




Patents and P2: Innovation and Technology Adoption for Environmental Improvements

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Abstract

In this paper, we identify factors that influence adoption of two types of environmental innovations, environmental patents and pollution prevention (P2) activities, and then measure the resulting influence of each on the pollution profile of the firm. We find that environmental patenting is most strongly driven by the technological capacity of the firm, including prior environmental patenting and prior P2 adoptions. While P2 activities are also influenced by prior adoptions of P2, other factors play an important role, including environmental innovation opportunities, the regulatory environment, and firm-specific characteristics. In terms of environmental outcomes, we find that both environmental technologies reduce pollution. Due to strong knowledge accumulation effects of environmental patents, the long-term impact of an environmental patent is stronger and longer lasting than the long-term impact of a P2 practice.

Keywords Environmental patents · GMM · Innovation · Knowledge accumulation · Pollution prevention · Technology adoption · Toxic releases

JEL Classification Q55 · O31 · Q53

1 Introduction

From local air or water pollution to global problems like climate change, new environmental technologies will be required to solve many environmental challenges we face today. Since most innovation occurs within firms, realizing the promise of environmental innovations depends on the willingness of firms to invest in their own capacities to develop and

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implement new green technologies. While firms are increasingly advertising their green credentials, it is unclear whether these pronouncements reflect actual commitments to environmental improvements or are simple greenwashing behavior (Lyon and Maxwell 2011). Taken at face value, recent commitments by firms, for example, to be ‘water positive’ by 2030 (i.e., to replenish more water than it uses) (Microsoft), to eliminate tailpipe emissions by 2035 (GM), to be zero waste (i.e., no landfill) (Disney), or to have net zero carbon emissions by 2040 (Amazon and Walmart), will require new environmental technologies. In this research, we explore how firms may engage in a portfolio of activities to contribute to their innovative potential and then measure the impact of these technologies on their environmental performance.

We consider two common types of environmental innovative activities, environmental patents and pollution prevention (P2) activities, and identify their impact on the chemical releases of the firm. Environmental patents and P2 activities serve as measures of a firm’s innovative potential, though they differ in several important respects. To be eligible for a patent, an innovation must be new, non-obvious, and useful. Acquiring an environmental patent takes time and effort, and hence, large and more important innovations are more likely to be patented. Pollution prevention (P2) or source reduction activities, on the other hand, involve modifying or tailoring pre-existing methods to a firm’s operations. They consist of practices that reduce or eliminate “waste at the source by modifying production processes, promoting the use of nontoxic or less toxic substances, implementing conservation techniques, and reusing materials rather than putting them into the waste stream” (US EPA 2021). Thus, while acquiring a patent is typically the result of sustained, broad, and extensive R&D effort, P2 activities are largely not proprietary or unique to a firm. In fact, the EPA publicizes materials that describe different P2 practices and manages a clearinghouse that allow firms to share knowledge about P2 that can be adopted by a variety of firms (US EPA 2020).

The different level of commitment and actions required to qualify for an environmental patent versus adopting a P2 activity suggest different drivers of adoption as well as different effectiveness in improving the environmental profile of the firm. In this paper, we explore the factors that promote environmental innovation in the form of environmental patents and P2 activities. Next, we investigate whether and how these innovations influence levels of toxic chemical releases. We identify if there is complementarity between the two environmental technologies and trace out the long-term impact of innovations on pollution by recognizing the role of knowledge accumulation from each type of innovation. This analysis provides a better understanding of the innovative capacity of firms in the environmental arena and the potential for innovations to yield improvements in environmental quality.

To address these questions, we develop a model of a cost-minimizing firm that jointly chooses environmental patenting activity and pollution prevention activity. The analytic model implies estimating equations for patents, P2 adoption, and chemical releases. We empirically test our hypotheses on a sample of manufacturing firms over a 12-year period using dynamic GMM models with instrumental variables and fixed effects. Results show environmental patenting is strongly influenced by the technical capacity of the firm, which is measured by past patenting experience in both the environmental as well as non-environmental arena, general R&D spending, and past P2 activities. P2 adoption is also influenced by prior P2 activity, but otherwise, the broader technology environment is not typically important. Rather, P2 adoption is influenced by the regulatory threat that firms face, the opportunities for P2 adoption based on the number of chemicals they use and the level of their releases, as well as firm-specific characteristics such as firm age and size. In terms

of the impact on pollution, we find evidence that both patenting and P2 adoption reduce pollution. While the immediate effects of a patent and P2 practice on pollution are modest, 5.6% and 2%, respectively, the long-term impact are larger due to knowledge accumulation effects of technology adoption. We identify a strong knowledge accumulation channel for patenting that is influenced by both prior patenting and prior P2 adoption.

The paper proceeds as follows: we review related literature in Sect. 2; Sect. 3 presents a conceptual model of firm behavior and the resulting empirical framework; Sect. 4 describes the sample and data. Results are presented in Sect. 5. Concluding comments and policy implications follow in Sect. 6.

2 Related Literature

2.1 Determinants of Patenting and P2 Adoption

The literature on patents and P2 have largely developed independently from each other. From the vast literature on innovation, patents are typically considered an outcome of directed research effort by the firm. Spending on research and development is a primary influence on patenting activities (Bound et al. 1984) but other firm specific factors such as the age, size, and profitability (Cohen 2010) as well as the type and concentration of the industry (Scherer 1965; Brunnermeier and Cohen 2003; Geroski 1990) have been found to influence the directed research effort of a firm and the level of general patenting activity. For patents in the environmental arena, in addition to the abovementioned factors, research identifies other important drivers such as the corporate governance of the firm (Amore and Bennedsen 2016; Nadeem et al. 2020), energy prices (Popp 2002; Aghion et al. 2016), the policy environment (Johnstone et al. 2010), and the technology forcing nature of some environmental regulations (Popp 2003; Bellas and Lange 2008, 2011). Compliance costs associated with environmental regulations have been found to have a mixed influence on environmental patenting behavior (Brunnermeier and Cohen 2003; Jaffe and Palmer 1997).

Many factors that affect patenting have also been found to influence P2 adoption. For example, higher spending on research and development as well as younger and larger firms have been shown to adopt more P2 practices (Harrington 2012). The literature on P2 adoption also places emphasis on the general regulatory environment: Harrington (2013), for example, finds that state level pollution legislation as well as state level policies and incentives for P2 adoption significantly affect firm activity in this area. Management practices [such as the implementation of a total quality environmental management system (Khanna et al. 2009)] and management-based regulations (Benneer 2007) have also been found to positively enhance P2 adoption.

Also useful for this current work are studies that link past experience with a technology to new innovative activity. Many studies find that lagged or cumulative stock of patents lead to more patenting in the future (Blundell et al. 1995, 1999, 2002; Ramani et al. 2008), though this is not universally found (Roper and Hewitt-Dundas 2015). Some studies argue that past patenting adds to general knowledge stock, which can lower the marginal cost of new innovation (a form of path dependence) to promote new patenting (Acemoglu et al. 2012; Aghion et al. 2016). Others suggest that past patenting promotes new patenting as a way to maintain or create technological leadership in an industry (Rave and Goetzke 2017). The role of learning and the impact of a knowledge stock has been found to influence P2 adoption as well. Lagged P2 has been shown to have a positive effect on new P2, perhaps

capturing path dependence, while cumulative P2 stock has a negative effect on new P2, which has been interpreted as capturing a diminishing effect of new P2 opportunities (Harrington 2013; Deltas et al. 2014).

While both environmental patents and P2 are commonly investigated environmental technologies, there is little direct empirical work that evaluates their joint adoption. This is one area where we seek to contribute to the literature. To our knowledge, the only direct work examining environmental patenting and P2 is Chang and Sam (2015).¹ They find that P2 activities as well as general patenting activity influence the acquisition of environmental patents. They do not consider whether patenting in turn affects P2 or how their adoption determines environmental performance.

2.2 Immediate and Long-Term Impacts of Patents and P2 on Pollution

Our work is also related to the literature that examines the impact of innovations on environmental quality. Early work related to the literature on regulation and innovation suggests that it is through patenting that firms meet tighter environmental standards. For example, to meet new regulatory standards under the Clean Air Act, Popp (2003) shows that firms acquired patents specifically related to scrubber technology while Bellas and Lange (2008) show how the stock of firm patents increased in response to this regulatory regime. Carrion-Flores and Innes (2010) examine the relationship between regulation-induced environmental innovation and releases of toxic air emissions of manufacturing facilities and find that new environmental patents are an important source of reductions of toxic chemical releases. Outside of a regulatory context, a second strand of the literature attempts to more directly quantify the impact of environmental patents on environmental performance. For example, Antonioli et al. (2018) find that knowledge stock (as measured by the stock of patents on general environmental management (i.e., air, water and waste)) increased recycling across Italian regions. Tobelmann and Wendler (2019) and Zhang et al. (2017) find the environmental patenting contributed to reductions in carbon dioxide emissions in the EU and China, respectively.²

P2 practices have also been shown to improve the environmental performance of firms. Bui and Kapon (2012) and Ranson et al. (2015) find reductions of around 10–15% in firm emissions of toxic chemicals following P2 implementation. Bi and Khanna's (2017) study suggests that the impact of P2 is magnified for firms that also participate in the 33/50 program. Finally, Lee and Bi (2020) find that environmental knowledge in one area (P2 practices related to toxic releases) can lead to improvements in environmental performance in another area (reduction in greenhouse gases) among a set of electric power plants. These

¹ Despite the limited literature that deals directly with joint adoption of P2 practices and patents, there is work related to joint adoption of voluntary environmental actions (like P2) and environmental innovations (like a patent). For example, Brouhle et al. (2013) and Lim and Prakash (2014) find positive relationships between participating in a voluntary program (Climate Wise and ISO 14001) and firm patents. Carrion-Flores et al. (2013), on the other hand, find a negative relationship between voluntary 33/50 program participation and environmental patents. Other work (see Cleff and Rennings 2000; Damanpour and Gopalkirshnan 2001; Wagner 2007; Rehfeld et al. 2007; Ziegler and Nogareda 2009; Ozusaglam et al. 2018; Horbach et al. 2012) explores the relationship between self-reported product innovations, process innovations and organizational innovations (such as environmental management systems).

² A number of studies consider the impact of environmental patents on a measure of environmental performance in relation to productivity, including Ghisetti and Quatraro (2017) and Weina et al. (2016).

studies, then, establish a positive impact of technology embedded in patent and P2 practices on the environmental performance of the firm.

Another area of the literature focuses on longer-term impacts on environmental outcomes from the adoption of environmental technologies such as patents and P2 practices. In Carrion-Flores and Innes's (2010) study, these long-term impacts on the steady state outcome are modest; they find that a 1% tightening of a standard induces 0.43% more patenting, which then yields 1.64% long-term emission reduction. Park (2014) finds that tighter regulations in the energy sector increased the cumulative number of patents over a 50-year time period which in turn increased the reuse rate of coal combustion by-product. Harrington et al. (2014) documents large pollution reductions from continuous P2 adoption over a 10-year period, though these long-term effects are in the end transitory as pollution reductions dissipate over time.

Our study makes two major contributions related to the impact of environmental technologies on environmental performance. First, our study recognizes that firms employ a suite of environmental technologies to improve environmental performance, in contrast to the existing literature that focuses on the impact of either patents or P2 activities. Second, we identify the long-term impact of technology adoption on pollution. In doing so, we measure knowledge accumulation effects and how adoption of one technology can enhance the stock of knowledge in either or both technologies, yielding greater pollution reduction. As such, we demonstrate the value of employing multiple environmental technologies on long-term environmental improvements.

3 Framework

3.1 Model

3.1.1 Optimal Innovative Activity Choices

Consider a cost-minimizing firm i at time t producing a target output level, \bar{Y} , which may also generate pollution Q_{it} as a by-product. To enhance the efficiency of production (which also reduces pollution), the firm may employ two types of environmental technologies: patents, P_{it} , and source reduction (i.e., pollution prevention) activities, S_{it} . These technologies contribute to the firm's stock of environmental technical knowledge, K_{it} . The firm's knowledge stock at any point in time is a function of the sum of current and discounted past experience with patents and P2, i.e., $K_{it} = k_i(P_{it}, S_{it}) = k_i\left(\sum_{\tau=0}^T \delta^\tau (P_{i,t-\tau}), \sum_{\tau=0}^T \delta^\tau (S_{i,t-\tau})\right)$. Recognizing the different effort and embodied knowledge in an environmental patent versus a P2 activity, the impact of each technology on the knowledge stock may differ, i.e., $k_P \gtrless k_S$. We make no assumption on the functional form of k to allow for any type of relationship between environmental technologies in the knowledge stock function (Roper and Hewitt-Dundas 2015).

The output of the firm depends on its raw material input usage and its technological knowledge, $Y_{it} = f_i(X_{it}, K_{it})$. We define purchased raw materials, X_{it} , but assume that only a portion of the raw material X_{it} is effectively transformed in production. Thus, effective input is $\hat{X}_{it} = \varphi_i(K_{it}) * X_{it}$, where $1 > \varphi_K > 0$. We assume that the production function exhibits diminishing marginal productivity in all its arguments, ($f_X > 0; f_{XX} \leq 0; f_K > 0; f_{KK} \leq 0$).

With a fixed output target, \bar{Y} , the firm's choice of P and S also determines the level of input use, i.e., $X_{it} = x_i(P_{it}, S_{it})$. Patents and P2 can therefore affect input use differently depending on whether each is a substitute or a complement to raw material inputs in production.

Any purchased raw material that is not converted to effective input is a residual or pollution, $Q_{it} = X_{it} - \hat{X}_{it} = g_i(X_{it}, K_{it})$ (Ayres and Kneese 1969). The function g allows for differences across firms on how they recycle, reuse, store, or treat the residual before it is released into the environment as pollution. We assume that pollution is increasing in raw materials ($g_X > 0$; $g_{XX} \geq 0$) and decreasing in knowledge stock ($g_K < 0$; $g_{KK} \geq 0$). Since the knowledge stock and input level are functions of P and S , patents and P2 can have different impacts on productivity and pollution through their different impacts on knowledge stock and raw material input use.

A firm chooses P and S to minimize total costs of producing target level of output, \bar{Y} , where the costs include cost of raw materials, costs of both abatement technologies, and costs of unabated pollution. Costs of unabated pollution may include costs of waste disposal and compliance, costs of regulations related to inspections, fines or penalties, or even indirect costs arising from neighborhood groups, lobby groups, or consumers groups protesting high pollution of the firm. The unit costs of these inputs are ϕ_X , ϕ_S , ϕ_P and ϕ_Q , respectively. Suppressing firm and time subscripts for notational simplicity, the cost minimization problem of the firm is:

$$\begin{aligned} \text{Minimize}_{S,P} \quad C &= \phi_X x(P, S) + \phi_P P + \phi_S S + \phi_Q g(x(P, S), k(P, S)) \\ \text{subject to} \quad \bar{Y} &= f(x(P, S), k(P, S)) \end{aligned}$$

The first order conditions are:

$$\begin{aligned} \lambda \left(f_K \frac{\partial K}{\partial P} + f_X \frac{\partial X}{\partial P} \right) - \phi_Q \left(g_K \frac{\partial K}{\partial P} + g_X \frac{\partial X}{\partial P} \right) &= \phi_P + \phi_X \frac{\partial X}{\partial P} \\ \lambda \left(f_K \frac{\partial K}{\partial S} + f_X \frac{\partial X}{\partial S} \right) - \phi_Q \left(g_K \frac{\partial K}{\partial S} + g_X \frac{\partial X}{\partial S} \right) &= \phi_S + \phi_X \frac{\partial X}{\partial S} \end{aligned}$$

These expressions show that, at the margin, the benefit of another unit of abatement technology (left hand side) is equal to the cost of using that technology (right hand side). The marginal benefits from an extra unit of each technology consists of higher revenue from productivity enhancements (via f) and avoided pollution costs (via g), each arising from two sources: enhanced capital stock from both technologies ($\frac{\partial K}{\partial P}$ and $\frac{\partial K}{\partial S}$) and change in raw material input use resulting from adoption of either technology ($\frac{\partial X}{\partial P}$ and $\frac{\partial X}{\partial S}$). The marginal cost of an additional unit of technology is simply the sum of unit adoption cost and the change in costs associated with the resulting raw material input use. Thus, the optimal choice of each technology may be affected by the adoption of the other according to whether and how much the other technology affects the size of its benefit and cost terms.

We use these first order conditions to empirically model how the optimal choice of patents and P2 depends on the knowledge stock of both technologies and on production and abatement technologies, reflected in f and g . Thus, the estimating equations for firm-level patent and source reduction activities adopted by firm i in year t are as follows:

$$P_{it} = \exp(a_P + b_P Q_{it-T} + c_P K_{it-T} + d_P Z_{it}^P + \eta_i^P + v_t + \epsilon_{it}^P) \tag{1}$$

$$S_{it} = \exp(a_S + b_S Q_{it-T} + c_S K_{it-T} + d_S Z_{it}^S + \eta_i^S + \nu_t + \varepsilon_{it}^S) \tag{2}$$

The vector of lagged knowledge stock, K_{it-T} , consists of most recent flow and further lagged stocks of patents and P2. Since production and abatement technology are unobserved, we use a variety of observable characteristics such as past level of pollution, denoted as Q_{it-T} , to indicate the level of production as well as scope of pollution generation that capture unobserved technical characteristics. The vectors Z_{it}^P and Z_{it}^S include other firm-specific exogenous variables that could affect patenting and P2 adoption such as firm size, broad measures of technical capacity, opportunity for technology adoption, and regulatory, market, and financial measures. It also includes measures for the scope of operations that can capture input use. Since many of these variables capture both production and abatement technology, we are unable to disentangle the productivity and abatement motives and the resulting effect on input choices inherent in the P2-patent relationship; we only empirically capture the total effects from all channels. In both equations, ν_t represents a vector of year dummies, η_i^P and η_i^S are firm-specific time-invariant factors that capture unobserved heterogeneity, and ε_{it}^P and ε_{it}^S are the random error terms.

3.1.2 Pollution Outcome

Pollution is not directly chosen by the firm but is an outcome from the optimal choice of patents and P2 through g and φ .³ We are interested in measuring and comparing how the choices of P and S affect pollution. We show that the effects of P and S on pollution are through raw material input use and the knowledge stock. The expanded expression for pollution can be used to analyze how it is influenced by patents and P2:

$$Q = X - \varphi X = x(P, S) * (1 - \varphi(k(P, S))) = g(X, K)$$

Accounting for the interrelated decisions to adopt patents and P2 (and raw materials), a change in environmental patents or source reduction will affect pollution through two major channels.⁴ First, an increase in technology increases the knowledge stock ($\frac{\partial K}{\partial P}$ and $\frac{\partial K}{\partial S}$), which enhances the efficiency of converting raw input to effective input. Second, an increase in technology can influence the level of raw material input used ($\frac{\partial X}{\partial P}$ and $\frac{\partial X}{\partial S}$). If patents or P2 discourage raw material input use, then lower input use reinforces the efficiency enhancing effect, unambiguously reducing pollution. But if patents or P2 encourage raw material input use, this complementarity may partially or fully offset the efficiency enhancing effect and pollution may increase or decrease. Because the impact of each technology on raw material input use may differ and each technology affects knowledge stock differently, we anticipate patents and P2 may have non-symmetric impacts on pollution, which we empirically test in the next section.

The foregoing analysis allows us to specify the estimating equation for the pollution equation as follows:

³ In a similar way, choosing S and P (which effectively determines X) define output, through the function f .

⁴ The channels that capture the full effects that account for inter-related patent and P2 decisions can be shown using the expression as follows: $\frac{dQ}{dP} = g_K \left(\frac{\partial K}{\partial P} \right) + g_X \left(\frac{\partial X}{\partial P} \right)$; $\frac{dQ}{dS} = g_K \left(\frac{\partial K}{\partial S} \right) + g_X \left(\frac{\partial X}{\partial S} \right)$. The first term in each expression captures the efficiency enhancing channels through which patents and P2 increase the knowledge stock which decreases pollution. The last term in each expression captures how each technology affects raw material input use.

$$Q_{it} = a_Q + b_Q Q_{it-1} + c_Q K_{it-T} + f_Q Z_{it}^O + \eta_i^O + \nu_t + \varepsilon_{Qit} \quad (3)$$

The vector of lagged knowledge stock measures, K_{it-T} consists of recent flows and lagged stocks of both patents and P2 similar to Eqs. (1) and (2). Elements of c_Q are expected to be negative, but the coefficients of specific patent and P2 variables may have different magnitudes. While the function g and its relevant derivatives are unobserved, firm-level characteristics are included in an attempt to capture some factors that embody g . The lagged pollution variable, Q_{it-T} , can capture the scope of pollution generation and target level of output. The vector Z_{it}^O includes various time-varying exogenous factors that capture the general technical capacity, enforcement actions and other firm specific characteristics embedded in g as well as measures to capture size and scale of operations that are related to extent of input use, X . η_i^O represents firm-specific time-invariant factors that capture unobserved heterogeneity, while ν_t represents a vector of year dummies. ε_{Qit} is the random error term.

3.2 Empirical Approach and Econometric Issues

For the technology adoption decisions [Eqs. (1) and (2)], a number of econometric issues arise that influence our estimation approach. First, the two dependent variables, patents and P2, are count in nature. The count of new patents applied for in a given year and the count of new P2 practices adopted in a given year contain a large number of zeros (61% of observations report zero environmental patents and 52% of observations report zero new P2) and exhibit significant range (from 0 to 223 for environmental patents and 0 to 277 for P2). We presume counts of environmental patents and source reduction are distributed Poisson.

The second issue relates to the specification of the lagged dependent variable to capture past experience or knowledge stock in patenting or P2. The dynamic model with lagged dependent variable can either be modeled as a linear or multiplicative dynamic feedback model (Blundell et al. 1999). Since our sample consists of many zero values for patenting and P2, we use the multiplicative feedback model as recommended by Cameron and Trivedi (2005, 2010). For estimation, we utilize a two-step GMM Poisson estimator with additive errors.

The third issue relates to the presence of unobservable firm-specific time invariant characteristics that might influence the acquisition of an environmental patent as well as the adoption of a P2 practice. Due to the count nature of the dependent (technology) variables and presence of lagged dependent variables, we cannot run a traditional fixed effects model. Instead, to account for firm level unobserved heterogeneity, we include several firm specific measures that capture time invariant propensity to innovate. In our patent equation, we use the average number of environmental patents received by each firm prior to our estimation window and its corresponding dummy variable (as in Blundell et al. 1999). In the P2 equation, we use the count of P2 adopted in the initial year of reporting and its corresponding dummy variable (as in Wooldridge 2005; Harrington 2012, 2013).

Fourth, we anticipate some endogeneity issues if time-varying unobserved factors jointly affect the P and S decisions. In the patent and P2 equations, we lag the other technology variable to remove any simultaneity between patenting and P2 adoption decisions. We also use different lagged specifications of patents and P2 flows and stocks to allow us to explore how different temporal specifications in knowledge and experience may affect each abatement strategy. Because lagging the technology (and pollution) variables may not remove all correlation between them and time-varying unobservables, we also utilize

instruments for these potentially endogenous variables in the two technology adoption decisions. The details of the instruments and tests statistics are provided in Sects. 5.1.1 and 5.1.2. With valid instruments, coefficient estimates from the two-step GMM will be consistent and efficient (Windmeijer and Santos Silva 1997). We use the GMM bias-corrected robust estimator clustered at the firm level (Windmeijer 2005).

Estimation of the pollution Eq. (3) involves addressing several econometric issues as well: endogeneity of P2 and patents and panel data with a lagged dependent variable. While pollution is not a choice variable but an outcome of the optimal choices of P2 and patents, endogeneity of P2 and patents arise because their impact on pollution operate through the unobserved pollution function, g . Despite including Q_{it-T} and Z_{it}^Q to capture some of these unobservables, there may be remaining unmeasured factors that influence pollution as well as P2 and patent choices, necessitating the use of instrumental variables. The presence of a lagged dependent variable in a panel data framework also renders the traditional fixed effects estimators inconsistent (Arellano and Stephen 1991). We therefore employ the dynamic panel GMM model that controls for the unobservable facility-specific effects through first differencing, while relaxing the assumption of strict exogeneity of regressors, patents and P2. This requires system estimation of Eq. (3) and its differenced version and the use of instruments for the pollution variables, patents and P2. The details on the instruments used for the levels and differenced equations as well as the tests statistics are described in Sect. 5.2. We report the two-step estimator and the bias-corrected standard errors (Windmeijer 2005).

4 Sample, Data Sources and Variable Description

The selection of our sample is primarily dictated by our choice of environmental performance measure: the level of toxic releases of the firm. Data for our technology and environmental performance measures are collected from the National Bureau of Economic Research (NBER) Patent database [as supplemented by Kogan et al. (2017)] and US EPA Toxic Releases Inventory (TRI). The NBER Patent database contains the count of patents granted to each parent company over time. For each parent company, we use each patent's application year to match the patent data to the TRI database to reflect the timing of the discovery when the knowledge was available to the firm (as in Carrion-Flores and Innes 2010; Popp 2003). The TRI contains annual facility-reported data on chemical-level pollution and source reduction (P2) activities for each year, aggregated to the parent company level.⁵ TRI reporters that do not appear in the NBER patent database are assigned a value of zero for patents. Firms that appear in the patent database but do not appear at least once in the TRI are excluded from the sample because we are ultimately interested in the environmental outcomes resulting from patenting and adoption of pollution prevention practices that are only available in the TRI. Thus, our findings apply to the technology adoption decisions and environmental performance of firms that are required to report to the TRI based on TRI reporting guidelines.

⁵ We aggregate data from facility to the parent company level data using the CUSIP code in the TRI and the GVKEY for patents. We obtain both CUSIP and GVKEY identifiers from the Center for Research in Security Prices (CRSP) and merged the TRI and patent database.

Reporting to the TRI is limited to those facilities that meet the reporting requirements related to industry classification, size and volume of releases of EPCRA section 313 listed chemicals.⁶ We focus our study on the manufacturing sector (SIC 20-39) from 1992 to 2004. The start date follows the passage of the Pollution Prevention Act of 1990 and our ending date is influenced by data availability and the desire to avoid any possible truncation issues that arise with the use of patent data. TRI reporting requirements have changed through the years with many chemicals having been added or deleted from the list in different years.⁷ Both P2 and toxic releases are reported at the chemical level, aggregated for each facility, then aggregated over all facilities of a parent company every year. We restrict our analysis to the chemicals that have been consistently reported during the sample period (Bi and Khanna 2017, 2012; Vidovic and Khanna 2007; Khanna and Damon 1999) to avoid mis-attributing changes in releases to P2 when chemical additions and deletions occur.⁸

We supplement our data on patents, P2 activities, and toxic releases with two additional datasets. First, we capture enforcement actions against firms from US EPA Enforcement and Compliance History Online (ECHO). While the TRI simply mandates the disclosure of facility level hazardous and toxic chemical releases, some of these releases are subject to different federal, state, or local statutes that restrict or provide guidelines for the use and disposal of these substances.⁹ Non-compliance with different environmental statutes, then, including those that govern the use of toxic chemicals, may result in violations, penalties, and/or inspections. We use the ECHO database to measure these enforcement actions against firms. TRI reporters that do not appear in the ECHO database are assumed to have received zero enforcement actions. The final data source for our study is the Center for Research in Security Prices (CRSP). From this database, we extract variables that capture market and firm financial characteristics. Some firms have missing data for some of these financial variables, and different equations use different sets of these financial variable as controls. Our sample size is 4223 observations, except for a few models that require 3-year lags of explanatory variables or 3-year lags of instruments.

We classify our variables into several groups: (1) technical capacity variables, (2) pollution variables, (3) regulatory variables, (4) market variables, and (5) other firm-specific production and financial variables. Our key interest is understanding the role of the technical capacity of the firm, which includes past patenting and source reduction activities as well as pollution, which is measured by total releases of toxic chemicals. The other categories include important control variables that might influence technology adoption

⁶ The facilities required to report to the TRI belong to specific industries (NAICS), meet a minimum size (full time employee equivalents) and meet minimum quantity of manufacture/import/process/use of any EPCRA section 313 chemicals (US EPA 2019).

⁷ See USEPA: https://www.epa.gov/system/files/documents/2022-02/tri-chemical-list-changes_2.23.22.pdf.

⁸ Restricting our analysis to the same set of chemicals allows us to focus on the innovative efforts and toxic releases associated with a fixed set of chemicals. While including newly added or dropping newly deleted chemicals may seem attractive, doing so changes the set of chemicals for which P2 and releases are reported. As a result, it is challenging to know whether *measured* changes in innovative efforts or releases reflect *actual* changes in innovative efforts or releases. If we observe changes in our measure of innovation (P2) or changes in our measure of releases, we cannot verify how much of the change is due to chemical substitution or due to changes in reporting requirements. The latter case is particularly problematic because a firm may keep the same P2 practices or keep releases constant over time but would cause our measure to increase or decrease if the chemical is newly added or deleted to the list of required chemicals. For these reasons, we restrict our analysis to the same set of chemicals and recognize that the adoption and innovation–pollution relationship we observe is for these fixed set of substances.

⁹ Information on such cross-listing can be found at: <https://www.epa.gov/epcra/consolidated-list-lists>.

and pollution as well as variables that satisfy the exclusion restrictions and can serve as potential instrumental variables. In Table 1, we identify which variables are used in each equation as well as the descriptive statistics for their original (unlogged) values. Some variables, detailed below, are transformed into natural log, and for these variables whose value may be zero, we added one before taking the natural log.

We capture firm technical capacity through several measures related to firm patenting, P2 activities, and general R&D. The dependent variable in the patent equation (Eq. 1) is *EnvPatents*, the count of environmental patents of each firm in a given year. Environmental patents are defined by World Intellectual Property Organization-International Patent Classification (WIPO-IPC) Green Inventory classification.¹⁰ This broad classification includes technology related to waste management, energy conservation, transportation, agriculture/forestry, alternative energy production, nuclear power generation and administrative, and regulatory or design aspects. We utilize this broad measure because environmental patents, unlike P2, are not necessarily targeted towards specific chemicals or substances in the TRI. Our measure, then, allows us to capture unforeseen and unknown spillovers between technology areas as well as spillovers between technologies that address pollution across different media (such as air, water, and land). Finally, our use of a broad measure, the WIPO's Green Inventory classification, matches the EPA's (broad) definition of P2 (discussed further below).

We develop other patent measures as explanatory variables. We recognize that new (environmental) patenting may be promoted by past knowledge by measuring the specific environmental knowledge and general technical knowledge of the firm (Blundell et al. 1995, 2002, 1999; Ramani et al. 2008). Specific environmental knowledge gained from previous environmental patents is measured with lagged *EnvPatents* and *EnvPatent Stock*, which is measured as the natural log of the depreciated stock of past environmental patents. General technical knowledge is measured with the natural log of the depreciated stock of non-environmental patents, denoted as *Non-EnvPatents Stock*. The patent stock measures are calculated as the cumulative sum of successful patent applications of firm i from 1987 through year $t-1$ weighted by industry specific depreciation weights (Ramani et al. 2008). We use industry depreciation rates from Park and Park (2006). Depreciation rates vary within a narrow range from 11.86% (tobacco) to 14.39% (electronics and electrical equipment). We expect these measures of past patenting to be positively correlated with current environmental patenting. We also define peer patents, *Avg Peer EnvPatents*, to capture technological spillovers between firms in the same industry. We calculate it as the natural log of the sum of all *EnvPatents* of a firm's 2-digit SIC peers divided by the number of peers. To control for unobserved heterogeneity in the patent equation (as in Blundell et al. 1999), we define *EnvPatents Pre-Sample* as the natural log of the average number of environmental patents received by each firm in our dataset from 1987 to 1992. We also include *EnvPatents Pre-Sample Dummy*, which is equal to one if a firm received any environmental patents in the pre-sample period, and 0 otherwise.

Another set of technical capacity variables relate to source reduction (P2) activities. The variable *Total P2* is the sum of 43 different P2 practices newly undertaken by each facility for each of its chemicals, summed up over all facilities of a parent company each year. Because only *new* P2 needs to be reported, low P2 counts may be due to potential

¹⁰ The Green Inventory was developed by the IPC Committee of Experts in order to facilitate patent information searches related to Environmentally Sound Technologies, as listed by the United Nations Framework Convention on Climate Change (UNFCCC) (WIPO 2021).

exhaustion (at least in the short term) of new P2 practices. These 43 pollution prevention activities are classified by the USEPA into eight broad categories: (1) good operating practices, (2) materials and inventory control, (3) spill and leak prevention, (4) raw material modifications, (5) equipment and process modifications, (6) cleaning and decreasing, (7) surface preparation and finishing practices, and (8) product modifications (US EPA 2018). Because facilities report (yes/no) which type of P2 they adopted for each chemical, while also reporting chemical-specific releases (to air, water, land, underground), the TRI reporting system allows facilities to directly link their abatement efforts like P2 and their pollution levels.

Consistent with other P2 studies (Harrington 2013; Deltas et al. 2014), we generate a number of measures of a firm's past experience with P2 as explanatory variables. First, we utilize lagged *Total P2*. The second measure is *Total P2 Stock*, which is the depreciated sum of a firm's past adoption of P2 activities. We use the same industry specific depreciation rate that was used to generate the environmental patent stock variable. When used as explanatory variables in the patent and pollution equations, we take the natural log of *Total P2* and *Total P2 Stock*. To capture spillover effects, we define *Avg Peer P2*, which is the natural log of the sum of all *Total P2* of a firm's 2-digit SIC peers divided by the number of peers. We expect that the past P2 variables and *Avg Peer P2* will be positively correlated with the number of new source reduction activities adopted by a firm. To control for unobserved heterogeneity in the *TotalP2* equation, we define *Total P2 Pre-Sample* as the number of P2 practices adopted by each firm in the first year the EPA collected P2 data, 1991 (as in Harrington 2012, 2013; Wooldridge 2005). We also include *Initial Total P2 Dummy*, which is equal to one if a firm adopted any P2 practices in 1991, and 0 otherwise.

The final measure employed to capture the technical capacity of the firm is its spending on research and development. To account for size-adjusted innovativeness, we use *R&D Intensity*, which we calculate as the natural log of the ratio of 3-year moving average of R&D expenditures to 3-year moving average of employees. Firms with greater technical capacity are expected to be better equipped to patent, undertake source reduction, and reduce releases.

Our second category of variables are pollution-related variables. The dependent variable in the pollution equation is *Total Releases*, which is the natural log of the sum (in pounds) of the toxic releases of all chemicals used, stored, processed and released by all facilities of each parent company that are reported annually to the TRI. Since pollution levels may generate opportunities for innovation and/or determine size and scope of operations, we also include lagged *Total Releases* as an explanatory variable in both the environmental patenting and P2 equations. Higher levels of releases present the firm more opportunities to benefit from innovative activity, and thus firms with higher releases are expected to have more environmental patenting and source reduction activities.

Our third category of variables are regulatory variables which are meant to capture differences in regulatory threats and liabilities that could affect innovation and pollution levels of the firm. *Violations* is the natural log of the sum of all violations of the facilities of the firm. *Inspections* is the natural log of the count of facilities of the firm that have been subjected to at least one inspection. *Penalties* is the natural log of the dollar value of all penalties assessed for all facilities. *Self-disclose* is the natural log of the count of facilities of the firm that have self-disclosed a violation. In our empirical models, 2-year lagged values of all regulatory variables are used as explanatory variables. Firms that have been subjected to more regulations or enforcement actions are expected to undertake more source reduction activities and choose lower level of releases.

Table 1 Descriptive statistics

Variable names	Mean	Std. Dev	Patents	P2	Pollution
<i>Dependent variables</i>					
EnvPatents	4.820	16.681	X		
Total P2	8.174	21.317		X	
Total releases (lbs)	2,563,215	9,354,847			X
<i>Explanatory variables</i>					
<i>Technical capacity variables</i>					
EnvPatent	4.820	16.681			X
EnvPatent Stock	21.398	68.465			X
Avg Peer EnvPatents	1.860	3.942	X		
Total P2	8.174	21.317			X
Total P2 Stock	16.147	41.069		X	X
Avg Peer P2	4.860	16,681		X	
Non-EnvPatent Stock _{t-1}	43.110	151.432	X		
R&D Intensity _{t-2} (Thd US\$/employee)	7.324	22.822	X	X	X
<i>Regulatory variables</i>					
Violations _{t-2}	1.257	7.601		X	X
Inspections _{t-2}	0.168	0.374		X	X
Self-disclose _{t-2}	0.075	2.079		X	
Penalties _{t-2} (US\$)	142,729.3	2,801,184		X	X
<i>Firm-specific variables</i>					
Capital Intensity _{t-2}	0.064	0.123	X		X
HHI _{t-2}	0.041	0.013	X		
Number of facilities	31.660	72.657			X
Number of chemicals	11,509.59	24,890.35		X	
Age _{t-2}	0.780	0.100	X	X	
Sales _{t-2} (Million US\$)	4,776.729	15,775.23	X	X	X
Debt to Asset Ratio _{t-2}	0.198	0.170		X	
ROA _{t-2}	0.037	0.502	X	X	X
EnvPatents pre-sample	2.457	8.628	X		
EnvPatents pre-sample dummy	0.496	0.500	X		
1991 P2	1.710	1.494		X	
1991 P2 dummy	0.0294	0.1688		X	
SIC 20 (food)	0.0393	0.1944	X	X	X
SIC 21–25 (tobacco, textile, apparel, wood, furniture)	0.0502	0.2184	X	X	X
SIC 26–27 (paper, printing)	0.1513	0.3584	X	X	X
SIC 28 (chemicals)	0.0694	0.2541	X	X	X
SIC 29–32 (petro, rubber, non-metal)	0.0552	0.2283	X	X	X
SIC 33 (metal)	0.0476	0.2129	X	X	X
SIC 34 (other metals)	0.1598	0.3665	X	X	X
SIC 35 (construction)	0.1589	0.3656	X	X	X
SIC 36 (electronic)	0.1193	0.3242	X	X	X
SIC 37 (motor vehicles)	0.0294	0.1688	X	X	X
SIC 38–39 (Lab Eqpt, Other Mfg)—omitted	0.1196	0.3245	X	X	X

The descriptive statistics are for all the variables expressed in levels (not natural log)

Our fourth category of variables are market and industry conditions that influence the firm's technology adoptions and/or pollution decisions. We use *Capital Intensity*, defined as the natural log of capital expenditures over sales, to further account for a company's ability to invest (acquire, upgrade, and maintain) physical assets such as property, industrial buildings, or equipment. Firms with higher capital intensity are hypothesized to have greater incentive and ability to undertake technology adoptions. We define *HHI* as the natural log of the Hirschmann-Herfindahl Index, the sum of squared market share of each firm within each 2-digit NAICS level, to capture market concentration. The effect of market concentration on innovation activities could be positive or negative (Cohen 2010). Other differences across sectors are captured with industry dummies.

Our fifth and final category is firm-specific production and financial variables. To account for the fact that P2 reporting is at the chemical level, we use *Number of Chemicals* of all facilities of a parent company as a measure of opportunities to undertake and report P2. To construct this variable, we aggregate all of the chemicals utilized across all facilities of a parent company.¹¹ Because parent companies with more facilities would have larger scale of operations and scope for pollution, we also include *Number of Facilities*. We include *Sales* and *Sales Squared* to capture firm size. Larger firms are expected to have more resources to undertake more environmental patenting and source reduction activities and/or may experience economies of scale in innovation and pollution reduction. The ratio of net income to total assets, *ROA*, proxies for the profitability of firms. More profitable firms are expected to do more patenting and source reduction and have lower releases. To control for risk, we use *Debt to Asset Ratio*, the ratio of total debt to total assets. Firms that are riskier may be less inclined to undertake costly activities such as source reduction. We calculate *Age* of a facility, as the ratio of total assets to gross assets. Older firms are expected to be less capable of innovative activity and less able to reduce pollution. Except for *Age* and *ROA*, we express all these firm-level variables in natural log, and all of the variables are lagged 2-years. Finally, we include year dummies in all equations.

Table 1 shows the descriptive statistics of all our variables. We note that our sample is comprised of large firms: the average firm in our sample has 32 facilities, reports 2,563,215 pounds of releases, and has sales of \$4.777 billion. The average number of innovations in a given year is modest (mean environmental patents is 4.82 and mean P2 is 8.17), though there is significant range as firms in the 95th percentile acquire 24 environmental patents and 36 P2 practices. We also compared our sample to all TRI reporting firms in terms of their distribution across industry classes. The industry composition of our sample is typically within 1–2 percentage points of the industry composition in the TRI.¹² We remind that the reader that our results most directly relate to TRI reporting facilities with similar characteristics.

¹¹ For instance, if one chemical is reported by all 100 facilities of a parent company, it will be counted as 100 since that captures and controls for the number of opportunities for innovative activity. The number of chemicals can be large for some firms due to the scope of their operations and the number of facilities of the firm. The number of chemicals is highly skewed: the mean is 11,509 and median is 3200 (min is 39, max is 289,559). The number of facilities is also skewed: the mean is 32 and median is 8 (min is 1, max is 912).

¹² Our industry representation is within 5 percentage point of the representation in the TRI with the exception of Other Metals (SIC 34) (under-represented) and Construction (SIC 35) and Electronics (SIC 36) (over-represented).

5 Results

We first present results from the adoption decisions of the two technologies: in Sect. 5.1.1, we look at factors that affect patent acquisition, and Sect. 5.1.2 looks at factors that affect P2 adoptions. In Sect. 5.2, we present results from our pollution equation. Section 5.3 integrates these findings by exploring the long-term pollution reduction effects of knowledge accumulation from an additional patent or P2 practice.

5.1 Drivers of Technology Adoption

5.1.1 Determinants of Environmental Patents

We estimate empirical models to explore the factors that influence patenting behavior based on our conceptual model and the literature. Our core interest is the extent to which the technical capacity of the firm, as represented by its own past experience with environmental patenting (*Env Patents* and *EnvPatents Stock*) and P2 activities (*Total P2* or *Total P2 Stock*), affect patenting. The technical capacity of the firm may also be influenced by other knowledge investments (*R&D Intensity* and *Non-EnvPatent Stock*) and technological spillovers from industry peers (*Avg Peer Env Patent*).

As outlined in Sect. 3.2, endogeneity concerns arise if unobserved factors jointly affect the technology adoption decisions as well as the pollution level. In addition to lagging all technology and pollution measures, we also employ instruments for *Total P2* (or *Total P2 Stock*) and *Total Releases*. We use exogenous variables that are correlated with P2 and releases as instruments; these include *Peer P2*, *Number of Chemicals*, *Number of Facilities*, *Violations*, *Self-disclose*, and *Inspections*, each lagged 2 years. Regulatory variables are an attractive set of instruments as they are not traditionally thought to affect patent decisions directly (Brunnermeier and Cohen 2003) but have been found to affect pollution prevention adoptions (Bi and Khanna 2012, 2017; Harrington et al. 2014) and releases (Brouhle et al. 2009; Carrion-Flores and Innes 2010). For models using *Total P2 Stock*, we use the sum of *Peer P2*, *Number of Chemicals*, and *Number of Facilities* from the beginning of our sample period up to the previous 2 years so that the instruments have a similar temporal structure to the endogenous stock variable. In results not shown, we find that the instruments are relevant; the joint F-test statistics are 27.44 and 106.47, respectively, in regressions of P2 and releases against their own sets of explanatory variables, including the variables which we use as instruments. Over-identification tests for all models (Table 2) indicate that we cannot reject the null hypothesis of instrument validity.

Table 2 presents results from different models that vary in their measurement of prior environmental patenting and prior P2 adoptions. Models I and II measure prior patenting using the firm's environmental patenting in the previous year; Models III and IV use the firm's environmental patent stock lagged 2 years. Prior P2 activity is identified using a 1-year lagged flow measure in Models I and III and 2-year lagged stock measure in Models II and IV. Across the first four models, our results indicate prior environmental patenting, whether measured as a flow (lagged *EnvPatents*) or stock variable (2-year lagged *EnvPatents Stock*), is an important driver of new environmental patenting by firms. The estimated elasticities of past environmental patenting on new environmental patenting are between 0.676 and 0.985, with the lower estimates obtained whenever lagged *EnvPatents Stock* is

Table 2 Determinants of environmental patent counts

Variables	Model I	Model II	Model III	Model IV	Model V	Model VI
<i>Prior environmental patenting</i>						
EnvPatents _{t-1}	0.9810*** (0.0420)	0.9849*** (0.0372)			0.8763*** (0.0607)	0.7393*** (0.0458)
EnvPatents Stock _{t-2}			0.6758*** (0.1313)	0.8799*** (0.0635)	0.1607** (0.0798)	0.3333*** (0.0535)
<i>Pollution prevention^a</i>						
Total P2 _{t-1} ^b	0.0880 (0.0710)	0.0776 (0.0522)	0.4157* (0.2296)		0.1363* (0.0780)	
Total P2 Stock _{t-2} ^b				0.2339** (0.1185)		0.1468** (0.0666)
<i>Other technical capacity measures</i>						
Non-EnvPatent Stock _{t-1}	0.0783** (0.0338)	0.0738** (0.0338)	0.4148*** (0.1107)	0.2797*** (0.0556)	0.0716* (0.0370)	0.0660* (0.0374)
R&D Intensity _{t-2}	0.1347*** (0.0325)	0.1416*** (0.0355)	0.0849 (0.0792)	0.0896* (0.0539)	0.1167*** (0.0342)	0.1264*** (0.0387)
Avg Peer Env Patent _{t-2}	0.0202 (0.0292)	0.0038 (0.0258)	0.1602* (0.0882)	0.0552 (0.0403)	0.0384 (0.0329)	0.0096 (0.0267)
<i>Chemical releases</i>						
Total Releases _{t-1} ^b	-0.0175 (0.0292)	-0.0099 (0.0225)	-0.1639* (0.0857)	-0.0849 (0.0568)	-0.0421 (0.0310)	-0.0377 (0.0315)
<i>Controls</i>						
Capital Intensity _{t-2}	1.3249*** (0.2763)	1.3557*** (0.3391)	1.4214*** (0.4501)	1.6456*** (0.5352)	1.2382*** (0.2718)	1.2372*** (0.3514)
Age _{t-2}	-0.1310 (0.2888)	-0.1836 (0.2688)	-0.1191 (0.6921)	0.1932 (0.4649)	-0.0263 (0.3278)	0.0966 (0.3108)
Sales _{t-2}	0.2527** (0.1135)	0.2245** (0.1126)	-0.1263 (0.1835)	-0.1699 (0.1182)	0.1962* (0.1090)	0.1020 (0.1012)

Table 2 (continued)

Variables	Model I	Model II	Model III	Model IV	Model V	Model VI
Sales Squared _{t-2}	-0.0139*** (0.0064)	-0.0125* (0.0065)	0.0065 (0.0120)	0.0087 (0.0076)	-0.0104* (0.0062)	-0.0055 (0.0059)
HHI _{t-2}	4.1251 (5.5906)	4.0650 (5.0599)	13.1889 (11.5960)	5.7337 (8.4664)	4.6217 (5.7667)	3.2189 (5.2952)
ROA _{t-2}	0.0961* (0.0570)	0.0967 (0.0604)	0.1456*** (0.0542)	0.1814*** (0.0508)	0.1167** (0.0511)	0.1386*** (0.0501)
EnvPatent Pre-Sample Avg	0.0007 (0.0289)	-0.0004 (0.0232)	-0.1015 (0.0971)	-0.1977*** (0.0466)	-0.0665 (0.0422)	-0.1262 (0.0294)
EnvPatent Pre-Sample dummy	0.3306*** (0.1227)	0.2801*** (0.1039)	-0.0987 (0.2599)	-0.1156 (0.1327)	0.2806*** (0.1085)	0.2118** (0.0877)
Constant	-2.3215*** (0.4978)	-2.2396*** (0.5086)	-0.5775 (0.9750)	-1.3312* (0.7544)	-2.1244*** (0.5213)	-2.1210*** (0.5233)
Year dummies	YES	YES	YES	YES	YES	YES
Industry dummies	YES	YES	YES	YES	YES	YES
Observations	4,223	4,122	4,223	4,122	4,122	4,122
Number of firms	550	550	550	550	550	550
Hansen's J test [<i>p</i> value]	1.1637 [0.8840]	1.8369 [0.7657]	4.0461 [0.3998]	3.7371 [0.4428]	0.5709 [0.9662]	2.3612 [0.6697]

^aThe natural log of this variable is used in all models

^bThese variables were treated as endogenous and coefficients were estimated using instrumental variables

Standard errors are in parentheses below coefficients; ****p*<0.01, ***p*<0.05, **p*<0.1. For all models, we use and report two-step, multiplicative GMM estimators and their bias-corrected robust estimator clustered at the firm level (Windmeijer 2005)

used. These elasticities translate to a 0.65–0.95 increase in new environmental patenting from one additional environmental patent in the prior year.¹³

We find some evidence that past experience adopting P2 activities also influence environmental patenting today. We find that previous P2 adoptions influence environmental patenting by firms whenever we use 2-year lagged *EnvPatents Stock*: 1 year lagged *Total P2* is statistically significant at 90% level (Model III), while 2-year lagged *Total P2 Stock* is significant at 95% (Model IV). A positive influence of P2 on environmental patenting is consistent with results found in Chang and Sam (2015). In Models III and IV, the marginal effect of an extra P2 adoption is 0.23–0.42 environmental patents. We note that the influence of P2 on environmental patenting is insignificant in models that include lagged *EnvPatents* (Models I and II).

Results from the first four models suggest that our two measures of prior environmental patenting have separate effects on firms' current patenting. Out of concern that including the flow and stock measures separately may bias our coefficient estimates in these regressions upward due to correlation between the measures, we include both prior patenting measures together in Models V and VI. We find evidence that both *EnvPatents* and *EnvPatents Stock* positively influence new environmental patenting regardless of which past P2 measure is used, though the elasticities are smaller than those implied Models I–IV. Further, we find that the elasticity for *EnvPatents* is significantly larger than that of the *EnvPatents Stock* elasticity (0.88 vs. 0.16 in Model V and 0.77 vs. 0.34 in Model VI). Our elasticity estimates for the effect of past patenting are comparable to those found by Blundell et al. (1999, 2002) who similarly used GMM-IV approach to estimate a multiplicative dynamic feedback model. Notably, we continue to find a positive association between environmental patenting and *Total P2 Stock* when both prior environmental patenting measures are included but P2 has a more modest impact on patenting in this case: an extra P2 yields an extra 0.14 (Model V) to 0.15 (Model VI) environmental patents. As in Models III and IV, 1 year lagged *Total P2* is significant at the 90% level, while 2 year lagged *Total P2 Stock* is significant at the 95% level.

Turning to our remaining regressors, our results indicate that knowledge investments measured by *Non-EnvPatent Stock* and *R&D Intensity* have a positive relationship with environmental patenting in most models, consistent with existing literature. We find limited evidence of technological spillovers from environmental patenting by peers. With respect to other covariates, we find environmental patenting is positively associated with capital intensity (as in Brunnermeier and Cohen 2003) and return on assets (as in Chang and Sam 2015), which suggests that firms with more capital assets and greater profitability have the resources to patent. Finally, we find no consistent evidence that releases of toxic chemicals, market concentration, sales, and age of capital directly affect environmental patenting.

5.1.2 Determinants of P2 Activities

We continue our exploration of the technology adoption decision by considering the determinants of P2 adoptions. Again, we pay special attention to the role of the technical capacity of the firm, which is represented by its own past experience with P2 activities (*Total P2*

¹³ Following Cameron and Trivedi (2010), the marginal effect can be calculated using the formula $\epsilon \times \frac{x}{y}$, where ϵ is the elasticity, x is the sample mean value of the independent variable of interest, and y is the predicted value of the dependent variable evaluated at the mean of the regressors. In this case, $0.9810 \times \frac{4.65}{4.82} = 0.95$.

and *Total P2 Stock*), environmental patenting (*EnvPatents* and *EnvPatents Stock*), general knowledge investments (*R&D Intensity*), and technological spillovers from industry peers (*Avg Peer P2*).

As in the patent equation, our analysis of source reduction activities pays attention to endogeneity concerns that arise from other technology adoption decisions as well as the emissions profile of the firm. As a result, the models instrument for both patents and releases. Instruments for *Total Releases* include further lagged values of releases and *Final Good*,¹⁴ while instruments for *EnvPatents* include the environmental patents of peers in one's industry, non-environmental patents of the firm, capital expenditures and HHI.¹⁵ In results not shown, we find that these instruments are relevant; the joint F-test statistics are 195.87 and 150.21, respectively, in regressions of releases and patents against their own sets of explanatory variables, including the variables we use as instruments. In all models, the Hansen J-statistic (shown in Table 3) gives us confidence in the validity of our instrument set.

Results of the P2 adoption decision are shown in Table 3. Models I and II measure prior P2 using the count of a firm's P2 adoptions in the previous year; Models III and IV use a firm's stock of P2 practices up to 2 years ago. Environmental patenting is identified using a 1-year lagged flow measure in Models I and III and 2-year lagged stock measure in Models II and IV. Coefficient estimates from the Poisson models are robust across the different specifications.¹⁶ We find that P2 adoption is positively related to past P2 experiences. Both measures of past P2 experiences—be it lagged *Total P2* or lagged *Total P2 Stock*—have a positive effect on current P2 adoption. This result is consistent with the literature (Bi and Khanna 2017; Harrington 2012, 2013) and suggests that firms leverage past P2 in adopting new P2. Given the significance of both the lagged flow and lagged stock measures of P2, we provide Model V and VI to tease out whether it is the most recent experiences with P2 or experiences further in the past with P2 that influences P2 today. In Model V and VI, we include the lagged flow of past P2 (*Total P2_{t-1}*) and further lagged stock of P2 (*Total P2 Stock_{t-2}*). Here, we see that it is only the recent flow of P2 that drives the results rather than the further lagged stock measure. Recall, for patents, both the recent experience and further stock of environmental patenting was important. In terms of the magnitude of the effects for P2, our results suggest a relatively small impact of past P2 on current P2. For lagged

¹⁴ Final good has been used as proxy for consumer pressure in other studies that explain environmental behavior or performance (Khanna and Damon 1999; Anton et al. 2004; Vidovic and Khanna 2007; Harrington 2012). In our sample of firms, the following 4-digit SIC codes are considered final goods: 1311, 2000, 2011, 2020, 2050, 2070, 2100, 2200, 2211, 2300, 2330, 2761, 2834, 2840, 2844, 3661, 3669, 3911, 3949, 3950, 4813, 5040, 5140, and 6141.

¹⁵ The form of the instruments matches the form as the environmental patent variable. When the environmental patent variable is expressed in the form of a flow (stock) variable, the instruments are also expressed as flow (stock) variable.

¹⁶ We note that our main results are also robust to exclusion of our initial condition variables, *Initial P2 dummy* and *1991 P2*, which capture unobserved firm heterogeneity. In the patent literature, these measures are frequently included to capture unobserved firm specific characteristics. A closely related paper in the environmental patenting literature (Carrion-Flores and Innes 2010) does not include such pre-sample measures. Exclusion of initial P2 adoption makes R&D Intensity, Peer P2, and Debt to Asset Ratio statistically significant but our core results are the same: we see a positive influence of past P2 and releases on P2 adoption and insignificance of environmental patents on P2 adoption.

Table 3 Determinants of P2 Counts

Variables	Model I	Model II	Model III	Model IV	Model V	Model VI
<i>Prior pollution prevention</i>						
Total P2 _{t-1} ^a	0.0091*** (0.0006)	0.0091*** (0.0006)			0.0084*** (0.0008)	0.0084*** (0.0008)
Total P2 Stock _{t-2} ^a			0.0045*** (0.0004)	0.0045*** (0.0004)	0.0005 (0.0004)	0.0005 (0.0004)
<i>Prior environmental patenting</i>						
Env Patent _{t-1}	0.0133 (0.0403)		0.0184 (0.0410)		0.0173 (0.0396)	
Env Patent Stock _{t-2}		0.0095 (0.0294)		0.0227 (0.0298)		0.0125 (0.0293)
<i>Other technical capacity measures</i>						
R&D Intensity	0.0252 (0.0348)	0.0259 (0.0326)	0.0278 (0.0350)	0.0238 (0.0333)	0.0222 (0.0345)	0.0229 (0.0325)
Avg Peer P2	0.0252 (0.0226)	0.0244 (0.0225)	0.0376 (0.0238)	0.0393 (0.0239)	0.0254 (0.0223)	0.0244 (0.0222)
<i>Chemical releases</i>						
Total Releases _{t-1} ^a	0.0458*** (0.0125)	0.0459*** (0.0125)	0.0446*** (0.0121)	0.0441*** (0.0120)	0.0457*** (0.0123)	0.0459*** (0.0123)
<i>Controls</i>						
Number of chemicals	0.1395*** (0.0225)	0.1398*** (0.0225)	0.1507*** (0.0233)	0.1500*** (0.0229)	0.1373*** (0.0217)	0.1377*** (0.0218)
Age _{t-2}	-0.4503* (0.2582)	-0.4452* (0.2596)	-0.4818* (0.2628)	-0.4552* (0.2618)	-0.4315* (0.2529)	-0.4258* (0.2555)
Sales _{t-2}	0.1220** (0.0587)	0.1185** (0.0555)	0.1386** (0.0659)	0.1394** (0.0616)	0.1298** (0.0583)	0.1254** (0.0557)
Sales Squared _{t-2}	-0.0120*** (0.0046)	-0.0118*** (0.0043)	-0.0131** (0.0052)	-0.0136*** (0.0048)	-0.0126*** (0.0045)	-0.0124*** (0.0043)

Table 3 (continued)

Variables	Model I	Model II	Model III	Model IV	Model V	Model VI
Debt to Asset _{t-2}	-0.1731 (0.1644)	-0.1705 (0.1652)	-0.1957 (0.1592)	-0.1912 (0.1586)	-0.1676 (0.1629)	-0.1638 (0.1641)
ROA _{t-2}	-0.0010 (0.0124)	-0.0004 (0.0117)	0.0003 (0.0117)	0.0008 (0.0119)	-0.0015 (0.0121)	-0.0008 (0.0125)
Inspections _{t-2}	-0.0516** (0.0206)	-0.0521** (0.0206)	-0.0607*** (0.0210)	-0.0610*** (0.0210)	-0.0535*** (0.0199)	-0.0539*** (0.0199)
Self-disclose _{t-2}	0.0247 (0.0324)	0.0276 (0.0314)	0.0673** (0.0306)	0.0669** (0.0303)	0.0246 (0.0325)	0.0279 (0.0312)
Penalty _{t-2}	0.0126*** (0.0035)	0.0128*** (0.0036)	0.0164*** (0.0038)	0.0165*** (0.0039)	0.0130*** (0.0035)	0.0132*** (0.0036)
1991 P2	0.2937*** (0.0356)	0.2953*** (0.0357)	0.2742*** (0.0338)	0.2752*** (0.0341)	0.2837*** (0.0344)	0.2857*** (0.0347)
1991 P2 dummy	-0.3762*** (0.0699)	-0.3792*** (0.0707)	-0.3999*** (0.0694)	-0.4026*** (0.0697)	-0.3617*** (0.0695)	-0.3651*** (0.0703)
Constant	3.7288*** (0.8250)	3.7019*** (0.8115)	4.2780*** (0.8975)	4.2971*** (0.8826)	3.8145*** (0.8177)	3.7778*** (0.8086)
Year dummies	YES	YES	YES	YES	YES	YES
Industry dummies	YES	YES	YES	YES	YES	YES
Observations	4112	4112	4112	4112	4112	4112
Number of firms	550	550	550	550	550	550
Hansen J test	1.74692	1.77473	1.98775	2.25237	2.07494	2.13822
[p value]	[0.6266]	[0.6204]	[0.5750]	[0.5217]	[0.5570]	[0.5442]

Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. For all models, we use and report two-step, multiplicative GMM estimators and their bias-corrected robust estimator clustered at the firm level (Windmeijer 2005)

*These variables were treated as endogenous and coefficients were estimated using instrumental variables

P2 (see Model I and II), our coefficient estimates imply that one extra P2 on the past will increase new P2 adoption by 0.05.¹⁷

We fail to document an influence of other elements of the technical environment of the firm on P2 adoption. In particular, *EnvPatents*, *R&D Intensity*, and *Avg Peer P2* are not significantly related to current P2 adoptions by the firm. As the variables *EnvPatents* and *R&D Intensity* capture more general technical capacity of the firm, the results suggest an absence of spill-over effects from general technical capacity of the firm to P2 adoption. The absence of an effect of R&D is consistent with the notion that P2 largely involves out of the box technologies that do not require large technical capacity or high general R&D by the firm. The absence of an effect for R&D is also found in work by Harrington (2012, 2013), Harrington et al. (2014), and Luan et al. (2016). The variable *Avg Peer P2* was included to measure potential technological spillovers from industry peers. We fail to document such a channel. While a spillover channel between facilities within a firm was identified in Harrington (2012, 2013), we don't find evidence of spillovers between firms.

Many of our control variables influence P2 adoptions. Consistent with our priors, we find that firms with higher past toxic chemical releases are more likely to adopt P2 practices in the following year. This suggests that, unlike the case for patents, firms look to P2 practices as a way to address toxic pollution concerns. As expected, the number of chemicals that firm reports to the TRI is also strongly associated with the number of P2 adoptions of the firm. Among the enforcement variables, firms who had a large penalty in the past are more likely to adopt source reduction/P2 practices. In some but not all models, firms that self-disclosed environmental violations in the past are more likely to adopt P2 practices (see Model III and IV). In contrast, firms inspected more frequently have fewer P2 adoptions. Among our firm specific financial variables, we find P2 is negatively correlated with the age of the firm (though this is statistically significant only at the 90% level), which is consistent with our prior. Larger firms (as measured by sales) are more likely to adopt P2 practices, though the marginal effect declines with size. Most of our year dummies are significant indicating variation in P2 over time. Industry dummies, though, are largely insignificant.

In summary, our results of patent and P2 adoptions suggest different factors motivate adoption of these technologies. While technical capacity is important for both, the nature of existing and past knowledge that is relevant for each varies. For patents, both the general technical environment (R&D and non-environmental patents) and specific environmental technical knowledge (past experience with patents and P2) matter. These findings suggest that to cross the high bar to qualify for a patent, the firm must have a mix of broad and specific experience and knowledge. For P2 activities, though, the only technology variable that matters is (recent) past P2 experience; past environmental patents and general R&D do not influence P2 activities. Rather, P2 activities are more robustly influenced by the existing opportunities for source reduction (number of chemicals and past pollution level), the regulatory environment (inspections and penalties), and firm specific characteristics (younger and larger). In addition to the different factors that motivate environmental patenting and P2 activity, we find that the magnitude of the coefficient of the past experience variable

¹⁷ Following the form of the dependent and independent variable in our Poisson model, the elasticity (ϵ) is simply the coefficient estimate on the variable of interest (α) times the same mean value of the variable x (P2 or patent), $\epsilon = \alpha * x$. In this case, $\epsilon = 0.0090 \times 4.620452 = 0.04$. Since the marginal effect is $\epsilon \times \frac{x}{y}$, where x is the sample mean value of the independent variable of interest, and y is the predicted value of the dependent variable evaluated at the mean of the regressors, $0.04 \times \frac{9.22}{8.17} = 0.05$.

is quite different. The impact of an environmental patent on new patenting is much larger than the impact of a P2 practice on new P2 adoptions. Different influences and different magnitudes of impact reinforce the fact that these environmental technologies are viewed differently by firms. Whether and how the two technologies lead to different impacts on the pollution profile of the firm is explored in the next two sections.

5.2 Innovation and Toxic Chemical Releases

Our second set of results investigate whether technological innovations of environmental patents and P2 practices reduce pollution. We pay attention to the form of the technology adoption (whether a recent flow of knowledge or a more sustained stock of knowledge) as well as the relative magnitude of the potential effect of each technology on pollution.

All pollution models include lagged pollution as a key explanatory variable to capture path dependence in pollution choices as well as unobserved production and abatement technology. We also include regulatory pressure variables among our set of controls. The inclusion of regulatory variables in the pollution equation is not meant to capture regulatory variables as “drivers” for pollution in the same way that regulatory pressure can drive abatement technology choice. Rather, the regulatory pressure variables are included to capture unobserved pollution function g that may explain a facility’s unobserved choices of other abatement technology (other than patents and P2) which can also determine pollution. We lag these regulatory variables 2 years to avoid simultaneity issues.¹⁸

To deal with the econometric challenges outlined in Sect. 3.2, all models in Table 4 use 2- to 7-year lags of *Total Releases* as GMM-type instruments. For *Total P2* and *EnvPatents* which we treat as potentially endogenous, their instrument set includes GMM-type instruments, other exogenous regressors in the pollution equation and other exogenous regressors unique to the patent and P2 equations. The length of lags of the GMM-type instruments for *Total P2* and *EnvPatents* slightly vary across models depending on the length of lags included for each endogenous variable. The AR tests for first and second order serial correlation in the first differenced errors show that the null hypotheses of no serial correlation are rejected for AR(1) but not rejected for AR(2), indicating that GMM type instruments are valid. The other instruments used are as follows: in the differenced equation, we include *Non-EnvPatent Stock*, *R&D Intensity*, *Peer EnvPatent Stock*, *Peer TotalP2*, *Number of Chemicals*, *Self-disclose*, *Sales*, *Sales Squared* and *ROA*; in both differenced and levels equation, we include *HHI*, *Age*, *Violations*, *Inspections* and *Penalties*. In the models where we use lags of *Total P2* and *EnvPatents* as explanatory variables, we still suspect their endogeneity because they may be correlated with the errors in Eq. (3) due to unobservable time-varying factors that capture abatement technology and abatement costs. We then use appropriately lagged GMM type instruments as well as the other exogenous factors from Tables 2 and 3 that are correlated with *Total P2* and *EnvPatents*. In results not shown, the joint F-test statistics are 122.7 and 34.2, respectively, in regressions of patents and P2 against their own sets of explanatory variables, including the variables we use as instruments. Sargan tests show that the moment conditions and the instruments are valid for all the models.

¹⁸ We investigate 1-year and 3-year lags of regulatory variables and find that the results are robust to using different lags. Results are available upon request.

Table 4 presents the determinants of toxic chemical releases. To explore and compare the role of the two types of abatement technologies, different columns in Table 4 use different specifications of the *EnvPatents* and *Total P2* variables. We measure the knowledge from environmental patents as a stock variable in Models I and III and as a flow variable in Models II and IV; P2 activities are measured as a stock variable in Models I and IV and as a flow variable in Model II and III. Across the four models, we find evidence that environmental patents and P2 activities reduce toxic releases of the firm. The coefficients on P2 are negative and statistically significant at the 95% level or higher across the four models. For environmental patenting, the coefficient is also negative across all four models, though the statistical significance is slightly less pronounced (the effect is statistically significant at the 95% level in Model I and statistically significant at the 90% level across the other three models).¹⁹ That both environmental technologies tend to reduce the level of releases of toxic chemicals suggests that simultaneously employing a portfolio of abatement strategies can yield higher levels of pollution reduction than a singular focus on a one type of technology.

Focusing on the magnitude of the coefficients of the *Total P2* and *EnvPatents* variables, we can see that the implied immediate impacts are quite similar across models: Model II suggests that a 10% increase environmental patenting reduces chemical pollution by approximately 2.7% while a 10% percent increase in pollution prevention activities reduces *Total Releases* by 1.65%. The differences in the coefficients of P2 and environmental patent variables are not statistically significant. These elasticities are very similar to those derived by Carrion-Flores and Innes (2010) for patents (2.48%) and by Harrington et al. (2014) for P2 (1.67%). For our sample, these elasticity estimates imply that chemical releases will be reduced by approximately 5.6% from one extra patent and about 2% from one extra P2 in the same year of adoption.^{20,21}

The signs and significance of the coefficients of other explanatory variables are robust across models. The models show that the level of toxic chemical releases increase with past level of releases and number of facilities but fall with sales. A ten percent increase in past releases increases current releases by approximately 3.4%. This value is slightly lower than estimates in other studies, none of which include *Number of Facilities* as an explanatory variable (Carrion-Flores and Innes 2010; Harrington et al. 2014; Harrington 2013). A 10% increase in number of facilities yields a slightly more than proportional increase in releases, about 12%. This coefficient is highly significant despite the inclusion of *Sales*, which is also a control for size. The negative significant coefficient of *Sales* suggests that there may be economies of scale in abatement or that larger firms may have better technology to undertake emission reduction. We find that firms with more R&D do not have lower releases. This finding indicates that the role of R&D in reducing pollution is indirect via

¹⁹ We investigate whether it is the current flow or lagged flow of P2 and environmental patents that influence pollution. For both technologies, we find stronger evidence that current flows matter compared to further lagged flows of the variable. Results are available upon request.

²⁰ The mean *Total P2* is 8.2 and mean *EnvPatents* is 4.8, one extra *Total P2* adopted is 12.2% of mean *Total P2* while one extra *EnvPatent* is 20.7% of mean *EnvPatents*.

²¹ Our estimated impact of P2 on chemical releases may be biased if P2 adoption influences whether or not a particular chemical is reported to the TRI at any given year. For example, if P2 activities result in reducing chemical releases below the reporting threshold even though it is not entirely eliminated from the production process, our results may underestimate the pollution reduction attributable to P2. Similarly, if P2 adoption has resulted in substitution of one TRI chemical for a non-TRI chemical, any reduction in chemical releases observed may again be an underestimate of the effect of P2 adoption.

Table 4 Determinants of chemical releases, dynamic panel GMM models

Variables	Model I	Model II	Model III	Model IV
<i>Lagged dependent variable</i>				
Total Releases _{t-1} ^{b/}	0.352*** (0.074)	0.349*** (0.075)	0.349*** (0.075)	0.346*** (0.075)
<i>Pollution prevention^a</i>				
Total P2 ^b		-0.165** (0.075)	-0.170*** (0.076)	
Total P2 Stock _t ^b	-0.155*** (0.056)			-0.155*** (0.070)
<i>Environmental patents</i>				
EnvPatents		-0.267* (0.155)		-0.274* (0.153)
EnvPatents Stock _t	-0.379** (0.163)		-0.272* (0.162)	
<i>Controls</i>				
Violations _{t-2}	-0.029 (0.025)	-0.022 (0.031)	-0.023 (0.032)	-0.022 (0.031)
Inspections _{t-2}	0.0065 (0.0058)	0.0052 (0.0064)	0.0662 (0.147)	0.085 (0.147)
Penalties _{t-2}	0.035 (0.152)	0.076 (0.146)	0.0049 (0.0064)	0.0053 (0.0063)
R&D Intesity _{t-2}	-0.063 (0.113)	-0.101 (0.113)	-0.099 (0.114)	-0.110 (0.112)
Sales _{t-2}	-0.134* (0.082)	-0.250*** (0.076)	-0.246*** (0.076)	-0.246*** (0.075)
Capital Intesity _{t-2}	1.221 (1.985)	1.963 (1.953)	2.110 (1.972)	1.772 (1.873)
Return on Assets _{t-2}	-0.0040 (0.0032)	-0.0102* (0.0062)	-0.0101* (0.0061)	-0.0097* (0.0060)
Number of Facilities	1.303*** (0.149)	1.259*** (0.140)	1.270*** (0.142)	1.253*** (0.139)
Constant	6.524*** (1.043)	7.092*** (1.089)	7.047*** (1.084)	7.155*** (1.082)
Year dummies	YES	YES	YES	YES
Observations	4,223	4,223	4,223	4,223
Number of firms	550	550	550	550
Sargan test [p value]	192.042 [0.606]	200.474 [0.477]	203.630 [0.415]	203.6305 [0.415]
1st order autocorr [p value]	-4.268*** [0.000]	-4.332*** [0.000]	-4.131*** [0.000]	-4.295*** [0.000]
2nd order autocorr [p value]	0.1248 [0.901]	0.116 [0.908]	0.112 [0.911]	0.118 [0.906]

Standard errors are in parentheses below coefficients; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All models assume iid. Models I and II are robust to using MA(1) error structure. For all models, we use and report two-step robust estimator (Windmeijer 2005)

^aThe natural log of this variable is used in all models

^bThese variables were treated as endogenous and coefficients were estimated using instrumental variables

environmental patents, which is shown in Table 2 to be positively associated with *R&D Intensity*. Finally, we find that inspections, violations, and penalties all have statically insignificant coefficients. The insignificance of the regulatory variables in the pollution equation is similar to findings by many in the literature which use regulatory variables as controls in a pollution equation, while focusing on the role of voluntary environmental action as the main explanatory variable of interest such as P2 (Bi and Khanna 2017; Harrington et al. 2014), state program or legislation (Harrington 2013), EMS adoption (Sam et al. 2009), or environmental program participation (Bi and Khanna 2017, 2012; Sam et al. 2009; Brouhle et al. 2005).

5.3 Long-Term Impacts on Pollution

The results presented in Table 4 describe the direct influence of patents and P2 on pollution on the year of adoption. But what is the impact of an additional environmental patent or P2 practice on pollution projected into the future? Given the interplay between P2, patents, and pollution outlined in Eqs. 1–3, technology adoption in one period has the potential to impact pollution in succeeding periods through several channels. To conduct this analysis, we choose the models that we believe best capture the relationships between current and past levels of patents, P2, and pollution (Model VI, Table 2; Model I, Table 3; and Model II, Table 4). Denoting current (lagged) *EnvPatents* as P_{it} (P_{it-1}), 2-year lagged *EnvPatent Stock* as P_{it-2}^{stock} , current (lagged) *Total P2* as S_{it} (S_{it-1}), 2-year lagged *Total P2 Stock* as S_{it-2}^{stock} , and lagged *Total Releases* as Q_{it-1} , we can express these models as follows:

$$P_{it} = \exp(a_p + b_p Q_{it-1} + c_{P2} S_{it-2}^{stock} + d_{P1} P_{it-1} + d_{P2} P_{it-2}^{stock} + e_p Z_{it}^P + \eta_i^P + \nu_t + \varepsilon_{it}^P) \quad (1')$$

$$S_{it} = \exp(a_S + b_S Q_{it-1} + c_S S_{it-1} + d_S P_{it-1} + e_S Z_{it}^S + \eta_i^S + \nu_t + \varepsilon_{it}^S) \quad (2')$$

$$Q_{it} = a_Q + b_Q Q_{it-1} + c_Q S_{it} + d_Q P_{it} + e_Q Z_{it}^Q + \eta_i^Q + \nu_t + \varepsilon_{it}^Q \quad (3')$$

To identify the effect of a one unit change in environmental patents and P2 adopted at time t on pollution at period $t + \tau$, $Q_{t+\tau}$, we take the derivative of Eq. (3') with respect to P_t and S_t (full derivation is shown in the Appendix):

$$\frac{dQ_{t+\tau}}{dP_t} = \left\{ \begin{array}{l} \underbrace{b_Q^\tau d_Q}_{\text{lagged pollution effect}} + \underbrace{d_Q [d_{P1}^\tau + d_{P2} \delta^{\tau-2} + d_{P1}^{\tau-1} b_P d_Q]}_{\text{same knowledge effect}} + \underbrace{c_Q [c_S^{\tau-1} d_S + c_S^{\tau-1} b_S d_Q]}_{\text{cross knowledge effect}} \end{array} \right\} * \hat{P} \quad \forall \tau \geq 1 \quad (4)$$

$$\frac{dQ_{t+\tau}}{dS_t} = \left\{ \underbrace{b_Q^r d_Q}_{\substack{\text{lagged pollution} \\ \text{effect}}} + \underbrace{c_Q [c_S^r + c_S^{r-1} b_S c_Q]}_{\substack{\text{same knowledge} \\ \text{effect}}} + \underbrace{d_Q [d_{P1}^{r-2} c_{P2} + d_{P2} \delta^{r-4} c_{P2} + d_{P1}^{r-1} b_P c_Q]}_{\substack{\text{cross knowledge} \\ \text{effect}}} \right\} * \hat{S} \quad \forall \tau \geq (5)$$

where \hat{P} and \hat{S} represent the percentage change in mean patent or mean P2 that is equivalent to a one-unit change in patent or P2 in our sample. Equations 4 and 5 illustrate that the adoption of a patent or P2 practice in one period will affect pollution in the future through several channels. The first term captures a lagged pollution channel. Here, a one unit increase in *EnvPatents* or *Total P2* yields lower releases in the same period, which then lowers the entire time path for pollution relative to what pollution would have been had that extra *EnvPatents* or *Total P2* not been adopted. The second and third terms capture knowledge accumulation channels when enhanced knowledge from *EnvPatent* or P2 adoption affects a firm’s ability to undertake new patenting and new P2 in the future. The second term represents the same-technology knowledge accumulation effect. This arises as a one unit increase in *Env Patent (Total P2)* will raise the entire time path for *Env Patent (Total P2)*, which in turn will influence pollution in the future. The last term represents the cross-technology knowledge accumulation effect. It measures the extent to which a one unit increase in *Env Patent (Total P2)* affects the adoption of the other technology, *Total P2 (EnvPatent)*, which shifts the other technology’s time path upward or downward depending on whether one promotes or discourages the other.

Utilizing the coefficient estimates and standard errors from our preferred models, we calculate the long-term impact of an extra *EnvPatent* and extra *Total P2* on pollution beyond the year of adoption (see Fig. 1).²² We note that in any given year, the long-term impact of an environmental patent is much greater than the impact of a P2 practice. In particular, the results suggest that the contribution of an additional patent is about 7–8 times higher than the impact of an additional P2 practice. This difference in magnitude is due to the following reasons (1) the coefficient of patenting is larger than the coefficient of P2 in the pollution equation; (2) the same technology knowledge accumulation effect of patenting is larger than that of P2; and (3) P2 promotes patenting, but patenting has no statistically significant effect on P2. The figure also shows the length of time that technology adoption (an extra patent or an extra P2) will continue to affect pollution. With knowledge depreciation and the importance of recent lagged values of technology on pollution (but not through longer-lived stock values), we observe statistically significant long-term reductions in pollution for a finite number of years: 10 years for an environmental patents and 6 years for a P2 practice. Summing up annual pollution reduction estimates from the years with statistically significant effects and adding them to the immediate impacts derived above, we find that an extra patent yields a cumulative pollution reduction of 28% while an extra P2 yields a cumulative reduction of only 5%. These results show that the effect of an extra patent is larger and lasts longer than that of an extra P2.

In summary, we find that patenting and P2 are significant contributors to long-term cumulative pollution reduction beyond the year of their adoption. That the effect is much

²² The coefficient of (unlogged) lagged P2 in the P2 equation from Table 3 is converted to an elasticity using mean value of P2 for consistency with interpretation of other coefficients.

more pronounced for patents than for P2 is an important finding that further demonstrates the differences between these two technologies. Not only are adoption decisions driven by different factors, but their different impact on long-term pollution reduction suggests that firms acquire and utilize knowledge from them differently to yield desired environmental outcomes.

6 Conclusions and Policy Implications

In this work, we have identified factors that influence firm environmental patenting and P2 adoption as well as the influence of those technologies on firm pollution. In terms of the adoption decision, we have two central findings. First, our results demonstrate that different factors influence patent and P2 adoption. We find that general technical capacity of the firm (such as R&D and the extent of patenting in environmental and non-environmental areas) matter strongly for environmental patents. For P2, the scope of opportunity to undertake P2 (extent of past emissions and numbers of chemicals), the regulatory exposure of the firm, and firm specific factors (size and age of the firm) are important motivators. These findings suggest that policy levers to promote patenting and P2 should target different pathways; for example, stimulating general knowledge accumulation to enhance patenting activity while creating a more stringent regulatory environment to promote P2 adoption. Our second main finding relates to the different mechanisms through which past experience affects future technology adoptions. While past experience in a technology is important for both patents and P2 (past experience with environmental patents promote new environmental patents and past experience with P2 promote new P2 adoptions), the cross-technology effects are different. We find that P2 promotes environmental patenting but not vice versa, which indicates that firms utilize knowledge in these areas in different ways and that policies promoting patents and P2 have the potential to differentially impact the environmental technical capacity of firms beyond the short-term. That promoting P2 adoption has additional spillover benefits in encouraging future environmental patenting is noteworthy.

With regards to the impact of technologies on pollution, we find evidence that patenting and P2 adoption have distinct impacts on pollution and that the distinct influence of each persists even after controlling for the level of R&D spending, the size of the firm, and the firm's past environmental performance. While the immediate impact of each technology on pollution reduction is modest, the strong knowledge accumulation effects of both technologies mean that the effect of each technology on pollution may be observed years after adoption. The long-term impact of an extra patent is larger and lasts longer than that of an extra P2. These findings underscore the importance of knowledge accumulation as a driver of long-term pollution reduction. Ignoring this effect not only underestimates the pollution reduction effects of patenting or P2 adoption but also gives rise to a cost of delaying innovative activity.

The larger long-term impact of environmental patenting on pollution reduction may naively imply that we need to focus our abatement efforts on these more sophisticated and novel innovations. But, in fact, promoting P2 has a place in the policymaker's toolkit for three reasons. First, early promotion of both P2 and patents is worthwhile because knowledge accumulation effects for both are robust and because P2 promotes further patenting. Second, the innovative process involved in patenting requires considerable time before knowledge is available and meets the standard for patenting, while

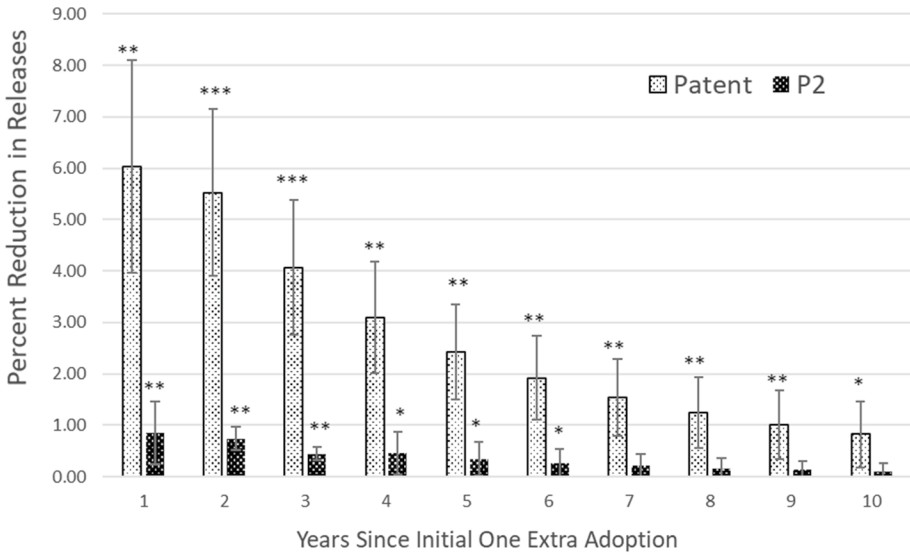


Fig. 1 Percent reduction in toxic releases from a one unit increase in patents or P2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

P2 technologies are more easily accessible and adaptable, bringing pollution reduction immediately. Third, P2 adoption is less resource intensive than patenting. Per unit costs of pollution reduction due to patenting is most certainly higher than those from P2 adoption. Thus, using the more costly patenting process may not be cost-effective. While a full-blown cost-effectiveness analysis and comparison of costs of P2 and patenting is beyond the scope of this paper, such an exercise would be valuable to enable comparison of costs of pollution reduction between patents and P2. Our analysis, thus, presents the case for examining a suite of environmental technologies to better inform environmental policy decisions that will promote a combination of technologies to take advantage of knowledge accumulation effects.

Moving beyond the specific findings of this work, we hope our research motivates and feeds into future research directions in the area of environmental innovations. We conclude by mentioning two broad avenues of future research that might build off the present work. First, because environmental innovations have the potential to impact a firm’s environmental footprint other than toxic releases, future work should identify and possibly compare how innovations bring about improvements in other measures of environmental performance. Second, our findings on knowledge accumulation and spillovers between technologies could be further explored in future work. Research that is directed at particular environmental problems that require more specialized technologies would allow a closer examination of spillovers between a specific set of environmental innovations and/or specific P2 practices (or other types of innovation such as management practices or process improvements). We believe these two areas of future explorations will enhance our understanding of the interplay between environmental technology and environmental outcomes.

Appendix

The empirical results allow us to specify our general expressions in (1) and (2) such that that patents are a function of 1-year lagged patent flow, 2-year lagged patent stock, and 2-year lagged P2 stock (Table 2, Model VI); while P2 is explained by 1-year lagged P2 flow and 1-year lagged patent flow (Table 3, Model I). Pollution is affected by contemporaneous P2 and patents (Table 4, Model II). Denoting current (lagged) *EnvPatents* as $P_{it}(P_{it-1})$, 2-year lagged *EnvPatent Stock* as P_{it-2}^{stock} , current (lagged) *Total P2* as $S_{it}(S_{it-1})$, 2-year lagged *Total P2 Stock* as S_{it-2}^{stock} , and lagged *Total Releases* as Q_{it-1} , we can express these models as follows:

$$P_{it} = \exp(a_P + b_P Q_{it-1} + c_{P2} S_{it-2}^{stock} + d_{P1} P_{it-1} + d_{P2} P_{it-2}^{stock} + e_P Z_{it}^P + \eta_i^P + \nu_t + \varepsilon_{it}^P) \tag{A.1}$$

$$S_{it} = \exp(a_S + b_S Q_{it-1} + c_S S_{it-1} + d_S P_{it-1} + e_S Z_{it}^S + \eta_i^S + \nu_t + \varepsilon_{it}^S) \tag{A.2}$$

$$Q_{it} = a_Q + b_Q Q_{it-1} + c_Q S_{it} + d_Q P_{it} + e_Q Z_{it}^Q + \eta_i^Q + \nu_t + \varepsilon_{it}^Q \tag{A.3}$$

In the derivations that follow, we simplify the notation when calculating marginal effects (as elasticities) using count models. For example, we denote $\frac{\partial P_{t+1}}{\partial P_t} = \frac{\partial \log[E(P_{t+1}|Q,K,Z)]}{\partial P_t}$, and $\frac{\partial S_{t+1}}{\partial S_t} = \frac{\partial \log[E(S_{t+1}|Q,K,Z)]}{\partial S_t}$. We use elasticities implied by estimates in Tables 2 and 3.

To calculate the effect of an extra environmental patent adopted at time t on pollution τ periods hence, we take the derivative of Eq. (3') with respect to P_t . We note that pollution at any period is a function of lagged pollution which is in itself a function of P_t and S_t , and of $P_{t+\tau}$ and $S_{t+\tau}$ that are themselves functions of P_t and S_t .

$$\begin{aligned} \frac{dQ_{t+\tau}}{dP_t} &= \underbrace{\frac{\partial Q_{t+\tau}}{\partial Q_{t+\tau-1}} \left[\frac{\partial Q_{t+\tau-1}}{\partial Q_{t+\tau-2}} \dots \frac{\partial Q_t}{\partial P_t} \right]}_{\text{pollution path dependence}} \\ &+ \underbrace{\frac{\partial Q_{t+\tau}}{\partial P_{t+\tau}} \left[\overbrace{\left(\frac{\partial P_{t+\tau}}{\partial P_{t+\tau-1}} \frac{\partial P_{t+\tau-1}}{\partial P_{t+\tau-2}} \dots \frac{\partial P_{t+1}}{\partial P_t} \right)}^{\text{via lagged patent}} + \overbrace{\left(\frac{\partial P_{t+\tau}}{\partial P_{t+\tau-2}^{stock}} \frac{\partial P_{t+\tau-2}^{stock}}{\partial P_t} \right)}^{\text{via patent stock}} + \overbrace{\left(\frac{\partial P_{t+\tau}}{\partial P_{t+\tau-1}} \frac{\partial P_{t+\tau-1}}{\partial P_{t+\tau-2}} \dots \frac{\partial P_{t+1}}{\partial Q_t} \frac{\partial Q_t}{\partial P_t} \right)}^{\text{adjustment factor}} \right]}_{\text{pollution change due to patent knowledge accumulation from extra patent}} \\ &+ \underbrace{\frac{\partial Q_{t+\tau}}{\partial S_{t+\tau}} \left[\overbrace{\left(\frac{\partial S_{t+\tau}}{\partial S_{t+\tau-1}} \frac{\partial S_{t+\tau-1}}{\partial S_{t+\tau-2}} \dots \frac{\partial S_{t+1}}{\partial P_t} \right)}^{\text{via lagged P2}} + \overbrace{\left(\frac{\partial S_{t+\tau}}{\partial S_{t+\tau-1}} \frac{\partial S_{t+\tau-1}}{\partial S_{t+\tau-2}} \dots \frac{\partial S_{t+1}}{\partial Q_t} \frac{\partial Q_t}{\partial P_t} \right)}^{\text{adjustment factor}} \right]}_{\text{pollution change due to P2 knowledge accumulation from extra patent}} \end{aligned}$$

The first term illustrates how the trajectory of pollution is lower due to patenting. The second term is the same-knowledge accumulation effect that results from most recent new patent and further lagged patent knowledge stock. The third term is the cross-knowledge accumulation effect because past patenting affects new P2 which in turn affects pollution. Note that for the second and third terms the learning effects include an adjustment factor arising from how the effect of an initial patent on pollution can encourage or discourage future patenting and future P2. Because patenting

occurring in the initial period can lower pollution immediately, $\frac{\partial Q_t}{\partial P_t} < 0$, the adjustment terms will reinforce (mitigate) the knowledge accumulation effects if lower pollution in the adoption year will encourage (discourage) subsequent patenting and P2, i.e., $\frac{\partial P_{t+1}}{\partial Q_t} < 0$; $\frac{\partial S_{t+1}}{\partial Q_t} < 0$ ($\frac{\partial P_{t+1}}{\partial Q_t} > 0$; $\frac{\partial S_{t+1}}{\partial Q_t} > 0$). All these effects will be felt 2 years after adoption because of the 2-year lagged effect of patent stock on new patent flow).

In the year of adoption, $\tau=0$, the only effect is through the contemporaneous impact which is the focus of Sect. 5.2, $\frac{dQ_t}{dP_t} = d_Q$.

One year after adoption at time $t + 1$, the effect of patenting at time t is:

$$\begin{aligned} \frac{dQ_{t+1}}{dP_t} &= \frac{\partial Q_{t+1}}{\partial Q_t} \left[\frac{\partial Q_t}{\partial P_t} \right] + \frac{\partial Q_{t+1}}{\partial P_{t+1}} \left[\left(\frac{\partial P_{t+1}}{\partial P_t} \right) + \left(\frac{\partial P_{t+1}}{\partial P_{t-1}^{stock}} \frac{\partial P_{t-1}^{stock}}{\partial P_{t-1}} \right) + \left(\frac{\partial P_{t+1}}{\partial Q_t} \frac{\partial Q_t}{\partial P_t} \right) \right] \\ &+ \frac{\partial Q_{t+1}}{\partial S_{t+1}} \left[\left(\frac{\partial S_{t+1}}{\partial P_t} \right) + \left(\frac{\partial S_{t+1}}{\partial Q_t} \frac{\partial Q_t}{\partial P_t} \right) \right] \end{aligned}$$

Since we are interested in a new patent adopted at time t , not any earlier, several terms are zero. By substituting for all coefficients from (1'), (2') and (3'):

$$\frac{dQ_{t+1}}{dP_t} = b_Q d_Q + d_Q [d_{P1} + 0 + 0] + c_Q [d_S + b_S d_Q] = b_Q d_Q + d_Q d_{P1} + c_Q [d_S + b_S d_Q] \tag{A.4}$$

Two years after adoption at time $t + 2$, the effect of patenting at time t is derived similarly, noting that new patenting at time $t + 2$ now also influenced by the effect of 2-year lagged patent stock, P_t^{stock} and the adjustment terms are non-zero.

$$\begin{aligned} \frac{dQ_{t+2}}{dP_t} &= \frac{\partial Q_{t+2}}{\partial Q_{t-1}} \left[\frac{\partial Q_{t-1}}{\partial Q_t} \frac{\partial Q_t}{\partial P_t} \right] \\ &+ \frac{\partial Q_{t+2}}{\partial P_{t+2}} \left[\left(\frac{\partial P_{t+2}}{\partial P_{t+1}} \frac{\partial P_{t+1}}{\partial P_t} \right) + \left(\frac{\partial P_{t+2}}{\partial P_t^{stock}} \frac{\partial P_t^{stock}}{\partial P_t} \right) + \left(\frac{\partial P_{t+2}}{\partial P_{t+1}} \frac{\partial P_{t+1}}{\partial Q_t} \frac{\partial Q_t}{\partial P_t} \right) \right] \\ &+ \frac{\partial Q_{t+2}}{\partial S_{t+2}} \left[\left(\frac{\partial S_{t+2}}{\partial S_{t+1}} \frac{\partial S_{t+1}}{\partial P_t} \right) + \left(\frac{\partial S_{t+2}}{\partial S_{t+1}} \frac{\partial S_{t+1}}{\partial Q_t} \frac{\partial Q_{t+1}}{\partial P_t} \right) \right] \end{aligned}$$

By substituting for all coefficients from (1'), (2') and (3') and noting that depreciated cumulated stock of patents can be expressed as $P_{it}^{stock} = \sum_{\tau} \delta^\tau P_{t-\tau}$:

$$\frac{dQ_{t+2}}{dP_t} = b_Q^2 d_Q + d_Q [d_{P1}^2 + d_{P2} \delta^0 + d_{P1} b_P d_Q] + c_Q [c_S d_S + c_S b_S d_Q] \tag{A.5}$$

Generalizing (A.1.2) for all years $\tau \geq 1$, we have

$$\frac{dQ_{t+\tau}}{dP_t} = b_Q^\tau d_Q + d_Q [d_{P1}^\tau + d_{P2} \delta^{\tau-2} + d_{P1}^{\tau-1} b_P d_Q] + c_Q [c_S^{\tau-1} d_S + c_S^{\tau-1} b_S d_Q] \tag{A.6}$$

After multiplying (8) by \hat{P} , which represents what one extra patent is as a proportion to mean patent, we derive Eq. (4) in Sect. 5.3.

The effect of an extra P2 adopted at time t on future emissions can be analyzed similarly. To calculate the effect of an extra P2 adopted at time t on pollution τ periods hence, we take the derivative of Eq. (3') with respect to S_t , recognizing that pollution at

any period is a function of lagged pollution which is in itself a function of P_t and S_t , and of $P_{t+\tau}$ and $S_{t+\tau}$, that are themselves functions of P_t and S_t .

$$\begin{aligned} \frac{dQ_{t+\tau}}{dS_t} &= \frac{\partial Q_{t+\tau}}{\partial Q_{t+\tau-1}} \underbrace{\left[\frac{\partial Q_{t+\tau-1}}{\partial Q_{t+\tau-2}} \dots \frac{\partial Q_t}{\partial S_t} \right]}_{\text{pollution path dependence}} \\ &+ \frac{\partial Q_{t+\tau}}{\partial S_{t+\tau}} \underbrace{\left[\left(\frac{\partial S_{t+\tau}}{\partial S_{t+\tau-1}} \frac{\partial S_{t+\tau-1}}{\partial S_{t+\tau-2}} \dots \frac{\partial S_{t+1}}{\partial S_t} \right) + \left(\frac{\partial S_{t+\tau}}{\partial S_{t+\tau-1}} \frac{\partial S_{t+\tau-1}}{\partial S_{t+\tau-2}} \dots \frac{\partial S_{t+1}}{\partial Q_t} \frac{\partial Q_t}{\partial S_t} \right) \right]}_{\text{pollution change due to P2 knowledge accumulation from extra P2}} \\ &+ \frac{\partial Q_{t+\tau}}{\partial P_{t+\tau}} \underbrace{\left[\left(\frac{\partial P_{t+\tau}}{\partial P_{t+\tau-1}} \frac{\partial P_{t+\tau-1}}{\partial P_{t+\tau-2}} \dots \frac{\partial P_{t+2}}{\partial S_t^{stock}} \frac{\partial S_t^{stock}}{\partial S_t} \right) + \left(\frac{\partial P_{t+\tau}}{\partial P_{t+\tau-2}} \frac{\partial P_{t+\tau-2}}{\partial P_{t+2}} \frac{\partial P_{t+2}}{\partial S_t^{stock}} \frac{\partial S_t^{stock}}{\partial S_t} \right) + \left(\frac{\partial P_{t+\tau}}{\partial P_{t+\tau-1}} \frac{\partial P_{t+\tau-1}}{\partial P_{t+\tau-2}} \dots \frac{\partial P_{t+1}}{\partial Q_t} \frac{\partial Q_t}{\partial S_t} \right) \right]}_{\text{pollution change due to patent knowledge accumulation from extra P2}} \end{aligned}$$

All expressions are analogous to the expression for patents. The first term illustrates how the trajectory of pollution is lower due to an additional P2 practice. The second term is the same-knowledge accumulation effect that results from most recent new P2. The third term is the cross-knowledge accumulation effect because P2 affects patenting which then affects pollution. There are again adjustment factors in the second and third terms arising from how the effect of an initial P2 on pollution can encourage or discourage future P2 and future patenting. Because P2 occurring in the initial period lowers pollution immediately, $\frac{\partial Q_t}{\partial S_t} < 0$, the adjustment terms will reinforce (mitigate) the knowledge accumulation effects if lower pollution in the adoption year will encourage (discourage) subsequent patenting and P2, i.e., $\frac{\partial P_{t+1}}{\partial Q_t} < 0$; $\frac{\partial S_{t+1}}{\partial Q_t} < 0$ ($\frac{\partial P_{t+1}}{\partial Q_t} > 0$; $\frac{\partial S_{t+1}}{\partial Q_t} > 0$). All these effects will be felt 4 years after adoption because of the 2-year lagged effect of patent stock on new patent flow, the 2-year lagged effect of P2 stock on new P2 flow, and the 2-year lagged effect of P2 stock on patents.

Differentiating Eq. (3') with respect to S_t , on the year of adoption, the only effect we can see is the immediate effect, $\frac{dQ_t}{dS_t} = c_Q$.

One year after adoption at time $t + 1$, the effect of an extra P2 adopted at time t is:

$$\begin{aligned} \frac{dQ_{t+1}}{dS_t} &= \frac{\partial Q_{t+1}}{\partial Q_t} \left[\frac{\partial Q_t}{\partial S_t} \right] + \frac{\partial Q_{t+1}}{\partial S_{t+1}} \left[\left(\frac{\partial S_{t+1}}{\partial S_t} \right) + \left(\frac{\partial S_{t+1}}{\partial Q_t} \frac{\partial Q_t}{\partial S_t} \right) \right] \\ &+ \frac{\partial Q_{t+1}}{\partial P_{t+1}} \left[\left(\frac{\partial P_{t+1}}{\partial S_{t-1}^{stock}} \frac{\partial S_{t-1}^{stock}}{\partial S_{t-1}} \right) + \left(\frac{\partial P_{t+1}}{\partial P_{t-1}^{stock}} \frac{\partial P_{t-1}^{stock}}{\partial S_{t-3}} \frac{\partial S_{t-3}^{stock}}{\partial S_{t-3}} \right) \right] \\ &+ \left(\frac{\partial P_{t+1}}{\partial Q_t} \frac{\partial Q_t}{\partial S_t} \right) \end{aligned}$$

Substituting the coefficients from (1'), (2'), the expression at $t + 1$ is:

$$\begin{aligned} \frac{dQ_{t+1}}{dS_t} &= b_Q c_Q + c_Q [c_S + b_S c_Q] + d_Q [0 + 0 + b_P c_Q] \\ &= b_Q c_Q + c_Q [c_S + b_S c_Q] + d_Q b_P c_Q \end{aligned} \tag{A.7}$$

Two and three years after adoption, the general expression can be extended to incorporate longer pollution path dependence effects and longer adjustment in the P2 knowledge

accumulation term. We are also able to capture the first expression in the third term. The second expression in the third bracket will still be zero because we are interested in an extra P2 at time t and not any earlier.

$$\begin{aligned} \frac{dQ_{t+2}}{dS_t} &= \frac{\partial Q_{t+2}}{\partial Q_t} \left[\frac{\partial Q_{t+1}}{\partial Q_t} \frac{\partial Q_t}{\partial S_t} \right] + \frac{\partial Q_{t+2}}{\partial S_{t+2}} \left[\left(\frac{\partial S_{t+2}}{\partial S_{t+1}} \frac{\partial S_{t+1}}{\partial S_t} \right) + \left(\frac{\partial S_{t+2}}{\partial S_{t+1}} \frac{\partial S_{t+1}}{\partial Q_t} \frac{\partial Q_t}{\partial S_t} \right) \right] \\ &\quad + \frac{\partial Q_{t+2}}{\partial P_{t+2}} \left[\left(\frac{\partial P_{t+2}}{\partial S_t^{stock}} \frac{\partial S_t^{stock}}{\partial S_t} \right) + \left(\frac{\partial P_{t+2}}{\partial P_t^{stock}} \frac{\partial P_t^{stock}}{\partial P_t} \frac{\partial P_t}{\partial S_{t-2}^{stock}} \frac{\partial S_{t-2}^{stock}}{\partial S_t} \right) + \left(\frac{\partial P_{t+2}}{\partial P_{t+1}} \frac{\partial P_{t+1}}{\partial Q_t} \frac{\partial Q_t}{\partial S_t} \right) \right] \\ \frac{dQ_{t+3}}{dS_t} &= \frac{\partial Q_{t+3}}{\partial Q_{t+2}} \left[\frac{\partial Q_{t+2}}{\partial Q_{t+1}} \frac{\partial Q_{t+1}}{\partial Q_t} \frac{\partial Q_t}{\partial S_t} \right] + \frac{\partial Q_{t+3}}{\partial S_{t+3}} \left[\left(\frac{\partial S_{t+3}}{\partial S_{t+2}} \frac{\partial S_{t+2}}{\partial S_{t+1}} \frac{\partial S_{t+1}}{\partial S_t} \right) + \left(\frac{\partial S_{t+3}}{\partial S_{t+2}} \frac{\partial S_{t+2}}{\partial S_{t+1}} \frac{\partial S_{t+1}}{\partial Q_t} \frac{\partial Q_t}{\partial S_t} \right) \right] \\ &\quad + \frac{\partial Q_{t+3}}{\partial P_{t+3}} \left[\left(\frac{\partial P_{t+3}}{\partial P_{t+2}} \frac{\partial P_{t+2}}{\partial S_t^{stock}} \frac{\partial S_t^{stock}}{\partial S_t} \right) + \left(\frac{\partial P_{t+3}}{\partial P_{t+1}^{stock}} \frac{\partial P_{t+1}^{stock}}{\partial P_{t+1}} \frac{\partial P_{t+1}}{\partial S_{t-1}^{stock}} \frac{\partial S_{t-1}^{stock}}{\partial S_t} \right) \right] \\ &\quad + \left(\frac{\partial P_{t+3}}{\partial P_{t+2}} \frac{\partial P_{t+2}}{\partial P_{t+1}} \frac{\partial P_{t+1}}{\partial Q_t} \frac{\partial Q_t}{\partial S_t} \right) \end{aligned}$$

Substituting the coefficients from (1'), (2') and noting that depreciated cumulated stock of P2 can be expressed as $S_{it}^{stock} = \sum_{\tau} \delta^{\tau} S_{t-\tau}$:

$$\frac{dQ_{t+2}}{dS_t} = b_Q^2 c_Q + c_Q [c_S^2 + c_S b_S c_Q] + d_Q [c_{P2} \delta^0 + 0 + d_P b_P c_Q] \tag{A.8}$$

$$\frac{dQ_{t+3}}{dS_t} = b_Q^3 c_Q + c_Q [c_S^3 + c_S^2 b_S c_Q] + d_Q [d_{P1} c_{P2} \delta^0 + 0 + d_P^2 b_P c_Q] \tag{A.9}$$

Four years after an extra P2 adoption, all terms are non-zero:

$$\begin{aligned} \frac{dQ_{t+4}}{dS_t} &= \frac{\partial Q_{t+4}}{\partial Q_{t+3}} \left[\frac{\partial Q_{t+3}}{\partial Q_{t+2}} \frac{\partial Q_{t+2}}{\partial Q_{t+1}} \frac{\partial Q_{t+1}}{\partial Q_t} \frac{\partial Q_t}{\partial S_t} \right] + \frac{\partial Q_{t+4}}{\partial S_{t+4}} \left[\left(\frac{\partial S_{t+4}}{\partial S_{t+3}} \frac{\partial S_{t+3}}{\partial S_{t+2}} \frac{\partial S_{t+2}}{\partial S_{t+1}} \frac{\partial S_{t+1}}{\partial S_t} \right) \right. \\ &\quad \left. + \left(\frac{\partial S_{t+4}}{\partial S_{t+3}} \frac{\partial S_{t+3}}{\partial S_{t+2}} \frac{\partial S_{t+2}}{\partial S_{t+1}} \frac{\partial S_{t+1}}{\partial Q_t} \frac{\partial Q_t}{\partial S_t} \right) \right] + \frac{\partial Q_{t+4}}{\partial P_{t+4}} \\ &\quad \left[\left(\frac{\partial P_{t+4}}{\partial P_{t+3}} \frac{\partial P_{t+3}}{\partial P_{t+2}} \frac{\partial P_{t+2}}{\partial S_t^{stock}} \frac{\partial S_t^{stock}}{\partial S_t} \right) + \left(\frac{\partial P_{t+4}}{\partial P_{t+2}^{stock}} \frac{\partial P_{t+2}^{stock}}{\partial P_{t+2}} \frac{\partial P_{t+2}}{\partial S_t^{stock}} \frac{\partial S_t^{stock}}{\partial S_t} \right) \right] \\ &\quad + \left(\frac{\partial P_{t+4}}{\partial P_{t+3}} \frac{\partial P_{t+3}}{\partial P_{t+2}} \frac{\partial P_{t+2}}{\partial P_{t+1}} \frac{\partial P_{t+1}}{\partial Q_t} \frac{\partial Q_t}{\partial S_t} \right) \end{aligned}$$

Substituting the coefficients from (1'), (2') and noting that $S_{it}^{stock} = \sum_{\tau} \delta^{\tau} S_{t-\tau}$:

$$\frac{dQ_{t+4}}{dS_t} = b_Q^4 c_Q + c_Q [c_S^4 + c_S^3 b_S c_Q] + d_Q [d_{P1}^2 c_{P2} \delta^0 + d_{P2} \delta^0 c_{P2} \delta^0 + d_P^3 b_P c_Q] \tag{A.10}$$

Generalizing for all years $\tau \geq 1$, and simplifying

$$\frac{dQ_{t+4}}{dS_t} = b_Q^{\tau} c_Q + c_Q [c_S^{\tau} + c_S^{\tau-1} b_S c_Q] + d_Q [d_{P1}^{\tau-2} c_{P2} + d_{P2} \delta^{\tau-4} c_{P2} + d_{P1}^{\tau-1} b_P c_Q] \tag{A.11}$$

After multiplying (13) by \hat{S} , which represents what one extra P2 is as a proportion to mean P2, we derive Eq. (5) in Sect. 5.3.

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