Intra-firm diffusion of pollution prevention technology: the role of organizational structure

By

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Abstract: This paper empirically examines the extent to which organization characteristics promote the diffusion of pollution prevention technologies within a firm (parent company). We use panel data on more than 5000 facilities reporting to the Toxics Release Inventory over the period of 1991 to 2011 to examine the number of pollution prevention technologies adopted by a facility with respect to its size, previous experience in adoption, its distances to its sibling facilities and firm's headquarter, and regional density. We use a two-part hurdle model to estimate the likelihood of adoption and the rate of adoption, while controlling for public and regulatory pressures that may have affected the adoption of pollution prevention technologies. We find that a facility that was located in the same city with its firm's headquarter were more likely to adopt pollution prevention technologies. Past experience in adoption of pollution prevention technology and firm's knowledge stock on pollution prevention technology increased both the likelihood and rate of adoption.

Key words: Pollution prevention, technology adoption, intra-firm diffusion, organizational structure, Toxics Release Inventory (TRI).

JEL Classification: L22, O33, Q52, Q55

1. Introduction

Pollution prevention is any practice that "reduces, eliminates, or prevents pollution at its source" (EPA 1992). The Pollution Prevention Act of 1990 (PPA) formally reorganized that pollution prevention should be the preferred approach over re-use, recycling, treatment, and disposal, since it has the potential to improve resource use efficiency and reduce pollutants being recycled, disposed and treated at the end of pipe. As per PPA, federal and state agencies rely on non-mandatory approaches to promote the diffusion of pollution prevention technologies. One of the key approaches is information disclosure through the Toxics Release Inventory (TRI). Following the passage of PPA in 1991, the TRI is expanded to include reporting of pollution prevention practices adopted for each TRI reporting chemicals by each TRI facility.

Previous studies on adoption of pollution prevention technologies by TRI facilities find that public pressures created through information disclosure motivated facilities to adopt pollution prevention technologies (Harrington 2012, 2013). Additionally, facilities were more likely to adopt pollution prevention technologies if their peers from the same industry or from the same parent companies have done so (Bi, Deltas, and Khanna 2011; Harrington 2012, 2013).

However, these studies have not examined the extent to which firm's organizational characteristics influenced intra-firm diffusion of pollution prevention technologies. Particularly, intra-firm information sharing is expected to stimulate the diffusion of pollution prevention technologies, since pollution prevention technologies are often tailored to specific production processes and depend on firm-specific knowledge and managerial philosophy. Thus intra-firm information sharing is likely to be affected by firm's organizational characteristics, which influences how firm respond to public and regulatory pressures (Doshi et al. 2013). Estimating the extent to which firm respond to non-mandatory pollution prevention policy through analyzing intra-firm diffusion of pollution prevention technologies could provide crucial information for policy makers to improve the existing pollution prevention policy.

The objective of this paper is two-fold. First, we empirically examine the extent to which organization characteristics promote the diffusion of pollution prevention technologies within a firm (parent company). Second, we examine whether the influence of organizational structure is different on the likelihood and the rate of adoption. To conduct the empirical analysis, we compile a panel dataset on 8,062 TRI facilities over the period of 1991 to 2011 using the annul TRI reports and the National Establishment Time Series (NETS) database.

Following the literature on technology diffusion, we examine the number of pollution prevention technologies adopted by a facility with respect to its size, previous experience in adoption, its distances to its sibling facilities and headquarter, and regional density of similar facilities to measure stock, rank and epidemic effects (Karshenas and Stoneman 1993). Two-stage hurdle models are estimated controlling for facility-specific effects, public and regulatory pressures that may have affected the decision to adopt pollution prevention (P2) technologies.

We find that organizational structure plays an important role in the diffusion of pollution prevention technology within a firm. Specifically, a facility that is located in the same city with its headquarter have a higher likelihood to adopt new P2 technology than a facility that is not located close to its headquarter. Conditional on being an adopter of P2, such facility adopts fewer number of P2 technologies. Additionally, we find that information spillover is affected by the complexity of production processes. A facility that has more siblings is less likely to become an adopter of P2. A facility whose parent company has more varieties of facilities, identified by the number of unique industry classifications, is more likely to adopt new P2 technology. Furthermore, we find that a facility that repots more TRI chemicals and is located in a state with an environmental friendly legislature is more likely to become an adopter for P2 and subsequently adopted greater number of P2 technologies. Consistent with previous studies, we find that past experiences in adoption of P2 technologies and firm's knowledge stock on P2 technologies motivate facilities to adopt new P2 technologies.

2. Literature Review

Two types of technology diffusion processes have been identified in the previous literature: inter-firm diffusion and intra-firm diffusion. Previous literature has employed numerous theoretical models to explain intra-firm diffusion. Karshenas and Stoneman (1993) categorize the determinants that affect inter-firm diffusion into rank, stock, order, or epidemic effects based on previous literature. The rank effect is referred to the assumption that potential adopters of technology have different inherent characteristics and consequently obtain different returns from employing new technology. These different returns generate different preferred adoption dates. The stock effect is referred to the assumption that the marginal profit from using one extra unit of new technology in time *t* depends on the firm's existing level of use. Since the marginal return is decreasing over time, it will only be profitable for the firm to extend the use of that new technology to a certain point, thus limiting the extent of intra-firm diffusion. The order effect results from assuming that the returns from adopting a new technology depend on its position in the order of adoption. Facilities that have higher potential returns are regarded as high order adopters. The epidemic effect treats the adoption process as endogenous learning, which is a process of self-propagation of information that grows with the spread of that technology. Information transfer reduces uncertainty costs, thereby speeding up the adoption process.

Battisti and Stoneman (2005) further argue that the method with which to measure the inter-firm diffusion can also be used to measure diffusion within firms. They use data for computerized numerically controlled machine tools (CNC) in the UK metalworking and engineering industry in 1993 to examine the rank and epidemic effects within firms. They use employment, firm age, research and development (R&D) activities, ownership type, and production system characteristics to capture the rank effects. Years since the first adoption and the number of plants that adopted CNC in the firm by the date of the first adoption are used to capture the epidemic effects. The model does not include variables to capture the stock effect because of the cross-sectional data.

Empirical evidence supporting Battisti and Stoneman's model is limited. Hollenstein and Woerter (2008) use Swiss firm-level information and communication technologies (ICT) data and find the presence of rank and epidemic effects but provide little evidence of stock and order effects. Haller and Siedschlag (2011) use data from Irish manufacturing firms from 2001 to 2004. Their results also support the existence of rank and epidemic effects.

In addition to the literature focusing on intra-firm technologies diffusion, studies related to the adoption of P2 technologies have examined the incentives for firms or facilities adopt P2 technology. Khanna, Deltas, and Harrington (2009) use firm-level data from 1991 to 1995 to evaluate the effect of firm's participation in a voluntary environmental program (EPA's 33/50 program) on P2 adoption. They find that program participants are more likely to adopt P2 technologies than nonparticipants. Florida and Davison (2001) use case studies to analyze the motivations behind P2 adoption. Harrington (2012) finds that facilities' motivation to adopt P2 activities differ by type of technology. Harrington (2013) also contrasts the effectiveness of state-level regulatory, management, and information-based regulations in promoting P2 adoption.

These studies have not examined intra-firm diffusion of P2 technologies under the current non-mandatory environmental policy that focuses on information disclosure through the TRI. This paper contributes to the existing related literature in three ways. First, we extend the scope of intra-firm diffusion studies to P2 technologies. Second, we examine the role of organizational structure and industry networks in promoting the diffusion of P2 technology. Last, we use a larger sample and a longer period than previous studies to examine whether the results from previous intra-firm diffusion studies on other technologies also apply to P2.

3. Framework and Hypotheses

This paper's main objective is to establish the correlation between a firm's organizational structures and the extent of its P2 adoption activities. This correlation may reveal the mechanism through which P2 technologies diffuse within a firm. Unlike previous literature on intra-firm diffusion, which uses firm-level data and uses the percentage of new technology adoption of a firm to represent the extent of intra-firm diffusion, we undertake facility-level analysis on the number of P2 technologies adopted with respect to facilitiy's characteristics firm's organizational structure. We do not use the percentage of adoption of a firm as the dependent variable because P2 technologies (activities) encompass up to 43 types of activities that aim at reducing wastes at source. As a result, TRI facilities may adopt more than one practice at any given year and may adopt different types of P2 practices over time. In contrast, previous studies on technology adoption typically focus on a single technology or a small group of technologies.

We assume that the likelihood and the rate of adoption depend on the facility's marginal benefits and marginal costs from adoption. A facility will choose to adopt a new P2 technology at the point when the marginal benefits equal the marginal costs. The organizational structures that affect the facilities' marginal benefits and marginal costs of adoption include geographical location, ownership structure, and firm size.

We expect that distances between siblings would influence a facility's cost of obtaining information. Knowledge transfer within the firm reduces the cost involved in searching for and learning new technologies. Previous literature shows that reducing the costs of searching for and adapting technologies increases the probability for and speed of adoption (Lenox and King 2004; Mansfield 1968). Geographic proximity can promote knowledge sharing (Szulanski 1996), since knowledge transfer becomes more difficult and costly as distance increases (Berchicci, Dowell, and King 2011). While proximity does not mean that such a transfer is inevitable, it does create a convenient opportunity for facilities that prefer face-to-face communication.

Furthermore, we expect that knowledge transfer is inversely related to the number of distinct industries that a firm encompass. Maritan and Brush (2003) find that the knowledge transfer is more difficult for establishments that have different operating procedures. The U.S. Environmental Protection Agency (EPA) classifies 43 different types of P2 activities into eight categories (EPA 2007). Two of these eight categories are process and equipment modifications and surface preparation and finishing, which relate to specific techniques. To adapt these two types of practices, facilities need to learn certain knowledge that can hardly be obtained from sibling organizations with different productive process. We assume that the facilities that belong to the same industry and have similar productive process, which means that they are more likely to exchange information about P2 technologies than siblings that are not from the same industry.

Hypothesis 1(a): *Facilities that have siblings in close proximity are more likely to adopt technologies than facilities without siblings in close proximity. This effect is more significant for facilities that have siblings in close proximity and in the same industry.*

Hypothesis 1(b): *Among facilities that have adopted new P2 technologies, facilities with proximate siblings are expected to adopt greater number of P2 technologies than facilities without proximate siblings. This effect is more significant for facilities that have proximate siblings in the same industry.*

We expect that the distances between facilities and their parent companies also influence the cost of obtaining technical help and facilities' degree of independence. Technological innovations may have been developed at the headquarters and disseminated to individual subsidiary facilities. We assume that headquarters would have a higher level of knowledge than its subsidiaries, and technical support from headquarters would reduce the facilities' costs to learn and adapt new technologies. Therefore, greater distances to headquarters may reduce the likelihood of a facility to adopt P2 technology. However, such effect may also depend on the complexity of production processes within a firm. For a complex enterprise with subsidiaries that belong to multiple district industries, close proximity to headquarter may not influence a facility's likelihood of adopting a new P2 technology.

Hypothesis 2(a) ：*Facilities that are in close proximity to their headquarters are more likely to adopt P2 technologies than those located further away from their headquarters.*

Hypothesis 2(b) ： *Among facilities that have adopted new P2 technologies, those in close proximity to their headquarters are expected to adopt more P2 technologies than those further away from their headquarters.*

A firm's ownership structure may affect its facilities' pathway to learn knowledge of new technologies, management costs, and expected return and costs of adoption. Erdilek and Wolf (1997) find that foreign-owned firms transfer new international technologies to domestic affiliates. La Porta, Lopez-de-Silanes, and Shleifer (1999) find that firms that have more than 20% private equity are more likely to adopt productivity-enhancing practices. This is due to the ownership concentration, which reduces inter-agency costs between managers and shareholders. Private and government companies usually have a higher degree of ownership concentration than do public- traded companies. Thus we expect that facilities that belong to privately held firms are more likely to adopt P2 technology.

However, publicly traded firms may be more motivated to reduce pollution and improve their public image. Konar and Cohen (1997) find that the disclosed information on toxic pollution affected public firms' stock prices. On one hand, publicly traded firms may be motivated to adopt P2 technologies to reduce pollution. On the other hand, the adoption of new P2 technologies may require huge investments in the first few years. These investments may negatively affect firms' profits, thereby reducing stock prices and returns to shareholders. Meanwhile, other types of pollution control methods, such as end-of-pipe abatements may be more cost effective. Thus, the effect of public ownership on P2 technology adoption may be ambiguous.

Hypothesis 3(a): *Facilities whose parent firms are publicly traded are more likely to adopt new P2 technologies than facilities whose parent firms are privately or government owned.*

Hypothesis 3(b): *Among facilities that have adopted new P2 technologies, those that are publicly traded will adopt more new P2 technologies than facilities whose parent firms are privately or government owned.*

Firm's size may affect its financial ability and costs for searching for an appropriate

P2 technology. Empirical findings on the effect of firm's size are mixed. Most findings suggest that larger firms are more likely to implement new technologies than smaller firms (Mansfield 1968; Karshenas and Stoneman 1995). Other literature finds that smaller firms tend to intensity their adoptions than larger ones after the first adoption of new technology (Mansfield 1963; Fuentelsaz et al. 2003). In other words, intra-firm diffusion of new technology is faster within smaller firms than larger firms. This is likely due to the differences in costs for adapting to a new technology between larger and smaller firms, such as the cost to train employees in its use. Small firms are able to increase the intensity to adopt new technology to lower the average costs for each facility.

Hypothesis 4(a): *Facilities in large firms are expected to be more likely to adopt new P2 technologies than those in small firms.*

Hypothesis 4(b): *Among the facilities have adopted new P2 technologies, Facilities those who in large firms are expected to adopt fewer number of new P2 technologies than those in small firms.*

4. Empirical Model

We use a two-part model to represent facilities' decision-making processes. We separate the facilities' adoption decisions into two steps: 1) whether or not they will adopt a new P2 practice and 2) how many activities they will adopt once they have decided to become adopters. These two stages can be considered independent of each other because the coefficients affecting whether facilities will adopt new P2 technologies may differ from those that affect the extent of facilities' adoption even we use same set of variables.

For the first part of this two-stage process, we assume that a facility would choose to adopt when the marginal profits are greater than the marginal costs. In other words, the facility will adopt at least one P2 technology when the net profit of adoption is greater than or equal to zero. We employ the logit model based on the property of the first stage:

$$D_{it} = 1 \; if \quad NP_{it} \geq 0$$

$$D_{it} = 0 \; if \quad NP_{it} < 0$$

$$NP_{it} = \beta_1 + \beta_2 X_{1it} + \beta_3 X_{2i} + \beta_4 Y_{1it} + \beta_5 Y_{2i} + \beta_6 Z_{it} + \varepsilon_{it} \,,$$

Where D_{it} is a dummy variable denoting the adoption decision of facility i at time t. D_{it} equals to one if the facility i adopts at least one new P2 technology at time t, and equals zero if the facility i does not adopt any new P2 technology at time t. NP_{it} is a latent index that represents the facility's net profit for adopting a new P2 technology. The vectors X_{1it} and Y_{1it} denote time varying firm characteristics and facility characteristics than can affect the facility's expected return from adoption. The vectors X_{2i} and Y_{2i} each denote the time invariant firm characteristics than can affect the facility's expected return for adopting new P2 technologies. The vector Z_{it} denotes the time varying external circumstances that may affect the facility's expected return from adoption. We assume the error term ε_{it} has a logistic distribution.

We employ a truncated Poisson model to estimate the second stage of the facility's decision-making process, conditioning on adopting at least one technology. In our dataset, we do not find an evidence for significant over-dispersion. A Poisson model is preferred to a negative binomial model as indicated by the Akaike and Schwarz's Bayesian information criteria (as shown in Table 1). For each facility i that adopts at least one new technology in time t ($D_{it} = 1$), we assume that the positive count of their P2 adoption fits a Poisson distribution. The expected number of adoption is expressed as follows:

$$E(P2_{it} \mid D_{it} = 1) = \exp[\partial_1 + \partial_2 X_{1it} + \partial_3 X_{2i} + \partial_4 Y_{1it} + \partial_5 Y_{1i} + \partial_6 Z_{it} + \mu_{it}]$$

$P2_{it}$ is the expected number of new P2 adoption for facility i at time t.

We use the same sets of explanatory variables for the truncated Poisson model as those used in the logit model. We expect that the coefficients of these variables differ as they have different effects on the likelihood and the rate of adoption. To control for the unobserved effects, we add a full set of year dummies to capture all unobserved time effects and add a full set of industry dummies to capture the unobserved industry-specific effects.

Our variables of interests focus on organizational structure and peer effects. Jaffe (1986) found that a facility's adoption decision is affected by the activities of other siblings belonging to the same parent company. He suggested that the experience of adoption in other siblings would have a spillover effect. In other words, facility's adoption of P2 technologies will be influenced by its sibling's previous P2 adoptions.

To identify the peer effect, we use the exogenous shock experienced by all TRI facilities in 1995. The EPA has expanded the list of chemicals requiring reporting since the TRI reports were first required in 1987. The number of TRI chemicals became 593 in 2011 versus 332 in 1987. The biggest change happened in 1995. The EPA extended the number of TRI chemicals from 363 to 606. We focus on 239 chemicals that were added in 1995 for the empirical analysis, while use the observations on P2 adoptions from the original 363 chemicals from the period of 1991 to 1994 to represent knowledge stock and approximate peer effects.

5. Data and Variable Construction

5.1. Data Construction

5.1.1. Dependent variable

We use two different variables to represent the results of the two stages of facilities' decision-making. Each facility is required to report its P2 adoptions for each TRI chemical with up to 43 categories. To construct these two dependent variables, we focus on a set of 239 chemicals. These 239 chemicals were added into the TRI reporting requirement in 1995, as EPA expanded the original list of TRI chemicals, and never experience reporting changes afterwards from 1995 to 2011.

The first dependent variable, *new P2 dummy*, is a dichotomous variable used in the logit model. *New P2 dummy* was coded as "1" if the sum of new P2 activities is greater than zero, which means the facility has adopted at least one kind of P2 activity for all of its 239 chemicals in a given year, and "0" otherwise.

The second dependent variable, *new P2*, is the count variable used in the truncated Poisson model. *New P2* is the aggregate level of new P2 activities from the 239 chemicals for each facility in a given year.

5.2.2. Independent variables

The elements of vector X_{1it} represent time varying firm characteristics, which represent external knowledge, the peers effect, and capital transfer.

We aggregate the number of employees from all subsidiaries that belong to the same parent company to yield the firm's total number of employees, which we used as the proxy of firm size. The variable *log firm employment* used the lagged one-year total of employees and natural log to reduce skewness. The variable *number of unique SIC code* represents the count of unique industries (defined by two digit SIC code) reported by a firm's subsidiaries. The variable *number of siblings* represents the number subsidiaries that a parent company owns. We use a binary dummy variable *public ownership* takes a value of 1 if the parent company is publicly owned and 0 if the parent company is privately or government owned in a given year.

Vectors X_{2i} represent time invariant firm characteristics, which include facilities' relative location to parent companies, parent company's ownership, and number of subsidiaries. These are the main independent variables of interest, which represent firm's organizational structures. We use seven variables to represent different aspects of a firm's organizational structure. The *sibling in same city* binary dummy variable has a value of 1 if the facility has at least one sibling located in the same city and 0 otherwise. The *same industry sibling in same city* binary dummy variable has a value of 1 if at least one of the facility's siblings is located in the same city and it also belongs to the same industry (i.e. Reporting the same two-digit SIC code) and 0 otherwise. The *headquarter in same city* is a binary dummy variable that takes a value of 1 if the facility is located in the same city as its headquarters and 0 otherwise.

Vectors Y_{1it} represent time varying facility characteristics, which include facilities' past experience, toxic releases, and number of employees. The total volume of release may proxy for the extent of specific facility regulatory pressure and further the cost of liabilities related to health risk and environmental governance. We create the variable *lagged toxic release*, which takes the value of the sum of toxic release of the 239 chemicals added in 1995. We take the natural log (plus one) of this sum to reduce skewness.

To control for the scope of the P2 technologies, we create the variable *number of chemicals*, which equals to the number of chemicals that belong to the group of 239 chemicals that were added in 1995. We use the *log facility employment* to represent logged the number of employee to approximate facility's size.

Vectors Y_{2i} represent time invariant facility characteristics, which include facility's propensity for adoption, industry classification, and number of toxic chemicals.

We created the variable *firm's average P2 adoption*, which takes the sum of the average adoption of P2 technologies by siblings belonging to the same parent company from 1991 to 1994. We use the existed adoption data of 363 types of chemicals on siblings from 1991 to 1994 as the proxy of the spillover effect from the siblings on the 239 newly added chemicals after 1995. We built a variable that capture a facility's past experience in the same called *facility's average P2 adoption*. The variable *facility's past P2* takes the sum of P2 technologies adopted by the facility from 1991 to 1994.

Vectors Z_{it} are used to represent exogenous time varying variables such as the pressure from the local community and state. Previous literature has shown that local communities' economic conditions affect a facility's environmental performance (Arora and Cason 1999; Earnhart 2004; Wolverton 2009). The local community can press a facility to adopt a new P2 technology through citizen suits or lobbying for stricter legislation (Earnhart 2004). We also created the variable *log county median income,* which uses the log of median household income in each county to represent the county-level community pressure. We created the variable *LCV score*, which uses the last year's League of Conservation Voters National Environmental Scorecard. The scorecard calculates the proportion of environmental bills voted on by member of Congress. The score takes a value from 0 to 1 (100 percent). We used this variable to capture state-level community pressure. We also include the industry dummies (SIC code) and time dummies into the model to control for the specific industry and time effects. The summary statistics are list in Table 2.

5.2. Data Source

The main components of our dataset are facilities' annual TRI data and the National Establishment Time-series (NETS) data from 1991 to 2011. The EPA requests that facilities belong to certain industry sectors to report the toxic release of chemicals on the list published by the EPA based on the Right-to-Know Act, which was issued in 1986. These public annual reports began in 1987. Besides the data of toxic release for each regulated chemical, the TRI reports also involve their location, standard industrial classification (SIC) code, information on the parent company, and the emission media. According to the Pollution Prevention Act of 1990, the TRI reports are expanded to include the number of P2 technologies adopted for each regulated chemical since 1991. We obtained the data of P2 adoption, location, release, SIC code and parent company from the TRI reports between 1991 and 2011. We obtained the annual TRI reports from the EPA's website (www.epa.gov/tri). We link the facilities in the TRI with their correspondent establishments in NETS data. The NETS involve establishment information between January 1990 and January 2011. We obtained facilities' number of employees and ownership type from the NETS data from 1991 to 2011.

The TRI report data are from a facilities-level database, while the NETS data are from an establishment-level database. These two databases do not match perfectly. An observation in one database may not have a corresponding data in another database. A small proportion of observations in the TRI has more than one corresponding observations in the NETS database. We only kept observations with a unique corresponding object in each database for a given year.

The information on facility location, number of employees, and parent company ownership are obtained from the NETS database. The subsidiaries of parent company that do not report to the TRI cannot be identified in our dataset.

Using the reported location of the facility from the TRI, we have merged this original dataset with the county's income data and the League of Conservation Voters (LCV) data at the state level over the period of 1995 to 2011. The county income data is obtain from United States Department of Agriculture (USDA) Economic Research Service (ERS) (http://www.ers.usda.gov/). The LCV data is from the website (http://scorecard.lcv.org/).

The final dataset contains 37,942 observations involving 4,786 facilities. The sample size used for the logit model and logit model for facilities that have siblings are 37,248 and 22,594, respectively. The truncated Poisson models only use the observations that have a positive dependent variable. The sample size used for the whole truncated Poisson model and truncated Poisson model for facilities that have siblings are 4,148 and 2,488, respectively.

6 Results and Discussion

6.1 Hurdle Logit Model

Table 3 presents our results on the logit model, which show the partial heterogeneity of the effect of factors across different groups of observations. The results in the first column of Table 3 are for the full sample, columns 2 and 3 are results on subset of the sample for those facilities with siblings.

We first summarize the general results across different samples. Facilities with a smaller size, a larger number of chemicals on the report list, more past P2 technology adoption, and residence in a state with higher voter participation on environmental bills are more likely to choose to adopt new P2 technologies.

Then we proceed with a summary of variables relating to our hypotheses. Column 2 of Table 3 shows that *sibling in same city* has a significant negative effect on facilities' decision to adopt new P2 technologies at a 10 percent significance level. Column 3 of Table 2 demonstrates that the similar variable *same industry sibling in same city* is not significant. These two results contradict our hypothesis that facilities with proximate siblings or proximate siblings belonging to same industry will be more likely to adopt new P2 technologies. The variable *same industry sibling in same city* is a subset of the variable *proximate sibling*, so we cannot put them into the same regression equation due to the problem of multicollinearity.

Doshi, Dowell, and Toffel (2013) show that sibling proximity will enhance a facility's environmental performance as measured by the amount of toxic releases. Facilities in the same city are faced with similar public pressures. It is possible that facilities may use other toxic abatement technologies excluding P2 technology to reduce toxic releases.

Table 3 shows that the variable *headquarter in same city* has a significant positive effect in column 2 at a 5 percent significance level and an almost significant positive effect in column 3 at a 10 percent significance level, which supports our hypothesis that facilities near their headquarters are more likely to adopt P2 technologies than facilities that are far from their headquarters.

Firm size is not significant either in column 2 or column 3, which contradicts our hypothesis that facilities of large firms are more likely to adopt new P2 technologies than those of small firms. This empirical result is similar to Astebro's (2004) finding in the case of CNC technology. The variable *public ownership* shows a significant negative effect on the full sample at a 1 percent significance level, but no significant effect for facilities with one or more siblings. This stands in contrast to our hypothesis that facilities whose parent firms are publicly owned are more likely to adopt new P2 technologies than facilities whose parent firms are privately or government owned. The effect of ownership type is likely greater for single facilities than facilities that are subsidiaries of a parent company. The variable *number of siblings* has a significant negative effect both in columns 2 and 3 at a 1 percent significance level. The variable *number of unique SIC code* has a significant positive effect in both columns 2 and 3 at a 1 percent significance level. These two variables are likely a proxy for organizational complexity. We assume organizational complexity creates obstacles to knowledge transfer. The variable *number of unique SIC code* likely has a significant positive effect because the barriers to knowledge transfer involving P2 technologies between different industries may not be as strong as we initially supposed. A firm that owns subsidiaries belonging to more than one industry may be in better financial condition, which may, in turn, promote the adoption of new P2 technologies.

This next section summarizes the empirical results for the control variable in our analysis. The variable *firm's average P2 adoption* has a significant positive effect both in columns 2 and 3. Sibling knowledge stock will have a spillover effect that provides a source of external information for facilities. This spillover effect seems to exist for different kinds of chemicals. The variable *log facility employment* has a significant negative effect in all columns. Facilities with fewer employees will require less investment in training and replacement equipment. This may be the reason that small facilities are more likely to adopt new P2 technologies than large facilities. The variable *number of chemicals* has a significant positive effect in all columns at a 1 percent significance level. Facilities with more chemicals on the report list may have greater choice in which kinds of chemicals they want to adopt a corresponding P2 technology. The variable *lagged toxic release* has no significant effect in any column, so other control variables may cover the effect of local community pressure. The variable *facility's past P2 adoption* has a significant positive effect in all columns at a 1 percent significance level. Past experience of P2 technology adoption promotes the decision to adopt for other chemicals. This variable may also reflect facilities' preference for P2 technology adoption. The variable *log county median income* has a significant negative effect in column 2 and 3, but no significant effect in column 1. Facilities with high levels of toxic chemicals released may prefer locations in counties with lower environmental preference, which may cause the significant negative effect we observed with the variable *log county median income*. The variable *LCV score* has a significant positive effect in all columns at a 1 percent significance level, suggesting that state-level community pressure regarding the environment will spur facilities to adopt P2 technologies.

6.2 Truncated Poisson Model

The regression results reflect the effect of various factors on facilities' decision on how many new P2 technologies they will adopt after deciding to adopt new P2 technologies, as we used *new P2* as the dependent variable in the truncated Poisson model. Table 4 presents results showing the consistent effect of factors across different groups of observations. The results of first column in Table 4 come from facilities that adopted at least one new P2 technology in a year and the other two from facilities that have adopted at least one new P2 technology and that have at least one sibling.

As we did with the hurdle logit model, we first summarize the general results across different samples. We find that facilities with a smaller size, a larger number of chemicals on the report list, and greater past P2 technology adoption to adopt more new P2 technologies after deciding to adopt new P2 technologies. Then we proceed with a summary of variables relating to our hypothesis. The results in columns 2 and 3 of Table 4 indicate that *sibling in same city* and *same industry sibling in same city* do not have a significant effect on how many new P2 technologies facilities will adopt. These results contradict our hypothesis that facilities with proximate siblings or proximate siblings belonging to same industry will adopt more new P2 technologies. This is because the main driver of facilities' adoption decision is local community pressure on each facility. The proximate sibling effect on increasing information transfer, which lowers adoption costs, may be the only important factor in promoting adoption.

The variable *headquarter in same city* has a significant negative effect at a 5 percent significance level in column 2 and a 10 percent significance level in column 3, which contradicts our hypothesis that facilities near their headquarters will adopt more new P2 technologies than facilities far from their headquarters. Firm size has a significant negative effect both in columns 2 and 3, which conflicts with our hypothesis that facilities for large firms are more likely to adopt new P2 technologies than those for small firms. This empirical result is similar to Astebro's (2004) findings in the case of CNC technology. The variable *public ownership* has a significant negative effect in the full sample at a 1 percent significance level but no significant effect for facilities with at least one sibling, which conflicts with our hypothesis that facilities whose parent firms are publicly owned are more likely to adopt new P2 technologies than facilities whose parent firms are privately or government owned. We hypothesized that the effect of ownership type would be greater for single facilities than for facilities that are subsidiaries of parent companies. However, the variables *number of siblings* and *number of unique SIC code* is not significant either in column 2 or 3 likely because neither *sibling in same city* nor *same industry sibling in same city* are significant.

Finally, we summarize the empirical results for the control variable in our analysis. The variable *firm's average P2 adoption* has a significant positive effect both in columns 2 and 3 at a 1 percent significance level. This spillover effect seems to exist between different kinds of chemicals. The variable *log facility employment* has a significant negative effect in all columns at a 1 percent significance level. Facilities with fewer employees will need to invest less in training and replacement equipment, which may be the reason small facilities are more likely to adopt more new P2 technologies than large facilities. The variable *number of chemicals* has a significant positive effect in all columns at a 1 percent significance level. Facilities with more chemicals on the report list will adopt more new P2 technologies in total if the rate of P2 adoption for each chemical is the same. Thus, we use the variable *number of chemicals* to control for facilities' specific characteristics. The variable *facility's past P2 adoption* has a significant positive effect in all columns at a 1 percent significance level. Past experience with P2 technology adoption will influence the number of new P2 technologies facilities will adopt. The variable *lagged toxic releases* and log *county median income* have no significant effect in any column, so other control variables may cover the effect of local community pressure regarding toxic chemicals released. The variable *LCV score* has a significant positive effect in both columns 2 and 3 at a 1 percent significance level and but no significant effect in column 1, suggesting that state-level community pressure regarding the environment promotes not only adoption but also the number of technologies adopted in each facility to improve its public image.

7 Conclusion

This paper investigates the influence of firms' organizational structure on the likelihood of adopting pollution prevention technology and the number of technologies. Overall, our empirical results show that firms' organizational structure exerts a significant influence on facilities' P2 adoption decision, but the influence may be heterogeneous in each stage. Specifically, headquarters proximity increases the likelihood of facilities' adoption of new P2 activities but reduces the number of adoptions. Sibling proximity decreases the likelihood of adoption but has no effect on the number of adoption. Firm size does not affect the likelihood of adoption, but small firm size will increase the rate of adoption. Private or government – owned facility have a higher likelihood and rate of adoption, but this effect may only significant for single facilities rather than for facilities belonging to a parent company. Our results prove that the positive effect of some organizational structure variables on environmental performance found in previous literature does not contribute to P2 technology adoption.

These findings have two implications for future policy. First, it is likely that some facilities would not adopt P2 technology to improve their public image and they would prefer to use other abatement methods like treatment or recycling to reduce toxic releases. If the government wants P2 technology to be the main pollution reduction method, it needs to consider the P2 adoption a higher priority when determining facilities' environmental performance. Particularly, a future policy making the public aware of the benefits of P2 technologies may have a positive effect on P2 adoption.

Second, our empirical results suggest that facilities make two assessments regarding adoption and that the effects of factors in these two stages may differ. Thus, the government should create a targeted policy based on its goal: either to increase the likelihood of adoption or increase the rate of adoption.

The control variables also have implications for future policy. Our findings show that facilities' past experience with P2 technology adoption and firms' P2 technology knowledge stock will increase both the likelihood and rate of adoption. These effects influence the P2 technology used for different kinds of chemicals, but facilities' past experience wields more influence than firms' knowledge stock. These findings suggest that if the government still regards P2 technology as the main strategy for reducing pollution in the long term, it should pay more attention to factors that will increase the rate of the P2 adoption because facilities' past experience, or the number of P2 technologies the facilities have adopted, has a strong positive influence on future adoption decisions and siblings' adoption decisions.

The positive impact of *LCV score* on likelihood and rate of P2 adoption suggests that a P2 is influenced by state's environmental friendly legislature. Following Harrington (2012), it is likely that states with mandatory information disclosure on P2 adoption or P2 planning are more likely to report greater adoptions of P2 technologies.

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Table 1. Model comparison between truncated Poisson model and truncated negative binomial model

Tests		Statistics			
Poisson	BIC= 12813.020	AIC= 12585.126	Prefer	Over	Evidence
vs NB	BIC= 12819.482	difference= -6.462	Poisson	NB	Strong
	AIC= 12585.257	difference= -0.131	Poisson	NB	
	LRX2= 1.869	prob= 0.086	Poisson	NB	p=0.086

Note: NB is the abbreviation for negative binomial model. The results of test show that the Akaike and Schwarz's Bayesian information criteria of Poisson model is smaller than them in negative binomial model, which suggests that the Poisson is preferred than negative binomial model. Countfit developed by Long and Freese (2014) is used in the analysis.

Table 2: Variable description and summary statistics

Variable	Description	Mean	Std. Dev.	Min	Max
New P2 dummy	Dummy variable: 1 if facility adopt any new P2 technology in certain year, 0 otherwise	0.11	0.31	0	1
New P2	Number of new P2 technology a facility adopt in certain year when the facility choose to be a adopter	1.86	1.57	1	22
Sibling in same city	Dummy variable: 1 if have sibling in same city, 0 otherwise	0.03	0.18	0	1
Same industry sibling in same city	Dummy variable: 1 if have same industry sibling in same city, 0 otherwise	0.02	0.15	0	1
Headquarter in same city	Dummy variable: 1 if have headquarter in same city, 0 otherwise	0.25	0.43	0	1
Log firm employment	Log of parent company's total employee (last year)	5.77	1.84	0	11.02
Number of unique SIC code	Kind of industry the parent company have	1.94	1.73	1	10
Number of siblings	Number of sibling belong to same parent company	4.23	6.84	0	40

Table 2 Continued

Variable	Description	Mean	Std. Dev.	Min	Max
Public ownership	Dummy variable: 1 if owned by public, 0 if owned by private or government	0.36	0.48	0	1
Firm's average P2 adoption	Average P2 adoption in sibling during 1991 to 1994	7.34	13.93	0	196
Log facility employment	Log of facility's employee (last year)	5.01	1.54	0	9.98
Number of chemicals	Number of chemical reported to EPA	0.42	1.16	0	20
Lagged Toxic release	Log of toxic release (last year)	19.7	0.09	19.49	19.86
Facility's past P2 adoption	Facility's P2 adoption during 1991 to 1994	10.51	22.77	0	333
Log county median income	Log of county income (last year)	15.7	1.78	9.87	19.85
LCV score	LCV National Environmental Scorecard	0.47	0.35	0	1

Table 3: Hurdle logit model

Dependent variable: New P2 dummy	(1)	(2)	(3)
VARIABLES	Full sample	Have siblings	Have siblings
Organizational Structure			
Sibling in same city		-0.186*	
		(0.11)	
Same industry sibling in same city			0.035
			(0.12)
Headquarter in same city		0.183**	0.135
		(0.09)	(0.09)
Log firm employment		0.003	0.000
		(0.02)	(0.02)
Number of unique SIC code		0.036**	0.036**
		(0.02)	(0.02)
Number of siblings		-0.019***	-0.019***
		(0.00)	(0.00)
Public Ownership	-0.165***	-0.059	-0.062
	(0.04)	(0.05)	(0.05)
Control Variables			
Firm's average P2 adoption		0.005***	0.005***
		(0.00)	(0.00)
Log facility employment	-0.057***	-0.064***	-0.063***
	(0.01)	(0.02)	(0.02)
Number of chemicals	0.054***	0.054***	0.053***
	(0.01)	(0.02)	(0.02)
Lagged toxic release	0.092	0.129	0.133
	(1.06)	(1.53)	(1.54)
Facility's past P2 adoption	0.015***	0.014***	0.014***
	(0.00)	(0.00)	(0.00)
Log county median income	-0.005	-0.026*	-0.027**
	(0.01)	(0.01)	(0.01)
LCV score	0.234***	0.297***	0.308***
	(0.05)	(0.07)	(0.07)
Industry dummies	Included	Included	Included
Time dummies	Included	Included	Included
Constant	-2.113	-1.991	-2.025
	(20.92)	(30.11)	(30.18)
Observations	37,248	22,594	22,594

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4: Truncated Poisson model

Dependent variable: New P2 VARIABLES	(1) Full sample	(2) Have siblings	(3) Have siblings
Organizational Structure			
Sibling in same city		0.177	
		(0.12)	
Same industry sibling in same city			0.005
			(0.14)
Headquarter in same city		-0.285**	-0.223*
		(0.12)	(0.12)
Log firm employment		-0.050*	-0.051**
		(0.03)	(0.03)
Number of siblings		-0.008	-0.007
		(0.01)	(0.01)
Number of unique SIC code		0.018	0.018
		(0.02)	(0.02)
Public ownership	-0.146***	-0.091	-0.089
	(0.05)	(0.06)	(0.06)
Control variables			
Firm's average P2 adoption		0.004***	0.004***
		(0.00)	(0.00)
Log facility employment	-0.069***	-0.068***	-0.065***
	(0.02)	(0.03)	(0.03)
Number of chemicals	0.156***	0.146***	0.146***
	(0.01)	(0.02)	(0.02)
Lagged toxic release	0.517	2.234	2.144
	(1.74)	(2.87)	(2.88)
Facility's past P2 adoption	0.004***	0.004***	0.004***
	(0.00)	(0.00)	(0.00)
Log county median income	0.018	-0.004	-0.002
	(0.01)	(0.02)	(0.02)
LCV score	0.007	0.224***	0.215***
	(0.07)	(0.08)	(0.08)
Industry dummies	Included	Included	Included
Time dummies	Included	Included	Included
Constant	-10.087	-43.176	-41.458
	(34.10)	(56.37)	(56.55)
Observations	4,148	2,488	2,488

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.