Do Voluntary Pollution Reduction Programs (VPRs) Spur or Deter Environmental Innovation? Evidence from 33/50

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Abstract

We study whether a government-sponsored voluntary pollution reduction program (VPR) promotes or deters the development of new environmental technologies that yield future emission reduction benefits. Using a panel of 127 U.S. manufacturing industries defined by 3-digit SIC classifications over the 1989-2004 period, we estimate impacts of industry-level participation in the 33/50 program, a VPR initiated by government regulators in 1991, on industry-level rates of environmental patenting. We find that higher rates of 33/50 program participation are associated with significant reductions in the number of successful environmental patent applications five to nine years after the program ended.

Keywords: Voluntary environmental programs, regulatory enforcement, environmental innovation, count panel models

JEL: Q28, K32, D62, L51, C33

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1. Introduction

Voluntary pollution reduction programs have become an integral part of U.S. environmental policy. The number of voluntary programs sponsored by the U.S. Environmental Protection Agency (EPA) has risen from 28 in 1996 to 54 by 1999 to 87 by 2005 (Khanna and Brouhle, 2009). Participants in these programs commit to reduce pollutant emissions beyond targets required by environmental laws. Recent partnership programs include ``AgStar" which promotes the use of biogas recovery systems to curb methane emissions at confined animal feedlot operations, ``EnergyStar" which seeks to reduce carbon dioxide emissions with energy conservation, and "Performance Track" in which participants sought reductions in water and air pollution.

Economists have developed a number of theories to explain why profit-maximizing firms participate in costly voluntary pollution reduction programs (VPRs). Arora and Gangopadhyay (1995) argue that firms want to attract a clientele of "green consumers" willing to pay more for goods produced in an environmentally friendly way. Voluntary pollution reductions may also deter lobbying by environmental groups for tighter regulatory standards (Maxwell, Lyon and Hackett, 2000); spur tighter environmental standards that "raise rivals' costs" (Innes and Bial, 2002); avoid future environmental liability; deter boycotts by environmental interest groups (Baron, 2001; Innes, 2006); and/or lessen the enforcement scrutiny of environmental authorities (Maxwell and Decker, 2006). Empirical work has sought to determine the extent to which these theories have operated in practice, most notably in the EPA's 33/50 program (e.g., see Arora and Cason, 1996; Videras and Alberini, 2000; Khanna and Damon, 1999; Vidovic and Khanna, 2007; Innes and Sam, 2008).

In the 33/50 program, over 1200 large firms pledged to reduce emissions of 17 key toxic pollutants beyond targets required by law; the 33/50 moniker is due to the program's objective to reduce target toxic pollution by one-third from 1988 levels as of 1992 and by one-half as of 1995. A number of empirical studies investigate the extent to which the 33/50 program reduced pollution beyond levels that would otherwise have been produced, accounting for potential firm self-selection into the program (e.g., Khanna and Damon, 1999; Innes and Sam, 2008; Bi and Khanna, 2012).

In this paper, we are interested in potential longer-run impacts of the 33/50 program. We study the extent to which participation in the 33/50 program promotes or depletes innovation in environmental technology as measured by successful environmental patent filings.[4] Prior work shows that innovation in environmental technology has a large impact on long-run levels of toxic pollutant emissions (Carrión-Flores and Innes, 2010).

To our knowledge, there is no specific theory to explain links between environmental VPRs and environmental innovation, although there are theoretical literatures on both of these phenomena in isolation. In the theoretical literature on environmental innovation, R&D is driven by potential cost savings in complying with governmental environmental regulations (see Requate, 2005a, for an excellent survey). Cost savings can be at the firm level and can also affect competition as imperfectly competitive firms seek to raise rivals' costs with innovation-induced tightening of government environmental standards (Montero, 2002; Innes and Bial, 2002).[5]

[4] Patent counts are generally considered to be good measures of technological progress, although they are not without limitations. See Johnstone et al. (2010) for an excellent discussion.

[5] Much of the literature focuses on how alternative forms of environmental regulation – including emission taxes, marketable pollution permits, and standards – affect R&D incentives (see, for example, Fischer et al.,

Participation in a VPR like the 33/50 program has a number of potential affects on costs of compliance and attendant incentives for environmental innovation. If a VPR spurs participating firms to reduce their pollution, and benefits of environmental innovation in saving pollution abatement costs are thereby raised, then VPR participation can "induce innovation."[6] On the other hand, participation in a VPR may have a *signaling effect*: it may signal a firm's pro-active approach to pollution abatement, which can induce a regulatory bargain favoring more lax government oversight (as in Maxwell and Decker, 2006), reduce government and public pressure for improved environmental performance, and/or preempt tighter emission regulation in the future (Glachant, 2007; Dawson and Segerson, 2008; Maxwell et al., 2000). The anticipation of more lax regulation may in turn reduce incentives for environmental R&D.

Alternately, VPRs may lead firms to raise their investments in environmental compliance and monitoring activities, substituting away from environmental research activities that produce new technologies.[7] Indeed, Sam et al. (2009) find that 33/50 participation induced firms to adopt Environmental Management Systems that improved environmental self-monitoring and compliance. Such a *substitution effect* – substituting

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2003). A number of papers distinguish between alternate forms of government commitment, for example, whether the government can commit to a set of technology-specific settings of environmental policies (as allowed in Innes and Bial, 2002, and Requate, 2005b, for example) or to a specific setting of environmental policy (Denicolo, 1999) or no commitment at all. In many analyses, innovation takes place by an innovator who is not an industry producer and who sells discovered new environmental technologies to producing firms (Parry, 1995; Denicolo, 1999; Kolstad, 2010). Others model producer / innovators who keep their discovered technology to reduce their own firm's cost of complying with environmental regulation (Montero, 2002; Innes and Bial, 2002).

[6] There is a robust literature on induced innovation in energy and environment related sectors. See, for example, Newell, Jaffe and Stavins (1999), Popp (2002), Popp, Newell and Jaffe (2009).

[7] Participants' more intensive investments in short-run emission monitoring and compliance activity can raise the implied cost of funds for other environmental-performance-improving investments such as environmental research. If a firm must rely on higher-cost sources of funds as more projects are undertaken (as in the "pecking order" theory of firm financing decisions, Fama and French, 2002), higher investments in one activity will substitute for other activities that face a higher cost of funds.

monitoring/compliance activity for some environmental R&D – could also lead ultimately to fewer environmental innovations.

Combining these arguments could yield a “spike and bust” innovation response to participation in a VPR such as 33/50, as firms initially raise innovative effort in order to meet the 33/50 commitments and then reduce innovation to prior levels after the program ends. Indeed, Popp (2006) observes spikes in environmental innovation, followed by reversion to prior levels of environmental patenting, in response to changes in the U.S. Clean Air Act in the early and mid 1990’s. If there are substitution or signaling effects of a VPR, the post-program reversion response may be larger than the initial spike, spurring reduced rates of environmental patenting over the longer run.

In this paper, we examine the primitive empirical question of whether, when, in what direction, and to what extent 33/50 participation affected industry-level environmental patenting, while remaining agnostic on the specific economic channels through which the 33/50 program may affect environmental innovation. We find that, over an initial period (1994-1999), 33/50 program participation has a positive and significant effect on environmental innovation. However, in the longer-run (2000-2004), program participation has a significant and persistent negative impact on environmental patenting. While we do not interpret these results as confirmation of any particular theory, our estimated long-run effect is troubling, suggesting that regulatory efforts to promote VPR participation can have the unintended side-effect of deterring the innovation that is crucial to long-run improvements in environmental performance.

Our study builds on a growing empirical literature on the determinants of environmental innovation, much of which focuses on the extent to which innovation is induced by tighter environmental performance standards and associated increases in pollutant abatement costs that firms face (Lanjouw and Mody, 1996; Jaffe and Palmer, 1997; Brunnermeir and Cohen, 2003; Carrión-Flores and Innes, 2010). Using European Patent Office (EPO) data, recent work studies determinants of climate mitigation technologies, their diffusion and transfer (Dechezlepretre, Glachant, and Meniere, 2008, 2013; Dechezlepretre et al., 2011) and impacts of alternate environmental policies on country-level renewable energy patents (Johnstone, Hascic, and Popp, 2010).[8]

To our knowledge, ours is the first paper to study whether – and the extent to which – participation in a VPR promotes or deters environmental innovation.[9] Using an industry-level panel, we estimate dynamic count fixed effects models of innovation that account for a wide variety of potential determinants of this activity. Following others (e.g., Brunnermeier and Cohen, 2003; Carrión-Flores and Innes, 2010; Johnson et al., 2010), we measure innovation by the number of successful environmental patent applications. We consider three alternative indicators of "environmental" classes ranging in their breadth from narrow (an air-pollution-related count) to somewhat broader (the count of Brunnermeier and Cohen, 2003) to broad (the encompassing count of Carrión-Flores and Innes, 2010). We measure 33/50 program effects at a 3-digit SIC industry level using rates of industry participation in the program.

Underpinning our approach is the presumption that environmental patents filed by an industry member are, to an extent, for use by that industry. If this were not the case, then one would not expect industry-level environmental regulation or programs to affect industry-level environmental patenting, as patenting for inter-industry sale would not be

[8] See Johnson and Lybecker (2012) for a recent literature review.
[9] Johnstone et al. (2010) consider the presence of country-level voluntary environmental programs in their cross-national panel of energy patents.

driven by intra-industry circumstances. Anecdotal evidence supports this notion. Cohen et al. (2000) survey almost 1500 research labs in the U.S. in 1994. They find that, for these labs, the most cited motive for patenting is to prevent copying of their technology by rivals (with 78 percent of respondents indicating that this is a central reason for patenting process innovations and 96 percent indicating so for product innovations). By contrast, the least cited reason for patenting (among six possible motives) is to license the technology for sale (with 23 and 28 percent citing licensing as a key motive for process and product innovations, respectively). This evidence suggests that research patenting is predominantly for use by the patenting company, rather than for sale. Furthermore, Brunnermeier and Cohen (2003) and Carrión-Flores and Innes (2010) identify empirical links between industry-level pollution abatement costs and industry-level emission regulation on industry-level environmental patenting, also supporting our underpinning premise that industry-level environmental regulation and practices can affect industry-level environmental innovation.

A key methodological challenge in this paper is the identification of both emission performance and 33/50 program participation rates as potentially endogenous determinants of innovation. For example, greater rates of environmental patenting may promote both reduced toxic emissions and increased propensities to participate in a VPR like 33/50. We use measures of government environmental enforcement activity (lagged four years) to identify these regressors. A substantial environmental enforcement literature documents the importance of enforcement to emission performance (see Gray and Shimshack, 2011), and recent work documents the importance of enforcement to 33/50 participation as well (see Innes and Sam, 2008). Indeed, Innes and Sam (2008) identify a striking structural break in Clean Air Act enforcement against 1991 33/50 participants, relative to non-participants. While participants were much more enforcement-intensive in the pre-participation period – indicating the relevance of enforcement to 33/50 participation – participants also experienced significantly lower changes in rates of inspection and enforcement action between pre- and post-participation intervals (Table 3, Innes and Sam, 2008); the latter is loosely consistent with a "signaling effect" of 33/50 participation on post-participation regulatory intensity. Consistent with this prior literature, our estimations indicate that our enforcement instruments are strong. Conversely, the only channel that we can envision for enforcement to affect innovation is via the emissions performance and VPR participation that (multi-lagged) enforcement influences. We discuss our identification strategy in detail in Section 4 below.

In the next section we briefly describe the 33/50 program, followed in section 3 by presentation of our empirical model. Our data and econometric methods are discussed in section 4. Section 5 reports our estimation results, and section 6 concludes.

2. The 33/50 Program

Started in 1991, the 33/50 program was the EPA's first formal effort to achieve voluntary pollution reductions by regulated firms. The EPA started the program shortly after creating the Toxic Release Inventory (TRI), a database compiling information on toxic releases of all firms with ten or more employees producing one or more of 320 targeted pollutants. The program sought to reduce releases of seventeen key TRI chemicals, roughly seventy percent of which were air pollutants (by 1988 weight of releases). A requirement to participate in the program was to prepare a plan that included a detailed description of how each facility would meet its pollution targets. In addition, a benefit from participating in the 33/50 program included technical assistance to aid participants in achieving program objectives.

In early 1991, the EPA invited the 509 companies emitting the largest volume of 33/50 pollutants to participate in the program; these companies were responsible for over three-quarters of total 33/50 releases as of 1988. In July 1991, the 4534 other companies with reported 33/50 releases in 1988 were asked to participate as well. With additional enrollments through 1995, the EPA invited a total of 10,167 firms to join the 33/50 program, and 1294 firms accepted. Once a firm joined the program, it did not leave. Overall, program participants accounted for 58.8 percent of 33/50 releases in 1990.

The 33/50 program was purely voluntary and its pollution reduction targets were not enforceable. Despite the absence of apparent regulatory teeth, total 33/50 releases declined by over 52 percent between 1990 and 1996 among reporting firms. In contrast, non-33/50 TRI releases fell by 25.3 percent over this period. Moreover, rates of 33/50 release reductions were greater for program participants (down 59.3 percent between 1990 and 1996) than for non-participants (down 42.9 percent over the same interval).

Because these numbers may mask other hidden determinants of firms' pollution – for example, participating firms may have been more apt to reduce pollution, regardless of participation in the 33/50 program – recent academic work controls for a wide variety of relevant determinants of pollution and potential selection bias in 33/50 program participation. Much of this work finds that the program led to significant reductions in participant emissions, including Khanna and Damon's (1999) early study of 33/50 impacts. While Vidovic and Khanna (2007) find that the Khanna and Damon (1999) results are sensitive to inclusion of time effects, Innes and Sam (2008) find that negative

33/50 program impacts on targeted pollution are robust to time effects using a broader dataset and more comprehensive accounting for relevant determinants of pollution. In Innes and Sam (2008), pollutant impacts are estimated to occur shortly after a firm joined the program, and to persist. Sam, Khanna, and Innes (2009) estimate additional benefits of program-induced pollution reduction in the post-program years of 1996-98. In contrast, Gamper-Rabindran (2006) studies impacts of facility level participation on emissions by industry, by media (air vs. water), and with toxicity-weighted measures, and finds that, while some industries experienced significant toxicity-weighted pollutant reductions as a result of 33/50 participation, others experienced insignificant reductions, and still others experienced increases. More recently, Vidovic and Khanna (2012) find that, for facilities of 33/50 participating firms (and controlling for these facilities' overall toxic pollution), a facility's 33/50 participation has a negative but statistically insignificant effect on the facility's 33/50 releases relative to non-participating facilities of the participating firm. However, Bi and Khanna (2012) study facilities of both 33/50 firms and non-participating firms and show that estimated benefits of 33/50 participation in reducing facility-level emissions are *larger* in magnitude than estimated benefits of firm-level 33/50 participation in reducing firm-level pollution, and apply to toxicity-weighted pollutant measures.

In this paper, we explore another potential channel of effect for the 33/50 program: its impact on industry-level innovative activity. Carrión-Flores and Innes (2010) estimate that a doubling of an industry's rate of environmental patenting can produce a 60 percent reduction in the industry's toxic emissions in the long-run. These estimates suggest that VPR effects on long-run environmental innovation are likely to be crucial to their long-run effects on environmental performance.

3. The Empirical Model

Building on Carrión-Flores and Innes (2010), we posit an underlying structural model that determines five outcomes, three observables (emissions, patents, and 33/50 participation rates) and two unobservables (effective industry pollution targets and environmental R&D). The defining equations for patents, emissions, and environmental R&D are as follows, reflecting intuitive relationships that we describe below:

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

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

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

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

For industry i at time t, P_{it} is an index of patentable innovations, 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 the industry, PR_{it} is the 33/50 participation rate, the vectors X_{pit}, X_{sit}, and X_{rit} represent exogenous observable variables that we describe below, the ε_{it}'s represent random disturbances (assumed independently distributed across industry, time, and equations), and E is an expectation operator.

Equation (1) indicates that patent outcomes are driven by lagged R&D effort and other lagged exogenous determinants (X_{pit-1}). Equation (2) indicates that pollutant outcomes are a function of pollution targets (S_{it}) which in turn depend upon lagged targets, technology outcomes, lagged voluntary participation in 33/50, and other variables (equation (3)). Because lagged targets (S_{it-1}) are included on the right, equation (3) implicitly captures *changes* in pollution targets which in turn depend upon *changes* in technology; the patent index P_{it} measures changes in the relevant technology stock. Equation (4) indicates that environmental R&D responds to present and future pollution targets, participation in the 33/50 VPR (PR_{it}), and other exogenous determinants (X_{rit}).

Lacking good empirical measures of pollution targets S_{it} and environmental R&D expenditures, we use equations (1)-(4) to construct an estimable relationship between emissions, 33/50 participation rates, and environmental patent outcomes. Specifically, lagging (4) to substitute for RD_{it-1} in (1), and using (2) to substitute for $E_t(S_{it+1})$ and S_{it-1}, gives the following:

(5) $$P_{it} = a_{it} + b\,E_{t-1}(Q_{it}) + cQ_{it-1} + dPR_{it-1} + fX_{it-1} + v_{it}$$

where $X_{it-1} = (X_{rit-1}, X_{pit-1})$.

To estimate (5), we substitute the realized value of emissions Q_{it} (which we observe) in place of its time (t-1) expectation (which we do not observe). Using the emission realization gives rise to the measurement error,[10]

(6) $$u_{it} = Q_{it} - E_{t-1}(Q_{it}) = d^*_q(X_{sit} - E_{t-1}(X_{sit})) + \varepsilon^*_{qit} + v_{it}$$

where $d^*_q = b_q c_s$ and $\varepsilon^*_{qit} = \varepsilon_{\text{qit}} - d_s \varepsilon_{\text{qit-1}} + b_q \varepsilon_{\text{sit}}$. In order to obtain consistent parameter estimates, we need instruments that are uncorrelated with both the equation (5) error v_{it} and the equation (6) measurement error u_{it}. Given our model structure (with the lagged equation (5) regressors, X_{it-1}), the following (arguably innocuous) assumption implies that our exogenous data satisfy both criteria:

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[10] Following Carrión-Flores and Innes (CI, 2010), equations (2)-(3) imply the structural form for emissions,

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

where $a^*_{qit} = a_{\text{qit}} - d_s a_{\text{qit-1}} + b_q a_{\text{sit}}$, $b^*_q = d_s$, $c^*_q = b_q b_s$, and $f^*_q = b_q f_s$. Together with equation (5), this structure directly implies equation (6). Given our model assumptions (including Assumption 1), this error is uncorrelated with the exogenous variables X_{it-1}.

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

Note that the lag length reflects the time between research and patent application, which we generally assume to be two years (see section 4).

We have two remaining sources of endogeneity. First, the observable regressor, Q_{it}, is jointly endogenous in the usual sense, with technological change potentially prompting revisions in emission standards. Second, there is potential selection correlation between 33/50 participation rates and innovation because more innovative industries (ceteris paribus) may be more likely to participate in the VPR. We therefore treat emissions (Q_{it}), lagged emissions (Q_{it-1}), and VPR participation (PR_{it-1}) as endogenous regressors in equation (5). As described below, we identify with measures of lagged government environmental enforcement scrutiny that are highly correlated with the endogenous regressors but have no discernable independent effect on innovation (Carrión-Flores and Innes, 2010; Brunnermeier and Cohen, 2003).

There are a number of determinants of innovative activity for which we control, beyond emissions and the key 33/50 participation effects of interest. First, we include industry fixed effects (at the level of our 3-digit industries) and fixed year effects. The former control for any unobserved heterogeneity across industries, while the latter control for arbitrary time trends in environmental patenting. Second, Popp (2006) observes spikes and troughs in patenting due to key changes in the Clean Air Act in the 1990's. While our toxic emissions measure and our fixed time effects capture impacts of these changes to some extent, different industries may be more or less sensitive to changes in Clean Air Act (CAA) regulations because they are more or less subject to regulation of criteria pollutants. To capture such potential effects, we construct a set of weighted time dummies with industry weights that reflect each industry's respective relative sensitivity to CAA criteria pollutant regulation. An industry's weight equals the ratio of its criteria air pollutant (CAP) emissions (in 2002) to average industry CAP emissions (in 2002).

Third, intra-industry spillovers in research activity may lead to environmental patent successes; we use non-environmental patent counts and overall industry R&D investments to control for these effects. Research spillovers can also occur across industries. We capture these effects by including, in addition to our 3-digit industry's own total R&D, the total R&D expenditure of all other 3-digit industries in the same 2-digit industry class; together with the year dummies, these two measures span (and thus implicitly include) total R&D by all industries included in our analysis outside of the specific (3-digit) industry's 2-digit industry class.

Fourth, we control for industry size using measures of real sales, size of workforce, number of firms, and number of facilities. Leonard and Decker (2012) document cross-plant economies in a voluntary electricity demand program. Such cross-plant economies may also in principle motivate participation in 33/50 and environmental R&D. Including firm numbers, numbers of facilities, and hence implicitly average numbers of facilities per firm, enables us to capture these impacts.

Fifth, we control for the nature of industry assets, both age and capital intensity. We expect industries with newer assets and more capital intensive production to have more scope for cost-reducing environmental R&D. Sixth, more rapidly growing industries may have either more or less incentive to innovate, whether because they have already modernized and hence have less scope for innovation or because they are more innovative by nature and hence more likely to innovate in the environmental realm as well. Seventh, more concentrated industries may be prone to either more or less environmental R&D. On one hand, concentration gives rise to "raising rivals costs" motives for heightened research (Innes and Bial, 2002); on the other hand, concentrated industries may collectively recognize the costs of higher R&D in spurring tightened environmental regulations, leading to a research deterrent (Carrión-Flores and Innes, 2010). We control for such effects by including a measure of industry concentration in our estimations. Eighth, an industry's exposure to international markets may affect incentives for environmental R&D due to a variety of potentially competing forces, including environmentalist pressure from abroad and/or domestic political pressures to soften environmental regulation in order to promote exports. We therefore control for each industry's export intensity.

Finally, because environmental patents are relatively sparse, we model and measure outcomes at an industry level. However, the model of equations (1)-(5) can be derived from firm-level counterparts, assuming common coefficients on right-side variables.[11] Non-linearities in the firm-level structural model imply that intra-industry heterogeneity should be reflected in the industry-level explanatory variables. We therefore include measures of intra-industry heterogeneity in some of our estimations.

[11] If firm level counterparts to equation (5) represent an individual firm index of patentability, our statistical model translates an industry index of patentability – the sum of the firm level indices, as given in equation (5) – into a probability distribution of patent counts as described in section 4 below. For the 33/50 participation variable, *PR*, this aggregation implies a variable measured by the industry number of participants, assuming that a firm's participation only affects its own R&D incentives and not those of its intra-industry rivals. In our empirical work, we normalize this variable to represent the fraction of an industry's 33/50-eligible facilities that participate in the program, and control for both the number of firms and the number of facilities. As a robustness check, we also consider the alternative measure, aggregated numbers of participating facilities. Our industry aggregation subsumes any intra-industry R&D responses of program non-participants to their rivals' 33/50 participation into the one 33/50 effect. For example, if non-participating firms respond to a greater extent of rival (intra-industry) 33/50 participation by raising (or lowering) environmental R&D, this spillover effect will be captured by our estimated coefficients on the 33/50 participation rates in our environmental patent equations.

Note that the underlying forces that we estimate at the industry level are the same as at the firm level. If an individual firm's (or facility's) participation in 33/50 promotes (or deters) innovation, industry aggregation implies that a *greater extent* of 33/50 participation by firms in an industry will also promote (or deter) industry-level innovation. We estimate the latter effects in this paper.

4. Data and Empirical Estimation

Data. Our sample is a balanced panel of 127 manufacturing industries defined by 3-digit SIC classifications (SIC codes 200-399) over the period 1989 – 2004. Merging data from all of our sources yields 2032 observations for the 16-year period. Table 1 presents variable definitions and summary statistics.

Following prior work, we use successful environmental patent applications (by date of application) to measure environmental innovation. Patents are assigned to the 3-digit SIC industry of the first filer listed on the patent application. Using data from the U.S. Patent and Trademark Office, we construct successful patent application counts by year, by industry, obtained by U.S. companies. We classify patents as environmental according to three alternative definitions. First is our most focused measure, limited to patent classes that relate to toxic air pollution (***AirPatents***). Because 33/50 is fundamentally an air toxics program, we consider this focused patent class our "baseline" measure. Second is the expanded measure of Brunnermeier and Cohen (2003) (***EnvPatentsBC***), which adds in patents related to water pollution and solid waste disposal. Third is the encompassing environmental classification of Carrión-Flores and Innes (2010) (***EnvPatentsCI***) that also includes patents related to recycling, alternative energy, and solid waste prevention. For control and falsification purposes, we also construct a non-environmental patent count (***NonEnvPatents***) based on the broadest (***EnvPatentsCI***) measure in order to ensure that no environmental patents are included in the count. The Appendix details the patent classes used for our three measures, including a breakdown of mean patent counts by type (air pollution, hazardous waste, solid waste, etc.). Our baseline patent count (***AirPatents***) averages 1.41 per year (per industry), roughly 2.5 percent of total annual patent counts (on average, by industry).

All of our environmental patent measures (even the most narrow) include patents that are not related to environmental performance. These unrelated counts add some error to our dependent variables, compromising precision of our estimates (but not compromising consistency). As a falsification check, we estimate a model with our non-environmental patent counts (***NonEnvPatents***) as the dependent variable; as expected, the endogenous environmental regressors (***Emissions***, lagged ***Emissions***, and 33/50 participation measures, as described below) have no significant correlation with the non-environmental counts (see Appendix).

Total toxic air emissions data are available from the EPA's Toxic Release Inventory (TRI) for 1989-2004.[12] Using the TRI facility level data, we construct industry level total toxic releases (***Emissions***) aggregated by industry by year. Facility releases reported in the TRI are assigned to the primary industry of the parent company. Chemicals included in our measure are those that are regulated under the Clean Air Act's National Emissions Standards for Hazardous Air Pollutants. We only include those CAA-regulated chemicals listed in the 1988 TRI and that were not delisted from the TRI as of 2004. As a result, we have a common set of 165 chemicals that are subject to Clean Air

[12] Because the first year of TRI release reports are considered incomplete and suspect, we only rely on post-1988 TRI data.

Act emission standards and monitoring requirements, and the reporting requirement of the Emergency Planning and Community Right to Know Act (EPCRA), throughout our study period.[13]

The EPA's Office of Environmental Information Records provided facility level data on 33/50 participation, as well as Federal and State enforcement activity under the Clean Air Act (CAA).[14] These data contain the list of 33/50 participating companies and the extent of participation in the 33/50 program at the facility level. We construct 33/50 participation rates for each industry for each year of program operation (1991 – 1995). An industry's participation rate for each of these years equals the ratio of (1) the number of the industry's facilities participating in the 33/50 program during that year, to (2) the number of the industry's 33/50-eligible facilities during that year. These raw participation ratios are then used to construct lagged measures of industry participation in 33/50 by year (***PR***). Facilities are assigned to their primary 3-digit SIC industry as recorded in the TRI database.

Because research produces patentable discoveries with a lag, potential impacts of 33/50 participation on innovation also occur with a lag. The length of the lag between research and patent application has been estimated to be between zero and three years (Progan, 2005).[15] For example, Daim et al. (2007) estimate a 5 to 6 year lag between the allocation of research funds and the issuance of patents in the U.S., while Popp et al.

[13] We measure emissions of the CAA-regulated TRI pollutants by aggregate weight. There are a number of reasons why toxicity-weighted counterparts are highly suspect for a broad measure of air toxics such as ours (see Carrión-Flores and Innes, 2010; Guerrero and Innes, 2013).

[14] Because the 33/50 program primarily relates to air releases, we focus on toxic air releases regulated by the Clean Air Act (CAA) and enforcement activity under the CAA.

[15] Estimating these lags is a complex topic beyond our scope. Hall et al. (1986) find a strong contemporaneous correlation between U.S. R&D expenditure and patent applications, which is sometimes interpreted as evidence of a zero-length lag (Progan, 2005); however, Hall et al. (1986) stress the difficulty of precisely identifying the lag structure.

(2004) show that the average lag between U.S. patent application and issuance has been between 26 and 32 months (from 1976 to 1996). Consistent with this evidence, our baseline analysis models potential 33/50 participation impacts with lags of roughly two years, of course with longer lags after the program ended. However, we also consider an alternative lag of one year as a robustness check.

In our (baseline) two-year-lag specification, our first participation variable is for 1994, and is measured as the average participation rate for 1991 (the first year of the program) and 1992. For subsequent years (up to 2000), the measured participation rate is the average participation rate over the prior two to five years, including only years of program operation. For example, ***PR1997*** measures industry participation rates for 1997 as the average of participation rates in the four years, 1992-1995. For 2000 and later, the measured participation rate reflects the 1995 participation ratio. For 1994 onwards, we thus have year-specific 33/50 participation rates (***PR1994***, ***PR1995***, and so on).[16] Average annual 33/50 participation rates in our sample manufacturing industries vary between 36 and 40 percent, with industry-specific rates ranging from lows of approximately 5 percent to highs of approximately 90 percent.

We consider a number of different breakdowns of the 33/50 participation variables, including (a) year-specific effects from 1994 onwards (to 2004), (b) aggregating over the entire sample period (1994-2004), and (c) aggregating effects into three subperiods: 1994-5, 1996-1999, and 2000-04. The latter partition distinguishes between program years (1994-5) and post-program years (1996-2004) in order to capture potential program year spikes, and between shorter (1996-99) and longer run (2000-04)

[16] With one-year lags (one of our robustness checks), the *PR* variables start in 1993 (when they are the average of 1991 and 1992 participation rates) and represent averages of participation rates over the prior one to four years. For 1999 and later, the measured participation rate reflects the 1995 participation ratio.

post-program effects. Of course, any short vs. long run partition is somewhat arbitrary; the 1994-99 vs. 2000-04 partition is chosen because we find positive year-specific participation effects during the first interval and negative year-specific effects in the second interval, suggesting a natural break.[17]

We also consider two alternative program participation measures. The first is based on the number of participating facilities by industry (rather than the proportion of 33/50 eligible facilities that participate).[18] The second partitions program effects by "early" and "later" joiners. "Early" joiners are firms / facilities that joined 33/50 at its inception in 1991 and 1992. "Later" counterparts are those that joined in 1993-95. For 1995 and onwards, participation rates can be partitioned into the "early joiner" component – the lagged proportion of 33/50-eligible facilities that participated as of 1992 – and the "later joiner" component – the lagged proportion that participated after 1992. These partitions enable us to examine whether participation by early and later joiners have distinct impacts on subsequent patenting.

From our enforcement data, we construct three measures of enforcement stringency: (1) counts of Federal and State Clean Air Act inspections (***Inspect***), (2) the numbers of facilities out of compliance with clean air laws (***Outcomp***), and (3) the numbers of reported self-inspections (***Selfinspect***). We use four-year lags in these enforcement variables to identify our endogenous variables, ***Emissions*** and ***PR***.[19] Because our participation rates represent 33/50 participation for years past (for example,

[17] We have obtained qualitatively similar results with other partitions (for example, 1996-98 vs. 1999-04).
[18] The numbers-based participation measure is the raw number of 33/50 participating facilities in an industry during the most recent year at least two years prior. This measure is motivated by the direct aggregation of firm-level analogs of the structural equations (1)-(5). See note 11.
[19] Lagging four years has the advantage of mitigating any potential for endogeneity between the endogenous regressors and enforcement. We considered other enforcement lags and found that four-year lags in our three enforcement variables performed the best as determinants of emissions.

with ***PR1994*** representing participation in 1991-92), we construct four-year lags in the enforcement instruments measured from the time of participation. For example, for ***PR1994***, we construct averages of the enforcement variables over 1987-1988, four years prior to the period of measured participation. For each year-specific participation regressor, we thus construct three year-specific enforcement instruments. Following standard practice, lagged emissions (***Emissions**$_{t-2}$*) are identified with corresponding lags in the exogenous data, including lags in the four-year-lagged enforcement instruments.

Financial and employment data was obtained from the Standard and Poor's Compustat Dataset. Deflators are obtained using producer price indices reported in the Economic Report of the President (2004). For controls, we include (deflated) industry sales volume (***Sales***) and number of employees (*Employees*) in order to account for potential effects of industry size on patents. We measure ***Capital Intensity*** by an industry's ratio of new capital and equipment expenditures to sales volume; ***Age of Capital*** by the ratio of net industry assets to gross industry assets (following Khanna and Damon, 1999); ***Export Intensity*** using the ratio of each industry's export sales to total sales; and overall industry-level research intensity (***R&D Intensity***) by the total level of research and development expenditures per-unit-sales.[20] For all of these variables, we consider intra-industry standard deviations to capture intra-industry heterogeneity.

Total R&D gives the 3-digit-level industry's total R&D spending, while the ***Spillovers*** variable represents total R&D spending by the two-digit level industry, excluding the 3-digit level spending measured by ***Total R&D***. Industry growth is

[20] In principle, the *R&D Intensity* and *Total R&D* variables contain some environmental R&D. However, targeted environmental R&D is a very small component of overall R&D, as indicated (for example) by the small share of air pollution patent counts in the total (2.5 percent). Still, in view of this concern, we have estimated our models both without *R&D Intensity* and *Total R&D*, and our qualitative results are robust.

measured by its ***Sales Growth***. To measure industry concentration, we construct a four-firm Herfindahl index (***Concentration***) using annual sales data.

Estimation. Our patent measures take a count form with a large proportion of zero's and a yet-larger proportion of counts equal to five or less.[21] We therefore estimate count panel Generalized Method of Moments (GMM) models with endogenous regressors, following Blundell, Griffith and Windmeijer (2002) (see also Windmeijer, 2002, and Windmeijer and Santos Silva, 1997). With this approach, we have a multiplicative error Poisson model (with endogenous regressors), where patent counts P_{it}^{*} are distributed Poisson,

$$\mathrm{E}(P_{it}^{*} \mid v_{it}) = \exp(P_{it}),$$

and P_{it} is determined by equation (5) with fixed industry and time effects that control for unobserved variation across industries and time.[22]

Identification. As always, there are two criteria to judge the merits of our identification strategy. First, are our identifying instruments highly correlated with our endogenous regressors? As the presumed purpose of enforcement is to improve compliance with environmental laws and thereby improve emission performance, there is compelling logic for enforcement to be important in driving industry emission outcomes. Substantial empirical literature supports this presumption with evidence that enforcement is effective in promoting improved environmental performance (see Gray and Shimshack, 2011; Magat and Viscusi, 1990; Gray and Deily, 1996; Decker and Pope, 2006).

[21] For our baseline *AirPatents* count, 53.74 percent of observations are zero's, 22.54 percent are ones, and 91.34 percent are five or less. For our broad *EnvPatentsCI* count, 23.72 percent of observations are zero's and 42.56 percent are five or less. For the narrower *EnvPatentsBC* measure, 38.26 percent of observations are zero's and 51.53 percent are five or less.

[22] This method embeds a mixture Poisson that allows for over-dispersion (Cameron and Trivedi, 1998, p. 98), thereby avoiding the main criticism of standard fixed effects Poisson models.

Enforcement intensity is also important in motivating firm participation in VPRs such as 33/50. On a theoretical level, Maxwell and Decker (2006) argue that VPR programs can represent a bargain between regulators and regulated firms; the firms are implicitly offered breaks in regulatory scrutiny in exchange for participation in the VPR.[23] Enforcement-intensive firms have more to gain from any such regulatory rewards, and are also likely to view a government-sponsored VPR like 33/50 as an opportunity to satisfy government inspectors, whether due to the compliance assistance that is provided by the program or the signal conveyed by participation about the firm's efforts in environmental improvement. Whatever the motives, empirical work documents the importance of environmental enforcement intensity in promoting 33/50 participation (Videras and Alberini, 2000: Khanna and Damon, 1999; Innes and Sam, 2008; Bi and Khanna, 2012).

Empirically, the strength of identifying instruments is generally judged by their performance in first stage regressions (Stock and Yogo, 2005). Table 2 presents pseudo-first-stage fixed-effects panel regressions for our endogenous regressors ("pseudo" because we do not have a standard two-stage estimator). The Table 2 regressions are linear panel models with fixed industry and time effects. Model II is estimated as a dynamic panel model with endogenous lag following Arellano and Bond (1991). Model III is estimated using the underpinning industry 33/50 participation rates for 1991-95.

[23] Implicit in the "regulatory bargain" theory is a premise that regulators obtain a benefit from VPR participation by regulated firms and are therefore willing to offer regulatory rewards in return for participation. While a full discussion of regulatory objectives is beyond our scope, such a goal of regulators is consistent with current literature on regulatory decision-making, with theories of regulatory choice falling generally into three camps: the "capture" school of Stigler (1971) and Peltzman (1976); the "minimal squawk" hypothesis of Leaver (2009) driven by principal-agent considerations; and the Niskanen (1971) model of regulatory budget-maximizers. A government-sponsored VPR like 33/50 is an outcome of these bureaucratic mechanisms and will motivate regulators to desire program success in order to satisfy business constituents (in the case of the capture school), principals in the hierarchy (in a "squawk"- type model), and/or legislative proponents of the program (in a Niskanen model).

Note that all three (lagged) enforcement instruments are statistically significant determinants of industry emissions. We expect increased enforcement scrutiny, as indicated by a higher number of inspections and instances of detected compliance violations, to promote emission reductions. We also expect that self-inspections may substitute for government scrutiny and thereby promote emission laxity. Our first stage emission estimations are consistent with these expectations, and easily pass standard (Stock and Yogo, 2005) tests for instrument strength (see Table 2 F statistics).

Rates of VPR participation are also expected to be higher for industries that experience more enforcement scrutiny, as measured by enforcement inspections and compliance citations. We also expect that pro-active self-inspection activity will be associated with higher rates of VPR participation. Our first stage regressions for the participation rate are consistent with these expectations, although only the "intensive scrutiny" variables (***Inspect*** and ***Outcomp***) are statistically significant. Collectively, the identifying instruments again easily pass standard tests for instrument strength.

The second criteria for successful identification is that the instruments be uncorrelated with the errors in our patent equation. 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 – that is, the emission targets that drive cost-based incentives for environmental innovation.[24] A rather far-fetched potential

[24] A referee raises the hypothetical of a plant for which there is no environmental enforcement; the plant would then have no incentive to innovate in its environmental technologies. Conversely, a plant experiencing enforcement has an incentive to innovate. However, the mechanism for enforcement to affect innovation incentives in this example is *emissions*; the lack of enforcement produces no incentive for emission abatement and, as a result, no cost-based motive for innovation; conversely, the presence of enforcement motivates emission abatement and a corresponding cost-based motive for innovation. Hence, for analyses that fail to account for the impact of regulation-induced emissions on environmental R&D, enforcement becomes relevant. For example, Brunnermeier and Cohen (2003) include a measure of government environmental inspections as an explanatory variable in their patent equation, finding no

counterpoint is that, to the extent there is serial correlation in both patenting and enforcement, there is the potential for joint determination of enforcement and innovative success, despite four year lags. For example, innovation could potentially spur fewer enforcement violations. However, in testing for serial correlation in patenting, we generally find none (consistent with Carrión-Flores and Innes, 2010). In addition, in standard tests of our over-identifying restrictions, we do not reject our maintained hypothesis of no correlation (see Hansen statistics in Tables 3-6).[25]

5. Results

Table 3 presents our main ("baseline") results from estimation of equation (5) using our ***AirPatents*** measure. We use a 2-year lag in our exogenous data, reflecting a 2-year-ahead policy forecast in the determination of R&D expenditures (equation (4)).[26] The table gives outcomes with two different instrument combinations and two alternative breakdowns of 33/50 impacts, one with a homogeneous effect over the period 1994-2004 and another that allows for distinct program (1994-95), early post-program (1996-99) and late post-program (2000-04) effects. Table 4 presents corresponding estimations using the broader environmental patent measures, ***EnvPatentsBC*** and ***EnvPatentsCI***. Table 5 presents estimations for all three patent measures allowing for year-specific effects of 33/50 participation. And Table 6 presents robustness checks that include standard

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significant effect. 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.

[25] Because we have three types of identifying instruments (*Inspect*, *Outcomp*, and *Selfinspect*), we can perform another diagnostic test – estimating our baseline model by including one of the three instruments as a regressor (and using the other two to identify). We do this for each of the three instruments and, in each case, find that the included instrument is statistically insignificant (with p values of .59, .21, and .40 for *Inspect*, *Outcomp*, and *Selfinspect*, respectively).

[26] We have also estimated "perfect foresight" models using contemporaneous counterparts to the exogenous data (see Carrión-Flores and Innes, 2010), and considered other instrument combinations. Results are very similar to those reported in Tables 3-6.

deviations of the Compustat-based regressors (to capture intra-industry heterogeneity) and that measure 33/50 participation effects in three alternate ways, one using one-year (vs. two-year) lags, another using numbers of participating facilities by industry (rather than participation rates), and the third partitioning participation effects between "early" (1991-92) and "later" (1993-95) program joiners.

Main Results. Two central findings are evident from the tables. First, in the "early" period of 33/50 effects (1994-1999), higher industry 33/50 participation rates are estimated to increase rates of successful environmental patenting. Second, in the longer-run period of 33/50 effects (2000-2004), higher industry 33/50 participation rates are estimated to reduce environmental patenting. Both effects are statistically significant, but the long-run impact is generally much larger than the short-run impact. When estimating a homogeneous program effect (e.g., Table 3, Models 1-2), the estimated effect of 33/50 participation on environmental patenting is negative, significant, and large.

To gauge the magnitude of 33/50 effects, note that the tables present Poisson coefficients that represent proportional marginal effects. For example, the homogeneous effect Model 1 (of Table 3) estimates that a 10 percent rise in the 33/50 participation rate (which represents roughly a 28 percent increase on the average) reduces environmental patenting by 24.3 percent. Similarly, Model 3 of Table 3 estimates that a ten percent rise in ***PR*** raises an industry's annual patent rate by 27.5 percent in each of the years 1996-1999, and reduces the industry's annual patent rate by 46.2 percent in each of the later years 2000-04. Aggregating over the entire 11 year period of 33/50 effects (1994-2004), the estimated cumulative effect (of a ten percent increase in ***PR***) on the number of air pollution patents (gauging effects at the sample mean) is a reduction of 1.64, the equivalent of slightly over one year of environmental patenting.

When allowing for year-specific participation effects (in Table 5), the estimated long-term impacts of 33/50 are somewhat less for the ***AirPatents*** measure, with estimated proportional effects of a 10 percent rise in ***PR*** varying between negative 24 and negative 29 percent per year over 2000-04. The estimated cumulative effect (over 11 years) is a reduction of 1.2 patents for the industry, somewhat less than one year of environmental patenting (on average).

Tables 4 and 5 reveal that these qualitative conclusions are robust to our alternative (broader) measures of environmental patent counts. Indeed, comparing results for our broadest measure (***EnvPatentsCI***) to those with our narrowest (***AirPatents***), the estimated proportional effects of 33/50 participation are larger (more negative) in the homogeneous effect model (Model 5 of Table 4, vs. Model 1 of Table 3), of roughly the same magnitudes in the 3-period-breakdown model (Model 6 of Table 4, vs. Model 3 of Table 3), and substantially larger during the later post-program years in the year-specific effect model (Model 11 of Table 5 vs. Model 9 of Table 5). These estimates indicate that the broader environmental patent classes exhibit as pronounced a response to 33/50 participation as do the more closely tied air-pollution-related patent classes.

Indirect and Net Effects. These estimates ignore *indirect* 33/50 program effects on innovation, due to any program-induced emission reductions that might occur. Carrión-Flores and Innes (CI, 2010) estimate statistically significant feedbacks of emission reductions on environmental patenting, the induced innovation effect. Our estimations also provide evidence of induced innovation, with significant negative effects of emissions on patent rates. If 33/50 participation spurs pollution reductions – as much of the literature suggests – there is the potential for offsetting indirect benefits of 33/50 in spurring innovation. How big might these effects be relative to the overall direct negative impacts that we estimate the program to have on long-run innovation?

For a number of reasons, these potential indirect benefits of 33/50 are likely to be small relative to the direct effects that we estimate. First, recall that the 33/50 literature estimates salutary program effects on emissions of the seventeen 33/50 chemicals; program impacts on *overall* toxic air emissions are less clear. For example, Gamper-Rabindran (2006) argues that there was some substitution in pollution between program-related chemicals and non-program and more toxic chemicals, so that overall air emission effects were smaller than studies of program impacts on 33/50 chemical releases estimate. Moreover, the innovation impacts of emission reductions that we estimate (like CI) are due to the entire set of 165 consistently regulated toxic air pollutants in the TRI. Second, even ignoring the distinction between 33/50 chemicals and other toxic air pollutants, induced innovation effects of pollutant reductions, while statistically significant, are small (Brunnermeier and Cohen, 2003; CI).

We cannot give precise estimates of these indirect 33/50 effects. However, a loose gauge of potential magnitudes is suggested by prior estimates of (1) effects of 33/50 participation on pollutant releases (Innes and Sam, 2008), and (2) impacts of pollutant reductions on our broad measure of environmental patenting (CI). From Innes and Sam (2008), a high-side estimated effect of increasing 33/50 participation rates by 10 percent is obtained by multiplying estimated point impacts of firm participation by 10 percent, and dividing by average firm releases; this exercise yields an estimated 7 percent reduction in 33/50 pollutants.[27] From CI, a permanent 7 percent reduction in toxic air emissions is estimated to increase the environmental patent counts ***EnvPatentsCI*** by 3 percent (CI, p. 40), by any reckoning a small proportion of the estimated longer-run direct effect of the 10 percent rise in 33/50 participation on the ***EnvPatentsCI*** measure – for example, 49 percent in the 3-period-breakdown Model 6 of Table 4.

While we conclude that the 33/50 program reduced long-run environmental innovation, how important are the estimated reductions in patenting for environmental performance? Results of CI suggest that ultimate impacts on pollution could be large. For example, estimates from their Model 3 (Table 5) indicate that the long-run impact of a 30 percent reduction in environmental patenting (evaluated at the sample mean) would raise pollution by 18 percent (ceteris paribus).

Robustness Checks. Table 6 reveals that our qualitative conclusions are robust to a variety of alternative specifications. When we include measures of intra-industry heterogeneity (Model 13) or use one-year lags to measure program effects (Model 14), the participation (*PR*) coefficients do not change appreciably and remain significant (comparing to Model 3 of Table 3). When we measure 33/50 participation using numbers of participating facilities (vs. participation rates), qualitative effects are again robust (Model 15). Over the short run (1996-99), a 10 percent increase in the number of participating facilities (on average) is estimated to increase environmental patenting by 17.5 percent; over the longer-run (2000-04), the estimated effect is to reduce environmental patenting by 36.3 percent. Finally, Model 16 reveals that the overall

[27] This estimate is on the "high side" not only because it presumes overall toxic air effects of program participation are proportionately the same as for 33/50 releases, but also that increases in participation (which must come from smaller polluters) achieve the same pollutant reductions as for the average 33/50 participant. Numerically, the 7 percent estimates is derived by multiplying the estimated program impact, -.35 (Innes and Sam, 2008, Table 5), by 10 percent and dividing by .51 (sample average releases).

negative estimated effects of 33/50 participation on environmental patenting applies to both early program joiners (from 1991-92) and late program joiners (from 1993-95), although the latter have larger negative effects on the *AirPatent* counts.

Other Results. Tables 3-6 reveal a number of other key economic drivers of environmental patenting. Similar to CI, environmental patenting is estimated to be greater in industries that are more rapidly growing, less concentrated, more capital intensive, with newer assets, more R&D intensive, and less dependent upon exports. Environmental patenting also rises with greater numbers of firms and numbers of facilities in the industry, the latter consistent with economies of scope in environmental R&D. There is also evidence of significant R&D spillovers within each industry (as indicated by coefficients on ***NonEnvPatents***) and between industries within the same 2-digit class (as indicated by the coefficients on ***Spillovers***). Also consistent with CI, tightened emission standards lead to increased patenting (as indicated by coefficients on the two endogenous ***Emission*** regressors).

The weighted time dummies (***WT1994*** through ***WT2004***) indicate the extent to which industry environmental patenting responds to the industry's relative sensitivity to regulation of criteria air pollutants. We consistently estimate positive and significant coefficients on ***WT1996*** and ***WT1998***, and negative and significant coefficients on ***WT2003*** and ***WT2004***. The former is consistent with local peaks observed by Popp (2006, Figure 6) in response to implementation phases of the 1990 Clean Air Act Amendments. The latter is suggestive of perceived changes in the regulatory posture of the EPA in the early 2000's.

6. Conclusion

The U.S. EPA's 33/50 program is the most exhaustively studied voluntary pollution reduction (VPR) initiative on the books. Although results of academic studies are mixed, several papers estimate beneficial impacts of the program in reducing targeted air pollution (Khanna and Damon, 1999; Innes and Sam, 2008; Sam et al., 2009; Bi and Khanna, 2012). However, the literature has focused on short-run emission reduction effects and ignored impacts on environmental innovation that have potentially profound implications for long-run environmental performance (Carrión-Flores and Innes, 2010).

In this paper, we estimate significant positive effects of greater industry-level participation in the 33/50 program on rates of environmental patenting in the early post-program years (1996-99), but larger (and again significant) negative effects several years after the program ended (2000-04). Estimated cumulative impacts over an 11 year span of post-participation innovation are large and negative. However, one must be careful in interpreting these results. The post-program period for which we estimate significant negative effects of 33/50 on environmental innovation corresponds with the onset of the (G.W.) Bush Administration. Indeed, we also find during this interval (2003-04 in particular) that industries more sensitive to Clean Air Act regulation experienced significantly lower rates of environmental innovation. Hence, our estimates may be picking up the confluence of pro-business EPA management and an administration philosophy particularly supportive of VPRs that together may have produced acute regulatory rewards to participants in the keystone 33/50 program. Our results suggest that, whether due to such rewards or to other symptoms of 33/50 participation, this particular VPR had a chilling effect on longer-run environmental research.

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Table 1. Variable Definitions and Summary Statistics

N = 2032, 127 Industries, 16 Years

Variable Name	Description	Mean	S.D.
	Dependent Variables		
AirPatents	Number of air pollution related patents	1.411	2.575
EnvPatentsCI	Number of environmental patents broad measure (CI, 2010)	24.786	22.459
EnvPatentsBC	Number of environmental patents reduced measure (BC, 2003)	7.293	16.813
	TRI emissions, 33/50 participation and CAA enforcement measures		
PR 1994 - 2004	Participation Rate for observations in years 1994 - 2004	0.3685	0.3116
PR 1994 - 1995	Participation Rate for observations in years 1994 - 1995	0.3645	0.3229
PR 1996 - 1999	Participation Rate for observations in years 1996 - 1999	0.3383	0.3388
PR 2000 - 2004	Participation Rate for observations in years 2000 - 2004	0.3611	0.3347
Total Fac 1992	Number of Participating Facilities as of 1992	210.63	346.02
Total Fac 1993	Number of Participating Facilities as of 1993	261.35	409.62
Total Fac 1994	Number of Participating Facilities as of 1994	326.23	469.52
Total Fac 1995	Number of Participating Facilities as of 1995	404.54	526.08
Emissions	Total toxic air emissions of CAA 112(B) chemicals on the TRI Core Chemical List (thousand of pounds)	24.919	126.07
Inspect	Number of Federal and State Clean Air Act inspections	96.2519	219.11
Outcomp	Number of citations for out of compliance with clean air laws	108.127	178.90
Selfinspect	Number of on-site tests conducted by firms	24.919	126.07
	Other Explanatory Data		
Sales	Real Industry Sales ($Billions)	56.96	206.09
	Per firm average real industry sales	2.3479	5.5912
	Standard deviation industry real sales	3.2401	7.0470
Employees	Number of employees (thousands)	178.73	442.77
	Per firm average number of employees	9.0305	17.6077
	Standard Deviation for number of employees	12.79	20.43
Capital Intensity	New capital and equipment (C&E) expenditures per-unit-sales	0.0992	0.2366
	Per firm average new C&E expenditures per-unit-sales	0.0125	0.0308
	Standard deviation new C&E expenditures per-unit-sales	0.0191	0.0468
Age of Capital	Net industry assets divided by gross assets	0.3027	0.3393
	Per firm average net industry assets divided by gross assets	0.0743	0.1376
	Standard deviation net industry assets divided by gross assets	0.1079	0.3979
Export Intensity	Real industry export sales per-unit-sales	0.0513	0.2784
	Per firm average real industry export sales per-unit-sales	0.0013	0.0041
	Standard deviation real industry export sales per-unit-sales	0.0036	0.0160
R&D Intensity	Real research and development expenditures per $100 sales	0.5283	0.2755
	Per firm average real R&D expenditure per $100 sales	0.4048	0.1799
	Standard deviation real R&D expenditures per $100 sales	0.4115	0.1653
Total R&D	Real research and development expenditures per $100 sales	0.2146	0.2865
Spillovers	Cross-Industry spillovers	0.1309	0.2440
Sales Growth	Real industry sales growth	0.0038	0.1471
Concentration	Four-firm Herfindahl index for each industry	0.0024	0.0085
Num Facilities	Number of Facilities per Industry	596.80	939.79
Num Firms	Number of Firms per Industry	26.58	51.93
NonEnvPatents	Non environmental patent count	30.78	88.39
WT 1994-2004	Weighted time dummies (weighted by 2002 relative Criteria Air Pollutant emissions)		

Table 2. Emission and Participation Rate Equation Fixed Effects (First Stage)

Dependent Variable	Emissions				Participation Rate	
Variable Instrumented	None		Emissions $_{t-2}$		None	
	Model I		Model II		Model III	
	Coef.	t-ratio	Coef.	t-ratio	Coef.	t-ratio
Selfinspect_{t-4}	0.0240	2.4566	0.0230	2.3524	0.0182	1.5473
Outcomp_{t-4}	-0.0515	-2.6952	-0.0493	-2.5808	0.4541	2.7811
Inspect_{t-4}	-0.0644	-2.1859	-0.0599	-2.0932	0.0522	2.0148
R&D Intensity_{t-2}	0.0633	1.4853	0.0606	1.4587	0.0975	1.6471
Capital intensity	4.7753	1.2912	4.5724	1.2366	-0.1218	-1.6699
Export Intensity	0.2970	1.8258	0.2844	1.7483	0.2891	2.3910
Concentration	-2.4920	-4.3190	-2.3863	-4.1285	-0.0333	-1.3274
$\text{Concentration}^{\wedge 2}$	0.5956	4.8924	0.5419	4.6895	0.0013	0.6542
Age of Capital	2.2411	1.5261	2.3647	1.4610	-0.4626	-2.3705
Real Sales	5.1487	2.0248	4.9912	1.9201	4.0608	1.6656
Sales Growth	2.6349	0.9174	2.5231	0.8473	0.0714	2.0146
Employees	2.4636	0.7256	2.3517	0.6984	0.0220	0.8552
NonEnvPatents	0.0121	1.8676	0.0116	1.7215	0.0111	0.8022
Total R&D	0.0264	1.6680	0.0647	1.5598	0.0599	0.9692
Spillovers	0.0098	1.6423	0.0095	1.5726	0.8417	1.2957
Num. Fac	0.0079	1.2215	0.0082	1.1697	0.7913	1.3379
Num. Firms	0.0083	1.3951	0.0081	1.3359	0.4657	1.1675
Emissions_{t-2}	*		0.8761	2.6284	*	
Constant	3.0726	1.7815	1.6841	1.7023	0.4081	2.4198
F-Test (Enf Instruments)	38.52		*		17.35	
p-value	0.0000				0.0000	
Hansen Test	*		9.5522		*	
p-value			0.2153			

t-stats calculated using robust standard errors.. Hansen is a test of over-identifying restrictions, asymptotically distributed as a chi-square under the null of instrument validity. The F-test is a test of joint significance of the three Enforcement instruments, Selfinspect, Outcomp, and Inspect.

Table 3. Patent Equation "Baseline" Model (Poisson Fixed Effects)

Dependent Variable	Air Pollution Patents (*AirPatents*)							
Variables Instrumented	Emissions, Emissions $_{t-2}$, and PR							
	Model 1		Model 2		Model 3		Model 4	
	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Emissions	-0.3815	-2.4170*	-0.3638	-2.4372*	-0.3356	-2.4292*	-0.3350	-2.4451*
Emissions $_{t-2}$	0.0097	2.1691*	0.0086	2.1471*	0.0077	2.1722*	0.0079	2.1843*
NonEnvPatents $_{t-2}$	0.0001	7.651**	0.0001	7.609**	0.0001	7.675**	0.0001	7.688**
Total R&D $_{t-2}$	0.0003	2.0940*	0.0003	2.0734*	0.0003	2.0849*	0.0003	2.0957*
Spillovers $_{t-2}$	0.0084	2.2484*	0.0072	2.2308*	0.0085	2.2394*	0.0081	2.2325*
Sales $_{t-2}$	0.0005	1.7621+	0.0004	1.7350+	0.0004	1.7288+	0.0004	1.7744+
Sales Growth $_{t-2}$	0.0665	1.6885+	0.0741	1.6769+	0.0643	1.6602+	0.0644	1.6648+
Employees $_{t-2}$	0.0028	1.3902	0.0032	1.3292	0.0027	1.3881	0.0027	1.3886
Concentration $_{t-2}$	-0.8257	-4.248**	-0.8514	-4.270**	-0.8781	-4.238**	-0.8780	-4.200**
Concentration$^{\wedge 2}$ $_{t-2}$	2.0344	1.9184+	2.0197	1.9351+	2.0635	1.9376+	2.0639	1.9663*
Capital Intensity $_{t-2}$	-2.5869	-2.3093*	-2.5550	-2.2890*	-2.5418	-2.3515*	-2.5414	-2.3863*
Age of Capital $_{t-2}$	1.2522	2.0551*	1.2013	2.0381*	2.2274	2.0448*	2.2271	2.0551*
Export Intensity $_{t-2}$	-0.3084	-1.8256+	-0.2890	-1.7817+	-0.3270	-1.9070+	-0.3279	-1.9152+
R&D Intensity $_{t-2}$	5.7288	2.5205*	5.6540	2.5026*	5.7804	2.5657*	5.7795	2.5733*
Number Facilities	0.0001	3.222**	0.0002	3.337**	0.0001	3.336**	0.0001	3.330**
Number Firms	0.0005	2.0714*	0.0006	2.0918*	0.0004	2.1032*	0.0004	2.0743*
PR 1994 - 2004	-2.4264	-3.586**	-2.4581	-3.598**	*		*	
PR 1994 - 1995	*		*		0.8408	2.612**	0.8401	2.601**
PR 1996 - 1999	*		*		2.7553	4.045**	2.7749	4.105**
PR 2000 - 2004	*		*		-4.6240	-2.4362*	-4.6233	-2.4522*
WT2004	-0.6298	-7.002**	-0.6004	-6.912**	-0.6890	-7.002**	-0.6889	-7.002**
WT2003	-0.3610	-6.228**	-0.3578	-6.171**	-0.3884	-6.266**	-0.3883	-6.329**
WT2002	0.2033	1.6764+	0.2117	1.6840+	0.1969	1.6424	0.1968	1.6270
WT2001	0.4264	1.7921+	0.4314	1.7518+	0.4732	1.7730+	0.4731	1.7332+
WT2000	0.1275	1.5049	0.1299	1.5058	0.1335	1.5421	0.1335	1.5646
WT1999	0.1171	1.8201+	0.1083	1.8169+	0.1123	1.8062+	0.1122	1.8329+
WT1998	0.1720	1.8964+	0.1716	1.8842+	0.1715	1.8888+	0.1714	1.8761+
WT1997	-0.1277	-1.6108	-0.1131	-1.6003	-0.1223	-1.6876+	-0.1222	1.7126+
WT1996	0.1791	3.871**	0.1731	3.868**	0.1655	3.890**	0.1647	3.918**
WT1995	0.1536	1.7554+	0.1452	1.7223+	0.1597	1.7912+	0.1596	1.7577+
WT1994	0.0834	1.2775	0.0804	1.2681	0.0744	1.2967	0.0749	1.3159
Instruments used:	SOI		OI		SOI		OI	
Hansen test p-value	0.2508		0.2033		0.2313		0.2271	
AR(1) test p-value	0.3345		0.3639		0.3683		0.3744	
AR(2) test p-value	0.6002		0.6199		0.6155		0.6264	

Year dummies are included in all specifications. t-stats calculated using robust standard errors . Instruments: Self-Inspect (S) , Outcomp (O), Inspect (I). AR tests for serial correlation, asymptotically distributed N(0.1) under the null of no serial correlation. Hansen is a test of over-identifying restrictions, asymptotically distributed chi-square under the null of instrument validity. + p<.10, *p<.05, **p<.01. Obs = 2032.

Table 4. Patent Equation Model (Poisson Fixed Effects)

Dependent Variable	Environmental Patents CI (*EnvPatentsCI*)				Environmental Patents BC (*EnvPatentsBC*)			
Var. Instrumented	Emissions, Emissions $_{t-2}$, and PR				Emissions, Emissions $_{t-2}$, and PR			
	Model 5		Model 6		Model 7		Model 8	
	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Emissions	-0.1877	-2.0457*	-0.1648	-1.7663+	-0.1845	-1.9938*	-0.1856	-1.880+
Emissions $_{t-2}$	0.0058	1.1699	0.0066	1.3750	0.0051	2.0766*	0.0055	2.0370*
NonEnvPatents $_{t-2}$	0.0006	2.1783*	0.0006	2.0000*	0.0034	1.6914+	0.0031	1.6316+
Total R&D $_{t-2}$	0.0052	3.003**	0.0045	2.4371*	0.0025	1.6847+	0.0034	1.9514*
Spillovers $_{t-2}$	0.2564	2.3044*	0.2609	2.3378*	0.2019	1.6744+	0.2460	1.9279*
Sales $_{t-2}$	0.0024	1.0283	0.0027	1.2857	0.0073	2.1370*	0.0069	2.3000*
Sales Growth $_{t-2}$	1.2027	1.0141	1.2143	1.0483	2.1339	1.7034+	2.1599	1.7219+
Employees $_{t-2}$	0.0545	0.3694	0.0539	0.4182	0.0059	1.9870*	0.0049	1.7500+
Concentration $_{t-2}$	-0.9462	-3.614**	-0.9683	-3.585**	-0.5841	-2.0316*	-0.6050	-2.498*
Concentration$^{\wedge 2}$ $_{t-2}$	5.3575	1.0001	5.2981	1.0594	2.1391	1.6912+	2.1535	1.6628+
Capital Intensity $_{t-2}$	-3.6431	-1.3718	-3.4814	-1.3258	-3.2294	-1.6611+	-3.2194	-1.675+
Age of Capital $_{t-2}$	1.0158	2.817**	1.0133	2.809**	1.0158	2.817**	0.9949	3.361**
Export Intensity $_{t-2}$	-0.0864	-1.2587	-0.0767	-1.1197	-0.0832	-1.3841	-0.0904	-1.3697
R&D Intensity $_{t-2}$	4.9281	3.774**	4.9138	3.708**	4.2245	3.901**	4.2373	3.922**
Number Facilities	0.0019	5.443**	0.0018	5.605**	0.0020	3.022**	0.0021	2.813**
Number Firms	0.0042	1.9170*	0.0045	1.6667+	0.0022	1.9447*	0.0023	1.9167*
PR 1994 - 2004	-3.4584	-2.576**	*		-2.9552	-2.3480*	*	
PR 1994 - 1995	*		0.1595	1.8943+	*		0.1243	1.9699*
PR 1996 - 1999	*		2.7943	2.4053*	*		2.0698	1.7104+
PR 2000 - 2004	*		-4.9023	-2.4460*	*		-2.3491	-1.878+
WT2004	-0.6985	-5.006**	-0.6739	-4.890**	-0.5460	-2.0177*	-0.5477	-2.085*
WT2003	-0.6223	-8.978**	-0.6676	-11.67**	-0.6647	-1.9874*	-0.6307	-1.870+
WT2002	0.3139	1.9681*	0.3384	2.1917*	0.3357	1.9821*	0.3349	2.0018*
WT2001	0.3509	1.7359+	0.3513	1.7120+	0.3496	1.7792+	0.3491	1.8088+
WT2000	0.0386	0.5026	0.0303	0.3840	0.0375	1.2288	0.0388	0.7293
WT1999	0.0598	0.5142	0.0591	0.5069	0.0479	1.3363	0.0479	1.4428
WT1998	0.2376	3.260**	0.2456	3.682**	0.2573	2.992**	0.2168	2.772**
WT1997	-0.0687	-1.1352	-0.0654	-1.0846	-0.6824	-1.5590	-0.6426	-1.4509
WT1996	0.1954	3.942**	0.2016	4.081**	0.1874	2.915**	0.1509	2.4029*
WT1995	0.1462	1.8346+	0.1455	1.8256+	0.1366	1.8873+	0.1362	1.9210+
WT1994	0.0855	1.2471	0.0853	1.2526	0.0911	1.5944	0.0927	1.6206
Hansen test p-val.	0.3136		0.2511		0.1675		0.1236	
AR(1) test p-val.	0.3339		0.3453		0.7270		0.7330	
AR(2) test p-val.	0.6412		0.6407		0.2127		0.2209	

Year dummies are included in all specifications. t-stats calculated using obust standard errors . All models use identifying instruments: Self-Inspect (S), Outcomp (O), Inspect (I). AR tests for serial correlation, asymptotically distributed N(0.1) under the null of no serial correlation. Hansen is a test of over-identifying restrictions, asymptotically distributed chi-square under the null of instrument validity. + p<.10, *p<.05, **p<.01. Obs = 2032.

Table 5. Patent Equation Model (Poisson Fixed Effects)

Dependent Variable	Air Pollution Patents (*AirPatents*)				Env. Patents CI (*EnvPatentsCI*)		Env. Patents BC (*EnvPatentsBC*)	
Var. Instrumented	Emissions, Emissions $_{t-2}$, and PR				Emissions, Emissions $_{t-2}$, and PR			
	Model 9		Model 10		Model 11		Model 12	
	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Emissions	-0.3715	-1.9732	-0.3786	-2.0040*	-0.1357	-2.1658*	-0.3144	-1.8713+
Emissions $_{t-2}$	0.0085	1.3974	0.0082	1.3121	0.0019	1.1589	0.0009	1.6714+
NonEnvPatents $_{t-2}$	0.0001	2.1676*	0.0001	2.1982*	0.0007	2.1786*	0.0095	2.0184*
Total R&D $_{t-2}$	0.0002	2.4115*	0.0002	2.4106*	0.0057	3.006**	0.0033	2.1497*
Spillovers $_{t-2}$	0.0075	2.2892*	0.0069	2.3145*	0.3943	2.3036*	0.1943	2.0020*
Sales $_{t-2}$	0.0004	1.0340	0.0004	1.0135	0.0053	1.0163	0.0061	1.6782+
Sales Growth $_{t-2}$	0.0503	1.4850	0.0488	1.4839	1.2823	1.0102	1.1944	1.6944+
Employees $_{t-2}$	0.0030	0.7996	0.0028	0.7919	0.0501	0.3556	0.0080	1.5567
Concentration $_{t-2}$	-0.7315	-2.817**	-0.7103	-2.795**	-0.9271	-3.337**	-0.6558	-2.5028*
Concentration^2 $_{t-2}$	2.0548	1.1943	2.0599	1.1947	5.3375	1.0017	2.1078	1.6741+
Capital Intensity $_{t-2}$	-2.6463	-1.5052	-2.7140	-1.5528	-3.6866	-1.4896	-2.7419	-1.6640+
Age of Capital $_{t-2}$	1.2649	2.697**	1.2703	2.717**	1.0139	2.887**	1.0722	2.0493*
Export Intensity $_{t-2}$	-0.0320	-1.4495	-0.0450	-1.5950	-0.0882	-1.3184	-0.0543	-1.3537
R&D Intensity $_{t-2}$	5.6493	3.626**	5.7025	3.801**	5.1049	3.815**	4.8716	3.227**
Number Facilities	0.0001	3.670**	0.0001	4.765**	0.0024	5.628**	0.0017	3.210**
Number Firms	0.0005	1.5150	0.0005	1.6031	0.0049	2.1575*	0.0065	2.1712*
PR2004	-2.3944	-1.9117+	-2.0147	-1.6047	-5.0782	-1.5742	-2.8136	-2.624**
PR2003	-2.8166	-1.8116+	-2.8757	-1.8386+	-5.8223	-1.8875+	-2.8751	-2.651**
PR2002	-2.5350	-1.3844	-2.1991	-1.2673	-6.2753	-1.3150	-2.7999	-1.9665*
PR2001	-2.9034	-1.9683*	-2.9935	-2.3376*	-4.7846	-2.3472*	-2.8759	-2.3492*
PR2000	-2.6219	-2.885**	-2.4460	-2.641**	-3.1140	-2.646**	-2.6410	-2.2477*
PR1999	2.4103	2.2039*	2.2172	2.0389*	2.9019	1.9891*	2.7903	1.7274+
PR1998	3.0254	2.1356*	3.0780	2.1956*	3.3961	2.0031*	3.0522	2.2214*
PR1997	1.3618	1.8843+	1.2856	1.7952+	1.0748	1.7208+	1.3044	1.9991*
PR1996	0.6420	1.9697*	0.6511	1.9779*	0.5576	1.6458+	0.5813	1.6179
PR1995	0.5119	2.1466*	0.4913	1.9729*	0.1415	1.8141+	0.1195	1.7445+
PR1994	0.3263	1.8129+	0.4358	1.8789+	0.1753	1.9543*	0.1352	1.7245+
Instruments used:	SOI		OI		SOI		SOI	
Hansen test p-val.	0.2553		0.2896		0.1927		0.2153	
AR(1) test p-val.	0.5088		0.4413		0.5462		0.8301	
AR(2) test p-val.	0.5966		0.6017		0.6478		0.8760	

Year dummies and weighted year dummies included in all specifications. t-stats calculated using robust standard errors . Instruments: Self-Inspect (S), Outcomp (O), Inspect (I). AR tests for serial correlation, asymptotically distributed N(0.1) under the null of no serial correlation. Hansen is a test of over-identifying restrictions, asymptotically distributed chi-square under the null of instrument validity. +p<.10, *p<.05, **p<.01. Obs = 2032.

Table 6. Patent Equation "Robustness Check" Models (Poisson Fixed Effects)

Dependent Variable	Air Pollution Patents (*AirPatents*)							
Variable Instrumented	Emissions, Emissions $_{t-2}$, and PR							
	Model 13		Model 14		Model 15		Model 16	
	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Emissions	-0.3446	1.6704+	-0.3512	-2.052*	-0.2553	-2.492*	-0.3701	-2.162*
Emissions $_{t-2}$	0.0019	1.9984*	0.0030	2.3794*	0.0039	2.2703*	0.0032	2.5175*
NonEnvPatents $_{t-2}$	0.0009	1.6398	0.0001	2.933**	0.0001	2.2442*	0.0001	3.090**
Total R&D $_{t-2}$	0.0033	1.6214	0.0002	2.0544*	0.0003	1.4221	0.0002	2.1551*
Spillovers $_{t-2}$	0.0053	1.6951+	0.0057	2.0304*	0.0018	1.6956+	0.0060	2.1097*
Sales $_{t-2}$	0.0019	0.8221	0.0004	1.7220+	0.0015	0.7565	0.0003	1.8147+
Sales Growth $_{t-2}$	1.1325	2.3690*	1.0604	1.6007	1.2060	1.2019	1.0975	1.6769+
Employees $_{t-2}$	0.0037	0.7325	0.0032	1.0224	0.0035	0.6046	0.0030	1.0552
Concentration $_{t-2}$	-0.7041	-1.972*	-0.7637	-1.983*	-0.8147	-2.153*	-0.7884	-2.047*
Concentration$^{\wedge 2}$ $_{t-2}$	2.0523	1.8874+	2.0390	1.9203+	2.1062	1.8807+	2.1051	1.9825*
Capital Intensity $_{t-2}$	-3.0332	-1.790+	-2.4719	-2.76**	-3.0498	-1.765+	-2.5517	-2.83**
Age of Capital $_{t-2}$	1.0583	1.7166+	2.2716	2.0651*	1.0799	1.7662+	2.3452	2.1320*
Export Intensity $_{t-2}$	-0.0553	-2.332*	-0.3291	1.7921+	-0.0315	-2.366*	-0.3398	1.8502+
R&D Intensity $_{t-2}$	1.8235	2.2993*	5.3958	2.5180*	1.9421	2.3338*	5.5707	2.600**
Number Facilities	0.0005	2.0315*	0.0001	3.066**	0.0004	2.0759*	0.0001	3.166**
Number Firms	0.0011	2.1496*	0.0004	2.3243*	0.0010	2.1736*	0.0004	2.3996*
SD Sales $_{t-2}$	0.0001	0.6350						
SD Employees $_{t-2}$	0.0289	0.8467						
SD Capital Intensity $_{t-2}$	-1.4848	-1.765+						
SD Age of Capital $_{t-2}$	4.3287	1.7243+						
SD Export Intensity $_{t-2}$	-1.7642	-1.6261	*					
SD R&D Intensity $_{t-2}$	0.8799	2.0042*			*			
PR 1994 - 1995	0.8644	2.0376*						
PR 1996 - 1999	2.7751	3.095**					*	
PR 2000 - 2004	-4.6836	-2.277*						
PR 1993 - 1995			0.6440	1.4492				
PR 1996 - 1999			2.7726	2.2434*				
PR 2000 - 2004			-4.6093	-2.490*				
Num. Part 94-95 (91-3)					5.30E-03	0.6781		
Num. Part 96-99 (92-5)	*				4.56E-03	2.691**		
Num. Part 00-04 (95)					-8.98E-03	-2.158*		
PR (Early Joiners) 1994 - 2004			*				-3.5480	-1.695+
PR (Later Joiners) 1996 - 2004							-6.4781	-1.665+
Hansen test p-value	0.4256		0.1519		0.3621		0.1588	
AR(1) test p-value	0.7245		0.4103		0.6091		0.4291	
AR(2) test p-value	0.6178		0.6843		0.6304		0.7056	

Year dummies included in all specifications. Weighted time dummies included in Models 14-16. t-stats calculated using robust standard errors . All models use the identifying instruments: Self-Inspect (S), Outcomp (O), Inspect (I). AR tests for serial correlation, asymptotically distributed N(0.1) under the null of no serial correlation. Hansen is a test of over-identifying restrictions, asymptotically distributed chi-square under the null of instrument validity. + p<.10, *p<.05, **p<.01. Obs = 2032.

APPENDIX

Table A1. Environmental Patent Classes

Patent Subcategory	U.S. Patent Classes	Mean Count Per Industry Per Year
Hazardous / Toxic Waste	588	0.041
Air-Pollution-Related Non-Vehicular	15,44,60,110,422,423	1.956
AirPatents Subtotal		1.997
Water Pollution	203,210,405	3.216
Waste Management	201,71,73	3.767
EnvPatentsBC Subtotal		8.980
Alternative Energy	49,62,104,180,204,222,228,242,248,280,340,343, 374,428,436, 440,708	7.967
Solid Waste Control	34,65,75,99,100,106,118,119,122,137,162,164,165, 198,205,209,216,239,241,264,266,425,431,432,435, 460,502,523,525,526	9.953
Air-Pollution-Related Vehicular	123	0.959
EnvPatentsCI Total		27.859

Note: Per-industry counts in this table apply to a wider set of industries than contained in our balanced panel, the latter excluding industries with missing explanatory data. As a result, mean counts differ slightly from those in Table 1.

Table A2. Falsification Tests

Dependent Variable	Non-Environmental Patents			
Variable Instrumented	Emissions, Emissions $_{t-2}$, and PR			
	Model A1		Model A2	
	Coeff.	t-ratio	Coeff.	t-ratio
Emissions	-0.0320	-0.7754	-0.0095	-0.4493
Emissions $_{t-2}$	0.0540	1.4472	0.0387	1.6294
PR 1994 - 2004	-0.2157	-1.0457	*	
PR 1994 - 1995	*		0.1188	0.2438
PR 1996 - 1999	*		1.1618	1.2418
PR 2000 - 2004	*		-0.6259	-0.6926

Models A1 and A2 use the same explanatory data (excluding *NonEnvPatents*) as Model 1 in Table 3 and Model 3 in Table 3, respectively. t-stats calculated using robust standard errors . Identifying instruments: Self-Inspect (S), Outcomp (O), Inspect (I). Obs = 2032.