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Voluntary Programs to Encourage Diffusion: The Case of the Combined Heat-and-Power Partnership

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ABSTRACT

In the last decade, voluntary environmental programs have increased considerably in number and scope. A novel use of these programs is to diffuse new technology in industry as means to improving their environmental outcomes. This paper tests whether the U.S. Environmental Protection Agency's Combined Heat-and-Power (CHP) Partnership has encouraged the diffusion of CHP systems. Using a nearest neighbor matching estimator with electricity plant data and conditional logit estimation for electricity and manufacturing plants in the U.S., we find evidence that the program has helped CHP systems spread, controlling for the selection of firms into the partnership. On average partner firms have a 3% higher probability of installing CHP.

Keywords: Voluntary Environmental Measures, Combined Heat and Power, Fossil Fuels

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1. INTRODUCTION

Since the start of the first voluntary environmental programs in the early 1990s, governments have increasingly used this type of policy tool to achieve emissions reductions, raise firms' environmental awareness or improve information provision to the public. This trend has consequently led to a growing importance of measuring those programs' success (Brouhle et al., 2005 and EPA, 2007). The majority of the programs call on participating firms (known as partners) to commit to an action such as a reduction of emissions. A more novel use of voluntary programs has involved the acceleration of technology diffusion to overcome problems like asymmetric information, principal-agent issues or to lower the threshold of network externalities. The U.S. Environmental Protection Agency's (EPA) Combined-Heat-and-Power Partnership (CHPP) was established in 2001 and represents this application of voluntary programs. Combined heat-and-power (CHP) adoption in the U.S. has always responded notably to incentives as well as to disincentives generated by policy makers.

The Public Utilities Regulatory Policy (PURPA) of 1978 led to increased installation of CHP plants, though this trend stopped in the early 1990s when the Energy Policy Act of 1992 altered the incentives for wholesale power purchases (Fox-Penner, 1990; Dismukes and Kleit, 1999). PURPA had given CHP generators wholesale generation privileges (utilities were required to buy from CHP generators if their costs were low enough), however the deregulation of electricity markets allowed independent producers to enter the wholesale generation market and compete with

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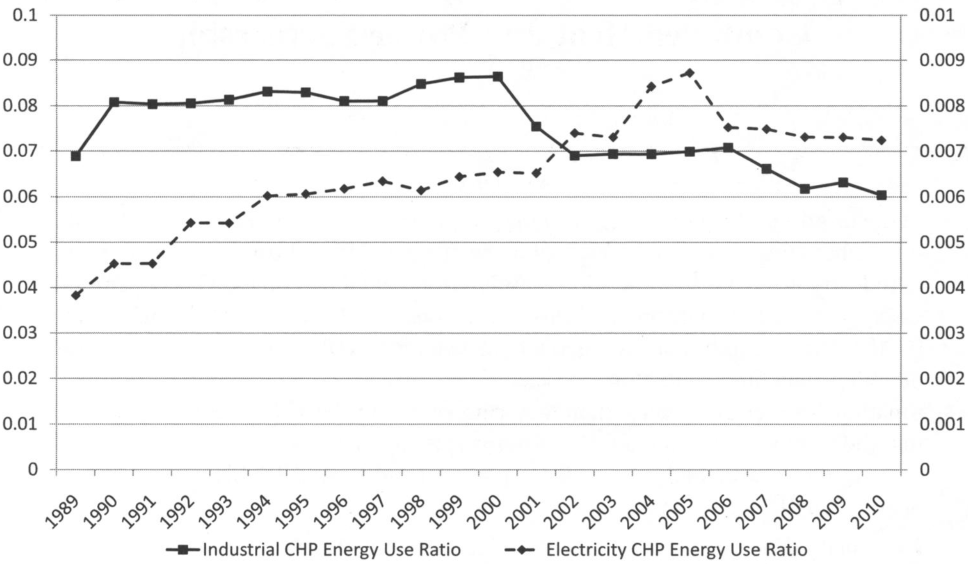
Figure 1: CHP Trends



Notes: Authors' calculations based on EIA (2011). Industrial CHP ratio is on the left axis (solid square line) and electricity CHP ratio is on the right axis (dashed diamond line).

CHP generators (Kaarsberg et al., 1999). In the late 1990s, it was recognized that the loss of wholesale generation privileges and other barriers to CHP adoption required new measures to encourage CHP installations. Since then the EPA, the Department of Energy, and the states have made more efforts to remove such barriers and strengthen adoption incentives (Shipley et al., 2008). Some of these trends in CHP use can be seen in Figure 1, which shows the ratio of heat used by CHP plants in the industrial and electricity sector to all heat used in these sectors over time.

The CHPP is a new attempt to reduce installation barriers and to promote the use of CHP. Designed as a multi-sector federal voluntary program, it aims to facilitate the diffusion of CHP systems by giving early-stage consulting support to firms, providing public recognition and hosting a platform for contacts and knowledge transfer. This paper attempts to fill a gap in the literature concerning the effectiveness of a program of this nature. Two hypotheses are to be tested here: (i) whether the partnership has encouraged the installation of CHP applications in electricity and manufacturing plants and (ii) if it has assisted knowledge transfers and spillovers that helped firms to utilize CHP more efficiently. We use a nearest neighbor matching estimator to test the installation hypothesis, with a robustness check using conditional logit model, and panel data techniques to test whether utilization of CHP is greater due to CHPP spillovers. Generally, the impact of the CHPP is positive; on average partners have a 3% higher probability of installation though there was no significant effect concerning learning spillovers and higher utilization of CHP due to the partnership. These results provide some evidence for a positive impact of the program on technology diffusion.

The trend in environmental and energy policy over the past two decades has been to use market-based instruments to encourage more efficient outcomes. While there have been many market-based regulation successes (the Acid Rain program and natural gas deregulation, for example), concern is growing that few policies have been enacted in recent years. For example, the U.S. has not passed a comprehensive environmental law since the 1990 Clean Air Act Amendments and is largely without a comprehensive energy strategy (Hayward, 2010). Of the more recent policies, many do not specify a specific instrument to reach the specified targets. The UK Climate Change Act of 2008 sets emissions targets for firms but does not provide direct instruments to meet these goals, creating the Committee on Climate Change to make recommendations instead. The European Union 20-20-20 system calls for a 20% reduction in energy use through increases in energy efficiency to be achieved with a number of initiatives across different sectors.

Most of these policies recommend a path to meeting such targets which rely on the use of new technologies that are either low-CO_2 emitting or improve the efficiency of a given amount of energy. However, new technologies do not spread throughout industry as efficiently as they should due to diffusion externalities such as learning-by-doing, incomplete information or network effects (Jaffe et al., 2005). Indeed, this explains why a basket of policy instruments are shown to be more efficient at achieving an emissions goal than any single instrument (Fischer and Newell, 2008). Voluntary programs like CHPP might be a potentially cost effective way to overcome these adoption and diffusion externalities. This type of program can complement policies that provide a goal but do not specify actions that need to be taken to achieve the goal. However, for this argument to hold, it must be shown that voluntary programs are overcoming the externalities they are meant to address.

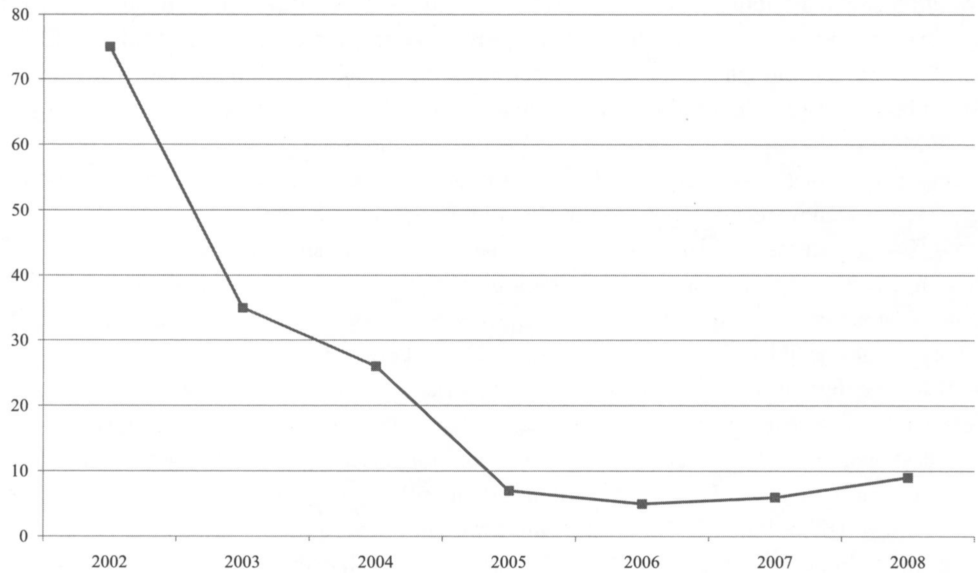
The only other evaluation of a voluntary environmental program that encourages the diffusion of a new technology that the authors are aware of is DeCanio (1998). DeCanio (1998) finds that the U.S. Green Lights program, a voluntary program that encouraged firms to use energy efficient lighting, has been successful at diffusing new lighting technology. In general, the empirical evidence is mixed regarding the effectiveness of the traditional voluntary programs in the economics literature. Boyd and Mason (2011) and Lyon and Maxwell (2007) discuss a number of reasons why it is difficult to undertake rigorous evaluations of voluntary programs.[1]

CHPP was established in 2001 with the goal of promoting the use of CHP as a means of reducing the environmental impact of power generation (CHPP, 2010). The economic rationale for a program like CHPP comes from the innovation and diffusion externalities that are common with new technologies (Jaffe et al., 2005). These externalities arise from a number of sources, such as the public good nature of knowledge, learning-by-doing effects, and/or incomplete information. Currently there are 369 partners including federal, state and local government agencies as well as private organizations like energy users and producers, service companies, CHP project developers, consultants and manufacturers. To join CHPP, firms need to fill out a short postcard and submit it to the partnership. No promise of installing a CHP system is given when firms join though they agree to designate a liaison to the partnership to provide information on any CHP decisions being made.

The CHPP utilizes a number of methods to encourage installation of CHP such as project-specific assistance, information and knowledge exchange opportunities, and public recognition. The project-specific assistance includes a basic cost-benefit analysis to determine whether CHP potentially generates net benefits at a given plant. Comprehensive information is provided on environmental, technical or policy related questions, potential funding opportunities, the next steps in the project development and contacts to engineers, parts suppliers and project developers to finalize the project. CHPP runs a number of workshops and web-seminars (webinars) for partners to discuss

1. Some examples of evaluations that find improved environmental outcomes are Khanna and Damon (1999), Innes and Sam (2008) for the 33/50 program. Gamper-Rabindran (2006), Vidovic and Khanna (2006), and Brouhle et al. (2008) find a lack of improvement in environmental outcomes for the programs they study which are 33/50, 33/50, and the Strategic Goals Program for Metal Finishers, respectively.

Figure 2: New CHP Installations



Notes: Authors' calculations based on EIA Form 906/920. Year 2001 includes installations of unknown timing from previous years and is therefore omitted from the graph.

their experience with CHP system. Finally, public recognition is granted by listing partners' names on the EPA's CHP website and through awards like the Energy Star CHP award.

2. DATA

The main data set used for the analysis is the EIA Form 906/920, a sample of utility and non-utility boilers for the years 2001 through 2008 in the U.S. The data are recorded annually at the plant level, and plants may contain more than one boiler. Only plants in the electricity generation or manufacturing sector are used in this analysis, North American Industrial Classification System (NAICS) 22 and 31-33, respectively.

The data contain information on plant specific characteristics: primary fuel consumption on site, amount of fuel used on site, average total heat consumed on site, the location and industry code of the plant as well as indicators for the existence of a CHP system on site. Although the data start in 2001, the first year also includes all CHP installations of unknown timing from previous years and therefore it cannot be determined how many CHP systems were installed in 2001. The dataset does not discuss which type of CHP system is installed. Figure 2 shows the number of new CHP systems installed over time.

Firms join CHPP at different times thus there is variation over time and between firms in this variable. No firms have quit CHPP after joining so once a firm becomes a partner it stays on for the duration of the sample. This information was taken from the CHPP Partnership Update of 2005 and 2007, available on the website.[2]

2. The years that eight firms joined the program are not given online; this information was provided by the CHPP. The eight firms are Archer Daniels Midland, Duke Energy, Austin Energy, Calpine Corporation, Gainesville Regional Utilites, Maui Electric Company Limited, Nebraska Public Power District, and Rochelle Municipal Utilites.

Further information on fuel and electricity prices and policy variables were added to the data set. The average annual industrial electricity price for the state a plant is located in was taken from the EIA Electric Power Annual (2010). The average annual industrial price of natural gas for the state a plant is located in was taken from the EIA Natural Gas Annual (2010). The average annual industrial price of fuel oil for the state a plant is located in was taken from the EIA Petroleum Marketing Annual (2009).[3]

The policy variables contain information on state incentives to promote CHP and emissions regulations. Information on policies to promote CHP was gathered from U.S. EPA CHPP (2008). There are three policy variables used in this analysis. They are the presence of a state environmental portfolio standard (EPS) that counts CHP as renewable energy source and the existence of state run financial support schemes. An EPS dummy equals one for all years after the state that a plant is located in passed EPS legislation and a Support dummy equals one in the year and all years after the state set up a program to promote CHP. In the opposite outcome, the dummies are equal to zero.

Emissions regulations effects are captured by using a NOx regulation dummy that is equal to one if the state participates in the NOx SIP Call and/or the NOx Budget Program. The NOx Budget Program replaced the NOx SIP Call and expanded the number of states that require compliance with a tradable permit scheme for summer months NOx emissions. For the electricity sector two more policies apply. A PM Non-attainment dummy equals one if the plant is located in a county that violated the PM 2.5 standard in 2006 and is zero otherwise. Data on which county the plant is located in comes from the EIA Form-767 and data on non-attainment status comes from the EPA. A New Source Performance Standard (NSPS) indicator equals one if the plant is subject to NSPS from either the 1970 or 1977 Clean Air Acts and is zero otherwise. Data on NSPS status comes from the EIA Form-767.

Finally, year, state, North American Electric Reliability Council Region, NAICS, and Census region dummy variables are created and take the value of one if the observation meets the given criteria and are zero otherwise. Summary statistics are provided in Table 1. The first column shows the unmatched sample across the years 2001–2008, which is used in the random effects conditional logit and panel utilization analysis. The second, third, and fourth column shows the matched sample (observations on the common support for the year 2008) for all plants, CHPP partners, and non-partners, respectively. The biggest difference between the CHPP partners and non-partners in the matched sample is that CHPP partner firms have more plants than non-partner firms.

3. ECONOMETRIC MODELS

We assume that the technology adoption decision depends on profit maximizing rationale which leads a firm to invest in the technology at any time when the future discounted benefits outweigh the costs of installing (DeCanio and Watkins, 1998). Previous attempts to model CHP installation have generally focused on particular sectors and include variables similar to those used here (see Bonilla et al., 2003 and Madlener and Wickart, 2004). The net benefits are a function of prices, plant size, and other incentives or policies affecting the decision. To examine the probability of installation for partners and non-partners we employ a nearest neighbor matching estimator. As a robustness check, we also estimate a conditional logit model; however participation of firms in

3. In a few instances, industrial prices were not available for the entire sample for either the gas or oil prices, thus commercial prices were used.

Table 1: Sample Summary Statistics

Sample Variable	Unmatched Sample Mean	Unmatched Sample S.D	Matched Sample Mean	Matched Sample S.D	Matched CHPP Plants Mean	Matched CHPP Plants S.D	Matched Non-CHPP Plants Mean	Matched Non-CHPP Plants S.D
CHP Plant	0.04	0.20	0.03	0.16	0.04	0.20	0.03	0.15
CHPP Partner Plant	0.03	0.18	0.10	0.30	1.00			
NOx Regulation	0.30	0.45	0.21	0.41	0.18	0.38	0.22	0.41
State EPS	0.08	0.27	0.10	0.30	0.16	0.36	0.09	0.28
CHP State Subsidy	0.20	0.40	0.25	0.43	0.25	0.43	0.24	0.43
PM Non-attainment	0.05	0.22	0.05	0.21	0.01	0.10	0.05	0.22
NSPS	0.06	0.21	0.06	0.21	0.05	0.20	0.06	0.21
No. of Plants in Firm	12.77	14.52	12.45	13.37	18.14	12.56	11.80	13.31
Oil Plant	0.31	0.44	0.32	0.46	0.36	0.48	0.31	0.46
Gas Plant	0.47	0.49	0.52	0.50	0.47	0.50	0.58	0.50
Coal Plant	0.21	0.41	0.15	0.36	0.17	0.37	0.15	0.36
Size (Heat in bln Btu)	13400	29105	11862	26647	12093	26173	11697	26398
Utility Sector	0.95	0.20	1.00		1.00		1.00	
Manufacturing Sector	0.05	0.21						
Heat Recycled (bln Btu)	875.07	1927.45						
Natural Gas Price ($ per 1000 Ft^3)	8.16	2.68						
Fuel Oil Price (Cents per gallon)	166.42	78.22						
Electricity Price ($ per MWh)	6.29	2.41						
N of Plants	2635		983		100		883	

Notes: Variables below the dashed line are used in the Conditional Logit and Utilization Analysis. The unmatched sample includes years 2001–2008 and is utilized for the Conditional Logit and Utilization Analysis. The matched sample includes the year 2008 only

CHPP is likely to be endogenous, which would bias the coefficients on CHPP in these models. Finally, panel estimation tests whether CHPP plants utilize their CHP more than non-CHPP plants. Before the evaluation methods are described in detail, the issue of endogeneity is discussed.

The problem of endogeneity in evaluating voluntary programs arises due to the self-selection of firms into partnership or non-partnership. For instance, certain firms may join CHPP although they would have installed CHP regardless of the existence of the program due to a predisposition towards such technologies (Videras and Alberini, 2000; Brouhle et al., 2005). Firms with this predisposition to join the program will consequently lead to an upward bias of CHPP estimates. On the other hand there also might be firms that join CHPP without having the actual intention of installing CHP and therefore free-ride on the program via green-washing as membership in the program can be displayed on firms' websites, for instance (Delmas and Keller, 2005). In this case of self-selection the estimates would be biased downwards and counter the previous effect. It is hard to say which effect is larger or whether they cancel each other out. We use nearest neighbor matching in order to recover the average treatment effect of CHPP on CHP installations in the electricity sector since 2001.

3.1 Matching Estimator

The preferred method for evaluating whether CHPP facilitated the installation of CHP systems is to use a matching estimator. Since it is impossible to observe both states of the world in which a plant installs CHP as a partner and as a non-partner, matching estimators are suited to shed light on this counterfactual setting. Although we cannot observe both outcomes for a single plant, we can observe both outcomes for two similar plants. Thus to circumvent the problem of selection bias, the nearest neighbor matching estimator identifies partner and non-partner plants that have similar propensity scores, i.e. the probability of treatment response, conditional on the matching covariates (Abadie et al., 2004). In the terminology of treatment effects estimation, the CHPP partners are the treatment group and the non-partners are the so-called control group. The difference across all matched partner and non-partner plants gives the average treatment effect $\mathrm{E}[I_i^1 - I_i^0]$ and the average treatment effect on the treated $\mathrm{E}[I_i^1 - I_i^0 \mid D_i = 1]$, where the superscripts 1 and 0 denote partners and non-partners, respectively. These treatment effects can only be estimated for observations which lie on the common support, i.e. the region in which there is sufficient overlap in the characteristics of treatment and control group for which there exist adequate matches. For observations outside the common support there is no other observation that can be matched to it in order to construct a counterfactual, hence average treatment effect for the treated is only estimable for observations which satisfy this condition (Caliendo and Kopeinig, 2008).

Nearest neighbor matching estimators can be used when it is not possible to randomly assign firms to a treatment or control group (Fowlie et al., 2012; Pizer et al., 2011). The estimator requires that matching is done over variables that are likely to affect the choice of being in the treatment group (Rosenbaum and Rubin, 1983).

The matching estimator uses as a dependent variable whether a plant changed from not having a CHP system in 2001 to having one in 2008. The treatment variable is whether the plant joined CHPP over this period. The optimal number of nearest neighbors was chosen using leave-one-out cross validation as in Fowlie et al. (2012). This method uses the control group observations to estimate the counterfactual I_i^0. This is done by leaving out the i$^{\text{th}}$ observation whilst using the remaining N$-$1 observations to estimate $I_{i,-i}^0$. Since the i$^{\text{th}}$ observation is excluded, the error $e_{i,-1} = I_i^0 - \hat{I}_{i,-i}^0$ can be seen as the out of sample forecasting error. After repeating this process for all N observations, the mean squared error can be used to compare different matching methods from which the one with the smallest MSE is preferred. In addition we still vary the number of matched neighbors to test the stability of the matching outcomes.

The matching estimator was unable to find sufficient matches on the common support for the manufacturing plants in the sample, which is expected given the smaller sample size for manufacturing plants (about 5% according to Table 1) and the fact that CHP systems are more prevalent in the manufacturing sample. As a result, the matching estimation is run for the electricity sector only. The variables used to match CHPP plants with non-CHPP plants are: Primary fuel type, Plant size, Firm size, PM Non-attainment status, NSPS, NOx regulation, State environmental portfolio standard, State support and State and Grid Network Dummies.

3.2 Random Effects Conditional Logit

For comparison to the matching estimator, a random effect conditional logit model is estimated. Here the installation of CHP is defined as adoption of at least one CHP unit at a given plant in period t, provided that this plant does not have any CHP installed prior to this point in time. The dependent variable is an installation dummy, $I_{i,t}$, which equals one if plant i installs CHP at time t and is zero otherwise with the condition being that there has been no CHP installed in previous periods.

The probability of installation is:

$$Pr(I_{i,t} = 1) = \frac{e^{CHPP_{i,t} + PL_i + D_{i,t} + S_{i,t}}}{1 + e^{CHPP_{i,t} + PL_i + D_{i,t} + S_{i,t}}} \tag{1}$$

for which $CHPP_{i,t}$ is the plants partnership with CHPP, PL_i is a vector of plant characteristics including size, fuels used and location indicators. $D_{i,t}$ is a vector of fuel and electricity prices, and $S_{i,t}$ is a vector of state policy variables like state support for CHP installation or EPS counting CHP as a renewable energy source. The estimation sample for the installation model includes partner and non-partner plants. Once a plant has installed a CHP system, the remainder of this plant's observations in the sample is dropped because otherwise the model would be trying to predict installation of a CHP system given that the plant has already installed. A Chow test rejects the null hypothesis that the impact of the independent variables is the same across the two sectors. Thus the conditional logit model is estimated for each sector separately.

3.3 Utilization Model

Another manner in which CHPP might contribute to the success of CHP systems is if knowledge transfers and spillovers accrue to program participants who have installed CHP systems that help them use more recycled heat. CHPP runs a number of workshops and webinars for partners to discuss their experience with CHP systems. To test for this type of attribution, we perform a CHP utilization analysis comparing plants with CHP system by their partner status. The CHP use decision is represented by the model:

$$R_{it} = \alpha_i + \beta_1 CHPP_{i,t} + \beta_2 PL_i + \beta_3 D_{i,t} + \beta_4 S_{i,t} + \epsilon_{i,t} \quad (2)$$

where R_{it} is the amount of heat recycled by plant i in year t, α_i is a plant fixed effect, $CHPP_{i,t}$ is the plant's partnership with CHPP, PL_i is a vector of plant characteristics including size, fuels used and location indicators. $D_{i,t}$ is a vector of fuel and electricity prices, and $S_{i,t}$ is a vector of state policy variables.[4] The CHP utilization analysis is performed with data for plants with a CHP system during the years which they have a CHP system installed.

4. RESULTS

The nearest neighbor matching estimates are listed in Tables 2 and 3. These results are for the electric utilities sector only. Figure 3 shows the graphical results from a covariate balancing test. It can be seen that the matched compared to the unmatched data achieves a significant bias reduction and balancing of the covariates. This supports the argument that the chosen matching estimator and its parameters have been adequately chosen. There are only 10 observations in the control group that are off the common support region (out of 993 matching observations in total). It is not much lost by removing those observations for the rest of the analysis. Observations are considered to lie on the common support if their propensity score is lower than the maximum and larger than the minimum propensity score of the control group. This is a common way to check the overlap between the treatment and control groups (Caliendo and Kopeinig, 2008).

All estimates in Table 2 match on the one nearest neighbor match as this is the number of neighbors suggested by the leave-one-out cross validation test. Column 1 shows the average treatment effect for the treated result when both the bias adjustment and heteroskedastic error term control are used. The coefficient implies that joining CHPP increases the likelihood of installing a

4. The Hausman specification test favors fixed effects over random effects. Test results are available from the authors on request.

Figure 3: Distribution of the Standardised Percentage Bias across Covariates

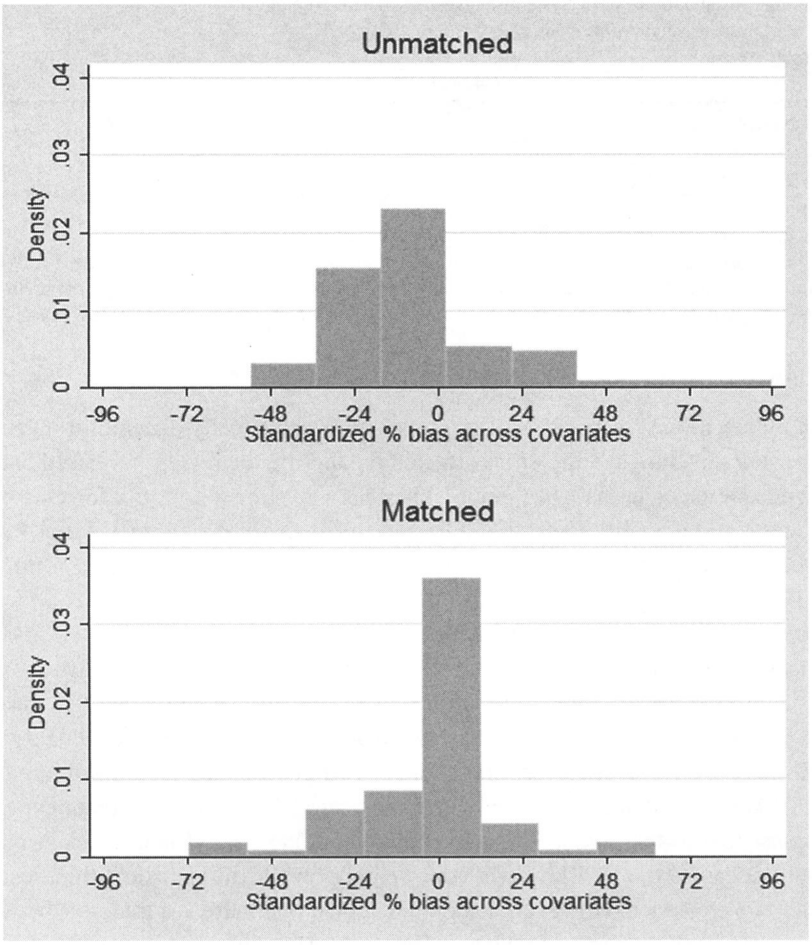


Table 2: Matching Estimator Results

Dependent Variable: Installation of CHP Systems between 2001 and 2008
Estimation Model: Nearest Neighbor Matching

Variable	Coefficient (S.E.)	Coefficient (S.E.)	Coefficient (S.E.)	Coefficient (S.E.)
Sample	Electricity Sector	Electricity Sector	Electricity Sector	Electricity Sector
CHPP Participation (Average Treated Effect for the Treated)	0.03* (0.01)	0.03 (0.03)	0.03* (0.01)	0.03 (0.03)
Bias Adjustment	Yes	Yes	No	No
Heteroskedastcity-Correction	Yes	No	Yes	No

*, **, *** indicates 10%, 5%, and 1% significance, respectively, against a null of no effect.
Matching is on Fuel Type, Plant Size, Number of Plants in the Firm, PM 2006 Non-Attainment, New Source Performance Standard, NOx Budget Program, State Environmental Portfolio Standard, State Support, State and Grid Network Dummies. Exact matching is on Fuel Type and State. There are 100 treated plants in this sample. All estimates are for matching on one nearest neighbor.

Table 3: Matching Estimator Robustness Check

Dependent Variable: Installation of CHP Systems between 2001 and 2008
Estimation Model: Nearest Neighbor Matching
Sample: Electricity Sector

Variable	Coefficient (S.E.)	Coefficient (S.E.)	Coefficient (S.E.)	Coefficient (S.E.)
CHPP Participation (Average Treated Effect for the Treated)	0.03* (0.01)	0.03* (0.01)	0.03** (0.01)	0.03** (0.01)
Number of Neighbors	1	2	3	4

*, **, *** indicates 10%, 5%, and 1% significance, respectively, against a null of no effect.
Estimator uses bias-corrected matching and corrects for heteroskedasticity. Controls are Fuel Type, Plant Size, Number of Plants in the Firm, PM 2006 Non-Attainment, New Source Performance Standard, NOx Budget Program, State Environmental Portfolio Standard, State Support, State and Grid Network Dummies. There are 100 treated plants in this sample.

CHP system by 3% in the electricity sector. The result is statistically different from zero. Columns 2–4 show how the matching coefficient is affected by altering the regression-based bias adjustment and heteroskedastic error terms assumption. The bias adjustment controls for bias that could be introduced due to a low quality match (Abadie and Imbens, 2006). Columns 2 and 4 show that the result is not robust to removing the heteroskedasticity correction though the result is robust to altering the bias adjustment assumption (Column 3).

Table 3 shows the average treatment effect for the treated for the electricity sector as the number of nearest neighbors use to construct the control group increases. In general, increasing the number of neighbors has an ambiguous effect on the quality of the match. If the next closest neighbor allows the control to look more like the treated observation, then the quality of the match increases. However, if the next closest neighbor is not a good match then it will erode the quality of the match (Abadie and Imbens, 2006). The estimates of the average treatment effect for the treated are consistent as the number of nearest neighbors increase. The coefficient is positive and statistically significant at the 10% level with one neighbor while the statistical significance increases as more neighbors are added. However, it should be noted that there is a trade-off between bias and efficiency as concerns the number of matches. Hence the 1:m matching serves more as a robustness check for the 1:1 matching results.

Table 4 gives the results of the random effects conditional logit model for installation of a CHP system. The first column shows the results for the electricity sector and the second column for the manufacturing sector. Overall, the sample includes over 2600 plants and 16,000 observations with a large portion of the observations coming from the electricity sector. Column 1 and 2 find that the coefficient on CHPP is positive but not statistically significant, though with a p-value of 0.13. The NOx regulation dummy is statistically significant at the 10% level for the electricity sector but not significant for the manufacturing sector. Oil-fired plants and bigger plants are less likely to install CHP systems across both estimations.

A second outcome metric evaluates whether CHPP increases the utilization of CHP systems. The results of this analysis are given in Table 5.[5] The first column shows the electricity sector results and the second column the manufacturing sector results. Both models find no statistical relationship between firms in the CHPP and the utilization of their CHP systems. Electricity firms use their CHP less when an EPS policy is in place. This could be due to renewable technologies

5. A nearest neighbor matching estimator was also run for the utilization of CHP systems and the results (not shown) find that the CHPP is not associated with increased utilization, consistent with the results in Table 5.

Table 4: Installation Model Results

Dependent Variable: Year CHP System Installed
Estimation Model: Random Effects Conditional Logit

Sample	Electricity Sector		Manufacturing Sector	
Variable	Coefficient	S.E.	Coefficient	S.E.
CHPP Partner	0.73	0.49	3.59	2.41
NOx Regulation	0.76*	0.43	0.22	1.25
State Envir. Performance Stnd	−0.12	0.58	3.33	2.16
State Subsidy for CHP	−0.44	0.4	1.98	2.34
Natural Gas Price	0.11	0.08	−0.32	0.42
Fuel Oil Price	−0.01	0.02	−0.09	0.08
Electricity Price	0.09	0.09	−0.23	0.48
Oil Plant	−1.62***	0.62	−9.28***	2.29
Gas Plant	−0.01	0.51	−4.38**	2.16
Size	−0.0006***	0.000034	−0.0002***	0.000051
Oil Plant Size Interaction	0.000029	0.000098	0.00157	0.00452
Gas Plant Size Interaction	0.000054	0.000037	0.0018***	0.000546
Observations	16229		418	
Plants	2503		139	

*, **, *** indicates 10%, 5%, and 1% significance, respectively, against a null of no effect.
Notes: Estimation sample includes all observations when a plant does not have a CHP system and the first observation with a CHP system. Other controls used are Year and Region Dummies.

Table 5: Utilization of CHP Systems Results

Dependent Variable: Amount of Heat Recycled

Sample	Electricity Sector	Manufacturing Sector
Variable	Coeff. (S.E)	Coeff. (S.E)
CHPP Partner Plant	−25.11	46.14
	(355.54)	(196.73)
State Envir. Performance Stnd	−418.63***	521.58
	(133.56)	(645.82)
NOx Regulation	116.19	434.01*
	(680.80)	(242.29)
Natural Gas Price	−0.65	−105.60*
	(63.96)	(56.92)
Fuel Oil Price	2.88	5.76*
	(7.82)	(7.34)
Electricity Price	0.84	−8.45
	(40.36)	(102.84)
Observations	367	369
Plants	88	85

*, **, *** indicates 10%, 5%, and 1% significance, respectively.
Notes: Estimation sample is electricity and manufacturing plants, respectively, which have installed and use a CHP system. Other Controls included are Year and Plant Dummy Variables. Errors are clustered by State.

entering the market and reducing the demand for a fossil fuel plant. Manufacturing plants in states with NOx regulation use their CHP more. An odd result is that the price of natural gas is negatively correlated with CHP use in the manufacturing sector.

The results across the two models of CHP installation give a cautiously favorable impression of CHPP. The installation of CHP systems is 3% more likely in CHPP partner plants than in the non-partner plants. Given that the CHPP employs one full-time staff member[6] and myriad of issues that impact firm investment decisions; this would seem to be a successful program. On the negative side, there is no statistical evidence that CHPP knowledge transfer has led to increased utilization of CHP systems at partner plants.

5. CONCLUSIONS

Voluntary programs are increasingly used to help facilitate energy and environmental policy goals. The initial wave of voluntary programs asked participating firms to commit to a specific environmental goal or provided information to the public. A new direction for voluntary programs is to encourage the use of more efficient technologies. Given the externalities that reduce the rate of innovation and diffusion, it may be possible for voluntary programs to remedy this market failure.

This analysis evaluates whether CHPP has indeed remedied the market failure by analyzing the diffusion of CHP systems and whether CHPP plants have utilized their CHP system more than non-CHPP plants. Nearest neighbor matching estimation is used to control for possible selection bias that may occur among plants that join the CHPP. Results show that partners are more likely to install CHP systems than non-partners by 3%, which is statistically different than zero. Further tests of CHPP's ability to encourage CHP find a positive, but generally not statistically significant estimate. Taken together, the results provide evidence that CHPP is successful but with room for improvement.

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