Does Peer Adoption Increase the Diffusion of Pollution Prevention Practices?

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Abstract

Voluntary adoption of pollution prevention (P2) practices has been used to reduce toxic emissions in the US. Spillovers among facilities owned by the same firm likely play an important role in the diffusion of P2 practices. This paper estimates the intrafirm spillover effects of P2 adoption. Using instrumental variables methods applied to facility panel data from the Toxics Release Inventory, we find that a facility's own adoption of P2 practices increases in response to greater P2 adoption by facilities from the same firm. Intrafirm spillovers are stronger among small firms and firms with higher degree of sibling homophily.

Key words: pollution prevention, Toxics Release Inventory (TRI), diffusion, spillovers, intrafirm spillovers

JEL Codes: Q55, Q58

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1. Introduction

Production-related toxic wastes in the United States declined from 37.16 to 30.57 billion pounds from 1991 to 2017 (EPA, 2019), but reducing exposure to toxic wastes remains a primary concern for the public (Hamilton, 1995; Konar and Cohen, 1997; Fung and O'Rourke, 2000; Gruber, 2018). Significant reductions in toxic waste emissions can be partly attributed to voluntary adoption of Pollution Prevention (P2) practices (Harrington et al., 2014; Ranson et al., 2015; U.S. EPA, 2019). But observations from the Toxics Release Inventory (TRI), a public information disclosure program on toxic emissions, indicate that wide differences in the intensity of P2 adoption persist across firms as well as within facilities owned by the same parent firm. Quantifying the factors driving such persist heterogeneity will aid the policy push to reduce use of hazardous materials and greenhouse gas emissions through P2 (Reibstein, 2009).

Use of P2 practices can be viewed through the lens of technology adoption and diffusion. While a rich literature exists on the diffusion of technologies across firms, less is known about intrafirm diffusion and characteristics of networks within firms that might facilitate or hamper the spread of technology (Abrahamson and Rosenkopf, 1997; Guler et al., 2002; Battisti and Stoneman, 2003; 2005; Hollenstein and Woerter, 2008). This gap in the literature persists despite significant evidence for the important role played by individual facilities and their managers in adopting new technologies and practices (Gupta and Govindarajan, 2000; Van Everdingen and Wierenga, 2002; Battisti and Stoneman, 2003; Delmas and Toffel, 2004; 2008; Lenox and King, 2004; Doshi, Dowell, and Toffel, 2013). Improved understanding of intrafirm P2 adoption spillovers and the firm-level characteristics that shape them could lead to better targeting of P2 promotion efforts.

In this paper, we study intrafirm spillover effects in the context of P2 adoption. More specifically, we estimate the extent to which an increase in P2 knowledge stock, measured by the cumulative adoption of P2 practices among sibling facilities with the same firm, increases own adoption of new P2 practices at the facility level. In addition, we examine how the characteristics of the knowledge-sharing network linking facilities of the same firm shapes the spillover effect of a change in knowledge stock. We use a panel dataset consisting of 10,224 manufacturing facilities associated with all US firms that had at least two TRI facilities at any point from 1991 through 2011. The length and comprehensive nature of the TRI data allow us to examine two decades of P2 adoption by public and private facilities that account for about 50% of U.S. manufacturing output (Berchicci, 2013).

Time-varying unobserved firm-level shocks may affect the adoption of P2 practices, making sibling P2 stock endogenous in a regression model of own P2 adoption. We address endogeneity by using twice-lagged state and federal inspections of sibling facilities as instrumental variables. We control for each facility's own lagged P2 adoption, facility size, own state and federal inspections, as well as fixed effects and time trends at the firm level. Conditional on these factors, we expect that sibling inspections are only correlated with facility's own P2 adoption through their correlation with lagged cumulative adoption by siblings.

We find that a TRI facility will increase adoption of new P2 practices by 20-23% in response to a one standard deviation increase in the stock of P2 practices from siblings. To explore how intrafirm network characteristics shape spillovers, we interact lagged cumulative adoption by siblings with measures of each firm's geographic scope (number

of states in which they operate), size (number of siblings), and similarity among siblings (share of siblings belonging to the same industry). We find that larger firm size and geographic scope impede the intrafirm diffusion of P2 practices, whereas a higher degree of similarity among siblings enhances intrafirm diffusion. Our findings are robust to alternative specifications where we change our set of covariates and instruments.

Most existing studies have focused on the effects of environmental inspection, community pressure, state-level P2 policy, and implementation of environmental management systems on P2 adoption by TRI facilities (Harrington, 2012, 2013; Khanna, Deltas, and Harrington, 2009; Sam, 2010). Our work is most closely related to Harrington (2012, 2013), who finds that a 10% increase in the average number of P2 practices adopted by sibling facilities results in an increase in own facility-level P2 adoption of about 3%.

We build on the work of Harrington (2012, 2013) and other previous studies in several ways. First, the sample used in Harrington (2012, 2013) consists of firms listed in the S&P 500 from 1991 to 2001. In contrast, we use a panel dataset of 10,224 facilities from all firms with at least two TRI facilities observed from 1991 through 2011, potentially giving our study strong external validity. Second, previous efforts to econometrically identify the effect of sibling adoption of environmental practices on own adoption have relied on Poisson fixed effects models without addressing endogeneity stemming from time-varying unobservables (Harrington 2012, 2013). Our empirical strategy allows for time-varying shocks that may be correlated with own adoption and knowledge stock from the siblings but not with our instruments.

2. Background and related literature

Disclosure of polluter P2 records through the highly-publicized TRI is one of the main policy instruments used to encourage polluters to voluntarily reduce toxics, as some TRI pollutants are not directly regulated (Khanna, 2001). The U.S. EPA established the TRI in 1987. All facilities above reporting thresholdsⁱ in selected industries annually report detailed information on their toxic emissions through direct releases and waste management through treatment for each TRI-listed chemical. The TRI has experienced several expansions since then, and the most significant extension was to include the reporting of recycling and P2 practices in 1991.

The U.S. EPA maintains an information clearinghouse allowing firms to exchange information on P2 while providing grants and technical assistance for P2 efforts (U.S. EPA, 2010). Around 36 U.S. states have their own P2 rules requiring additional reporting or planning to encourage P2 adoption (O'Rourke and Lee, 2004; Harrington, 2013). The disclosure rules associated with being listed in the TRI have motivated firms to voluntarily adopt P2 practices, participate in voluntary environmental programs, and reduce toxic emissions in response to pressure from the market, the public, and stakeholders (Hamilton, 1995; Khanna, 2001; King and Lenox, 2000; Maxwell and Decker, 2006; O'Rourke and Lee, 2004; Bi and Khanna, 2012, 2017).

Adoption of P2 practices allows facilities to improve their environmental performance in two ways. First, adopting P2 practices enables facilities to control costs related to complying with environmental regulations (Christmann, 2000; Sam 2010; Harrington, 2012, 2013), and may provide cost advantages over competitors (Christmann, 2000). Second, the pro-environmental signal sent by P2 adoption may reduce pressure on

91 facilities from outside organizations like environmental interest groups and local
92 authorities (Konar and Cohen, 1997; Khanna, 2001; Khanna, Deltas, and Harrington, 2009;
93 Harrington, 2012 and 2013). As suggested by the literature on technology diffusion, the
94 total benefits of P2 adoption will depend on the intensity of adoption by subsidiaries within
95 firms as well as the number of firms adopting P2 practices (Battisti and Stoneman, 2003;
96 2005; Hollenstein and Woerter, 2008).

97   Although parent firms may make decisions regarding P2 adoption, enforcing
98 adoption by individual facilities may be challenging. Even if a parent firm pushes its
99 subsidiaries to uniformly adopt a given management practice, subsidiaries may vary in
100 their adoption intensity or not adopt at all because of heterogeneity in absorptive capacity
101 or responses to institutional pressure (Oliver, 1991; Rosenzweig and Singh, 1991; Tsai,
102 2001; Gupta and Govindarajan, 2000; Delmas and Toffel 2004; 2008; Escribana and Tribo,
103 2009; Doshi et al., 2013). In the case of environmental practices, case studies suggest that
104 subsidiary adoption is often much lower than expected by corporate management (Lenox,
105 King, and Ehrenfeld, 2000). Surveys of facility managers indicate that the decision to adopt
106 an environmental practice is often up to individual facility managers, and that managers
107 balance financial, environmental, community, and regulatory pressures from the parent
108 firm as well as external stakeholders while not considering impacts on other facilities
109 (Delmas and Toffel 2004; 2008).

110   Recognizing the limitation of the corporate top-down approach for promoting the
111 diffusion of P2, U.S. EPA published an organizational guide that encourages a systematic
112 bottom-up approach. This approach focuses on subsidiaries with parent firm endorsement
113 and dissemination (U.S. EPA, 2001) to initiate P2 innovations. Consistent with the

approach taken by EPA, our conceptual and empirical framework consider facilities as the decision makers regarding the adoption of P2 practices and examine how the practice of P2 is adopted across facilities as a consequence of knowledge diffusion within a firm.

3. Conceptual framework

We assume that facilities update their expectations of the benefits of adopting a given P2 practice prior to making any new adoption decisions in the current period, and that the updating process accounts for experience from own adoption and that of peers (Westphal, Ranjay, and Shortell, 1997; Guler, Guillén, and Macpherson, 2002). P2 adoption is costly, not only because a new P2 practice may require investment to adjust management practice, production techniques, and equipment (Jaffe et al., 2003), but also because proper P2 implementation requires information and knowledge. A facility's own past P2 adoption and the cumulative P2 adoptions by sibling facilities affects its present P2 adoption through two channels: reducing costs (monetary and otherwise) of knowledge and information acquisition and updating beliefs with respect to net benefits of P2 adoption. For example, by observing the adoption practices of sibling facilities, facility managers can reduce the cost of implementing new P2 practices by imitating the choices of successful siblings. By learning from own past experience and from observing the experiences of sibling facilities, facility managers can improve their ability to assimilate information on previously unfamiliar P2 practices. Finally, own past experience with P2 adoption can have a demonstration effect that makes it easier to leverage external support for additional P2 adoption. Each of these cost-reduction mechanisms is described in previous literature (Lenox and King, 2004; Cohen and Levinthal, 1989). New knowledge and information

acquired through own experience and that of sibling facilities is then used to update the beliefs of facility managers prior to making additional P2 adoption decisions.

Descriptive evidence suggests that our assumptions are appropriate in the context of P2. Harrington (2013) finds that a facility's P2 adoption in the current period is correlated with its own lagged P2 adoption. In addition, the role of learning from peers is supported by a large literature in technology adoption (e.g., Besley and Case, 1993; Doring and Schnellenbach, 2006; Harrington, 2012; Brouhle, Graham, and Harrington, 2013). In our study, the relevant set of peers consists of sibling facilities. The existing literature suggest that facilities are more likely to trust and learn from their siblings than facilities of other firms about new practices (Singh, 2005; Hollenstein and Woerter, 2008). But the ease with which knowledge and information about P2 practices will diffuse among facilities of a given parent company will depend on the intrafirm network linking sibling facilities. We explore the issues above more formally in the next section.

Model of diffusion

To approximate the process of learning among sibling facilities and from own past experience, we follow the theoretical framework outlined in Bass (1969) and applied by Midgley, Morrison, and Roberts (1992) and Flight and Palmer (2013).ⁱⁱ The original Bass (1969) model was used to depict a S-shaped cumulative adoption curve of a product over time and while assuming that the flow of information from earlier adopters moderated by the existing number of adopters and total anticipated number of adopters over time (market size) will shape the rate of adoption.

As shown in equation (1), we adapt the Bass (1969) framework to the adoption of P2 practices. In equation (1), P2 practices adopted in year t by facility i in a firm j (T_{ijt}) are influenced by external communications from other facilities within a firm ($s_{(i)jt-1}$). The strength of the influence of other facilities is governed by a parameter (P_{jt}) whose value depends on the network linking facilities within the same firm. Other factors affecting P2 adoption include the facility's ceiling on the total number of P2 practices that can be adopted over the study period (m_i), the facility's ability to internalize its previous experience on adoption of P2 practices (q_i), the facility's own cumulative adoption of P2 practices through the previous year ($\sum_{t=1}^{t-1} T_{ijt-1}$), and other characteristics that might affect diffusion (X_{ijt}), such as technological changes affecting all facilities in the same industry, shocks affecting all facilities in the same location, public and regulatory pressures to reduce toxic emissions, and output demand shocks:

$$T_{ijt} = \theta * P_{jt} * s_{(i)jt-1} + \beta * q_i * \frac{\sum_{t=1}^{t-1} T_{ijt-1}}{m_i} * (m_i - \sum_{t=1}^{t-1} T_{ijt-1}) + X_{ijt}' \gamma \quad (1)$$

Note that $s_{(i)jt-1} = \sum_{k \neq i}^J \sum_{t=1}^{t-1} T_{kjt-1}$ (i.e. practices adopted by siblings through $t - 1$ equals the sum of sibling adoption through $t - 1$), and J represents the total number of facilities within firm j .

The functional form of equation (1) and the ceiling on P2 adoption given by m_i ensure that the relationship between time and total P2 practices adopted by facility i can be represented by an S-shaped curve, with total practices initially increasing at an increasing rate, then increasing at a decreasing rate, and finally hitting an adoption ceiling. S-shaped curves have been used to describe technology adoption since the classic work of Griliches on hybrid corn (Griliches, 1957), on new product adoption (Bass, 1969), and many other

cases of diffusion (e.g., Mahaja et al., 1995; Bass, 2004). Other studies adopt the framework of Bass to study intra-firm diffusion of organizational practices and innovations (e.g., Midgley et al., 1992; Flight and Palmer, 2013; Tsai, 2008; van Everdingen and Wierenga, 2002).

Equation (1) shows that as P_{jt} increases, knowledge flow within the firm improves, and the effect of cumulative sibling knowledge on the facility's decision to adopt P2 practices becomes stronger. Equation (1) also shows that cumulative sibling knowledge indirectly affects facility i 's adoption through own past adoption. As $s_{(i)jt-1}$ increases, T_{ijt} and $\sum_{t=1}^{t-1} T_{ijt-1}$ will increase, and a higher value of $\sum_{t=1}^{t-1} T_{ijt-1}$ implies increased adoption by facility i in period $t + 1$ (T_{ijt+1}). Furthermore, as the number of P2 practices adopted by facility i at time t ($\sum_{t=1}^{t-1} T_{ijt-1}$) increases, the value of the spillover variable affecting other facilities besides i (e.g., $s_{(k)jt}$ for $k \neq i$) increases as well. The higher value of the spillover variable faced by facilities other than i at time t will increase other facilities' P2 adoption in period $t + 1$. In other words, the effect of $s_{(i)jt-1}$ on T_{ijt} is amplified over time through multiple feedback channels.

Additionally, as facility i 's own cumulative knowledge ($\sum_{t=1}^{t-1} T_{ijt-1}$) increases, the number of new practices adopted in the next period will increase but at a decreasing rate as a result of the capacity limitation set by m_i and the functional form of equation (1). As the firm's ceiling of adoption (m_i) increases, the adoption of new P2 practices increase given that the partial derivative of T_{ijt} with respect to m_i is positive. As the facility's own ability to internalize its past P2 knowledge (q_i) increases, facility's new adoption of P2 practices will increase, because the marginal effect of q_i is positive given m_i is at least as

large as $\sum_{t=1}^{t-1} T_{ijt-1}$. The marginal effect of cumulative adoption on current becomes zero when $m_i = \sum_{t=1}^{t-1} T_{ijt-1}$ and the ceiling of the total number of P2 practices is reached.

Factors affecting knowledge flow within a firm

The existing literature shows a positive relationship between adoption of environmental practices and the strength of connections among siblings (Ochsner and Chess, 1996; Sharma and Vredenburg, 1998; Van Everdingen and Wierenga, 2002; Lenox and King, 2004; Bhupendra and Sangle, 2015). Features such as familiarity among members of a network and homophily (i.e. similarity among members) can enhance knowledge transmission within a network (Inkpen and Tsang, 2005; Kremer and Miguel, 2007; Oster and Thornton, 2009; Szulanski, 1996).

We are interested in examining the impact of homophily on a facility's absorption of previous knowledge generated by sibling P2 adoption. Therefore, we allow the impact of lagged cumulative sibling P2 adoption to depend on the degree of similarity among siblings. We approximate similarity by calculating the percentage of siblings that operate in the same industry (where industry is classified by a facility's primary 2-digit SIC code). We expect the strength of spillover effects to increase with the number of siblings operating in the same industry.

We also test whether the intrafirm spillover effect is increasing or decreasing in parent firm size. Information dissemination within a firm may depend on adjustment, training employees, and intrafirm coordination (Jaffe, Newell and Stavins, 2003). Although large firms may be better able to finance technology adoption than small firms (Karshenas and Stoneman, 1993, 1995; Florida and Davison, 2001; Snyder, Miller, and Stavins, 2003), small firms have been found to intensify their subsequent adoption faster than larger firms

after the initial adoption of a new technology. Greater speed and intensity of adoption among small firms may be a result of relatively low coordination and monitoring costs (Fuentelsaz, Gomez, and Polo, 2003). At the same time, having a larger number of facilities could translate into a greater quantity and diversity of knowledge and larger spillover effects among siblings (Gupta and Govindarajan, 2000; Todo, Matous, and Inoue, 2016).

Additionally, the pattern of knowledge diffusion within a firm may be influenced by the geographic dispersion of knowledge (Singh, 2005). To shed light on this possibility, we explore the relationship between P2 diffusion and the geographic scope of operation. Earnhart and Leonard (2013, 2016) find that facilities from firms that operate in multiple states employ more environmental audits than other facilities. They suggest that firms operating in multiple states are more visible to regulators and therefore more likely to implement best practices in all subsidiaries to reduce potential regulatory conflicts. But having operations across different states may increase the effort needed to disseminate knowledge and reduce effective communication among subsidiaries. Previous studies show that proximity between senders and recipients of information matters, as neighbors tend to share informal social interactions, share more trust, use common resources, and face similar pressures (Downing and White, 1986; Besley and Case, 1993; Jaffe, Trajtenberg, and Henderson, 1993). Additionally, the effect of sibling's cumulative P2 adoption by an out-of-state sibling facility may be small if facilities in different states face different environmental issues or regulatory frameworks. Hence, we test whether the effect of P2 spillovers are positively or negatively correlated with the geographic scope of operation as defined by the number of states in which a parent firm operates.

4. Empirical approach

Given the above conceptual framework, we estimate the effects of own lagged P2 adoptionⁱⁱⁱ and cumulative P2 knowledge among sibling facilities on facility-level P2 adoption, while allowing the latter effect to vary with firm-level network characteristics. We begin with the empirical specification shown in equation (2) below:

$$T_{ijzdt} = \alpha_i + \delta_j t + \beta_1 T_{ijzdt-1} + \beta_2 s_{(i)jt-1} + X_{ijzdt-1}' \beta_3 + P_{jt}' \beta_4 + C_{zt}' \beta_5 + \rho_{dt} + \pi_{zt} + s_{(i)jt-1} \times (P_{jt} - \overline{P_{jt}})' \theta + \lambda_{jt} + v_{it} \quad (2)$$

In equation (2), the dependent variable (T_{ijzdt}) represents the number of new P2 practices adopted by facility i of firm j in industry d and state z in year t , while $T_{ijzdt-1}$ is its lag. Our main explanatory variable of interest, $s_{(i)jt-1}$, represents the cumulative number of P2 practices adopted by sibling facilities of the same firm j through year $t - 1$. Note that we use facilities that were siblings at time $t - 1$ to calculate $s_{(i)jt-1}$, even if a change in ownership occurred at time t . The vector $X_{ijzdt-1}$ contains facility characteristics observed in year $t - 1$, while P_{jt} is a vector of firm j 's network characteristics observed in year t .

To absorb unobserved correlates of own P2 adoption that might also be correlated with our main explanatory variables of interest, we include fixed effects for facility i , industry d in year t , and state z in year t . These fixed effects are given by α_i , ρ_{dt} , and π_{zt} , respectively. $\delta_j t$ is a firm-level linear time trend, λ_{jt} is a time-varying shock that is shared by all facilities in firm j , and v_{it} is a time-varying shock specific to facility i . Examples of firm-specific or facility-specific shocks that would not be absorbed by industry-year or

state-year fixed effects might include localized demand shocks, changes in ownership, or unobserved changes in public pressure to adopt P2 practices directed at individual firms or facilities. The latter two terms comprise the regression error. Note that we subtract sample means from each network characteristics P_{jt} prior to creating the interaction terms thereby ensuring that β_2 in equation (2) is properly interpreted as the average marginal effect of $s_{(i)jt-1}$ (Wooldridge, 2010).

Variable construction

The dependent variable in equation (2) is a non-negative integer, as only the adoption of incremental (new) P2 practices are reported to TRI on an annual basis.^{iv} We use a log-linear specification in estimation following Narayanan and Nair (2013). Specifically, we applied the inverse hyperbolic sine transformation to convert the dependent variable into a natural log value and to ensure positive conditional mean (Yen and Jones, 1997).^v This log-linear specification allows us to use instrumental variables to control for the endogeneity of facility's own lagged adoption ($T_{ijzdt-1}$) and cumulative number of practices adopted by sibling facilities ($s_{(i)jt-1}$), while controlling for large number of state, industry, and year fixed effects. While an obvious alternative approach would be to use a Poisson model, we are not aware of any Poisson estimators that are appropriate for high-dimensional fixed effects, lagged dependent variables, and endogenous explanatory variables.

Our measure for $s_{(i)jt-1}$ is the total number of new P2 practices reported by sibling facilities of the same parent firm, beginning in 1991 up to the preceding year. We refer to this variable as *Sibling P2 Stock* hereafter. We use a cumulative measure because knowledge is cumulative. Similar measures have been used in the literature to represent

the “installed base” or the knowledge stock of earlier adoptions when examining the effect of contagion in marketing (e.g., Narayanan and Nair, 2013). However, we check the robustness of our results to allowing the effect of sibling knowledge to decay over time.

Our effect of interest is an example of what is known as an “endogenous effect” in the networks literature, i.e. the response of individual behavior to group behavior. According to Manski (1993), correlated effects (similar behavior among group members is a result of shared characteristics or environments) and contextual effects (individual behavior is a function of group characteristics) could give rise to spurious correlation between adoption decisions at individual facilities and adoption decisions by siblings. To minimize the risk of bias from contextual effects, we control for time-varying firm characteristics (P_{jt}) and firm-level time trends. The latter will control for firm-specific unobserved determinants of P2 adoption that are changing systematically over time. Our industry-year and state-year fixed effects will control for time-varying shocks common to all facilities within an industry or state in a given year, purging our estimates of one potential source of bias from correlated effects.

Facility-level covariates include the number of employees as in Lenox and King (2004) and the amount of toxic releases reported by the facility in the previous period as in Harrington (2012, 2013). Following previous studies, both variables are in natural log form to reduce skewness and are lagged by one year. To control for the size of the firm relative to other firms in the industry, we use *Percentage of a Firm’s Sales in an Industry* (where industry is defined by the 4-digit SIC code of the parent firm).

Finally, we control for the local industrial agglomeration effect using the number of TRI facilities in a county. The clustering of toxic facilities can attract the attention of

regulators (Gray and Shadbegian, 2007), which may lead facilities to adopt more P2 practices to abate pollution. Meanwhile, the number of toxic facilities could generate an agglomeration effect that lowers the costs of adopting P2 practices. We include the unemployment rate of the county in which the toxic facility is located to control for community pressure on facilities to voluntarily adopt P2 practices and reduce reliance on toxic materials (Earnhart, 2004). We would expect unemployment to be inversely related with public pressure for reduced emissions.

To assess whether intrafirm spillover effects vary with network characteristics, we allow the effect of $s_{(i)jt-1}$ to depend on network size, homophily, and geographic scope. We create dummy variables based on the sample distribution of each network variables to avoid imposing linearity of the impact of network variables on spillover effects. More specifically, for each network characteristic we create two dummy variables: a dummy that is equal to one for any facility with a value above the median for the network characteristics in question and zero otherwise, and another dummy variable equal to one for facilities with values above the 75th percentile and zero otherwise. By interacting each of these dummy variables with our measure of sibling knowledge, we can check whether the spillover effect is a nonlinear function of firm size without imposing strong functional form assumptions.

We take the first difference of equation (2) prior to estimation, thereby eliminating facility-level fixed effects as well as firm-level fixed effects for facilities that did not change ownership over the observed time horizon.

After taking first differences, we have equation (3), in which δ_j represents the first-differenced firm-specific linear time trend and $\Delta\lambda_t$ is the first-differenced firm-level shocks.

$$\Delta T_{ijzdt} = \delta_j + \Delta \mu_t + \beta_1 \Delta T_{ijzdt-1} + \beta_2 \Delta s_{(i)jt-1} + \Delta X'_{ijzdt-1} \beta_3 + \Delta [s_{(i)jt-1} \times (P_{jt} - \overline{P_{jt}})]' \theta + \Delta P'_{jt} \beta_4 + \Delta C'_t \beta_5 + \Delta \rho_{dt} + \Delta \pi_{zt} + \Delta \lambda_{jt} + \Delta v_{it} \quad (3)$$

341

342 Recall that $s_{(i)jt-1}$ is constructed by summing P2 adoption for sibling facilities through
 343 year $t - 1$, i.e. summing the dependent variable in equation (3) for all sibling facilities
 344 through the previous year. Since T_{ijzdt} is a function of λ_{jt} , and the latter is common to all
 345 facilities of firm j , $s_{(i)jt-1}$ will be a function of the firm-specific shocks $\{\lambda_{j1}, \dots, \lambda_{jt-1}\}$.
 346 After taking first differences, ΔT_{ijzdt} is a function of $\Delta \lambda_{jt}$ while $\Delta s_{(i)jt-1}$ is a function of
 347 $\Delta \lambda_{jt-1}$. In other words, $\Delta s_{(i)jt-1}$ is endogenous in equation (3) even after taking first
 348 differences. The sign of the bias will depend on the autocorrelation structure of $\Delta \lambda_{jt}$. If λ_{jt}
 349 follows an AR(1) process or is not autocorrelated, estimates of the spillover effect that do
 350 not address endogeneity will be downward biased. The sign of the bias is ambiguous under
 351 more complex autocorrelation structures.

352 To deal with the endogeneity of $\Delta s_{(i)jt-1}$, we employ two instrumental variables:
 353 the second lag of the average number of inspections of sibling facilities by the EPA, and
 354 the second lag of the average number of inspections of sibling facilities by state agencies.
 355 In other words, to calculate each instrument we add up the number of times sibling facilities
 356 were inspected by the EPA or state agencies (as the case may be) and divide by the number
 357 of siblings. For environmental inspections, we focus on inspections under the Clean Air
 358 Act (CAA) because 78% of the toxic air releases reported in the TRI are emitted into the
 359 air (EPA, 2019; Harrington, 2012, 2013).

360 For our instruments to be valid, they must have predictive power with respect to
 361 lagged cumulative sibling P2 adoption and satisfy the exclusion restriction. We use the

second lag of inspections to predict the first lag of cumulative sibling P2 adoptions because polluters form their expectations with respect to regulatory threats based on previous inspections (Shimshack and Ward, 2005, 2008). Previous studies have shown that facilities adopt P2 practices to avoid compliance costs or reduce future inspections (Sam, 2010; Harrington, 2012). An increase in the average number of inspections on sibling facilities owned by the parent firm two years before the current period may lead siblings to adopt more P2 practices one year prior to the current period, which would give our instruments predictive power with respect to cumulative lagged sibling P2 adoption.

We believe the exclusion restriction is likely to hold because any direct effect of sibling inspections on own P2 adoption is likely to operate through impacts on own inspections. For example, a facility manager observing an increase in inspections of siblings may adopt additional P2 practices in response, but only because she expects a greater number of inspections on her facility in the near future. Although we cannot directly observe expectations regarding own inspections, the exclusion restriction seems likely to hold once we condition on facility's own lagged environmental inspections as well as all other terms held fixed in equation (3). Additionally, environmental inspection is likely driven by policy and enforcement variation across industries and states, as well as the ability of the community around polluters to apply public pressure (Helland, 1998). These factors driving inspections on siblings in the lagged periods are likely to be exogenous to a facility's own environmental performance in the current period. Nevertheless, we subject our identifying assumptions to robustness checks, as described later in the paper.

Finally, since we include own lagged adoption in equation (3) to control for facility's learning from its own experience, we use the second lag of facility's own P2

adoption ($T_{ijzdt-2}$) as an instrument to deal with the endogeneity of $\Delta T_{ijzdt-1}$. Following the literature on dynamic panel data models (Anderson and Hsiao, 1981), we assume that sequential exogeneity holds, i.e. that the error term in equation (3) is uncorrelated with past values of own and sibling P2 adoption but may be correlated with their future values (Wooldridge, 2010). If sequential exogeneity holds, the validity of the exclusion restriction is ensured. To summarize, we use 2SLS IV estimation on two endogenous variables (lagged Spillover and Lagged own P2 adoption) with three instrumental variables (second lag of own P2 adoption and second lags of the average number of inspections on siblings by state and EPA). We test orthogonality of the IVs to the error terms and their correlation with the endogenous variables using Hansen’s J statistics and rk statistics, respectively (Baum, Shaffer, and Stillman 2005). To assess endogeneity, we compare the spillover effect obtained with and without instrumental variables using a Hausman test.

5. Data

Our data include manufacturing facilities (2-digit SIC codes between 20 and 40) located in the lower 48 U.S. states that belong to a firm with at least two TRI facilities from 1991 to 2011. In 1995, 1998, 2000, 2001, and 2011, the EPA changed the TRI chemical requirements and the reporting thresholds to include more reportable chemicals and industry sectors (U.S. EPA, 2017). In this analysis, we focus on 295 chemicals that have been consistently reported to the TRI from 1988 onwards and refer to them as the core chemicals. Both the dependent variable and *Sibling P2 Stock* are based on the total number of P2 practices for the 295 core chemicals reported by a facility in a given year.

To access data on facility and firm characteristics other than P2 adoption and emissions, we use facility-specific data from the National Establishment Time-Series (NETS) database (Walls and Associates, 2011).^{vi} In order to merge the TRI with the NETS database, we used the facility TRI identifier provided by the NETS, to merge the TRI with the NETS database. The resulting set of facility characteristics includes annual sales (in dollars), number of employees, facility ownership type, facility and headquarters location, SIC codes, and Dun and Bradstreet (D&B) parent company identification numbers. We identify sibling facilities as those that belong to the same parent company in a given year using parent company information.

To obtain data on the inspections and penalties incurred by each facility, we use the facility TRI identifier to merge our data set with the EPA's AIRS Facility Subsystem database (U.S. EPA, 2012). We aggregate the total number of inspections at a facility each year and separate inspections conducted by EPA and local state agencies. We use the county and state location of each facility to merge the dataset on county-level unemployment rate (U.S. BLS, 2011).

Appendix Figure 1 shows the percentage of TRI facilities in our sample that reported the adoption of P2 practices at least once. Since the inception of P2 reporting, the rate of adoption increased, then fell over time, following an S-shaped curve. Appendix Figure 2 shows that the average number of new P2 practices adopted each year by TRI facilities declined from 1.5 to 0.25 over the sample period, perhaps because the marginal benefits of additional P2 practices decreased once a facility began to adopt P2 practices (Sam, 2010; Harrington 2012, 2013). Additionally, the firm-level *Sibling P2 Stock* increased from 10 to 90 over the sample period as shown in the Appendix Figure 3.

Table 1 provides summary statistics of the explanatory variables, instrumental variables, and dependent variable used in the empirical analysis.

[Insert Table 1]

6. Results

First stage results

Estimates corresponding to the first-stage estimation of equation (3) are presented in Table 2. In columns 1 and 2, we present the coefficients and the standard errors from regressing the first-differenced lagged own adoption ($\Delta T_{ijzdt-1}$) on three instrumental variables and other covariates. Columns 3 and 4 report the coefficients and the standard errors from regressing lagged first-differenced sibling P2 stock ($\Delta s_{(i)jt-1}$) on the same set of variables. As expected, the number of P2 practices adopted by a facility two periods prior ($T_{ijzdt-2}$) is negative and strongly correlated with $\Delta T_{ijzdt-1}$ by construction, since $\Delta T_{ijzdt-1} = T_{ijzdt-1} - T_{ijzdt-2}$ (column 1, row 1, table 2).

Environmental inspections on sibling facilities two periods prior are significantly correlated with the lagged first-differenced stock ($\Delta s_{(i)jt-1}$) (column 3, rows 2 and 3), but they do not significantly affect facility's own first-differenced lagged adoption ($\Delta T_{ijzdt-1}$, column 1, rows 2 and 3, table 2). As we would expect, the coefficients on each of the two instrumental variables on inspections for $\Delta s_{(i)jt-1}$ are negative, since each instrument is likely to be positively correlated with $s_{(i)jt-2}$, and $\Delta s_{(i)jt-1} = s_{(i)jt-1} - s_{(i)jt-2}$. The Hansen's J statistics for orthogonality of all three instruments is not statistically significant at the 5% significance level, implying that we cannot reject orthogonality of the instruments. The instruments are strongly correlated with the endogenous variables,

indicated by the statistically significant rk statistics. Note that the rk statistics are valid even with a non-i.i.d. error term (Baum, Shaffer, and Stillman, 2005; Correia, 2017). Additionally, Hausman test on the estimated coefficients on *Sibling P2 Stock* with and without IV rejects the null hypothesis that the two effects are equal (test statistics $\chi^2(1) = 6.739$, p-value = 0.001), implying that IV is indeed necessary.

[Insert Table 2]

Main results

Column 1 of Table 3 presents our estimates of equation (3) without the interactions between lagged *Sibling P2 Stock* and parent firm network characteristics. Columns 2 through 4 of Table 3 present the results with the network characteristics and their interactions with lagged *Sibling P2 Stock*. We estimate one interaction effect in each model because collinearity prevented precise estimation of all effects in a single specification. More specifically, in column (2) we drop our continuous measure of firm size “Number of siblings” and replace it with an indicator for having more than the median number of siblings, an indicator for having more than the 75th percentile quantity of siblings, and interact the two indicators with *Sibling P2 Stock*. In columns (3) and (4) we proceed in a similar manner for number of states in which the firm operates and percent of siblings in the same industry, respectively.

[Insert Table 3]

As shown in the first row of Table 3, lagged own P2 adoption has a positive and significant effect on own P2 adoption in the current period. The reported coefficient on lagged own P2 adoptions is properly interpreted as an elasticity because P2 practices are in natural log form. The results shown in row 1 of Table 3 indicate a 10% increase in the

adoption of P2 practices in the previous year causes a 4.9% increase in the adoption of P2 practice in the current year, on average.

Lagged *Sibling P2 Stock* also has a positive and significant effect on own P2 adoption in the current period (row 2 of Table 3), where a 10% increase in the total number of P2 practices adopted by sibling facilities up to the preceding year increases own adoption of P2 practices in the current year by between 0.77% and 0.90% on average. To put our results in context, consider that the mean of lagged *Sibling P2 Stock* is 66 with a standard deviation of 171. Our estimated coefficient indicates that a one standard deviation increase in the lagged *Spillover P2 stock* above the sample mean will increase a facility's adoption of P2 practices by 20% to 23% in the current period.

In comparison to own lagged P2 adoption by a facility itself, the direct effect of intrafirm spillover approximated by the lagged *Sibling P2 Stock* is much smaller, a result that is consistent with findings in Harrington (2013). But the importance of spillover effects in spurring P2 adoption is understated by only looking at the results in Table 3. As we discussed in the conceptual framework, spillovers are amplified by multiple feedback channels over the long term. Spillovers give rise to a feedback effect wherein P2 adoption by siblings in the previous period increases a facility's own adoption of P2 practices in the current period, and this facility's own adoption will then create a spillover effect onto adoption by sibling facilities in the next period. We demonstrate the importance of the feedback effect over time using a simulation after presenting the remainder of our econometric results.

Heterogeneous spillover effects

In columns 2 through 4 of Table 3, we allow the effect of lagged *Sibling P2 Stock* to depend on the firm's network characteristics. Since network characteristics may be correlated with unobserved determinants of own P2 adaptations, we do not claim that the interaction terms measure the casual effect on the impact of lagged *sibling P2 stock* bought about by changing network characteristics. Rather, our interaction terms will accurately describe how the average effect of lagged *Sibling P2 Stock* varies in our population of interest as a function of observed network characteristics.

In column 2 we present results obtained by adding firm size dummies and their interactions with lagged *Sibling P2 Stock* to the model. Recall that our firm size variables include a dummy equal to one for facilities owned by firms with more than the median number of facilities (i.e. six TRI facilities) and another dummy equal to one for facilities owned by firms with more facilities than the firm at the 75th percentile (i.e. fourteen TRI facilities). The interaction terms are found in the fifth and sixth rows of Table 3, while the result in the second row can again be interpreted as the average spillover effect.

For facilities owned by firms above the median size, the coefficient of -0.063 reported in the fifth row indicates that the average response to a 10% increase in lagged *Sibling P2 stock* is 0.63 percentage points lower than the average response among facilities owned by firms at or below the median. For facilities owned by firms above the 75th percentile in size, both size dummy variables are equal to one. The sum of the interaction term coefficients reported in rows five and six (-0.063 and -0.021) is almost equal to the average spillover effect, indicating that the average spillover effect is approximately zero for firms beyond the 75th percentile of size.

Column 3 reports results obtained when allowing the effect of lagged *Sibling P2 Stock* to depend on the parent firm's geographic scope. Once again, we create two dummy variables: a dummy equal to one for facilities owned by firms operating in more than the median number of states (i.e. four states) and another dummy equal to one for firms operating in more states than the firm at the 75th percentile (eight states). As indicated by the results reported in rows five and six of column 3, greater geographic scope is associated with a smaller average spillover effect. For example, the average spillover effect is -0.021 lower among firms operating in more than eight states than the average spillover effect among firms operating in four to eight states.

Finally, in column 4 we allow the average lagged *Sibling P2 Stock* to depend on our measure of network homophily, i.e. the share of facilities operating in the same industry. In contrast to our results for heterogeneous spillover effects by size and geographic scope, greater homophily is associated with a larger average response to an increase in sibling P2 adoption. For facilities owned by firms with the greatest degree of homophily, the average spillover effect is nearly twice the size of the average spillover effect for firms below the median level of homophily.

Simulated long-term effect of intrafirm spillovers

To further illustrate the importance of knowledge diffusion within firms over time, we simulate the number of new P2 practices adopted using a hypothetical firm that has six identical TRI facilities with characteristics equal to the sample means evaluated in year 1991. In the initial period of 1991, we assume that each facility has already adopted one P2 practice. A single facility, referred to as the "leader" hereafter, adopts an additional P2

practice in 1991, bringing its total P2 practice to two. The increase in P2 practices adopted by the leader will create a spillover effect onto the leader's five sibling firms (the "follower" facilities), increasing their adoption of P2 practices. Increased adoption by the follower facilities generates further spillovers affecting all facilities within the firm. This feedback process continues over the observed time horizon.

To illustrate the process described above, we run 1,000 simulations following the method described in Krisinsky and Robb (1986). At the start of each iteration, we randomly draw the parameters of equation (3) from a multivariate normal distribution with means and a parameter covariance matrix taken from our estimation in column 1 of Table 3. We then calculate the resulting path for P2 adoptions by the leader and one of its five sibling followers from 1992 through 2011. The point estimate for P2 practices newly adopted in any given year is given by the average of the 1000 simulations.^{vii} Additionally, we present the simulated sequence of P2 adoption for both the leader and followers assuming the coefficient of lagged *Sibling P2 Stock* is zero for comparison.

Panels (a) and (b) in Figure 1 depict four paths. The horizontal axis denotes year and the vertical axis denotes predicted number of new P2 practices. In panels (a) and (b), the solid line shows the number of new P2 practices adopted when allowing for spillovers, with panel (a) showing the leader firm and panel (b) the follower. The dotted lines in each panel show new P2 practices adopted without allowing for spillovers. As shown by the solid line in panels (a) and (b), the difference in new P2 practices adopted by the leader and follower facilities diminishes over time, as the spillover effect closes the initial gap between the two firm types. Eventually the facilities reach a steady state where both leader and follower adopt 0.4 additional P2 practices each year with spillovers.

The dashed lines in panels (a) and (b) represent the predicted number of new P2 practices for the leader and the follower, respectively, in the absence of spillover effects. When not allowing for spillovers, the steady-state number of P2 practices adopted each year falls by 75% relative to the case with spillovers, from 0.4 to 0.1. If we calculate the total number of P2 practices adopted by all facilities over time under the two scenarios, we find that each facility adopts approximately six more P2 practices with intrafirm spillovers than without over the study period.

Panels (a) and (b) compare the spillover and no-spillover scenarios while holding network characteristics fixed at their sample averages. In panels (c) - (h), we show additional simulations with different network characteristics. Specifically, these additional simulations are based on the estimates from columns 2, 3, and 4 in Table 3. Panels (c) - (h) illustrate the simulations for the leader and the follower when the respective firm's characteristics fall below the median (dash-dot line), between median and the 3rd quartile (dash line), and above the 3rd quartile (solid line). Comparing the predicted number of new P2 practices at the steady-state level, we can see that the effect of *Sibling P2 Stock* is twice as large when the firm's size is below the median relative to firms above the median for both the leader and the follower (panels c and d). We see similar patterns when the number of states in which the firm operates is below the median versus when the firm operates in more than 4 states (panels e and f). When the level of homophily is above the 75th percentile (i.e. 100% similarity), the effect of sibling P2 stock is the greatest, and it is smallest when the level of homophily is below the median, for both the leader and the follower (panels g and h).

[Insert Figure 1]

Robustness checks

We present estimates under alternative assumptions in Table 4. First, we estimate our main specification in column 1 without including the lagged dependent variable while treating lagged *Sibling P2 Stock* exogenous using pooled OLS. The effect of *Sibling P2 Stock* becomes insignificant. Second, we treat lagged *Sibling P2 Stock* with instrumental variables while excluding lagged own adoption in column 2. The effect of *Sibling P2 Stock* is very close to the main results. Third, we estimate the same model with lagged own adoption but treat lagged *Sibling P2 Stock* as exogenous (column 3). We use the second lag of own adoption as IV for the lagged own adoption, but we find that the effect of lagged *Sibling P2 Stock* is statistically insignificant (column 3, row 1). The insignificant estimates for lagged *Sibling P2 Stock* in columns 1 and 3 are expected as discussed earlier that firm-level time-varying shocks may cause negative correlation between the differenced lagged *Sibling P2 Stock* with the error term in equation (3). In column 4, we create alternative instruments for the lagged *Sibling P2 Stock* by only using siblings that are located outside of a facility's home state. Own inspections and sibling inspections could both be driven by the same unobserved factors when facilities are geographically proximate, e.g. policy changes at the county level. By only using out-of-state inspections, we remove this threat to instrument validity. We find that the estimates based on our redefined instruments are similar to our main results, though the magnitude of the coefficient falls from 0.077 to 0.065 (column 3, row 1).

Additionally, we include second lags of each facility's own environmental inspections in column 5 (rows 6 and 7). In our econometric models, we assume that twice-

lagged sibling inspections are only correlated with own adoption in the current period through their correlation with sibling adoption, after conditioning on a variety of fixed effects and observables as described above. But the exclusion restriction would be threatened if sibling inspections are correlated with time-varying firm-level compliance efforts (e.g. federal inspectors target the firm as a whole). Endogeneity in this case could arise because sibling inspections would be correlated with own inspections through the firm-wide compliance shock, and own inspections (even if twice lagged) might be correlated with own adoption. We assess this possibility by conditioning on own twice-lagged inspections. We find that these further lags of facility's own inspections are statistically insignificant.

The variable *Sibling P2 Stock* includes P2 practices adopted by siblings from the beginning period to the preceding year. It is likely that some of the earlier knowledge may have become obsolete, and this cumulative measure should be depreciated over time. We report another set of robustness check in Table 5, in which we modify the variable of *Sibling P2 Stock* by only accounting for P2 practices adopted by siblings in the previous period. In other words, we check the extreme case of placing zero weight on knowledge accumulated more than one year prior to the current period. We find that the effect of *Sibling P2 Stock* is still positive and statistically significant but is reduced slightly from 7.7% to 6.0% (with lagged own adoption) and 5.7% (without lagged own adoption), respectively (row 2). Additional robustness checks are discussed in the Appendix, in which the average effect of *Sibling P2 Stock* increases from 7.7% to 11% and 14% depending on model specifications.

7. Conclusion

Previous studies focus on public and regulatory pressures as explanations for heterogeneity in the use of P2 practices by TRI facilities. Our study contributes to the literature by quantifying the extent to which the heterogeneity can be attributed to knowledge spillovers within firm and how intrafirm spillover effects are influenced by a firm's network structure.

Using first-differenced instrumental variable estimators, we find a positive and statistically significant intrafirm spillover effect on the number of P2 practices adopted by a TRI facility, in addition to a positive and significant effect from a facility's own lagged P2 adoption. More specifically, we find that a one standard deviation increase in the total number of P2 practices adopted by sibling facilities in the preceding year (i.e., the knowledge stock) increases in the number of P2 practices adopted by a facility in the current year by between 20% and 23%, on average. Additionally, the spillover effect is stronger for facilities with a high percentage of siblings operating in the same industry. In contrast, the spillover effect diminishes as the number of sibling facilities and the number of states in which firms operate increases.

Our results have implications for evaluating the effects of grants or assistance programs to encourage P2 adoption for reducing toxic waste and greenhouse gas emissions voluntarily in the U.S. First, we find that intrafirm spillovers are significant drivers of P2 diffusion within firms. The budget for P2-related programs implemented by the EPA was \$11 million in 2016 and \$13 million in 2017 in addition to P2-related programs initiated by states. To the extent that policies to encourage P2 adoption succeed in increasing the number of adopted P2 practices at targeted facilities, overall policy effects will be underestimated if spillovers are not considered. The available empirical evidence suggests some

state policies encouraging P2 adoption are indeed effective (O'Rourke and Lee, 2004; Harrington, 2013; Bui and Kapon, 2012), and that the adoption of P2 practices leads to reduced toxic releases by 20-30% over a five-year time horizon (Harrington, Deltas, and Khanna, 2014). Our results suggest that policies to promote P2 adoption may be more effective than previously believed because of intrafirm spillovers.

Second, our empirical results provide support for earlier studies based on surveys and interviews (e.g., Lenox et al., 2000) that suggest intrafirm efforts to disseminate and promote best environmental practices are important drivers for diffusion of best practices. Through simulations, we find that both leader and sibling facilities reach a higher level of P2 adoption thanks to spillovers. It is likely that the observed heterogeneity in both firm-level and facility-level P2 adoption is partly attributable to differing abilities to internalize and diffuse knowledge within firms. Thus, including intrafirm information dissemination mechanisms in the design of P2 assistance program may improve the intensity of P2 adoption.

Third, we find that the spillover effect within a firm varies by the size and/or complexity of a firm's network. Specifically, the effect of intrafirm spillover is stronger for firms below the median size in our sample and for firms that operate in a single state. To facilitate P2 diffusion, P2 assistance programs should target firms with operations in multiple jurisdictions and facilitate intrafirm information sharing. This may also apply to other OECD countries that are establishing reporting system following the example of the TRI with the intention to facilitate the exchange of information on best available P2 techniques (OECD, 2018).

Forth, our findings on network characteristics and their influence on the diffusion of P2 practices within firms are consistent with studies on knowledge spillovers and knowledge sharing across firms using data on patent citations. Those studies have identified that geographical, technical, and social proximity influence knowledge spillovers and sharing (see review in Jaffe and Rassenfosse, 2017). Similarly, we find that similarity between siblings enhance knowledge spillovers, while larger network and geographical scope impedes knowledge spillovers. Admittedly, our measures of network characteristics do not perfectly capture connection diversity, strength, and complexity within firms. Additionally, we do not focus on diffusion of P2 practices among geographic neighbors or within an industry. These limitations can be addressed by future studies.

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Endnotes

ⁱ Facilities report, “if they have 10 or more full-time employees and manufacture, process, or use any of the TRI chemicals in amounts exceeding 25,000 pounds per year or 10,000 pounds per year for otherwise use” (U.S. EPA, 2019).

ⁱⁱ The original model is set up to produce a S-shaped cumulative adoption curve and the parameters of internal and external influences are estimated with a hazard model using observed adoption rate. Modifications have been proposed to the original Bass model. Since our goal is not to estimate the parameters of a Bass model, we choose a simplified version as in Midgley et al. (1992).

ⁱⁱⁱ In the empirical estimation, we opt to use facility’s own lagged adoption to represent the first order effect of facility’s own cumulative adoption through $t-1$. This simpler representation allows us to identify the main effect of interests, sibling P2 stock, while still controlling facility’s own ability to learn from its most recent experience. As we discuss later, we use twice-lagged inspections on siblings as IVs for sibling’s P2 stock, because they are unlikely to be correlated with facility’s own P2 adoption in the current period conditional on facility’s own lagged inspections. We expect that controlling facility’s own lagged adoption is sufficient to identify our main effect of interest, sibling’s P2 stock. If inspections on siblings increased two periods ago, a facility manager may have anticipated increased inspections on her own facility one period ago, and responded by increasing P2 adoption one period ago. Thus, to the extent that inspections on siblings have a direct effect on facility’s own adoption after conditioning on own lagged inspections, this direct effect is most likely operate solely through an effect on facility’s own adoption one period ago.

^{iv} Due to this specific reporting requirement, only new P2 practices are reported in a given year for a particular TRI chemical, and we cannot observe whether any previously adopted pollution prevention practices were discontinued.

^v $ihs(y) = \log(\sqrt{y^2 + 1} + y)$. Bellermare and Wichman (2018) show that elasticity estimates after the inverse hyperbolic sine transformation may be substantially different from models estimated using variables in linear form, particularly if the transformed variable is positive but below 10. In the appendix, we examine how our estimates vary by the assumptions used in the transformation.

^{vi} The TRI report data are from a facility-level database, whereas the NETS data are from an establishment-level database. These two databases do not match perfectly. We kept only observations that had a unique corresponding facility in each database for a given year. The matching between the TRI and NETS is based on location, name, and 8-digit sic code for a given year (Walls and Associates, 2011).

^{vii} Confidence intervals of the estimates are available upon request.

Table 1. Summary statistics (1991 to 2011)

	Mean	SD.
<i>Dependent Variable</i>		
Number of P2 practices adopted (log)	0.317	0.743
<i>Explanatory Variables</i>		
Sibling P2 stock (log)	2.701	2.374
Percent of sibling in the same industry	0.706	0.311
Firm operating in multiple states (dummy)	0.334	0.471
Facility's number of employees (log)	5.550	1.307
Facility's toxic releases (log)	6.890	4.884
Facility's inspections by EPA (frequency)	0.012	0.118
Facility's inspections by State (frequency)	0.317	0.728
Number of siblings (log)	2.467	1.106
Share of parent firm's sales in the industry (percent)	10.39	15.68
Number of TRI facilities in a county (log)	3.047	1.270
County's unemployment rate (percent)	5.910	2.415
<i>Instrumental Variables</i>		
Avg. number of inspections on siblings by state	0.256	0.384
Avg. number of inspections on siblings by EPA	0.001	0.061
Note: N=128,421		

Table 2. First-stage regression results of endogenous variables and instrumental variables

Variables	Lagged Own P2 adoption		Lagged Sibling's P2 Stock	
	Coefficient	SE	Coefficient	SE
Second lagged P2 adoption	-0.320***	(0.005)	-0.021***	(0.003)
Second lagged sibling inspection by EPA	3×10^{-5}	(0.004)	-0.160***	(0.021)
Second lagged Siblings inspection by state	-0.040	(0.028)	-0.141***	(0.042)
Lagged facility toxic releases	0.018***	(0.001)	0.003*	(0.001)
Lagged facility employment	-0.003	(0.004)	0.005	(0.008)
Lagged facility inspection by EPA	-0.008	(0.011)	0.021	(0.014)
Lagged facility inspection by state	2×10^{-4}	(0.002)	-0.003	(0.002)
No. of siblings	-0.009	(0.006)	-0.277***	(0.014)
Firm operating in multiple states	0.013	(0.009)	-0.132**	(0.020)
Percent of sibling in the same industry	-0.007	(0.017)	-0.053	(0.036)
Share of firm's sale in an industry	0.001	(3×10^{-5})	-2×10^{-4}	(6×10^{-6})
No. of facilities in a county	-0.020*	(0.011)	0.003	(0.019)
County's unemployment rate	-4×10^{-4}	(0.002)	0.002	(0.004)
Shea Partial R-Squared	0.215		0.141	
Over identification test statistics (Hansen's J)		1.0079 p=0.299		
Weak identification test stats (Wald F stats.)		27.46***		

Note: N= 101,161. All explanatory variables are first-differenced. *** p<0.01, ** p<0.05, *p<0.10. Standard errors in parentheses, clustered at facility level. Firm-level fixed effects and their interactions with year trend; state-level, and industry-level fixed effects (2digit SIC) and their interactions with year dummies are included in all models. The first-stage estimates correspond to the main results reported in column 1 in table 3.

Table 3. Main and heterogenous effects of sibling P2 stock

Variables	(1) Main	(2) Firm Size	(3) Firm scope	(4) Firm industry concentration
Lagged own adoption	0.494*** (0.012)	0.493*** (0.012)	0.493*** (0.012)	0.494*** (0.012)
Lagged sibling P2 stock	0.077** (0.032)	0.083** (0.036)	0.090** (0.040)	0.082** (0.033)
If firm characteristics above median ^a		-0.036** (0.016)	-0.061*** (0.022)	0.019 (0.014)
If firm characteristics above 75 th percentile ^b		-0.020 (0.013)	-0.035** (0.016)	0.014 (0.016)
Above median × Lagged sibling P2 stock ^c		-0.063** (0.028)	-0.064** (0.028)	0.023** (0.010)
Above 75 th percentile × Lagged sibling P2 stock ^c		-0.021** (0.009)	-0.011 (0.009)	0.034** (0.014)
No. of siblings	0.021 (0.013)		0.038** (0.019)	0.021* (0.012)
Firm operating in multiple state	-0.023* (0.014)	0.002 (0.018)		-0.013 (0.014)
Percent of siblings in the same industry	0.002 (0.024)	-0.033 (0.023)	0.015 (0.025)	
Lagged facility's toxic releases	-0.012*** (0.001)	-0.012*** (0.001)	-0.012*** (0.001)	-0.012*** (0.001)
Lagged facility's employment	0.003 (0.006)	0.004 (0.006)	0.003 (0.006)	0.003 (0.006)
Lagged facility's inspection by EPA	0.024 (0.018)	0.026 (0.018)	0.026 (0.018)	0.025 (0.018)
Lagged facility's inspection by State	0.003 (0.004)	0.003 (0.004)	0.003 (0.004)	0.003 (0.004)
Share of firm's sale in industry	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
No of facilities in a county	0.035** (0.015)	0.036** (0.015)	0.033** (0.015)	0.036** (0.015)
County unemployment rate	-0.004 (0.003)	-0.033 (0.023)	-0.004 (0.003)	-0.004 (0.003)
Observations		101,161	101,161	101,161
Over identification test statistics (Hansen's J)		1.147	1.001	1.007
P-value of Hansen's J		0.284	0.317	0.316
Weak identification test statistics (Wald F stats.)		10.43	9.636	11.40

Note: All variables are first-differenced. Robust standard errors in parentheses and are clustered at the facility level.

*** p<0.01, ** p<0.05, * p<0.10. Firm-level time trend and industry 2 digit SIC-year and state-year fixed effects are included. Firm size is defined by the number of siblings, firm scope is defined by the number of states the firm operates, and firm industry concentration is defined by the percentage of sibling facilities that belong to the same industry. ^a Dummy variable that equals to 1 if firm's characteristics of interests is greater than the sample median. ^b Dummy variable that equals to 1 if firm's characteristics of interests is greater than the third quartiles. ^c Firm

characteristics are demeaned in the interaction terms. For all models, the Hansen's J statistics indicate the orthogonality of the instrumental variables cannot be rejected. Wald F statistic based on the Kleibergen-Paap rk statistics in the presence of clustered standard errors (Baum, Shaffer, and Stillman 2007).

Table 4. Comparison with alternative specifications

Variables	(1) IV	(2) IV for lagged own adoption ^a	(3) Alternative IV ^b	(4) IV w. additional inspections
Lagged own adoption		0.499*** (0.012)	0.495*** (0.012)	0.503*** (0.013)
Lagged sibling P2 stock	0.073*** (0.028)	-0.002 (0.003)	0.065** (0.026)	0.064* (0.033)
Lagged facility's toxic releases	0.000 (0.001)	-0.012*** (0.001)	-0.012*** (0.001)	-0.012*** (0.001)
Lagged facility's employment	0.003 (0.004)	0.003 (0.006)	0.003 (0.006)	0.002 (0.006)
Lagged facility's inspection by EPA	0.021 (0.014)	0.026 (0.018)	0.024 (0.018)	0.018 (0.019)
Lagged facility's inspection by State	0.003 (0.003)	0.003 (0.004)	0.003 (0.004)	0.003 (0.003)
Second lagged facility's inspection by EPA				-0.004 (0.020)
Second lagged facility's inspection by State				-0.004 (0.004)
Number of siblings (log)	0.014 (0.011)	-0.001 (0.009)	0.017 (0.012)	0.020 (0.013)
Firm operating in more than one state	-0.015 (0.011)	-0.032** (0.013)	-0.024* (0.013)	-0.032** (0.015)
Percent of siblings in same industry	-0.002 (0.019)	-0.002 (0.024)	0.001 (0.024)	0.001 (0.026)
Share of firm's sale in the industry	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Number of TRI facilities in a county	0.028** (0.012)	0.036** (0.015)	0.035** (0.015)	0.037** (0.016)
County unemployment rate	-0.005* (0.003)	-0.004 (0.003)	-0.004 (0.003)	-0.002 (0.003)
Firm-level time trend	Yes	Yes	Yes	Yes
Industry 2digit SIC-year and state-year fixed effects	Yes	Yes	Yes	Yes
Hansen's over identification test	0.195	N/A	0.29	2.44
P-value of the overt identification test	0.659	N/A	0.590	0.134
Weak identification test	41.62	289	74.32	24.93
Observations	101,161	101,161	101,161	90,080

Note: All variables are first-differenced. Robust standard errors in parentheses and are clustered at the facility level. *** p<0.01, ** p<0.05, * p<0.10. ^a IV for lagged own adoption is second lagged own adoption. ^b Alternative IVs are the average number of EPA and state inspections on siblings located *in different states* two period prior. For models with IVs, the Hansen's J statistics indicate the orthogonality of the instrumental variables cannot be rejected. Wald F statistic based on the Kleibergen-Paap rk statistics in the presence of clustered standard errors (Baum, Shaffer, and Stillman 2007).

Table 5. Effects of the most recent sibling P2 stock

Variables	(1) With lagged own adoption	(2) Without lagged own adoption
Lagged own adoptions	0.496*** (0.012)	
Lagged sibling's P2 stock	0.060** (0.025)	0.057*** (0.022)
Lagged facility's toxic releases	-0.012*** (0.001)	0.000 (0.001)
Lagged facility's employment	0.003 (0.006)	0.003 (0.004)
Lagged facility's inspection by EPA	0.024 (0.018)	0.021 (0.014)
Lagged facility's inspection by State	0.003 (0.004)	0.004 (0.003)
Number of siblings	0.009 (0.010)	0.003 (0.008)
Firm operating in more than one state	-0.028** (0.013)	-0.020* (0.011)
Percent of siblings in same industry	0.003 (0.024)	-0.001 (0.019)
Share of firm's sale in the industry	0.000 (0.000)	0.000 (0.000)
Number of TRI facilities in a county	0.034** (0.015)	0.027** (0.012)
County unemployment rate	-0.004 (0.003)	-0.005* (0.003)
Firm-level time trend	Yes	Yes
Industry 2digit SIC-year and state-year fixed effects	Yes	Yes
Hansen's over identification test	1.215	0.265
P-value of the overt identification test	0.270	0.606
Weak identification test	27.34	41.16
Observations	101,161	101,161

Note: All variables are first-differenced. Robust standard errors in parentheses and are clustered at the facility level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. We only aggregate sibling's adoption of P2 practices in the last period in these estimations, as 89% of the variation in sibling P2 stock can be explained by its most recent lag. For both models, the Hansen's J statistics indicate the orthogonality of the instrumental variables cannot be rejected. Wald F statistic based on the Kleibergen-Paap rk statistics in the presence of clustered standard errors (Baum, Shaffer, and Stillman 2007).

Figure 1. Simulated path of new P2 adoption for leader and follower facility by firm's characteristics