Can embedded knowledge in pollution prevention techniques reduce greenhouse gas emissions? A case of the power generating industry in the United States

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Abstract
Following the well-known public information disclosure program, the Toxics Release Inventory (TRI), the United States established the Greenhouse Gas Reporting Program (GHGRP), which documents annual direct GHG emissions from major point-source polluters from 2010 onwards. While recorded GHG emissions in the GHGRP have declined over time, few studies have shed light on the mechanism through which such reduction is achieved. This paper empirically examines whether experience in managing toxic pollutants subject to the TRI pre-GHGRP contributed to the decrease in GHG emissions post-GHGRP. We use data from electrical power plants to construct various measures for the magnitude and diversity of knowledge in pollution prevention (P2) pre-GHGRP. Using a difference-in-differences framework with first-differenced panel data, we find that electrical power plants with abundant experience in P2 achieved a greater reduction in GHG emissions by 2.3%–4.8% compared to less-experienced plants post-GHGRP. This suggests that policymakers can leverage a plant’s prior knowledge and experience with P2 techniques to develop targeted strategies to facilitate the transfer of embedded knowledge to other firms and pollutants.

1. Introduction

The United States Environmental Protection Agency (EPA) launched the Greenhouse Gas Reporting Program (GHGRP) to provide a better understanding of GHG sources and to help policymakers develop programs to reduce emissions (EPA 2009). In the absence of a direct mandate to reduce GHG emissions, the GHGRP is an information disclosure program that requires all industrial sources that emit 25 000 metric tons or more of carbon dioxide equivalent (CO₂e) per year to report the annual GHG directly emitted at the facility level from 2010 onwards. Direct GHG emissions reported to the GHGRP decreased by 12.0% from 2011 through 2017 (EPA 2018a). However, few studies have analyzed the mechanism through which GHG reduction was achieved post-GHGRP. For example, the reduction in GHG emissions can be partly attributed to a facility's internal environmentally friendly stewardship motivated by existing information disclosure policies that encourage voluntary abatement of other unregulated pollutants.

The establishment of the GHGRP follows the example of the Toxics Release Inventory (TRI), an information disclosure program to encourage a voluntary reduction in toxic pollutants. Overall, The TRI is considered an effective policy instrument, as toxic releases dropped by 40% during the first decade of the TRI (Bui and Mayer 2003, EPA 2015). It has motivated firms to (1) voluntarily reduce toxic pollution through pressure from investors, consumers, and the public (Hamilton 1995, Khanna 2001, Bui and Mayer 2003, Mastromonaco 2015), (2) identify the magnitude of their pollution and wasteful use of resources, and (3) develop innovative ways to implement pollution prevention (P2) techniques and environmental management system (Khanna et al 2007, Sam et al 2009). The adoption of P2 techniques is one of the driving forces in reducing toxic pollution
experience gained from managing toxic pollutants subject to the TRI and the internal knowledge about P2 techniques for reducing toxic pollution can be transferable to reduce GHG emissions under the GHGRP, as suggested by previous literature on knowledge management. Accumulated tacit experience and knowledge on process management and innovations are typically embedded knowledge within a firm (Nonaka 1991; Asheim and Isaken 2002, Walker and Maqsood 2007), and they form stable routines to help firms better respond to internal and external pressures (Nelson and Winter 1983, Zollo and Winter 2002, Chun and Montalegre 2007).

Specifically, internal knowledge and experience of P2 techniques can contribute to the reduction in GHG emissions through several channels. First, P2 techniques aimed at reducing pollution before it enters the waste stream (e.g. releases, treatment, recycling, or re-use) can be directly used to reduce GHG emissions through redesigning processes, improving resource use efficiency, and eliminating new sources of GHG emissions (Reibstein 2009, EPA 2010). Second, a plant’s environmentally friendly efforts through adopting and implementing P2 techniques can increase awareness and understanding about a plant’s comprehensive production process, as shown by studies on pollution control (e.g. King 1999, Dutt and King 2014). This enhanced understanding of the production process helps managers identify feasible solutions and conduct environmental innovation to reduce GHG emissions (Chang and Sam 2015). Third, a plant’s successful implementation of P2 techniques can lead to reputational improvement with the public, lessen regulatory pressures and costs, and further advance innovations (Vidovic and Khanna 2007, Innes and Sam 2008, Sam 2010, Carrión-Flores et al 2013, Harrington et al 2014). We hypothesize that plants that experience these benefits are more likely to actively respond and to accelerate the assimilation of new knowledge to reduce GHG emissions in the presence of new pressure, such as the GHGRP.

To examine this hypothesis, we focus on electric power plants, which are one of the major GHG emission sources in the U.S. economy. Although they account for only 18.1% of the total number of GHGRP reporting plants, they are responsible for 61.9% of the total direct GHG emissions (EPA 2018a). Focusing on them allows us to observe GHG emission performance before and after the GHGRP (pre-GHGRP and post-GHGRP) by using the US EPA’s Emissions & Generation Resource Integrated Database (eGRID) that provides the characteristics of all power plants in the United States. In contrast, GHG emissions from other GHGRP reporting plants may not provide an accurate estimate on global GHG emissions as they may import electricity elsewhere (offsite) while reducing direct GHG emissions onsite.

Using the information on the GHG emission rates of plants subject to the both TRI and GHGRP in the eGRID, we examine the extent to which embedded knowledge (i.e. experience with P2 techniques) pre-GHGRP influenced the voluntary reduction in GHG post-GHGRP.

This study contributes to the literature in the following ways. First, it is the first study on whether experience with P2 techniques affected the performance in voluntary GHG reduction. The findings can contribute to developing targeted voluntary policies to transfer embedded knowledge to other facilities for reducing overall GHG emissions. Second, we create a set of variables to measure the presence, duration, magnitude, and diversity of P2 techniques adopted pre-GHGRP. Using these measures, we use the difference-in-differences (DID) approach to examine the effects of various P2 measures on the rate of GHG emission reduction post-GHGRP while controlling for a facility’s size, primary fuel type, and local economic conditions. We find that post-GHGRP, plants with more abundant experience in pollution prevention pre-GHGRP achieved more reduction in GHG by 2.3% to 4.8% compared to plants with a lower level of P2 experience.

2. Data and methodology

Our empirical model is constructed to examine the extent to which the P2 experience gained pre-GHGRP influenced the GHG emission rate after 2010, using the plants confined to those involved with the TRI, GHGRP, and eGRID. These three datasets are merged using the unique identifier from the EPA’s facility registry service (FRS). To set up a plant-year level panel dataset, we first identify all plants that have commonly reported to the TRI and GHGRP across all industrial sectors to evaluate the degree of experience with P2 techniques of each plant relative to other TRI reporters. We then link the data to the eGRID, limiting the sample to power plants (appendix figure 1 shows the flow of data merge). Although the eGRID has been available since 1996, it is not consistently reported annually or biannually. Considering that the GHGRP was initiated in 2010, we focus on the period 2004–2016 in all three datasets to provide

3 FRSID creates linkages among programmatic identification code in each US EPA program. In our analysis, “TRIFID” and “GHGRPID” were matched with the FRSID in eGRID.

4 Power plants are identified by the six-digit NAICS code (221 112). The final data set includes eGRID plants that have both ‘TRIFID’ and ‘GHGRPID’.

5 As of March 2020, the available years of eGRID are 1996, 1997, 1998, 2000, 2004, 2005, 2007, 2009, 2010, 2012, 2014, and 2016.
enough observations pre- and post-GHGRP. Since both the TRI and GHGRP have their own particular reporting criteria, restricting our data to the power plants subject to both programs ensures similarities in plant-level characteristics between the treatment and control groups pre-GHGRP (figure 1 and appendix table 3 show the average GHG emission rates pre- and post-GHGRP by groups).

Our empirical model is shown in equation (1). The outcome variable \( \ln \text{GHG}_i \) is the logarithm of GHG intensity per electricity generation calculated by net GHG emission in pounds divided by a net generation in megawatt per hour (MWh) of plant \( i \) in year \( t \). We use the inverse hyperbolic sine transformation for taking the logarithm that allows zero and negative values in the variable (Burbidge et al 1988, Chang and Sam 2015). \( TREAT_{i,t}^2 \) indicates the treatment variable measuring P2 experience pre-GHGRP. \( POST_t \) is a dummy variable that takes one if the observation is on and after 2010 (i.e. post-GHGRP), otherwise zero. \( TREAT_{i,t}^2 \times POST_t \) is an interaction term of the treatment with P2 experience. \( X_{i,t} \) is an observable characteristic of plant \( i \) in year \( t \) including the log of net electricity generation, primary fuel variable (coal = 1, oil = 2, and natural gas or others = 3), and local unemployment rate. \( \gamma_t \) and \( u_t \) are unobservable time and facility-fixed effects terms, respectively. \( \varepsilon_{it} \) is the error term.

The parameter of interest is on the interaction term \( \beta_3 \). This captures the treatment effect of the prior P2 experience on the rate of GHG emissions post-GHGRP. We hypothesize that \( \beta_3 \) will be negative and statistically significant.

\[
\ln \text{GHG}_i = \beta_1 TREAT_{i,t}^2 + \beta_2 POST_t + \beta_3 (TREAT_{i,t}^2 \times POST_t) + \delta X_{it} + (u_t \times \gamma_t) + (State_t \times \lambda_t) + \gamma_t + u_t + \varepsilon_{it}
\]

Equation (1) is estimated by taking the first difference to remove unobservable plant fixed effects \( u_t \), as shown in equation (2). Because a plant’s prior P2 experience does not change over time, first differencing also removed \( TREAT_{i,t}^2 \). However, it does not affect the identification of the parameter of interest.

\[
\Delta \ln \text{GHG}_i = \beta_3 \Delta POST_t + \beta_3 (\Delta TREAT_{i,t}^2 \times POST_t) + \delta \Delta X_{it} + (u_t \times \Delta \gamma_t) + (State_t \times \Delta \lambda_t) + \Delta \gamma_t + \Delta \varepsilon_{it}
\]

(2)

For the time fixed effects \( \gamma_t \), we utilize cubic trend terms rather than year dummies. This is a flexible way to control for non-linear technological progress over the time span, as shown in Cullen and Mansur (2017) and Fell and Maniloff (2018). In contrast, year dummies can effectively absorb the annual variations, but our data have inconsistent annual variations due to irregular time intervals before 2010 due to data availability. Using cubic trend terms is likely to be more flexible in addressing variation over time because of an irregular time span.

To precisely identify \( \beta_3 \) in equation (2), the key assumption is the exogeneity of prior P2 experience and the implementation of the GHGRP. In our case, establishing GHGRP is determined at the federal level and exogenous to plant-level GHG emissions. Although the knowledge gained from implementing P2 techniques may have been used for GHG emissions pre-GHGRP, we are interested in their additional effect Post-GHGRP. GHG emission reduction post-GHGRP is unable to affect the reported number of types of P2 techniques adopted pre-GHGRP. To control for time-varying unobservables at the plant level and the state level, we use several interaction terms. We use state specific-time trend \( (State \times \lambda_t) \) to control location-specific time-varying effects and plant-specific cubic trends \( (u_t \times \gamma_t) \) to reflect the non-linear effect of technological changes on GHG emissions and time-varying plant-specific unobservables (Cullen and Mansur 2017, Fell and Maniloff 2018). Furthermore, we empirically test the assumption on treatment exogeneity by utilizing a placebo test and the event study design in the robustness checks. We discuss the results and robustness checks in the Results section.

3. Explanatory variables

3.1. Measures of the P2 experience

While this study focuses on P2 experience of the power plants, the degree of P2 experience is measured at facilities that reported to TRI and GHGRP, including manufacturing sectors and power plants that meet all the following criteria: (1) belong to a TRI-reportable industry sector, (2) have 10 or more full-time (or equivalent) employees; and (3) use TRI-listed chemicals in an amount reportable industry sector, (2) have 10 or more full-time (or equivalent) employees; and (3) use TRI-listed chemicals in an amount reportable industry sector, (2) have 10 or more full-time (or equivalent) employees; and (3) use TRI-listed chemicals in an amount reportable industry sector. We use the inverse hyperbolic sine transform-

6 GHGRP reporting is required for plants that emit at least 25 000 CO2e tonnes (EPA 2009) while the TRI reporting is required for plants that meet all the following criteria: (1) belong to a TRI-reportable industry sector, (2) have 10 or more full-time (or equivalent) employees; and (3) use TRI-listed chemicals in an amount above the reporting thresholds that vary by chemical (EPA 2015). Although both programs are designed for industrial plants, not every power plant was observed in all periods from 2004 to 2016 in the TRI and GHGRP due to the reporting thresholds.

7 We used the reported ‘Plant Annual CO2 Equivalent Total Output Emission Rate (Bb/week)’ from the eGRID. It is computed by dividing the annual net CO2 equivalent emissions by the annual net generation of the plant. Net generation may have negative value when onsite electricity consumption is greater than gross output.

8 We also used categorical variables to represent primary fuel categories; the results are not influenced by using categorical variables.

9 The plant-specific time-invariant term \( u_t \) can be also be estimated with fixed-effect estimation of equation (1). In our case, given the uneven time intervals of the observations from years 2004, 2005, 2006, 2007, 2009, 2010, 2012, 2014, and 2016, and the potential nonlinearity in reducing GHG emissions due to process change, we used first-differenced estimation that allows us to include flexible forms of controls for time and plant-specific time varying unobservables. In the appendix table 1, we report the results of estimating equation (1) with the fixed-effect model as a robustness check.

10 Yer trend, trend2, and trend3 are included in the model.
generating sector, to allow us to objectively evaluate the relative degree of experience in P2 in comparison to all TRI reporting plants and enhance the exogeneity of the measures used for the empirical model with the power plant in the sample. Information on P2 adoption is collected from the TRI dataset from 1991 to 2010 only for the plants that also appeared in the GHGRP. To maintain consistency over time, we focus on the P2 practices adopted for a group of core toxic chemicals that have been consistently listed in the TRI.\footnote{This group consists of 296 toxic chemicals consistently reported from 1988 onwards, one year since the inception of the TRI (EPA 2018b)}

We measure the degree of experience (knowledge) with P2 techniques in various ways. First, we create a binary variable, \textit{P2 experience}, that equals one if a plant had adopted any P2 techniques pre-GHGRP, otherwise zero. Second, three different measures are developed to gauge the degree of P2 experience: (1) total years since a plant became an adopter, (2) the cumulative number of P2 techniques adopted pre-GHGRP, and (3) the diversity in P2 techniques. Third, we utilize the latter three measures to generate a set of binary variables to indicate whether a plant’s specific measure in P2 is higher than the sample median value (i.e. more experienced) of all the plants that reported to the TRI and GHGRP. Each measure in the set of binary variables is computed as below.

\textit{High P2 duration:} We compute the total number of years from when a plant first became an adopter until 2010 to create the variable \textit{High P2 duration} that equals one if it is greater than the corresponding median value from all the plants that reported to the TRI and GHGRP, otherwise zero.

\textit{High P2 magnitude:} We aggregated the number of adoptions in P2 techniques in each year until 2010 to create the variable \textit{High P2 magnitude} that equals one if it is greater than the corresponding median value from all the facilities that reported to the TRI and GHGRP, otherwise zero.

\textit{High P2 diversity:} The US EPA categorizes P2 techniques into eight categories depending on their approaches.\footnote{They are good operating practices, inventory control activities, spill and leak prevention activities, raw material modification, process modification, cleaning and degreasing activities, surface preparation and finishing activities, product modification.} Based on the eight categories, we measure diversity in cumulative P2 techniques by using Shannon’s entropy index, which was designed to gauge the value of information (Shannon and Weaver 1949). Using this index allows us to consider all eight categories of P2 techniques. The index ranges from zero to one, where greater value means higher diversity (Martin and Rey 2000). While different categories of P2 techniques have different effects on pollution (Sam 2010, Ranson et al 2015), the combination of techniques or knowledge indicates the innovativeness of a plant (Stirling 2007, Østergaard et al 2011). Specifically, according to the TRI reporting requirement, only incremental (new) P2 techniques are reported in a given year. Thus, reporting various P2 techniques in a given year could indicate a holistic
approach to reduce pollution through the production process instead of a piecemeal approach. King (1999) and Dutt and King (2014) argued that any efforts that enhance the awareness and understanding of the whole waste-generation process are embedded internal knowledge, which can increase a plant’s ability to respond to new external pressures. Thus, we hypothesize that experience with a diverse set of P2 techniques will enhance a plant’s ability to reduce GHG emissions in response to the public and regulatory pressures induced by GHGRP.

The entropy index is computed every year from 1991 to 2010 for all plants reporting to the TRI and GHGRP based on the eight categories, as seen in equation (3). We then take the average for each plant for the study period.

\[ P2\text{diversity}_{it} = - \sum_{kt} P_{kit} \cdot \ln(P_{kit}) \]  

(3)

\( P_{kit} \) is a probability of \( k \)th type of P2 techniques (\( k = 1,2,\ldots,8 \)) in plant \( i \) in year \( t \). The probability is calculated by \( n_{kit}/N_{kit} \) (\( n_{kit} \) is the total number of \( k \)th P2 technique type adopted by a plant \( i \) in year \( t \), and \( N_{kit} \) is the total number of \( k \)th type of P2 technique adopted by all plants in the sample in year \( t \)). Lastly, we create a binary variable that equals one if a plant’s entropy value is greater than the median value from all plants that reported to the TRI and GHGRP, otherwise zero.

3.2. Control variables
We use three control variables: \( \ln(\text{gen}) \), primary fuel type, and unemployment rate.

\( \ln(\text{gen}) \): We approximate the size of a plant by using the level of the net generation from the eGRID. To keep zero or negative values, we also apply the inverse hyperbolic sine transformation.

Primary fuel type: Since the amounts of GHG emissions heavily depend on fuel type, we include the information as reported to the eGRID by creating a categorical variable: one represents coal (and coal-related energy) products, two represents oil (and oil-related) products, and three represents natural gas and others. The order of \( \text{CO}_2 \) intensity is ranked from 1 (high) to 3 (low).

Unemployment rate: The literature finds that firms’ polluting behaviors are affected by public pressure, which is often proxied by economic conditions (Arora and Cason 1999, Bell and Ebisu 2012, Bi 2017). We match each plant with an annual unemployment rate at the county level from the U.S. Bureau of Labor Statistics (BLS 2020).

3.3. Summary statistics
The constructed unbalanced plant-year level panel data include 725 unique plants with 4767 observations in the period 2004–2016. The number of plants in the sample represents 13.9% of all plants in the eGRID, which covers almost all power plants connected to the U.S. electric grid. The total reported GHG emissions in the sample accounted for 80.4% of total emissions in the eGRID.\(^{13}\)

Following the three functional classifications of P2 techniques in Sam (2010),\(^{14}\) the number of P2 techniques involved with equipment change and operating procedure modification account for 53.9% and 32.6% of the total number of P2 adopted by the sample plants pre-GHGRP, respectively. Unlike the case in Sam (2010), in which material modification-related technique is the most frequently adopted P2 technique, this technique only accounted for 13.5% in our sample. It is likely that power generating plants have limited options to change raw materials compared to other manufacturing sectors that can switch to less toxic chemicals.

Summary statistics of variables used in the models are presented in table 1. About 18.4% of the plants in the sample is identified as P2 experiencer treatment pre-GHGRP. We find that 13.1%, 10.9%, and 13.0% of the plants in the sample have richer P2 experiences than the median values determined by all industrial plants that report to the TRI and GHGRP in terms of duration, magnitude, and diversity, respectively (table 1, row 3 to row 5). Thus, compared to plants in the TRI and GHGRP, power plants seem to be relatively less experienced with P2 techniques pre-GHGRP, since electricity generation processes are involved with a limited number of TRI-chemicals. From this perspective, those power plants identified as a high experiencer at the whole TRI-GHGRP group level indicate their enthusiastic efforts to respond to the mandatory information disclosure program.

4. Results
The regression results for the set of measures are presented in table 2. We find empirical evidence that prior P2 technique experience contributed to reduced GHG emissions, as shown by the significant treatment effects for all P2 measures (table 2, rows 2–5). The first column shows that having P2 experience pre-GHGRP reduced GHG emissions by approximately \(-4.4\%\) compared to those without P2 experience. Power plants with longer P2 experience achieved faster GHG emission reductions compared to the plants with shorter P2 experience by \(-2.3\%\) post-GHGRP (column 2). Columns 3 and 4 present the impacts of greater P2 experience in terms of magnitude and diversity, respectively. Their parameter

\(^{13}\) From the 2010 data, the number of plants in the sample and the total number of plants in the eGRID are 703 and 5667, respectively. Total GHG emissions from the sample and all plants in the eGRID are 1929 million and 2400 million \text{CO}_2e\text{ tonne}, respectively.

\(^{14}\) Sam (2010) further classified the eight types of P2 techniques reported in the TRI into three categories based on their technological attributes. They are procedure changes, environmentally friendly equipment changes, and source material changes.
estimates appear in size at −4.8 to −3.8%, respectively. Considering that the annual rate of reduction achieved by reducing CO₂ emission intensity by all power plants was −1.8% from 2005 to 2018 (EIA 2018), we find that the effects of prior P2 experience are meaningful.

Other estimates of covariates are consistent with our expectations. The rate of reduction in GHG emissions is 21.2%–21.7% higher post-GHGRP compared with pre-GHGRP. A county’s higher unemployment rate is positively associated with GHG emissions, which reflects the notion that economically lagging regions are likely to be particularly vulnerable to GHG emissions (Kaswan 2008, Martinez 2017). Larger power plants are associated with greater GHG emissions. The primary fuel type in reverse order of CO₂ intensity is negatively associated with GHG emissions, as expected.

We conduct the two different robustness tests on the assumption of treatment exogeneity. First, we tested whether there is any effect of P2 experience in the pre-treatment period with an event study design following Clarke and Kathya (2020) with fixed-effects estimations in order to keep all the observations in the sample. We find that all coefficients for pre-event leads are statistically insignificant (table 3, rows 5–8). Also, the effect of P2 experience on GHG reduction is mainly in the first observation period between 2010 and 2012 after GHGRP was initiated (table 3, row 9). Since the majority of P2 techniques implemented by sample plants are procedure changes and equipment changes. Our finding indicates that the effectiveness of P2 experience is short-lived. A previous study on TRI facilities also found that the effect of P2 techniques dissipated quickly within five years of adoption (Harrington et al 2014). This indicates a need to implement P2 techniques continuously in order to reap their long-term benefits. Second, we used a time placebo test by assigning the time of treatment to 2007 instead of 2010 in the primary model.

Table 1. Descriptive statistics in power plant sample.

| Variables | Mean | St.d. | Min | Max | Definitions |
|-----------|------|-------|-----|-----|-------------|
| Dependent variables | | | | | Log of GHG emission (lb) per net generation (MWh) |
| lnGHG | 8.065 | 1.111 | −11.524 | 17.36 | |
| Treatments: Measures of P2 experience | | | | | |
| P2 expericer | 0.184 | 0.388 | 0 | 1 | If P2 adopter, 1, otherwise 0 |
| High P2 duration | 0.131 | 0.337 | 0 | 1 | If P2 duration > median*, 1, otherwise 0 |
| High P2 magnitude | 0.109 | 0.311 | 0 | 1 | If P2 magnitude > median*, 1, otherwise 0 |
| High P2 diversity | 0.130 | 0.336 | 0 | 1 | If P2 diversity > median*, 1, otherwise 0 |
| Other controls | | | | | |
| Primary fuel type | 1.812 | 0.948 | 1 | 3 | 1 = coal, 2 = oil, and 3 = gas or others (categorical variable) |
| lnGEN | 14.157 | 2.703 | −11.590 | 17.730 | Log of annual net generation |
| Unemployment rate (%) | 6.971 | 2.838 | 2 | 28.8 | County-level annual unemployment rate |

Note: N = 4767; The number of unique plants = 725. * median value is determined by all plants that report to the TRI and GHGRP.

Table 2. Effects of P2 experience on GHG emission rates by difference-in-differences.

| lnGHG | (1) P2 Presence | (2) P2 Duration | (3) P2 Magnitude | (4) P2 Diversity |
|-------|----------------|----------------|----------------|----------------|
| Post-GHGRP | −0.212*** | −0.217*** | −0.215*** | −0.215*** |
| (0.054) | (0.058) | (0.061) | (0.061) |
| P2 expericer × Post-GHGRP | −0.044*** | −0.023*** | −0.048*** | −0.038*** |
| (0.002) | (0.003) | (0.002) | (0.003) |
| High P2 duration × Post-GHGRP | −0.189* | −0.189 | −0.189** | −0.189* |
| (0.072) | (0.083) | (0.051) | (0.077) |
| lnGEN | 0.478*** | 0.478*** | 0.478*** | 0.478*** |
| (0.016) | (0.022) | (0.023) | (0.019) |
| Unemployment rate (%) | 0.026*** | 0.026*** | 0.026*** | 0.026*** |
| (0.004) | (0.003) | (0.003) | (0.002) |
| Observations | 4767 | 4767 | 4767 | 4767 |
| R-squared | 0.545 | 0.545 | 0.545 | 0.545 |

Note: All variables are first differenced. Cubic time trends, plant-specific-cubic polynomial trends, and state-specific time trends are included in all models and are not reported for brevity. Robust standard errors are in parentheses (clustered by treatment and control groups interacted with pre- and post-GHGRP). *** p < 0.01, ** p < 0.05, * p < 0.1.
because many plants may have predicted the introduction of GHGRP by 2009 and we lost the observations in the year 2004 after first-differencing, and the year 2005 becomes the first to enter in the sample. The placebo test results suggest that our primary results are valid treatment effects, as the coefficients of P2 measures that interacted with the GHGRP assigned in 2007 are statistically insignificant, indicating that the measures of P2 experiences are exogenous pre-GHGRP (appendix table 2).

5. Conclusion and discussion

This study examines the extent to which embedded knowledge (experience with P2 techniques) affected voluntary reduction in GHG emissions post-GHGRP using data from electrical power plants. We use the DID approach and apply various measures on the presence, duration, magnitude, and diversity of P2 technique experience. Additionally, we implemented several robustness checks using fixed-effects estimations and an event study. We find that a higher level of P2 technique experience is associated with a greater reduction of GHG emissions post-GHGRP, particularly in the program’s first year after the GHGRP initiated. Given that most P2 techniques adopted by the power plants are involved with the procedural and equipment modifications, it is likely that implementing these P2 techniques provides positive spillover to amplify reducing GHG emissions. However, there is a need for continuous efforts to ensure the long-term reduction in GHG emissions.

Our findings suggest that it is important for policymakers to transfer embedded knowledge concerning pollution abatement from more experienced plants to less experienced plants or other pollutants. External policy push to transfer such knowledge is necessary to reduce the ‘stickiness’ of embedded knowledge (Szulanski 1996, Dutt and King 2014). For example, Walker and Maqsood (2007) and Maqsood et al. (2006) provide practical methodologies, capability maturity models (CMMs), and soft system methodologies (SSM), respectively, as useful tools to reduce the ‘stickiness.’ King (1999) also proposes that ‘sticky information’ can be transferred to downstream processes in the internal ‘value-chain’ through inter-dependent projects.

This is the first study on how experience with P2 techniques affected performance in voluntary GHG reduction. There are several caveats. First, this analysis is only applied to power plants that report to the TRI and GHGRP. Since P2 experience may have different roles in GHG reduction for other sectors, we do not generalize our findings to all industries. Second, the current empirical analysis treats TRI plants without any records of P2 adoptions as non-adopters (i.e. zero adoption). If the effects of missing P2 information are not negligible, our identified effect

Table 3. Revisiting the effects of P2 experience on GHG emissions with an event study design and fixed effects estimation.

|                | (1) P2 Presence | (2) P2 Duration | (3) P2 Magnitude | (4) P2 Diversity |
|----------------|-----------------|-----------------|-----------------|-----------------|
| Post-GHGRP     | −0.218**        | −0.223**        | −0.225**        | −0.225**        |
|                | (0.058)         | (0.056)         | (0.056)         | (0.056)         |
| Primary fuel type | −0.279*** | −0.282*** | −0.282*** | −0.281*** |
|                | (0.031)         | (0.031)         | (0.031)         | (0.031)         |
| Ln(gen)        | 0.398***        | 0.398***        | 0.398***        | 0.398***        |
|                | (0.006)         | (0.006)         | (0.001)         | (0.006)         |
| Unemployment rate (%) | 0.015*** | 0.017*** | 0.016**  | 0.017**  |
|                | (0.007)         | (0.000)         | (0.007)         | (0.007)         |
| Pre-treatment (t-4) | −0.085 | −0.025 | −0.224 | −0.034 |
|                | (0.092)         | (0.106)         | (0.115)         | (0.106)         |
| Pre-treatment (t-3) | −0.135 | −0.109 | −0.065 | −0.049 |
|                | (0.088)         | (0.103)         | (0.112)         | (0.103)         |
| Pre-treatment (t-2) | −0.117 | −0.085 | −0.110 | −0.093 |
|                | (0.090)         | (0.105)         | (0.113)         | (0.105)         |
| Pre-treatment (t-1) | −0.002 | −0.018 | 0.004  | −0.007 |
|                | (0.091)         | (0.105)         | (0.114)         | (0.105)         |
| Post-treatment (t + 1) | −0.163* | −0.214** | −0.255** | −0.170* |
|                | (0.087)         | (0.102)         | (0.111)         | (0.102)         |
| Post-treatment (t + 2) | −0.056 | −0.084 | −0.088 | −0.070 |
|                | (0.092)         | (0.106)         | (0.113)         | (0.106)         |
| Post-treatment (t + 3) | −0.037 | −0.105 | −0.100 | −0.082 |
|                | (0.095)         | (0.109)         | (0.119)         | (0.110)         |
| Joint significance test H0: all betas of pre-treatment terms are equal to zero |
| F-statistic     | 1.00            | 0.41            | 0.46            | 0.25            |
| (Prob > F)      | (0.406)         | (0.803)         | (0.767)         | (0.910)         |

Note: To keep all years before treatment, we use fixed-effect model rather than the first differencing estimation. Cubic time trends, plant-specific-cubic polynomial trends, and state-specific time trends are included in all models and are not reported for brevity. Baseline year is 2010. **∗ p < 0.01, ** p < 0.05, ∗ p < 0.
may be underestimating the effect of P2 on GHG emissions. Third, our DID estimators represent the average treatment effects pre- and post-GHGRP. It is possible that some plants might have started to use P2 techniques to reduce GHG emissions in anticipation of the GHGRP before 2010. If this is the case, the impact of P2 experience may be underestimated. Last, we did not control regulatory enforcement information on power plants. Suppose regulatory pressure is positively correlated with a plant’s P2 experience, the effect of P2 experience could over estimated. These limitations remain for the merits of future research.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/XPDJFB.
Appendix

Appendix Table 1. Fixed Effects Estimation on the Effects of P2 Experience on the Levels of GHG Emissions with State-by-year Interactions.

|                     | (1) P2 Presence | (2) P2 Duration | (3) P2 Magnitude | (4) P2 Diversity |
|---------------------|-----------------|-----------------|-----------------|-----------------|
| P2 expericer × Post-GHGRP | −0.047****      | −0.122***       | −0.104***       | −0.111***       |
| (0.005)             | (0.007)         | (0.003)         | (0.003)         |
| High P2 duration × Post-GHGRP | −0.143***      | −0.143**        | −0.144**        | −0.143**        |
| (0.023)             | (0.025)         | (0.026)         | (0.026)         |
| Primary fuel type   |                 |                 |                 |                 |
| (1 = Coal, 2 = Oil, 3 = Gas & others) |         |                 |                 |                 |
| lnGEN               | 0.218***        | 0.218***        | 0.217***        | 0.218***        |
| (0.031)             | (0.033)         | (0.033)         | (0.033)         |
| Unemployment rate (%)| −0.010         | −0.010          | −0.010          | −0.010          |
| (0.006)             | (0.005)         | (0.005)         | (0.005)         |
| Constant            | 5.316***        | 5.316***        | 5.320***        | 5.319***        |
| (0.449)             | (0.476)         | (0.480)         | (0.473)         |
| Observations        | 5512            | 5512            | 5512            | 5512            |
| R-squared           | 0.354           | 0.355           | 0.355           | 0.355           |

Note: Year dummies, plant-specific year dummies and state-specific year dummies are included in all models and are not reported for brevity. Robust standard errors are in parentheses (clustered by treatment groups and periods). *** p < 0.01, ** p < 0.05, * p < 0.1

Appendix Table 2. Time placebo test (assuming GHGRP started in 2007).

|                     | (1) P2 Presence | (2) P2 Duration | (3) P2 Magnitude | (4) P2 Diversity |
|---------------------|-----------------|-----------------|-----------------|-----------------|
| P2 expericer × Placebo year | 0.038           | 0.040           | −0.031          | −0.029          |
| (0.028)             | (0.028)         | (0.030)         | (0.028)         |
| High P2 duration × Placebo year |               |                 |                 |                 |
| High P2 magnitude × Placebo year |               |                 |                 |                 |
| High P2 diversity × Placebo year |               |                 |                 |                 |

Note: Parameters are first differenced estimators. Other variables were included following our main models reported in table 2 and not reported for brevity. *** p < 0.01, ** p < 0.05, * p < 0.1
# Appendix Table 3. Comparison between treatment and control groups by the measures of P2 experience.

|                                            | Panel (A): P2 experiencer | Panel (B): P2 duration |
|--------------------------------------------|---------------------------|------------------------|
|                                            | Experiencer | Non-experiencer | High group | Low group |
| Number of observations                     | 878         | 3889           | 623        | 4144      |
| Net generation (MWh)                       | 3329        | 2759           | 3564       | 2759      |
| Net CO\(_2\)e emission/MWh                | 1968        | 1914           | 1911       | 1926      |
| ln(NetCO\(_2\)e/MWh)                      | 8.08        | 8.06           | 8.06       | 8.07      |
| Coal plant (%)                             | 63.78       | 54.36          | 63.40      | 55.00     |
| Oil plant (%)                              | 5.81        | 6.84           | 4.65       | 6.95      |
| Gas & others plant (%)                     | 30.41       | 38.80          | 31.94      | 38.06     |
| t-statistics on ln(NetCO\(_2\)e/MWh)      | 2.147(0.032) |                | 1.123(0.261) |          |
| (p-value) before treatment                 |             |                |            |           |
| t-statistics on ln(NetCO\(_2\)e/MWh)      | −0.278(0.781) |                | −0.268(0.789) |          |
| (p-value) after treatment                  |             |                |            |           |

|                                            | Panel (C): P2 magnitude | Panel (D): P2 diversity |
|                                            | High group | Low group | High group | Low group |
| Number of observations                     | 600        | 4914      | 618        | 4149      |
| Net generation (MWh)                       | 3319       | 2811      | 3256       | 2806      |
| Net GHG emission/MWh                       | 1967       | 1939      | 1939       | 1922      |
| ln(NetCO\(_2\)e/MWh)                      | 8.09       | 8.06      | 8.07       | 8.06      |
| Coal plant (%)                             | 66.00      | 55.31     | 64.72      | 54.81     |
| Oil plant (%)                              | 5.67       | 7.08      | 5.66       | 6.80      |
| Gas & others plant (%)                     | 28.33      | 37.61     | 29.61      | 38.39     |
| t-statistics on ln(NetCO\(_2\)e/MWh)      | 1.973(0.049) |           | 2.059(0.04) |           |
| (p-value) before treatment                 |             |           |            |           |
| t-statistics on ln(NetCO\(_2\)e/MWh)      | −0.734 (0.4597) |           | −0.706(0.442) |           |
| (p-value) after treatment                  |             |           |            |           |
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