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

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Abstract

The purpose of this paper is to study the empirical strength of the bi-directional linkages between environmental standards and performance, on the one hand, and environmental innovation, on the other and, hence, the role of policy in spurring environmental R&D and, in turn, ultimate environmental performance. We study these links using an alternative measure of policy stringency, namely, pollutant emissions themselves. Specifically, we examine 107 manufacturing industries at the three-digit SIC code for the period 1989 - 2002. In view of the joint determination of research and pollution outcomes, we estimate a system of simultaneous equations, using appropriate instruments to identify each endogenous variable. Our empirical results reveal that there is a negative and significant relationship between emissions and environmental patents, in both directions. Thus, environmental R&D both spurs the tightening of government environmental standards and is spurred by the anticipation of such tightening, suggesting that U.S. environmental policy (at least in the context of the manufacturing industries that we study) has been responsive to innovation and effective in inducing innovation. Preliminary 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.

Keywords: Environmental Innovation and Pollution; Dynamic panel data; Count Panel data models

JEL Classification: Q20; Q23; O30

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Introduction

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

In a growing literature, economists have studied the links between different environmental policy instruments and innovation incentives on a theoretical level, comparing emission taxes, marketable permits, technology mandates and performance standards, with and without technology spillovers and patent protections (see Fischer, et al., 2003). In this literature, the government is typically modeled as a first-mover, committing to a given setting of a given regulatory instrument and allowing innovation to respond accordingly. The government may consider the effect of its policy standard on innovation; for example, it may set a seemingly ambitious pollutant standard in order to spur environmental R&D. Alternately, there is considerable anecdotal evidence that government environmental policy *responds* to environmental innovation, often with requirements for adoption of the "best available control technology" (Jaffe, et al., 2002). Such responsive policies also provide strong incentives for environmental innovation, as they offer successful innovators a "ready market" for their products (Jaffe, et al., 2002). Innes and Bial (2002) study such responsive policies in an imperfectly competitive market setting, showing how flexible emission taxes and standards can be combined to elicit both optimal pollution levels and optimal environmental R&D.

With responsive policies, there are bi-directional links between environmental standards and performance, on the one hand, and environmental innovation, on the other. Pollutant emissions and environmental R&D are jointly determined as successful R&D

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

The purpose of this paper is to study the empirical strength of these bi-directional linkages and, hence, the role of policy in spurring environmental R&D and, in turn, ultimate environmental performance. We study these links using an alternative measure of policy stringency, namely, pollutant emissions themselves[2]. Specifically, we examine 107 manufacturing industries at the three-digit SIC code for the period 1989 - 2002. The change in environmental technology, as measured by the number of patents, is assumed to drive changes in effective environmental standards, which in turn drive observed emissions. On the other hand, emissions 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 a system of simultaneous equations, using appropriate instruments to identify each endogenous variable. Our empirical results reveal that there is a negative and significant relationship between emissions and environmental patents, in both directions. Thus, environmental R&D both spurs the tightening of government environmental standards and is spurred by the anticipation of such tightening, suggesting that U.S. environmental policy (at least in the context of the manufacturing industries that we study) has been responsive to innovation and effective in inducing innovation. Preliminary 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.

This paper contributes to a surprisingly small empirical literature on environmental innovation. This literature focuses on the effects of pollution abatement expenditures (PAE) on innovative activity. In doing so, scholars have sought to test the "induced innovation" hypothesis. The latter hypothesis posits that higher pollution abatement costs, costs that can be reduced by innovative success, spur more innovative activity (ceteris paribus). Jaffe and Palmer (1997) find evidence for this hypothesis in using 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

[2] Implicitly we are assuming that pollutant emissions are always at the maximum permissible level.

on environmental patents and control costs from the U.S., Germany and Japan. Brunnermeir and Cohen (2003) are the first to estimate a model that links PAE to U.S. environmental patent counts, again finding evidence in support of the induced innovation hypothesis.

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

The remainder of the paper is organized as follows. In the next section, we present the conceptual framework relating emissions and number of patents. Section 3 details data and variables used in our analysis. Section 4 highlights some estimation issues that need to be considered. Our empirical findings are discussed in Section 5. Finally, Section 6 concludes and provides viable suggestions for future research.

Empirical Model

Our objective is to study empirical linkages between environmental research and development, on the one hand, and environmental policy on the other. In our data, observable outcomes of environmental R&D are environmental patents, and observable outcomes of environmental policy are emissions per-unit-output (as measured by the ratio of emissions to the real value of sales). Specifically, we envision an underlying structural model that determines four outcomes, our two observables (emissions and patents) and two unobservables (effective environmental standards and environmental R&D). Let us suppose that this model takes the following simple form:

$$(1) \quad P_{it} \; ? \; a_{ip} \; ? \; b_p \, RD_{it\text{-}1} \; ? \; c_p \, X_{pit} \; ? \; e_{pit}$$

$$(2) \quad Q_{it} \; ? \; a_{iq} \; ? \; b_q \, S_{it} \; ? \; c_q X_{qit} \; ? \; e_{qit}$$

$$(3) \quad S_{it} \; ? \; a_{is} \; ? \; b_s \, P_{it} \; ? \; c_s X_{sit} \; ? \; d_s S_{t?1} \; ? \; e_{sit}$$

$$(4) \quad RD_{it} \; ? \; q_r \; ? \; b_r \mathrm{E}_{(t)} \, (S_{it}) \; ? \; c_r X_{rit} \; ? \; d_r S_{it} \; ? \; e_{rit}$$

where P_{it} is time t environmental patents in industry *i*, RD_{it-1} is lagged environmental R&D in industry *i*, Q_{it} is the time t change in emissions (per unit sales) in industry *i*, S_{it} are environmental standards for industry *i*, the *X's* represent exogenous observable variables, the e_{it}'s represent random errors, and *E* represents an expectation operator. Eq. (1) indicates that patent numbers are determined by lagged industry R&D (among other variables). Eq. (2) indicates that emissions reflect changes in environmental standards. Eq. (3) indicates that environmental standards are determined (in part) by improvements in environmental technology as measured by the number of environmental patents. Finally, Eq. (4) indicates that R&D expenditures are determined (in part) by anticipated changes in environmental standards.

Lagging (2) and (3) and then substituting (3) into (2), gives the following structural form for emissions:

$$(5) \quad Q_t \ ? \ a_q^* \ ? \ b_q^* Q_{t?1} \ ? \ c_q^* P_t \ ? \ d_q^* X_{qt} \ ? \ e_q^* X_{q(t?1)} \ ? \ f_q^* X_{st} \ ? \ ?_{qt}^*$$

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 Eq. (5) is b_q^*, which incorporates the effects of patents on standards (b_s).

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

$$(6) \quad P_t \ ? \ a_p^* \ ? \ b_p^* E_{(t?1)}(Q_t) \ ? \ c_p^* E_{(t?1)}(X_{qt}) \ ? \ d_p^* Q_{t?1} \ ? \ e_p^* X_{q(t?1)}$$
$$? \ f_p^* X_{r(t?1)} \ ? \ g_p^* X_{pt} \ ? \ ?_{pt}^*$$

Intuitively, emissions proxy for the changes in standards that drive environmental R&D and, hence, resulting patents. The key parameter of interest in equation (6) is b_p^*, which incorporates the effects of policy changes (S_{it}) on environmental R&D (b_r). In sum, estimating Eq. (5) tests for effects of R&D on environmental policy, and estimating Eq. (6) tests for effects of environmental policy on environmental R&D. Note that Eq. (5) is identified by X_{it}, which incorporates determinants of changes in "effective standards," S_{it}. As discussed below, key among such determinants are government enforcement activity that increases the stringency of environmental regulations. Eq. (6), in turn, is identified by X_{pt} and $X_{r(t-1)}$, those variables that drive research and patent outcomes.

Data and Summary Statistics

We construct a panel of 107 manufacturing industries (SIC codes 20-39) for the period 1989 - 2002. Our data comes from a number of sources. Emissions data are available from two sources, the EPA's Toxic Release Inventory (TRI) and the EPA's Air Office. Using the TRI, we construct industry level total toxic releases (by aggregated weight) by year from 1989 to 2002. Facility releases reported in the TRI are assigned to the primary industry of the parent company. Data from the EPA's Air Office gives us industry level releases of criteria air pollutants from 1995 to 2001. We perform estimations using appropriate panels for both sets of emissions data.

Using a dataset from the U.S. Patent and Trademark Office, we construct successful patent application counts by year, by industry, environmental and non-environmental, for U.S. and foreign companies[3]. Environmental patents are determined by patent classifications that relate to air or water pollution, hazardous waste prevention, disposal and control, recycling and alternative energy. We determined the SIC industry to which each of these patents belonged to using the primary line of business of the organization that is named first on the patent application[4].

Financial data is obtained from Compustat and the U.S. Department of Commerce. Deflators are obtained using producer price indexes reported in the Economic Report of the President (2004). Compustat is composed of three datasets, which contains information on about 1500 of the largest industrial companies, 2500 smaller industrial companies, and companies dropped after major events, such as bankruptcies, mergers and

[3] The literature suggests that it is preferable to count them by date of application rather than by date of grant, because that is the time at which the inventor perceives that he or she has made a potentially valuable invention, and the lag between application and grant is somewhat variable and affected by the vagaries of the patent office operations. The average lag between application and grant was 2 years.

[4] It is important to clarify that there will be some misclassification if an organization is granted a patent for a product or process different from its primary line of business. Unfortunately for our case, the patent Office does not ask applicants to identify themselves by industry, and there is no documentation to aggregate patent data to the industry level in a better way. Also, note that this classification has been used by previous studies, such as Brunnermeier and Cohen (2003), Jaffe and Palmer (1997).

liquidators.

Environmental inspection, compliance and enforcement data is culled from the EPA's IDEA dataset. The IDEA dataset is a facility level data that incorporates data from the Aerometric Information Retrieval System (AIRS) Facility Subsystem (AFS), the National Pollutant Discharge Elimination System (NPDES) and the National program management and inventory system of RCRA hazardous waste handlers. AFS contains compliance and enforcement data on stationary sources of air pollution. Regulated sources cover a wide spectrum; from large industrial facilities to relative small operations. IDEA includes data on non-federally reportable facilities, including facilities that operate seasonally, temporally shut down, and shut down. However, IDEA does not include facilities that are solely asbestos demolition and/or renovation contractors, or landfills.

In our emissions equation (5), the dependent variable is the industry emission level (as a ratio of real sales). Emission level consists of toxic releases reported at the facility level in the TRI. Total emissions are reported in pounds for all chemicals released in the air, water, landfills and waste[5].

Exogenous regressors are lagged U.S. environmental patents; measures of industry concentration (such as the Herfindahl index[6]) at the 3-digit SIC code, capital intensity is calculated dividing new capital expenditures by real sales, age of capital is calculated dividing total assets by gross assets. Age of capital should be between zero and one, a higher ratio means (closer to one) newer assets. Export intensity (the ratio of export-related sales to real sales); scope (equals to one if the industry has R&D programs over 500,000) and measures of regulatory scrutiny (lagged U.S. industry environmental inspections, number of visits with sampling and the number of enforcement actions over the prior year). Environmental enforcement activity is widely cited as a stimulus to pollution abatement (e.g., Magat and Viscusi (1990), Gray and Deily (1996), Laplante and Rilstone (1996), Nadeau (1997)). However, there is no evidence, in theory or

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[5] Note the TRI des not have some SIC codes that are present in the patent dataset. These observations should be considered as missing observations since it is not feasible that these SIC have zero emissions. The emission sample includes 0.03 % of observations that are in patent but not in emissions. These observations are deleted form the sample. Therefore we should expect biased estimates but the percentage is so small that we should not be concerned.

empirical work, that enforcement activity affects innovative activity; indeed, in testing for such effects, Brunnermeier and Cohen (2003) find none of significance. We therefore use measures of enforcement activity as identifying instruments in our emission equation[7].

In our patent equation (6), the dependent variable is the number of U.S. successful environmental patents applications by U.S. companies by industry (as defined by three-digit SIC class)[8]. Patents were classified environmental or non-environmental by year granted by industry. This classification of environmental and non-environmental is according to the list constructed using patent class. Exogenous regressors are measures of industry concentration, capital intensity, export intensity, scope, foreign patents (the number of U.S. patents by foreign companies), and U.S. non-environmental patents (the number of U.S. non-environmental patents by U.S. companies). There is debate in the literature on potential effects of industry concentration, size and capital intensity on innovative activity. Industries more sensitive to exports may also be more sensitive to green consumerism abroad; including the export intensity regressor controls for such effects on environmental R&D. The last two patent variables provide useful instruments for our patent equation; U.S. environmental patent activity for a given industry is lkely to be correlated with corresponding foreign patent activity (see Jaffe and Palmer (1997), for example) and innovative activity in non-environmental technologies, while the latter instruments are unlikely to be driven by U.S. environmental policy or performance .

Table 1 presents the mean, standard deviation, minimum and maximum value across all industries and years, for each variable used in the analysis.

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

[7] The simple correlation coefficients between emission per output and the number of actions, inspections and visits are 0.27, 0.34 and 0.22 respectively.

[8] In this case we also have a mismatch between emissions and patents, specifically there are some SIC codes present in the emission dataset but missing from the patent dataset. In this case, it is reasonable to believe that the SIC code missing from the patent dataset refers to zero patents. Another potential problem we face when dividing the patent sample is that there might be some patents that are counted as non-environmental when in reality they might be. This is a risk we will have to take because it is not possible to examine each patent individually. We have to believe that out environmental patent classification is exhaustive.

Table1. Summary Statistics

		Regression Sample, N= 103 T=14			
Variables	Measurement	Mean	Std. Dev.	Min	Max
VISISTS	Number	34.40	113.05	0	1655
INSP	Number	29.65	41.03	0	332
ACTIONS	Number	27.65	63.89	0	793
R&D EXP	Million Dollars	2.638	5.709	0	54.12
REEXPORT	Percent	0.34	1.85	0	30.72596
REKAPINT	Percent	0.80	3.97	0.066	120.40
SIZE	Dummy	0.43	0.50	0	1
SCOPE	Dummy	0.50	0.27	0	1
HHI4	Ratio	0.11	0.25	0	0.98
USENV	Number	104.11	274.15	0	2657
EMISSION	Ratio	76.19	159.19	0.0003	1743.52
AGE	Ratio	1.31	0.81	0.4828	27.86
USNON	Number	114.72	285.35	0	2281
4EINGENV	Number	92.62	229.24	0	1362

Empirical Model and Moment Conditions

Because patents take a count form, we should use an econometric model that takes in account the nature of patents. In addition, since equations (5) and (6) are simultaneous equations, the estimation method must also account for endogeneity. We apply the generalized method of moments (GMM) estimator developed by Windmeijer and Santos-Silva (1997) for count data models with endogenous regressors.

From our previous notation, P_{it} denotes the count of patents for which the conditional mean is specified as[9]:

$$(7) \qquad E ? p_i \mid x_i ? ? Var ? p_i \mid x_i ? ? ?_i ? e^{x_i ? ?}$$

where X_i, is a k-dimensional vector of explanatory variables and $?$ is a k-dimensional vector of parameters. If a probability density function like Poisson or a negative binomial distribution is assumed, the coefficients can be estimated by maximum likelihood.

The conditional mean specification of (7) implicitly defines a regression model:

$$(8) \qquad p_i ? \exp ? x_i ? ? ? ?_i ? ? ?_i ? \exp ? x_i ? ? ?_i ? ?_i ? ?_i ?_i ? ?_i$$

where $?_i ? \exp(?_i)$ and $?_i$ are multiplicative and additive error terms, reflecting unobserved heterogeneity between industries. If some of the elements of x_i are endogenous, the Poisson model will be inconsistent because either $E(u_i|x_i) \neq 1$ or $E(\varepsilon_i|x_i) \neq 0$. Windmeijer and Santos-Silva (1997) derive GMM estimators for both specifications of endogeneity. The model with multiplicative error term u_i is motivated by treating the observables x_i and unobservables u_i symmetrically. In principle, both models are observationally equivalent when only the conditional mean is specified. GMM techniques are applicable if instruments z_i are available, such that $E(u_i|z_i) = 1$ or $E(\varepsilon_i|z_i) = 0$. Windmeijer and Santos Silva (1997) indicate that a set of instruments can only be orthogonal to either multiplicative or additive errors. This paper only displays results from the multiplicative specification, as tests for the over-identifying restrictions support this specification. The GMM estimator is based on the residual $u_i - 1$ which is equal to $(p_i - \mu_i)/\mu_i$. The estimator proposed by Windmeijer and Santos-Silva (1997) minimizes the objective function

$$(9) \qquad (p - \mu)' M^{-1} Z (Z' \Omega Z)^{-1} Z' M^{-1} (p - \mu)$$

where $M = diag(\mu_i)$, Z is an $N \times g$ matrix of instruments[10].

This is equivalent to a heteroscedasticity corrected objective function, which allows for over-dispersion and its minimization will not yield Poisson ML results.

We treat innovators $(p_i > 0)$ and non-innovators $(p_i = 0)$ identically. Therefore, we make the implicit assumption that the observed over-dispersion and excess zeros are solely caused by unobserved heterogeneity, and not by separate probability models for zero and non-zero models. Vuong tests of a standard negative binomial model versus zero-inflated ones for the number of successful patents applications did not support the zero-inflated model. Even though the standard negative binomial model is not identical to the multiplicative Poisson model applied in this study, both are similar, in as

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[9] The primary equation of the model is $\text{Prob}(P_i = p_i | x_i) = \dfrac{e^{-\mu_i} \mu_i^{p_i}}{p_i!}$.

[10] For Eq. (5), we will use measures of enforcement activity as instruments. These instruments are valid due to previous empirical evidence that found no relation between enforcement and innovation activities. For Eq.(6), we use US non-environmental patents and foreign patents as identifying instruments. Empirical evidence suggests that foreign patent activity is correlated with domestic environmental patent activity but it will not be driven by US environmental policy.

much as both allow for over-dispersion caused by unobserved heterogeneity. Therefore, the result of the Vuong test supports the chosen multiplicative Poisson GMM approach[11].

As explained before the count of successful patent applications and the emission level are modeled with a simultaneous equation approach. The number of successful patent applications p_i depends on the level of emissions e_i and covariates X_i.

The emission equation (5) will be estimated using a fixed effects panel data model[12]. Implicitly, we are assuming that our specification is correct, where the observed differences must be due to the zero-correlation between the error and the exogenous regressors.

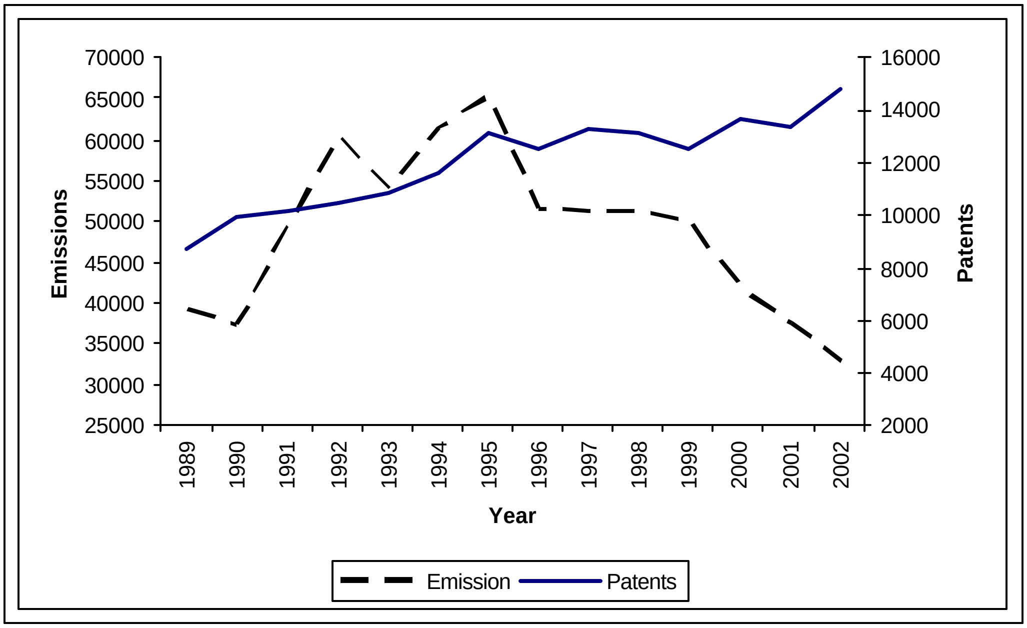
Results

Our analysis provides evidence that environmental R&D both spurs the tightening of government environmental standards and is spurred by the anticipation of such tightening.

Figure 1 describes US environmental patent applications and emission level for the period 1989 - 2002. This figure indicates the negative relationship between patents and emission level.

[11] Vuong Test of Zero- Inflated Negative Binomial vs. Neg. Bin: Std. Normal = -5.36

12 We performed the Breusch Pagan Lagrangian multiplier test for random effects along with a Hausmann specification test. From the B-P LM test we concluded that the classical regression model with a single constant term is innappropriate for our data. Moreover, we reject the hypothesis that the individual effects are uncorrelated with other regressors in the model. Combining results from both tests make FE a better choice.



The number of successful U.S. environmental patent is specified to be conditional on industry size, age, capital and export intensity, real R&D expenditures, scope and emission level. In the following paragraphs, the results of the patent estimations are discussed. In addition to the test for over-identifying restrictions, a test for serial correlation is carried out. Table 3 portrays the estimation results for number of patents and the emission level as a potential endogenous regressor. The first two columns correspond to the Multiplicative Poisson Model (Model 1) where we don't control for endogeneity of the variable emission per unit output. Model 2 corresponds to the GMM estimation described above. In this case we correct for endogeneity using the lagged enforcement measures as instruments. Finally, we consider model 3 where we have a linear feedback model. The sign the coefficients remain stable when comparing the results from the multiplicative Poisson and the GMM estimation.

For the Herfindahl index, we find that its coefficient is negative and significant in models (2) and (3), suggesting that innovation is positively related to domestic competitiveness. The coefficient in the lagged R&D expenditure is positive and significant in model (2) and (3). We expect that under model 2 there is an increase of 2% in patents when R&D expenditures increase by $1 million (and other variables are held constant). Thus, we can say that the magnitude of the R&D impact on environmental innovation is economically and statistically significant.

Scope has a negative and significant coefficient for models (2) and (3). This is somewhat counter-intuitive because we would expect that those industries with large R&D programs would be the most innovative. The coefficient of age is negative and significant which means that industries with older capital have an incentive to innovate. This consistent with the innovation and pollution abatement costs literature, where we find that as pollution abatement cost rises, innovation is a solution to lower costs.

The positive and significant coefficient in export intensity in models (2) and (3) is consistent with previous literature, where it indicates that greener products spur environmental innovation. Model (2) shows that an increase of 1% in export intensity leads to an increase of 5% in the number of patents.

As a test for over-identifying restrictions is not rejected the instruments seem to be valid. In other words, the restrictions implied by the instruments are accepted. M2 tests for the second order serial correlation based on the first difference equation, in other words, M2 tests for lack of second order serial correlation in the 1st difference residuals. Thus, GMM will be consistent because the assumption of no serial correlation in the error is satisfied.

Emission per unit output is significant only in model (2). This is consistent with the idea that tighter standards spur innovation. In the linear feedback model, the negative effect of emissions per output has a greater impact than in model (2). This leaves open lines of research and explore the dynamic nature of environmental policy and innovation

Table 2. Patent Equation						
Variables	Model 1		Model 2		Model 3	
	Multiplicative Poisson		Multiplicative GMM		Dynamic GMM	
	Coefficient (Robust SE)	t-ratio	Coefficient (Robust SE)	t-ratio	Coefficient (Robust SE)	t-ratio
HHI4	-0.4094 (0.6500)	-0.6298	-1.4827 (0.0539)	-27.5232	-3.0239 (0.3713)	-8.145
R&D EXP_{T-1}	0.0017 (0.0024)	0.6869	0.0205 (0.0010)	20.0641	0.0356 (0.0056)	6.3551
SCOPE	-0.2033 (0.1275)	-1.5949	-0.4226 (0.0356)	-11.8857	-1.4712 (0.2825)	-5.2082
SIZE	0.361 (0.2281)	1.5827	0.1472 (0.0303)	4.858	3.2929 (0.7264)	4.5329
AGE	-0.0001 (0.0016)	-0.042	-0.0073 (0.0008)	-8.622	-0.0059 (0.0014)	-4.2274
REKAPINT	0.0012 (0.0017)	0.6764	0.1135 (0.0070)	16.122	0.0141 (0.0169)	0.8331
REEXPINT	0.0001 (0.0006)	0.112	0.0055 (0.0002)	31.7101	0.0041 (0.0004)	9.5287
EMISSION	-0.0009 (0.0006)	-1.4264	-0.0004 (0.0000)	-30.9215	-0.0011 (0.0006)	-1.7018
$ENVPAT_{T-1}$	*	*	*	*	-1.1224 (0.0855)	-13.1294
			Statistic	p-value	Statistic	p-value
SARGAN TEST	*	*	29.8669	0.2293	20.4322	0.4941
SERIAL	M1	*	1.0686	0.2853	-0.9682	0.3330
CORRELATION	M2	*	1.0671	0.2859	1.0660	0.2864

Now, we discuss the results for the emission equation where emission level per output unit is explained by lagged number of visits, inspections and actions. Moreover, the number of US environmental successful patent applications, export intensity, capital intensity, size and scope and the additional instruments discussed above. Table 3 displays the estimation results of the emission equation, where Model 4 refers to a simple fixed effects model that ignores the problem of endogeneity. Model 5 instruments for environmental patents. Finally Model 6 introduces a lagged value of emission per unit output but is not controlling for the endogeneity problem between emissions and patents. The enforcement variables are negative and highly significant. This is the expected result because we can expect that an increase in enforcement activity is related to a decrease in emission per level output. The patent coefficient is model (5) is negative and significant, this implies that an increase in innovative activity reduces the levels of emissions. Note that in model 6 there is positive relationship between lagged emission per unit output and current emissions per output.

Table 3. Emission Equation

Variables	Model 4 Fixed Effects		Model 5 IV Fixed Effects		Model 6 Dynamic Panel Model	
	Coefficient (Robust SE)	t-ratio	Coefficient (Robust SE)	t-ratio	Coefficient (Robust SE)	t-ratio
VISISTS $_{t-1}$	-1.0244 (0.1976)	-5.18	-1.0180 (0.2002)	-5.08	-0.2036 (0.0752)	-2.71
INSP $_{t-1}$	-0.0028 (0.0003)	-7.30	-0.0028 (0.0003)	-7.16	-0.0002 (0.0001)	-1.47
ACTIONS $_{t-1}$	-2.8575 (0.3372)	-8.47	-2.8700 (0.3430)	-8.37	-0.7302 (0.1620)	4.51
R&D EXP	-0.4368 (0.1624)	-2.69	-0.4375 (0.1625)	-2.69	-0.8693 (0.3833)	-2.27
REEXPORT	0.2990 (0.0636)	4.70	0.2958 (0.0656)	4.51	0.1068 (0.0751)	1.42
REKAPEXP	2.0482 (0.6315)	3.24	2.0472 (0.6316)	3.24	0.4112 (0.8384)	0.49
SIZE	88.713 (21.438)	4.14	88.7328 (21.440)	4.14	14.247 (13.588)	1.05
SCOPE	-76.4157 (33.241)	-2.30	-76.6742 (33.270)	-2.30	-5.1244 (15.967)	-0.32
CONS	117.311 (30.827)	3.81	119.875 (33.418)	3.59	-4.0933 (1.551)	-2.64
USENVPAT	-0.1289 (0.0567)	-2.27	-0.1029 (0428)	-2.40	0.0654 (0.0305)	2.14
EMISSION $_{t-1}$	*	*	*	*	0.4975 (0.0321)	15.49
					Statistic	p-value
SARGAN TEST	*	*	*	*	49.33	0.6901
SERIAL	M1	*	*	*	-3.62	0.0003
CORRELATION	M2	*	*	*	0.34	0.7327

Conclusions

This paper investigates the relationship between environmental policy and environmental innovation. A model was estimated using panel dataset of 103 US manufacturing industries at the three digit level from 1989 to 2002. We find that, other things held constant, that environmental R&D both spurs the tightening of government environmental standards and is spurred by the anticipation of such tightening. Although we can speculate the economic magnitude of this relationship, this results should be considered as preliminary. Nevertheless, our findings suggest the need for further research in understanding the relationship between the environmental innovation process and environmental policy. The immediate step is to improve the estimation in the emission equation using a more flexible program, such as the one developed by Arellano and Bond. Using this program will allow us to control for endogeneity in model (6).

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