | |
| R&D INTENSITY | -0.0394 | -1.19 | -0.0785 | -1.33 | -0.0513 | -1.22 | -0.1293 *** | -2.91 | -0.1164 *** | -2.57 |
| | (0.0331) | | (0.0590) | | (0.0420) | | (0.0444) | | (0.0453) | |
| CAPITAL INTENSITY | 10.734 * | 1.88 | 55.109 ** | 2.00 | 53.019 * | 1.93 | 63.141 | 1.62 | 62.919 * | 1.67 |
| | (5.7096) | | (27.5545) | | (27.4710) | | (38.9759) | | (37.6760) | |
| CONCENTRATION | -95.175 | -0.95 | -82.015 | 0.81 | -85.178 | 0.80 | -58.194 ** | 2.05 | -53.173 ** | 2.12 |
| | (100.1842) | | -(101.2531) | | -(106.4725) | | -(28.3873) | | -(25.0816) | |
| AGE OF CAPITAL | 10.746 | 1.33 | -2.075 ** | -2.01 | -2.113 ** | -2.02 | -5.136 ** | -1.96 | -5.358 * | -1.92 |
| | (8.0797) | | (1.0323) | | (1.0460) | | (2.6204) | | (2.7906) | |
| SALES | 0.3918 * | 1.83 | 0.2916 ** | 2.09 | 0.271 ** | 2.11 | 0.3371 *** | 2.89 | 0.3392 *** | 2.82 |
| | (0.2141) | | (0.1395) | | (0.1284) | | (0.1166) | | (0.1203) | |
| SALES GROWTH | -5.1349 | -0.21 | -7.018 ** | -2.16 | -8.074 ** | -2.08 | -14.143 *** | -3.92 | -14.562 *** | -3.95 |
| | (24.4519) | | (3.2491) | | (3.8817) | | (3.6079) | | (3.6866) | |
| EMPLOYEES | 0.2817 | 1.62 | 0.3471 ** | 1.97 | 0.3081 * | 1.83 | 0.3513 ** | 2.05 | 0.3143 ** | 2.02 |
| | (0.1739) | | (0.1762) | | (0.1684) | | (0.1714) | | (0.1556) | |
| EXPORT INTENSITY | -0.053019 | -1.5 | -0.0819 | -1.55 | -0.0283 * | -1.68 | -0.0275 * | -1.85 | -0.0316 * | -1.88 |
| | (0.0353) | | (0.0528) | | (0.0168) | | (0.0149) | | (0.0168) | |
| CONSTANT | 36.094 ** | 2.44 | 37.186 ** | 2.30 | 32.854 ** | 2.24 | 25.164 ** | 2.06 | 24.138 ** | 2.05 |
| | (14.7926) | | (16.1678) | | (14.6670) | | (12.2155) | | (11.7746) | |

| | Model 1 Statistic | Model 1 p-value | Model 2 Statistic | Model 2 DoF | Model 2 p-value | Model 3 Statistic | Model 3 DoF | Model 3 p-value | Model 4 Statistic | Model 4 DoF | Model 4 p-value | Model 5 Statistic | Model 5 DoF | Model 5 p-value |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Hansen Test | * | | 46 | 9 | 0.3216 | 40.19 | 10 | 0.409 | 45.44 | 9 | 0.412 | 43.81 | 9 | 0.437 |
| AR(1) | * | | -1.36 | | 0.1592 | -1.34 | | 0.142 | -1.34 | | 0.141 | -1.34 | | 0.142 |
| AR(2) | * | | 1.25 | | 0.258 | 1.2 | | 0.262 | 1.2 | | 0.262 | 1.21 | | 0.261 |

*Notes.*

1. Year dummies are included in all specifications
2. Asymptotic standard errors, asymptotically robust to heteroskedasticity, are reported in parenthesis.
3. AR are tests for first order and second ordern serial correlationin the first differenced residuals, asymptotically distributed as N(0,1) under the null of no serial correlation.
4. Hansen is a test of over-identifying restrictions, asymptotically distributed as chi-square under the null of instrument validity

**Table 6A. Patent Equation Estimations Results**
**PERFECT FORESIGHT**

| Dependent Variable | ENVPATENTS | | | | | | | | ENVPATENTSBC | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable Instrumented | Emissions and Emissions$_{t-2}$ | | | | | | | | | | | | | | | |
| | Model 1 | | | | Model 2 | | | | Model 3 | | | | Model 4 | | | |
| Exogenous Variables | Coefficient (Robust SE) | | t | | Coefficient (Robust SE) | | t | | Coefficient (Robust SE) | | t | | Coefficient (Robust SE) | | t | |
| EMISSIONS | -0.01152 *** | | -4.04 | | -0.01049 *** | | -3.74 | | -0.0078 * | | -1.85 | | -0.0072 * | | -1.81 | |
| | (0.0028) | | | | (0.0028) | | | | (0.0042) | | | | (0.0040) | | | |
| EMISSIONS$_{t-2}$ | 0.00389 ** | | 2.26 | | 0.003914 ** | | 1.97 | | 0.0072 * | | 1.83 | | 0.0069 ** | | 1.96 | |
| | (0.0017) | | | | (0.0020) | | | | (0.0039) | | | | (0.0035) | | | |
| R&D INTENSITY$_{t-2}$ | 5.7294 *** | | 2.84 | | 5.82 ** | | 1.98 | | 2.2723 | | 1.50 | | 2.3184 | | 1.55 | |
| | (2.0174) | | | | (2.9394) | | | | (1.5149) | | | | (1.4957) | | | |
| CAPITAL INTENSITY | 6.6195 *** | | 2.96 | | 6.782 *** | | 2.92 | | 9.5836 ** | | 2.09 | | 9.5869 ** | | 2.01 | |
| | (2.2363) | | | | (2.3226) | | | | (4.5855) | | | | (4.7696) | | | |
| CONCENTRATION | -10.2902 ** | | -2.51 | | -8.114 ** | | -2.10 | | -7.3247 ** | | -2.39 | | -7.8257 *** | | -2.58 | |
| | (4.0997) | | | | (3.8638) | | | | (3.0647) | | | | (3.0332) | | | |
| AGE OF CAPITAL | -0.6522 * | | -1.67 | | -0.6859 | | -1.30 | | -0.2844 | | -0.99 | | -0.2522 | | -0.97 | |
| | (0.3905) | | | | (0.5276) | | | | (0.2873) | | | | (0.2600) | | | |
| SALES | -11.1013 *** | | -2.75 | | -10.32 ** | | -1.98 | | -8.6847 | | -1.63 | | -8.6369 * | | -1.67 | |
| | (4.0368) | | | | (5.2121) | | | | (5.3280) | | | | (5.1718) | | | |
| SALES GROWTH | 0.42503 * | | 1.69 | | 0.4291 | | 1.61 | | 0.231 | | 1.20 | | 0.2665 | | 1.29 | |
| | (0.2515) | | | | (0.2665) | | | | (0.1925) | | | | (0.2066) | | | |
| NONENVPATENTS | 0.5556 ** | | 2.22 | | 0.5184 ** | | 2.20 | | 0.7753 ** | | 2.25 | | 0.7112 ** | | 2.27 | |
| | (0.2503) | | | | (0.2356) | | | | (0.3446) | | | | (0.3133) | | | |
| EMPLOYEES | 0.0493 ** | | 2.29 | | 0.0395 ** | | 2.25 | | 0.0423 * | | 1.90 | | 0.0208 * | | 1.89 | |
| | (0.0215) | | | | (0.0176) | | | | (0.0223) | | | | (0.0110) | | | |
| EXPORT INTENSITY | -0.27629 *** | | -2.81 | | -0.2958 *** | | -2.76 | | -0.1871 ** | | -2.09 | | -0.1967 ** | | -2.10 | |
| | (0.0983) | | | | (0.1072) | | | | (0.0895) | | | | (0.0937) | | | |
| Instruments used | | | | | | | | | | | | | | | | |
| SELFINSPECT$_{t-4}$ | YES | | | | YES | | | | YES | | | | YES | | | |
| OUTCOMP$_{t-4}$ | YES | | | | YES | | | | YES | | | | YES | | | |
| ACTIONS$_{t-4}$ | NO | | | | YES | | | | NO | | | | YES | | | |
| | Statistic | DoF | p-value | | Statistic | DoF | p-value | | Statistic | DoF | p-value | | Statistic | DoF | p-value | |
| Hansen Test | 19.9302 | 20 | 0.3368 | | 22.642 | 22 | 0.4221 | | 23.668 | 20 | 0.2572 | | 25.3252 | 22 | 0.2818 | |
| AR(1) | 1.2794 | | 0.2008 | | -1.269 | | 0.2041 | | -1.1825 | | 0.237 | | -1.3427 | | 0.1794 | |
| AR(2) | 0.4554 | | 0.6488 | | 0.5267 | | 0.5984 | | 0.4685 | | 0.6394 | | 0.4650 | | 0.6419 | |

*Notes.*

1. Year dummies are included in all specifications
2. Asymptotic standard errors, asymptotically robust to heteroskedasticity, are reported in parenthesis.
3. AR are tests for first order and second ordern serial correlationin the first differenced residuals, asymptotically distributed as N(0,1) under the null of no serial correlation.
4. Hansen is a test of over-identifying restrictions, asymptotically distributed as chi-square under the null of instrument validity

**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 | -0.01015 *** | | -4.01 | -0.01027 *** | | -3.90 | -0.0081 ** | | -2.56 | -0.0083 ** | | -2.49 |
| | (0.0025) | | | (0.0026) | | | (0.0032) | | | (0.0033) | | |
| EMISSIONS$_{t-2}$ | 0.00349 *** | | 4.93 | 0.0038 *** | | 4.88 | 0.0060 * | | 1.72 | 0.0062 * | | 1.69 |
| | (0.0007) | | | (0.0008) | | | (0.0035) | | | (0.0037) | | |
| R&D INTENSITY $_{t-2}$ | 5.8314 *** | | 2.68 | 5.7059 ** | | 2.44 | 2.9133 * | | 1.67 | 2.8614 * | | 1.71 |
| | (2.1759) | | | (2.3385) | | | (1.7445) | | | (1.6733) | | |
| CAPITAL INTENSITY $_{t-2}$ | 4.1028 *** | | 3.91 | 4.0186 *** | | 3.95 | 6.8816 *** | | 3.25 | 6.5096 *** | | 3.14 |
| | (1.0493) | | | (1.0174) | | | (2.1174) | | | (2.0731) | | |
| CONCENTRATION $_{t-2}$ | -9.1867 *** | | -3.04 | -9.692 *** | | -3.17 | -7.681 ** | | -2.10 | -7.858 ** | | -2.13 |
| | (3.0219) | | | (3.0574) | | | (3.6576) | | | (3.6892) | | |
| AGE OF CAPITAL $_{t-2}$ | -0.4759 * | | -1.90 | -0.457 * | | -1.81 | -0.2774 | | -1.42 | -0.1982 | | -1.39 |
| | (0.2505) | | | (0.2525) | | | (0.1954) | | | (0.1426) | | |
| SALES$_{t-2}$ | -9.5439 ** | | -2.37 | -7.5737 ** | | -2.46 | -6.8142 * | | -1.78 | -6.8234 * | | -1.79 |
| | (4.0270) | | | (3.0787) | | | (3.8282) | | | (3.8120) | | |
| SALES GROWTH $_{t-2}$ | 0.4587 * | | 1.79 | 0.4191 * | | 1.73 | 0.6246 * | | 1.68 | 0.6426 | | 1.62 |
| | (0.2563) | | | (0.2423) | | | (0.3718) | | | (0.3967) | | |
| NONENVPATENTS$_{t-2}$ | 0.6782 ** | | 2.43 | 0.6274 ** | | 2.40 | 0.3751 * | | 1.76 | 0.391 * | | 1.71 |
| | (0.2791) | | | (0.2614) | | | (0.2131) | | | (0.2287) | | |
| EMPLOYEES$_{t-2}$ | 0.0347 * | | 1.89 | 0.0345 * | | 1.81 | 0.0178 ** | | 2.11 | 0.0181 ** | | 2.13 |
| | (0.0184) | | | (0.0191) | | | (0.0084) | | | (0.0085) | | |
| EXPORT INTENSITY $_{t-2}$ | -0.309 *** | | -3.09 | -0.3137 *** | | -3.02 | -0.1088 ** | | -2.43 | -0.1061 ** | | -2.41 |
| | (0.1000) | | | (0.1039) | | | (0.0448) | | | (0.0440) | | |
| Instruments used | | | | | | | | | | | | |
| SELFINSPECT $_{t-4}$ | YES | | | YES | | | YES | | | YES | | |
| OUTCOMP $_{t-4}$ | YES | | | YES | | | YES | | | YES | | |
| ACTIONS$_{t-4}$ | NO | | | YES | | | NO | | | YES | | |
| | Statistic | DoF | p-value | Statistic | DoF | p-value | Statistic | DoF | p-value | Statistic | DoF | p-value |
| Hansen Test | 23.873 | 20 | 0.1725 | 24.105 | 22 | 0.1623 | 18.92 | 20 | 0.2086 | 18.84 | 22 | 0.2039 |
| AR(1) | -1.31 | | 0.1888 | -1.3721 | | 0.17 | -1.326 | | 0.1847 | -1.325 | | 0.1849 |
| AR(2) | 1.067 | | 0.2859 | 1.06 | | 0.2864 | 1.115 | | 0.2646 | 1.054 | | 0.2915 |

*Notes.*

1. Year dummies are included in all specifications
2. Asymptotic standard errors, asymptotically robust to heteroskedasticity, are reported in parenthesis.
3. AR are tests for first order and second ordern serial correlationin the first differenced residuals, asymptotically distributed as N(0,1) under the null of no serial correlation.
4. Hansen is a test of over-identifying restrictions, asymptotically distributed as chi-square under the null of instrument validity

## 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 |