Journal of Environmental Management 153 (2015) 84–92

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Corporate environmentalism and environmental innovation

Ching-Hsing Chang [a], Abdoul G. Sam [b,*]

[a] Department of BioBusiness Management, National Chiayi University, No.580. Sinmin Rd., Chiayi City 600, Taiwan, ROC
[b] Department of Agricultural, Environmental & Development Economics, Ag. Administration Building # 338, The Ohio State University, 2120 Fyffe Rd, Columbus, OH 43210, USA

A R T I C L E I N F O

Article history:
Received 6 August 2014
Received in revised form
8 December 2014
Accepted 6 January 2015
Available online 14 February 2015

JELcodes:
Q55
L51
C23

Keywords:
P2 adoption
Corporate environmentalism
Environmental innovation
Instrumental variable Poisson

A B S T R A C T

Several papers have explored the effect of tighter environmental standards on environmental innovation. While mandatory regulation remains the central tenet of US environmental policy, the regulatory landscape has changed since the early 1990s with the increased recourse by federal and state agencies to corporate environmentalism–voluntary pollution prevention (P2) by firms–to achieve environmental improvements. We therefore estimate the effects of voluntary P2 activities on the patenting of environmental technologies by a sample of manufacturing firms. With our panel data of 352 firms over the 1991–2000 period, we adopt an instrumental variable Poisson framework to account for the count nature of patents and the endogeneity of the P2 adoption decision. Our results indicate that the adoption of voluntary P2 activities in the manufacturing sector has led to a statistically and economically significant increase in the number of environmental patents, suggesting that corporate environmentalism can act as a catalyst for investments in cleaner technologies. Our findings are internationally relevant given the increasing ubiquity of corporate environmentalism in both developed and developing economies.

1. Introduction

US firms devote considerable financial resources to the development of cleaner production technologies. For example, statistics in Carrión-Flores and Innes (2010) indicate that on average between 927 and 3150 patents for environmentally friendly technologies were granted every year between 1989 and 2002 to firms in the manufacturing sector.[1] Such figures explain in part the debate in the environmental economics literature regarding the determinants of environmental innovation (see e.g., Jaffe et al., 2002 for a survey). An important facet of this ongoing debate concerns the relationship between environmental regulation and innovation. Porter and van der Linde (1995) contend that, in a dynamically competitive environment, stricter environmental standards may incentivize firms to invest in cleaner technologies that reduce their compliance costs, leading to a “win–win” situation where both pollution levels and firms' operating costs are abated. A number of papers have sought to test the empirical validity of what has become known as the Porter hypothesis (see Horbach, 2008 for a survey). Many of these studies find a causal effect of stricter regulations on environmental innovation, in congruence with the Porter hypothesis (e.g., Brunnermeier and Cohen, 2003; Carrión-Flores and Innes, 2010).

However, a new regulatory paradigm has emerged in recent years with the increasing reliance by federal and state regulatory authorities on corporate environmentalism, that is on firm-initiated or government-sponsored voluntary P2 programs designed to achieve environmental improvements. Firms participating in these programs make a voluntary pledge to exceed emission standards set forth by environmental laws and/or reduce unregulated pollutants.

The 1990 Pollution Prevention Act (PPA) established a federal policy of incentivizing firms to voluntarily adopt source reduction

* Corresponding author.
E-mail addresses: chc@mail.ncyu.edu.tw (C.-H. Chang), sam.7@osu.edu (A.G. Sam).

[1] Carrión-Flores and Innes (2010) consider a broad measure and a conservative measure of environmental patents. These numbers are obtained by multiplying the reported sample averages for the two measures (24.8 and 7.3) by the number of industries (127) in their sample. The recently released Clean Energy Patent Growth Index which tracks patents granted by the US Patent and Trademark Office (USPTO) for environmentally friendly technologies shows an upward trend between 2002 and 2013; patenting activity reached the highest level in 2013 with 3175 grants made http://cepgi.typepad.com/heslin_rothenberg_farley_/.

http://dx.doi.org/10.1016/j.jenvman.2015.01.010
0301-4797/

activities, also referred to as pollution prevention (P2) practices.[2] Shortly after the passage of the PPA, the Environmental Protection Agency (EPA) created its first voluntary program, the 33/50, to reduce emissions of 17 highly toxic chemicals; over 1200 firms self-selected into the program. The apparent success of the 33/50 program and a growing awareness among firms and the public of the effects of climate change paved the way for several more voluntary P2 programs such as Energy Star which seeks to decrease carbon dioxide emissions, and the National Environmental Performance Track designed to encourage environmentally proactive firms through rewards and public recognition. From 1996 to 2005, the number of EPA-sponsored P2 programs increased from 24 to 87 (Khanna and Brouhle, 2009).

In addition to government-sponsored voluntary P2 programs, many firms have shifted away from a regulatory driven approach to a more proactive and beyond-compliance strategy towards environmental management.[3] For example, in the wake of a tragic gas leak that killed thousands in Bhopal India, the chemical manufacturing industry responded by creating, on its own volition, the Responsible Care program to enhance environmental performance and occupational safety above and beyond member firms' legal obligations. The apparent success of Responsible Care led the BP Oil Spill Commission to recommend the creation of a like-minded program for the oil and gas industry (Gamper-Rabindran and Finger, 2013) in the aftermath of the Deepwater Horizon oil spill in the Gulf of Mexico in 2010. Other notable examples of firm led initiatives to rein in waste generation include the multinational conglomerate 3M's Pollution Prevention Pays (3P) program and Chevron's Save Money and Reduce Toxins (SMART) program.[4]

In developing and transition economies with lax environmental enforcement agencies, many businesses have embraced corporate environmentalism in order to reassure downstream buyers about their commitment to environmental quality or as a condition of doing business with them. This is more likely to be the case for export-oriented businesses in developing economies who act as suppliers to larger multinational companies that cater to clients in richer economies. Anecdotal evidence indicates that many suppliers in developing economies have faced pressure from their customers in developed countries to seek ISO certification (Prakash and Potoski 2012). China, for example, has the highest number of ISO 14001-certified businesses in the world and empirical evidence in McGuire (2014) indicates that ISO certification has improved environmental compliance for a sample of Chinese manufacturing firms.

Despite the increased recourse to these voluntary environmental programs in developed, transition, and developing economies, surprisingly little has been done to ascertain their effects on environmental innovation. The main objective of our study is to explore whether the voluntary adoption of P2 activities by regulated firms impels or impedes their investments in environmental technologies.[5] To our knowledge, only few papers (e.g., Johnstone et al. (2010), Brouhle et al. (2013), Carrión-Flores et al. (2013)) have studied the link between P2 programs and environmental innovation For example, using country-level data, Johnstone et al. (2010) find no effect of the presence of "voluntary environmental policy"–captured by a dummy variable—on environmental patenting activity. Brouhle et al. (2013) examine the effect of participation in the Climate Wise program on firm-level environmental innovation, finding that Climate Wise participation enhanced the technical capacity of less R&D-intensive firms, which in turn led to a statistically significant increase in the number of environmental patents. Specifically, they find that a participant firm with median R&D intensity had 18% more environmental patents as a result of participation in the Climate Wise program. Carrión-Flores et al. (2013) also evaluate the effect of P2 program participation on environmental innovation at the industry level. They find that participation in the 33/50 program led to increased environmental patenting in the short-run (between 1994 and 1999) but had a negative effect in the long-run (between 2000 and 2004). Per their results, a 10% increase in the industry-level 33/50 adoption rate was estimated to increase environmental patents by 27.5% between 1996 and 1999, and reduce said patents by 46.2% in years 2000—2004.

Both the 33/50 (Carrión-Flores et al., 2013) and Climate Wise (Brouhle et al., 2013) were designed with short-term pollution reduction objectives for a narrow target of emissions. For example, the 33/50 program sought to abate emissions of 17 toxic chemicals by 33% by 1992 and by 50% by 1995 relative to 1988 baseline levels (Khanna and Damon, 1999). Likewise, Climate Wise was in effect from 1993 to 2000 and focused on the nonutility manufacturing sector to achieve reductions in greenhouse gas (GHG) emissions. Unlike these two narrow "short-term" programs, the P2 program–spawned by the PPA and is our focus–is far broader in scope (targets all 683 chemicals and chemical categories in the Toxics Release Inventory (TRI)) and does not have any explicit time-sensitive emission reduction goals. It consists of a diverse set of 43 P2 practices ranging from good operating practices (e.g., improved maintenance scheduling, recordkeeping), to improved procedures, to raw material and process modification (e.g., modified equipment, layout, or piping). Between 1991 and 1995, over half of all TRI facilities had adopted at least one P2 practice (Sam, 2010); in the same period, only 12% of eligible firms had joined the 33/50 program.

Moreover, unlike Carrión-Flores et al. (2013), we use firm-level data instead of aggregate industry-level data. We do so for two main reasons. First, both decisions to invest in patentable environmental research as well as adoption of P2 activities are made by firms. Second, aggregation at the industry level may serve to attenuate the real impact of voluntary P2 activities on

[2] The PPA defines a source reduction practice as "any practice which (i) reduces the amount of any hazardous substance, pollutant, or contaminant entering any waste stream or otherwise released into the environment (including fugitive emissions) prior to recycling, treatment, or disposal; and (ii) reduces the hazards to public health and the environment associated with the release of such substances, pollutants, or contaminants."

[3] Businesses and industries have taken unilateral steps to proactively improve their environmental management by adopting the International Organization for Standardization (ISO)'s 14001 standards and related environmental management systems–such as Total Quality Environmental Management (TQEM)–that enable them to identify the environmental impacts of their products and internalize those impacts in their operational decisions (Sam et al., 2009).

[4] These slogans illustrate that private firms' investments in cleaner technologies are also motivated by shareholder wealth maximization, which manifests itself via a number of channels. Specifically, cleaner technologies have the potential to i) reduce operating expenses and lower the number of costly inspections and enforcement actions (Maxwell and Decker, 2006), ii) help preempt costly boycott campaigns (Innes and Sam, 2008), iii) enhance the appeal of a firm's products among environmentally conscious consumers (Khanna and Damon, 1999); iv) spur tighter standards that raise rivals' costs (Salop and Scheffman, 1983; Innes and Bial, 2002), iv) forestall negative public reaction in media and financial markets (Hamilton, 1995) by reducing the frequency of environmental infractions and the volume of toxic chemicals produced. Eccles et al. (2014) classify firms based on their adoption of sustainability policies by 1993 and track their financial performance over an 18 year period. They find that *high sustainability* firms (those that voluntarily adopted sustainability practices) outperformed otherwise similar *low sustainability* firms in terms of stock market performance and accounting rates of returns (return on equity and return on assets). Sharma and Vredenburg (1998) also find that environmental proactiveness was associated with a number of competitive benefits such as lower operating costs and improved corporate reputation.

[5] By environmental innovation, we are referring to successful patents of environmental technologies.

environmental innovation when there is significant heterogeneity in P2 adoption within an industry.

Our results indicate that the adoption of P2 practices leads to a direct and significant boost in environmental patents at the firm-level. We also find that stricter environmental standards stimulate environmental innovation, reaffirming the critical role of regulatory compliance in spurring innovation as evidenced in previous work by Brunnermeier and Cohen (2003), Carrión-Flores and Innes (2010), and Jaffe and Palmer (1997). The remainder of the paper is organized as follows. Section 2 provides a brief literature review on environmental regulation and innovation and presents the main hypothesis tested; Section 3 presents the data and econometrics; Section 4 discusses the results; Section 5 concludes.

2. Background and main hypothesis

2.1. Background

Several studies, mostly theoretical, have sought to analyze the relationship between the environmental regulation and innovation. Theoretical papers by Downing and White (1986), Fischer et al. (2003), Jung et al. (1996), Malueg (1989), and Milliman and Prince (1989) analyze the economic incentives provided by different policy instruments (taxes, subsidies, permits, and emission standards) toward the development and adoption of greener production technologies (see e.g., Requate (2005) for a review of findings). Porter and van der Linde (1995) argue that tougher environmental regulation can act as a spur to environmental innovation that lowers emissions and compliance costs. They offer anecdotal evidence in support of their hypothesis which has become famously known as the Porter hypothesis.

A few empirical papers explore the effect of regulatory stringency on environmental innovation. For example, using a panel data of a sample of US manufacturing industries, Brunnermeier and Cohen (2003) find that pollution control costs are positively associated with the number of environmental patents after controlling for several covariates. Per their Poisson results, a one percent increase in pollution abatement costs leads to a small (0.05 percent) increase in environmental patents. In the same realm, Jaffe and Palmer (1997) find that lagged pollution abatement costs are positively associated with research and development (R&D) expenditures; however they do not find such association between pollution control costs and patents. Carrión-Flores and Innes (2010) argue that causality between environmental innovation and regulatory stringency runs in both directions; that is while environmental policy could trigger the development of clean production technologies, environmental innovation could in turn spur a tightening of environmental standards. If so, failure to account for the bi-directional links biases econometric results. Using emissions of regulated TRI pollutants and environmental patents as measure of innovation, they find evidence in support of the hypothesized bi-directional links. In terms of the magnitude of the induced innovation, they find that a 1% permanent tightening of emission standards spurs a 0.43% long-run increase in environmental patents.

These studies do not, however, estimate the separate effects of voluntary P2 programs which have become an integral part of US environmental policy. In 1990, the PPA was passed to promote widespread adoption by businesses of voluntary P2 activities. One year later, the EPA created its most studied P2 program, the 33/50, which sought the cooperation of regulated firms to achieve release reductions for 17 toxic chemicals by a third by 1992 and by 50 percent by 1995, relative to 1988 baseline levels.

Due to the cost and non-enforceability of corporate P2 commitments, the extant literature has understandably focused on investigating the motives for their adoption and their effectiveness at curbing pollution from levels that would otherwise have been produced (Arora and Cason, 1996; Bi and Khanna, 2012; Gamper-Rabindran, 2006; Harrington et al., 2014; Hsueh, 2013; Innes and Sam, 2008; Khanna and Damon, 1999; Sam et al., 2009; Videras and Alberini, 2000; Vidovic and Khanna, 2007; Welch et al., 2000). In contrast to these papers, our aim is to gauge if P2 activities play a catalyzing role in promoting firm-funded environmental innovation. The apparent success of the 33/50 program, the PPA's emphasis of voluntary P2 practices, and greater willingness of private firms to self-regulate served as a springboard for several more ongoing EPA-sponsored P2 programs (www.epa.gov/partners) and several state-based P2 programs such as Ohio Tox-Minus (modeled after the 33/50) and Encouraging Environmental Excellence (E3) initiatives. The relevance of our study stems from the increasing pervasiveness of the voluntary approach to environmental regulation nationally and internationally as discussed in the introduction, combined with the role of technological innovation as an indispensable driver of pollution abatement. In the next section, we introduce and discuss the key hypothesis empirically tested in the paper.

2.2. Main hypothesis

Honoring P2 commitments often requires the implementation of costly environmentally-friendly activities (National Pollution Prevention Round Table, 1997; Sam et al., 2009). To the extent that firms take their voluntary commitments of pollution reduction seriously, P2 programs could enhance the attractiveness of new environmental technologies that reduce the costs of self-imposed emission reductions, hence eliciting more spending on environmental research.[6] Both anecdotal and empirical evidence indicate that some participants in P2 programs follow through with their pledges to reduce emissions. Despite the lack of enforceability of commitments by 33/50 participants, Bi and Khanna (2012), Innes and Sam (2008), Khanna and Damon (1999), and Sam et al. (2009) find that the 33/50 program was responsible for significant reductions in the emission of targeted chemicals among participant firms. Hsueh (2013) reports that a voluntary agreement between the EPA and the pressure-treated wood industry lowered arsenic use “to levels not seen since the 1920s.” Also, unlike targeted programs such as the 33/50 program, voluntary P2 practices have a much wider coverage of toxic chemicals and therefore have more room for new ideas regarding pollution prevention technologies. Furthermore, a source reduction clearinghouse was formed under the PPA to gather and share information about new environmental control technologies related to P2 practices. Such knowledge exchange may generate positive spillovers that translate into more environmental patenting at the firm level. For all these reasons, we conjecture that:

> *Voluntary P2 activities increase the incentives for environmental R&D and therefore lead to more environmental patents*

[6] It is noted however that not all empirical studies have found the same effect. For example, Vidovic and Khanna (2007) find that this negative impact of the program on targeted releases vanishes if prior reductions in pollution achieved before the start of the program and time fixed effects are taken into account. Examining impacts by industry and media, Gamper-Rabindran (2006) comes to a more mixed conclusion, with some industries and media experiencing significant release reductions due to the 33/50 program effect, and others not.

Table 1
Variable definitions.

Variable name	Definitions	Mean	St. Dev.
Env. patents broad	Number of firm-level environmental patents (broad)	10.41	26.42
Env. patents narrow	Number of firm-level environmental patents (narrow)	5.750	15.38
Releases	Aggregate releases of core CAA-regulated chemicals, in 100,000 of lbs.	6.639	18.50
Weighted releases	Aggregate toxicity-weighted releases of core CAA-chemicals, in billions of toxicity-weighted lbs.	7.952	79.399
P2	Number of P2 activities adopted by a firm in year t	6.771	13.17
Workforce	Number of employees, in thousands	24.36	49.08
Cumulative P2	Cumulative number (stock) of P2 practices adopted by a firm between 1991 to year t-1	42.019	83.537
Env. industry patents	Number of industry-wide environmental patents	470.9	330.9
All industry patents	Number of all industry-wide patents	2635	2276
Age of capital	Ratio of net assets to gross assets	0.773	0.0979
Capital intensity	Ratio assets to sales	0.0605	0.0570
Retained earnings	Three-year moving average of retained earnings to Sales	0.154	1.056
Sales	Sales revenue, in billions	5.657	14.93
Sales growth	Growth rate of sales revenue	11.27	33.50
Retained earnings	Three-year moving average of retained earnings to Sales	0.154	1.056
R&D intensity	Ratio of R&D expenditures to Sales	4.336	33.86
Herfindahl index	Herfindahl index calculated at the two-digit SIC	5.744	2.610
Inspections	Number of inspections by federal and state environmental agencies	4.186	9.400
Enforcement actions	Number of enforcement actions	1.203	3.166
Out of compliance	Number of instances a firm is out of compliance	2.964	7.450
Self-inspections	Number of firm-conducted inspections	0.0463	0.425

Notes: Averages are based on 2876 observations for Sales growth and 3306 observations for the remaining variables (sample prior to lagging observations).

3. Data and methods

3.1. Data

Several data sources are combined, resulting in an unbalanced panel of 352 manufacturing companies (SICs 20–39) over the period of 1991–2000. Following previous studies (Brouhle et al., 2013; Brunnermeier and Cohen, 2003; Carrión-Flores and Innes, 2010; Carrión-Flores et al., 2013; Jaffe and Palmer, 1997; Johnstone et al., 2010), successful environmental patent applications are treated as proxies for environmental innovation. Environmental patents are distinguished by patent classifications that relate to air and water pollution, hazardous waste prevention and control, waste disposal, recycling, and renewable energy (Carrión-Flores and Innes, 2010). The patent data is acquired from United States Patent and Trademark Office (USPTO). Data on toxic chemical releases, voluntary P2 practices (source reductions), and parent company names are obtained from the EPA's TRI database. Following Carrión-Flores and Innes (2010), we restrict our attention to the 153 core chemicals included in the TRI in 1988 that are subject to the emission standards and monitoring under Title III of the Clean Air Act (CAA). We therefore aggregate the releases related to these chemicals at the firm level to obtain our measure of emissions. Facility-level enforcement and inspection actions are obtained from the Integrated Data for Enforcement Analysis (IDEA) database. We aggregate facility-level environmental data (releases, source reduction activities, and enforcement data) annually to obtain firm-level values. Financial data (sales, retained earnings, R&D expenditures, assets, employment) are extracted from the Standard & Poor's Compustat database. Following Innes and Sam (2008), we restrict our study to firms in the manufacturing industry (SICs 20–39) which is responsible for vast majority of the TRI chemicals releases. Table 1 reports the descriptive statistics of the variables used in the study.

3.2. Model specification

Following our discussion above, our dependent variable is the count of environmental patents measured at the firm level as in Brouhle et al. (2013) and our key covariate of interest is the number of voluntary P2 activities adopted by a firm. Besides the effects of voluntary P2 activities and CAA-regulated releases, we control for several other covariates that have been hypothesized to impact environmental innovation. First, we control for R&D intensity since R&D spending is a key input in the patenting process and because firms that are more research intensive may be more apt at capitalizing on knowledge spillovers from industry or government research (Cohen and Levinthal, 1990).

Second, we add sales and workforce of the firm as explanatory variables to control for effects of firm size on innovation. Larger firms may enjoy learning economies (larger firms are more likely to have been around longer) and economies of scale and scope advantages relative to smaller companies (Macher and Boerner, 2006) when it comes to innovation.

Third, research in cleaner technologies by other firms in a related line of business may incentivize firms to spend more on environmental research (Jaffe and Palmer, 1997) in order to take advantage of positive spillovers or for competitive reasons (Brouhle et al., 2013); we use aggregate industry patents to control for these effects, and further categorize them into environmental patents and non-environmental patents.[7]

Fourth, opportunities and incentives to innovate may also depend on the structure of a firm's production process with more capital intensive processes presenting more scope for cost-reducing environmental R&D (Carrión-Flores et al., 2013). We therefore use the ratio assets to sales as our measure of capital intensity. We expect the coefficient on capital intensity to be positive.

Fifth, we include the age of capital calculated as the ratio of net assets to gross assets (Khanna and Damon, 1999) to capture the effect of newness of production assets on environmental innovation. Firms with newer assets (ratio closer to 1) may be less dirty and therefore less likely to invest in cleaner production technologies. A negative relationship between age of capital and environmental innovation is therefore expected (Carrión-Flores and Innes, 2010).

[7] For each firm, this variable is created by adding up all environmental patents at the 2-digit SIC level, minus the patents of the firm in question.

Sixth, industry concentration may spur environmental R&D since concentration gives rise to “raising rivals' costs” motives for heightened environmental research (Innes and Bial, 2002). Conversely, high industry concentration may jeopardize research spending since competitive pressures are lower (see e.g., Cohen and Levin, 1989 for a discussion of concentration and R&D). Carrión-Flores and Innes (2010) find a negative relationship between de degree of market concentration and environmental innovation. Following standard practice, we include the Herfindahl index calculated at the 2-digit SIC level to capture the effects of market concentration.

Seventh, economists have argued that a firm's internal financial resources are a critical determinant of its R&D investment in part because of asymmetric information and the high costs of mitigating it. Asymmetric information arises because R&D projects are inherently riskier, and the innovator has more information about the likelihood of success of a R&D project than potential investors. This problem is exacerbated by the ease of imitating successful innovation which precludes full disclosure to potential investors. External parties are therefore prone to decline or demand higher premium in order to finance R&D projects (Hall, 2002). Consequently, we use a three year moving average of retained earnings normalized by sales as an explanatory variable.

Our empirical model follows directly from the structural model in Carrión-Flores et al. (2013) which itself simply extends the model in Carrión-Flores and Innes (2010) by adding the effects of participation in the 33/50 program. The fact that Carrión-Flores et al.'s (2013) model incorporates a voluntary program makes it particularly attractive for our purpose since we also consider a (different) voluntary P2 program. The model posits that both contemporaneous CAA-regulated emissions (which proxy for changes in the stringency of environmental standards) and lagged emissions (which proxy for the initial level of emission standards) are determinants of environmental patents and that the remaining control variables (described above) affect environmental patents with a two-year lag which is the assumed average delay between R&D and patent application.[8]

3.3. Econometric issues

Reverse causality bias between contemporaneous emissions and environmental patents is a key concern; specifically, environmental innovation may lead to tighter emission standards as evidenced in Carrión-Flores and Innes (2010). Also, lagging notwithstanding, P2 activities are likely endogenous thanks to unobserved random factors that affect both decisions to patent and to participate in voluntary programs. For example, firms with environmentally proactive management may be more likely to invest in patentable environmental research and self-select into voluntary pollution control initiatives. We use four firm/time-varying instruments to identify the effects of these two variables. Specifically, we use enforcement variables as instruments as there is significant empirical evidence that more inspections and enforcement actions spur emission reductions (Foulon et al., 2002; Gray and Deily, 1996; Gray and Shimshack, 2011; Innes and Sam, 2008; Laplante and Rilstone, 1996; Shimshack and Ward, 2008) and participation in voluntary programs (Bi and Khanna, 2012; Gamper-Rabindran, 2006; Innes and Sam, 2008; Videras and Alberini, 2000) but have no significant effect on innovation (Brouhle et al., 2013; Brunnermeier and Cohen, 2003; Carrión-Flores and Innes, 2010; Carrión-Flores et al., 2013). Following Carrión-Flores et al. (2013), we consider the number of inspections visits, the number of enforcement actions, the number of instances a firm is deemed out of compliance with environmental laws, and the number of self-inspections. All four instruments are lagged three-years.

Consonant with previous econometric treatment of patents as dependent variables (e.g., Hausman et al., 1984) and because of the endogeneity of some of the covariates, we estimate the model using an instrumental variable Poisson method.[9] In addition to the variables discussed above, we also control for industry and time fixed effects to account for industry differences in propensity to patent and common trends in technological innovation. Finally, we compute and report standard errors clustered at the firm-level which are robust to heteroskedasticity and serial correlation within firms.

4. Results and discussion

The coefficient estimates are displayed in Table 2. All models presented in Table 2 are estimated with an instrumental variable Poisson as mentioned above.[10] We present five models to test the robustness of our main results to alternative measures of environmental patents and toxic releases and to allow for persistence and nonlinearities in the effects of P2 practices. Following Carrión-Flores and Innes (2010), Models (1)–(4) are estimated using a broad count of environmental patents. This broad definition of environmental patents includes all patents related to wind energy, solid waste prevention, water pollution, recycling, alternative energy, alternative energy sources, geothermal energy, air pollution control, solid waste disposal, and solid waste control.

Model (1) is our baseline model; Model (2) adds to Model (1) a square of the lagged P2 variable to test if the effects of P2 adoption

[8] Briefly, the model conceptualizes four relationships into structural equations: the first equation assumes that environmental patents are determined by (twice) lagged environmental R&D and other controls; the second equation assumes that actual emissions are determined by prevailing emission standards; the third equation posits that said emission standards are explained by contemporaneous environmental technology (patents), lagged standards, and lagged voluntary P2 reductions. The fourth equation specifies environmental R&D as a function of expected (next period) emission standards or targets, current standards, and voluntary P2 adoption. Therefore P2 adoption impacts environmental technology via its effects on environmental R&D and emission standards. See Carrión-Flores and Innes (2010) and Carrión-Flores et al. (2013) for a detailed derivation of the model.

[9] Let y_{it} be the count of environmental patents; we posit the following Poisson relationship between y_{it} and the control variables:$y_{it} = \rho_{it} + \varepsilon_{it} = \exp(x_{it}\beta) + \varepsilon_{it}$, where x_{it} is the $1 \times k$ vector of controls, β is the $k \times 1$ parameter vector, and ε_{it} is represents random unobserved heterogeneity. In our model, it is assumed that $E(\varepsilon_{it}|x_{it}) \neq 0$ owing to endogeneity of P2 adoption and emissions. As shown in Windmeijer and Santos Silva (1997), with valid instruments z_{it}, $E(\varepsilon_{it}|z_{it}) = 0$; hence we can obtain, in two steps, consistent, efficient, and asymptotically normal Poisson coefficient estimates by minimizing: $(y-\rho)' Z(\widetilde{Z'\Omega Z})^{-1} Z'(y-\rho)$, where $(\widetilde{Z'\Omega Z}) = \sum_{i=1}^{n} (y_{it} - \tilde{\rho}_{it})^2 z_{it} z'_{it}$ is an estimate of the asymptotic variance of $Z'(y-\rho)$ and $\tilde{\rho}_{it} = \exp(x'_{it}\tilde{\beta})$ is obtained from the first round estimation of β. We use the IV POISSON command in Stata to estimate the model parameters.

[10] To explore the robustness of our results with respect to functional form, we estimated the following inverse hyperbolic sine (IHS) transformation model: $\log(y_{it} + (1 + y_{it}^2)^{1/2}) = X_{it}\beta + \varepsilon_{it}$, where the variables are as defined in the previous footnote. Following MacKinnon and Magee (1990) and Pence (2006), we use the IHS transformation of the dependent variable $(\log(y_{it}\ (1 + y_{it}^2)^{1/2})$ in order to appropriately account for the prevalence of zeroes in firm level patent data. Small values of y_{it} aside, the IHS transformation is approximately equal to $\log(2^*y_{it})$ or $\log(2) + \log(y_{it})$; hence coefficient estimates are interpreted the same way as if $\log(y_{it})$ was used as the dependent variable. The key advantage of the IHS transformation is that it is defined when $y_{it} = 0$ while the regular log transformation $(\log(y_{it}))$ is not. Doing so, we find results that are quite consistent with the Poisson estimates reported in Table 2. Specifically, we find the P2 adoption spurs a statistically significant increase in environmental patents as hypothesized. We also find evidence that both the expectation of stricter emission standards as well as initial standards boost environmental patents. We note, however, that the magnitudes of the estimated effects are higher in the IHS results reported above than in the Poisson results. Due to both space considerations and out of concern for consistency with previous literature–which has mostly relied on Poisson regression, we have not reported the full IHS results in the paper. They are available upon request.

Table 2
Instrumental variable Poisson estimation of the determinants of environmental innovation.

Variables	Broad count				Narrow count
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
$Release_t$	−0.110**	−0.111**	−0.101**	−0.0467*	−0.117*
	(0.0514)	(0.0433)	(0.0421)	(0.0274)	(0.0598)
$Release_{t-2}$	0.0756**	0.0766***	0.0714**	−0.00600	0.0805**
	(0.0356)	(0.0297)	(0.0297)	(0.00811)	(0.0410)
$P2_{t-2}$	0.0243***	0.0302*	0.0281***	0.0299***	0.0266***
	(0.00620)	(0.0157)	(0.0103)	(0.00935)	(0.00632)
$P2_{t-2}$ squared		−6.49e-05			
		(0.000138)			
Cumulative $P2_{t-2}$			−0.00140		
			(0.00209)		
$Workforce_{t-2}$	0.000549	0.000894	0.000689	0.00306	−1.89e-05
	(0.00387)	(0.00360)	(0.00347)	(0.00262)	(0.00452)
Environ. industry $patents_{t-2}$	0.00269***	0.00221***	0.00246***	0.00178**	0.00239**
	(0.000844)	(0.000852)	(0.000888)	(0.000737)	(0.000941)
All industry $patents_{t-2}$	−0.000663***	−0.000637***	−0.000675***	−0.000569***	−0.000532***
	(0.000134)	(0.000138)	(0.000155)	(0.000138)	(0.000161)
Age of $capital_{t-2}$	−3.120**	−3.122***	−3.073***	−3.008**	−3.053**
	(1.304)	(1.185)	(1.184)	(1.228)	(1.353)
Capital $intensity_{t-2}$	4.719***	4.937***	4.408***	4.811***	3.693***
	(1.098)	(1.183)	(1.219)	(1.224)	(1.309)
$Sales_{t-2}$	0.0308**	0.0292**	0.0294**	0.0255**	0.0350**
	(0.0146)	(0.0134)	(0.0128)	(0.0118)	(0.0165)
Sales $growth_{t-2}$	−0.00790*	−0.00778*	−0.00812*	−0.00960*	−0.00981*
	(0.00471)	(0.00425)	(0.00449)	(0.00522)	(0.00530)
Retained $earnings_{t-2}$	0.218***	0.214***	0.211***	0.231***	0.153***
	(0.0572)	(0.0543)	(0.0575)	(0.0667)	(0.0589)
R&D $intensity_{t-2}$	0.0163**	0.0156**	0.0158**	0.0193**	0.0133*
	(0.00742)	(0.00753)	(0.00747)	(0.00756)	(0.00686)
Herfindahl $index_{t-2}$	−0.0860	−0.127	−0.0632	−0.191**	−0.0386
	(0.107)	(0.115)	(0.124)	(0.0962)	(0.112)
Constant	1.519	1.816	1.304	1.848	1.132
	(1.393)	(1.190)	(1.429)	(1.476)	(1.474)
Observations	2031	2031	2031	2031	2031
Industry fixed effects	YES	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES	YES
Instruments	YES	YES	YES	YES	YES
Hansen test p-value	0.263	0.463	0.197	0.106	0.72

Notes: Cluster-robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

are subject to diminishing marginal returns. Since the $P2_{it-2}$ variable only captures *new* P2 practices adopted by a firm in year t-2 (Harrington, 2012), Model (3) adds to Model (1) the lagged cumulative number (stock) of P2 practices adopted by a firm between 1991 to year t-3 to examine the persistence of P2 effects on environmental innovation. Given the different degrees of toxicity of the chemicals considered, we re-estimated our baseline Model (1) using a toxicity-weighted aggregate of the same chemicals to further explore the robustness of our findings.[11] The toxicity weighted measure we use is computed by the EPA based on their Risk Screening Environmental Indicators (RSEI) model and obtained from the EPA's TRI.NET database. Model (4) presents the results based on toxicity-weighted releases of the CAA-chemicals.[12] To mitigate the concern about the dependent variable (environmental patents) being too broad, we re-estimate Model (1) using a more conservative measure of environmental patents based on a narrower definition as in Brunnermeier and Cohen (2003). The results for this narrow count of environmental patents are in Model (5).[13] Before delving into the discussion of P2 effects, we first note that the Hansen test of overidentification fails to reject the null of instrument exogeneity in all models with p-values ranging between 0.1 and 0.72 (bottom of Table 2).[14] Also, overall, the results are quite robust to the specification of the

[11] We should note that simple aggregation of releases is commonly done in this literature in part due to concerns for the accuracy of toxicity weights; Guerrero and Innes (2013, footnote 10) have a good discussion of why simple aggregation by weight is generally preferred to toxicity weighted aggregation when the number of chemicals is large.

[12] Toxicity weights of chemicals are constructed using four main parameters: Reference Dose (RfD), Reference Concentration (RfC), Oral Slope Factor, and Inhalation Unit Risk. In addition, uncertainty for certain chemical toxicity weights is adjusted by the weight of evidence determination. The RfD or RfC are defined as daily exposure level to a hazard chemical that can be tolerated over a lifetime without an appreciable risk of noncancer effects (USEPA, 1988). The Oral Slope Factor is constructed to measure the incremental lifetime risk of cancer resulting from oral intake of the chemical. The Unit Inhalation Risk is the estimated upper-bound lifetime risk of cancer due to continuous exposure to a chemical at a concentration level of 1 mg/m^3 in air. The technical appendix (see link) explains in detail the construction of the toxicity weights. http://www.epa.gov/oppt/rsei/pubs/technical_appendix_a_toxicity_v2.3.1.pdf.

[13] Given the diversity of the P2 practices, we followed Sam (2010) and disaggregated them into three broad categories: practices that require the implementation of improved operating procedures; practices that focus on investment in environmentally friendly equipment, and practices that involve material modifications. We re-run model (1) using the three separate P2 measures instead one single aggregate P2 measure. Doing so, we did not find any of the three P2 variables to be statistically significant. We suspect that the reason for the lack of significance is the high degree of correlation between the three measures: 0.81 between procedural and equipment P2s, 0.71 between material and procedural P2s, and 0.65 between material and equipment P2s. However when we only include equipment and non-equipment P2s, the coefficient on equipment P2s is marginally significant at the 10% level.

[14] We also regressed the endogenous variables (emissions and P2 activities) on the instruments and found them to the jointly significant in both regressions, corroborating the instrument relevance documented in Carrión-Flores et al. (2013) and others as discussed above.

dependent variable (broad vs. narrow count of patents) and pollutant releases (toxicity-weighted or unweighted); with the exception of lagged releases (not significant in Model (4)) and the Herfindahl index (significant in Model (4)), all explanatory variables are statistically significant in all five models.

The results indicate that an anticipated tightening of emission standards leads to a significant increase in environmental patents, as evidenced by the negative coefficient on contemporaneous emissions in all five specifications.[15] Specifically, an anticipated reduction of 1% in unweighted CAA-regulated emissions (based on the sample mean of 6.639) is estimated to increase the number of environmental patents by between 0.73 and 0.78 percent.[16] Interestingly, our coefficient estimates on (unweighted) contemporaneous emissions are similar in magnitude to corresponding estimates reported Carrión-Flores et al. (2013)'s industry-level study–approximately −0.11 in our Table 2 models vs. −0.13 in their model 11 of Table 5, suggesting the industry-level aggregation does not significantly affect the point estimates of induced innovation effects. This may be explained by less within-industry heterogeneity when it comes to responses to stricter emission standards as firms in the same industry tend to use the same pollutants. Likewise, we also find that the tightening of initial level of emission standards induces a small but significant increase of environmental patents.[17]

As expected, industry-level environmental patents, sales, age of capital, capital intensity, retained earnings, and R&D intensity carry coefficients that are significant in the expected direction. An additional environmental patent by another firm in the same industry leads to a 0.27 percent (per Model (1)) increase in the number of firm-level patents likely owing to positive spillovers from related research. Conversely, an increase in the number of non-environmental industry patents has the opposite effect once the effect of environmental patents is controlled for, although the effect is small. We postulate that out of concern for their competitiveness, firms may respond to a greater number of non-environmental industry patents by redirecting R&D resources to non-environmental research. The coefficients on sales and retained earnings indicate that larger, more deep-pocketed firms are more likely to invest in patentable environmental research. The growth of annual sales is found to negatively impact environmental patents, which is not surprising given that firms with higher growth are generally smaller companies that do not have the financial resources to undertake environmental research on the same level as larger firms.

Turning to estimated impact of P2 adoption, we find that the adoption of an additional P2 practice leads between 2.4 and 3 percent increase in the number of environmental patents, lending support to our main hypothesis.[18] This effect is significant statistically and economically. The coefficient estimate in Model (1) implies that firms that go from no P2 adoption to the sample average of P2 practices per firm (approx. 7 practices) enjoy on average a 17 percent bump in environmental patents, which corresponds to about 1.8 patents based on the average number of 10.4 environmental patents per firm. The effect is smaller but still significant for the narrower measure of environmental patents in model (5). Specifically, an increase of 7 P2 practices (sample average) yields approximately one additional environmental patent for the alternative measure of the dependent variable based on the average of 5.75 patents per firm. We did not find evidence that the P2 effects are subject to diminishing marginal returns; the coefficient on the squared P2 in Model (2) is negative but not significant. Likewise, the coefficient on cumulative count of P2 adoption in Model (3) is not significant, suggesting that P2 effects on environmental innovation are not time-persistent.[19]

We should also note the reported impact of P2 adoption on environmental patents in this study only represents the *direct* impact. In addition to the direct effect, P2 adoption also may *indirectly* increase environmental patents by lowering pollutant releases. For example, Harrington et al. (2014) find that P2 adoption "leads to lower steady-state releases, with estimated reductions between 35% and 50%." Per our findings and those of Carrión-Flores and Innes (2010), lower releases (spurred by P2 adoption) will, in turn, lead to more environmental patents.

Our results stand in contrast to Carrión-Flores et al. (2013) who report an average negative impact of the 33/50 voluntary program on environmental patents and Brouhle et al. (2013) who find that participation in Climate Wise boosted environmental patents only for firms in the lower spectrum of R&D intensity. The differences between these three studies may be explained by the nature of the voluntary programs considered. As mentioned earlier, both the 33/50 (Carrión-Flores et al. (2013) and Climate Wise (Brouhle et al. (2013) were designed primarily to achieved short term reductions of a specific set of emissions. These programs' explicit short-term objectives may have incentivized program participants to invest in short-term reduction activities (e.g., improved monitoring procedures) at the expense of patentable research after the programs ended. However, this myopia on short-term environmental performance is far less likely to occur for the P2 practices we consider in this analysis which do not have explicit short-term pollution reduction goals.

It is important to also note that the difference between our finding and Carrión-Flores et al.'s (2013) in particular may also have to do with the use of firm-level data vs. industry-level data. Unlike emission standards, P2 adoption decisions are voluntarily made by firms; therefore considerable within-industry (firm) heterogeneity is expected. In the presence of such heterogeneity, firm-level data is more appropriate then industry-level aggregate data which may attenuate the true effects of voluntary P2 activities.

5. Conclusion

In light of the growing reliance by the federal and state governments on voluntary P2 programs, the empirical literature has been largely confined to explaining firms' motives for participating in them and whether they are effective in reducing emissions. Using a sample of large US manufacturing firms, this paper focuses on the effects of voluntary P2 adoption on firm-level environmental

[15] Based on previous findings in the literature, there is evidence to suggest that emission targets are influenced by both regulatory standards and non-regulatory abatement pressures from environmental interest groups, market forces, stakeholders etc., leading to self-selection into voluntary P2 programs. As such, we caution that lower emissions may not be entirely ascribed to changes in regulatory standards as discussed in Brunnermeier and Cohen (2003).

[16] We obtained the 0.73 percent figure by multiplying the coefficient estimate for contemporaneous releases in Model (1) (−0.11) by a 0.06639 which represents a 1% increase in the sample mean of emissions per Table 1. The figure 0.78 percent was likewise obtained by multiplying 0.06639 by 0.117, the coefficient in model (5).

[17] The impact of the initial emission standards is obtained by summing the two coefficients on contemporaneous and lagged emissions. The sum is negative and statistically different from zero in all but Model (4).

[18] The Poisson coefficients can be interpreted as semi-elasticities.

[19] However, the stock of P2 practices may indirectly affect environmental innovation by stimulating new P2 adoptions. To check this possibility, we regressed the P2 variable on the (twice-lagged) level and square of cumulative P2s and the remaining covariates. We found that firms with higher cumulative P2s are more likely to adopt new P2s, subject to diminishing returns. Specifically, we found that the marginal effect of cumulative P2 on new P2 adoptions is positive for firms with fewer than 112 cumulative P2s and negative for firms with more. These results suggest that the history of P2 at least indirectly impacts environmental innovation.

innovation, controlling for the effects of several relevant covariates. We find that the adoption of P2 practices triggers a significant increase in environmental patents. Specifically, we find that the adoption of one P2 practice results in about 2.5% increase in the number of environmental patents on average. Our results also show that the stringency of environmental regulation (proxied by CAA-regulated emissions) has a significantly impact on environmental innovation, in congruence with Porter's hypothesis.

Our reported impact of P2 activities on environmental innovation stands in contrast with the findings of similar studies. Carrión-Flores et al. (2013) find that the 33/50 led to a net reduction in environmental patents in the long-run while Brouhle et al. (2013) find tenuous evidence that the Climate Wise program led to increased environmental patenting for less R&D intensive firms. Conversely, we provide evidence of significant salutary effects of P2 practices on environmental patents. The difference between our finding and results discussed above may be explained by design of the P2 programs under consideration. Both the 33/50 and the Climate Wise were designed to achieve short-term pollution relief with explicitly stated target dates and as such may have encouraged participants to embrace and invest in short term waste prevention efforts so as to achieve these goals. We conjecture that the positive effects reported in this study may be the result of the broadness and flexibility of the PPA's P2 program which affords firms with the time to set their own pollution reduction goals and to choose the appropriate cost-reducing technologies to achieve them. This aligns broadly with Johnstone and Hascic (2011)'s finding that more flexible regulation fosters higher quality innovations.

Overall, our study adds to a limited number of studies on the causal links between corporate environmentalism and innovation and points to another beneficial channel of P2 programs, beyond direct pollution reduction (e.g., Harrington et al., 2014) and improved compliance record (Sam, 2010), that has not yet been widely recognized.

Acknowledgments

We are grateful to the editor (Jason Evans), four anonymous referees, and participants at the Tenth Biennial Pacific Rim Conference of the Western Economic Association International in Tokyo (Japan) for very constructive comments. The usual disclaimer applies.

References

Arora, S., Cason, T.N., 1996. Why do firms volunteer to exceed environmental regulations? Understanding participation in EPA's 33/50 program. Land Econ. 72 (4), 413–432.
Bi, X., Khanna, M., 2012. Reassessment of the impact of the EPA's voluntary 33/50 program on toxic releases. Land Econ. 88 (2), 341–361.
Brouhle, K., Graham, B., Harrington, D.R., 2013. Innovation under the climate wise program. Resour. Energy Econ. 35 (2), 91–112.
Brunnermeier, S.B., Cohen, M.A., 2003. Determinants of environmental innovation in US manufacturing industries. J. Environ. Econ. Manag. 45 (2), 278–293.
Carrión-Flores, C.E., Innes, R., 2010. Environmental innovation and environmental performance. J. Environ. Econ. Manag. 59 (1), 27–42.
Carrión-Flores, C.E., Innes, R., Sam, A.G., 2013. Do voluntary pollution reduction programs (VPRs) spur or deter environmental innovation? Evidence from 33/50. J. Environ. Econ. Manag. 66 (3), 444–459.
Cohen, W.M., Levin, R.C., 1989. Empirical studies of innovation and market structure. In: Schmalensee, R., Willig, R. (Eds.), Handbook of Industrial Organization. Elsevier, Oxford, UK.
Cohen, W.M., Levinthal, D.A., 1990. Absorptive capacity: a new perspective on learning and innovation. Adm. Sci. Q. 35 (1), 128–152.
Downing, P.B., White, L.J., 1986. Innovation in pollution control. J. Environ. Econ. Manag. 13 (1), 18–29.
Eccles, R., Ioannou, I., Serafeim, G., 2014. The impact of corporate sustainability on organizational processes and performance. Manag. Sci. 60 (11), 2835–2857.
Fischer, C., Parry, I.W.H., Pizer, W.A., 2003. Instrument choice for environmental protection when technological innovation is endogenous. J. Environ. Econ. Manag. 45 (3), 523–545.
Foulon, J., Lanoie, P., Laplante, B., 2002. Incentive for pollution control: regulation or information? J. Environ. Econ. Manag. 44 (1), 169–187.
Gamper-Rabindran, S., 2006. Did the EPA's voluntary industrial toxics program reduce emissions? A GIS analysis of distributional impacts and by-media analysis of substitution. J. Environ. Econ. Manag. 52 (1), 391–410.
Gamper-Rabindran, S., Finger, S.R., 2013. Does Industry self-regulation reduce pollution? Responsible care in the chemical industry. J. Regul. Econ. 43 (1), 1–30.
Guerrero, S., Innes, R., 2013. Self-policing statutes: do they reduce pollution and save regulatory costs? J. Law Econ. Organ. 29 (3), 608–637.
Gray, W.B., Deily, M.E., 1996. Compliance and enforcement: air pollution regulation in the U.S. steel industry. J. Environ. Econ. Manag. 31 (1), 96–111.
Gray, W.B., Shimshack, J.P., 2011. The effectiveness of environmental monitoring and enforcement: a review of the empirical evidence. Rev. Environ. Econ. Policy 5 (1), 3–24.
Hall, B.H., 2002. The financing of research and development. Oxf. Rev. Econ. Policy 18 (1), 35–51.
Hamilton, J.T., 1995. Pollution as news: media and stock market reactions to the toxics release inventory data. J. Environ. Econ. Manag. 28 (1), 98–113.
Harrington, D.R., 2012. Two-stage adoption of different types of pollution prevention (P2) activities. Resour. Energy Econ. 34 (3), 349–373.
Harrington, D.R., Deltas, G., Khanna, M., 2014. Does pollution prevention reduce toxic releases? a dynamic panel data model. Land Econ. 90 (2), 199–221.
Hausman, J.A., Hall, B.H., Griliches, Z., 1984. Econometric models for count data with an application to the patent R and D relationship. Econometrica 52 (4), 909–938.
Horbach, J., 2008. Determinants of environmental innovation – new evidence from German panel data sources. Res. Policy 37 (1), 163–173.
Hsueh, L., 2013. Beyond regulations: industry voluntary ban in arsenic use. J. Environ. Manag. 131, 435–446.
Innes, R., Bial, J.J., 2002. Inducing innovation in the environmental technology of oligopolistic firms. J. Ind. Econ. 50 (3), 265–287.
Innes, R., Sam, A.G., 2008. Voluntary pollution reductions and the enforcement of environmental law: an empirical study of the 33/50 program. J. Law Econ. 51 (2), 271–296.
Jaffe, A.B., Newell, R., Stavins, R., 2002. Environmental policy and technological change. Environ. Resour. Econ. 22 (1), 41–70.
Jaffe, A.B., Palmer, K., 1997. Environmental regulation and innovation: a panel data study. Rev. Econ. Stat. 79 (4), 610–619.
Johnstone, N., Hascic, I., Popp, D., 2010. Renewable energy policies and technological innovation: evidence based on patent counts. Environ. Resour. Econ. 45 (1), 133–155.
Johnstone, N., Hascic, I., 2011. Environmental policy design and the fragmentation of international market for innovation. In: Ghosal, V. (Ed.), Reforming Rules and Regulations: Laws, Institutions and Implementation. MIT Press, Cambridge, MA.
Jung, C., Krutilla, K., Boyd, R., 1996. Incentives for advanced pollution abatement technology at the industry level: an evaluation of policy alternatives. J. Environ. Econ. Manag. 30 (1), 95–111.
Khanna, M., Brouhle, K., 2009. Effectiveness of voluntary environmental initiatives. In: Delmas, M., Young, O. (Eds.), Governance for the Environment: New Perspectives. Cambridge University Press, New York, pp. 144–182.
Khanna, M., Damon, L.A., 1999. EPA's voluntary 33/50 program: impact on toxic releases and economic performance of firms. J. Environ. Econ. Manag. 37 (1), 1–25.
Laplante, B., Rilstone, P., 1996. Environmental inspections and emissions of the pulp and paper industry in Quebec. J. Environ. Econ. Manag. 31 (1), 19–36.
Macher, J.T., Boerner, C.S., 2006. Experience and scale and scope economies: tradeoffs and performance in development. Strateg. Manag. J. 27 (9), 845–865.
MacKinnon, J.G., Magee, L., 1990. Transforming the dependent variable in regression models. Int. Econ. Rev. 31 (2), 315–339.
Malueg, D.A., 1989. Emission credit trading and the incentive to adopt new pollution abatement technology. J. Environ. Econ. Manag. 16 (1), 52–57.
Maxwell, J.W., Decker, C.S., 2006. Voluntary environmental investment and responsive regulation. Environ. Resour. Econ. 33, 425–439.
McGuire, W., 2014. The effect of ISO 14001 on environmental regulatory compliance in China. Ecol. Econ. 105, 254–264.
Milliman, S.R., Prince, R., 1989. Firm incentives to promote technological change in pollution control. J. Environ. Econ. Manag. 17 (3), 247–265.
National Pollution Prevention Round Table, 1997. Pollution Prevention Regulatory Integration Case Studies. Washington DC. Available at: www.p2pays.org/ref/04/03037.pdf.
Pence, K.M., 2006. The role of wealth transformations: an application to estimating the effect of tax incentives on saving. Contrib. Econ. Anal. Policy 5 (1), 1–26.
Porter, M.E., van der Linde, C., 1995. Toward a new conception of the environment-competitiveness relationship. J. Econ. Perspect. 9 (4), 97–118.
Prakash, A., Potoski, M., 2012. Voluntary environmental programs: a comparative perspective. J. Policy Anal. Manag. 31 (1), 123–138.
Requate, T., 2005. Timing and commitment of environmental policy, adoption of new technology, and repercussions on R&D. Environ. Resour. Econ. 31 (2), 175–199.
Salop, S.C., Scheffman, D.T., 1983. Raising rivals' costs. Am. Econ. Rev. 73 (2), 267–271.
Sam, A.G., 2010. Impact of government-sponsored pollution prevention practices on

environmental compliance and enforcement: evidence from a sample of US manufacturing facilities. J. Regul. Econ. 37 (3), 266–286.
Sam, A.G., Khanna, M., Innes, R., 2009. Voluntary pollution reduction programs, environmental management, and environmental performance: an empirical study. Land Econ. 85 (4), 692–711.
Sharma, S., Vredenburg, H., 1998. Proactive corporate environmental strategy and the development of competitively valuable organizational capabilities. Strateg. Manag. J. 19 (8), 729–753.
Shimshack, J.P., Ward, M.B., 2008. Enforcement and over-compliance. J. Environ. Econ. Manag. 55 (1), 90–105.
U.S. Environmental Protection Agency, Environmental Criteria and Assessment Office, 1988. Reference Dose (RfD): Description and Use in Health Risk Assessments (Cincinnati, OH).
Videras, J., Alberini, A., 2000. The appeal of voluntary environmental programs: which firms participate and why. Contemp. Econ. Policy 18, 449–460.
Vidovic, M., Khanna, N., 2007. Can voluntary pollution prevention programs fulfill their promises? Further evidence from the EPA's 33/50 program. J. Environ. Econ. Manag. 53 (2), 180–195.
Welch, E.W., Mazur, A., Bretschneider, S., 2000. Voluntary behavior by electric utilities: levels of adoption and contribution of the climate challenge program to the reduction of carbon dioxide. J. Policy Anal. Manag. 19 (3), 407–425.
Windmeijer, F., Santos Silva, J., 1997. Endogeneity in count data models: an application to demand for health care. J. Appl. Econ. 12, 281–294.