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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 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 US Environmental Protection Agency's Combined Heat-and-Power Partnership has encouraged the installation of CHP applications since its start in 2001. Two hypotheses are tested here, whether (i) the Partnership has encouraged the installation of CHP applications and (ii) if the partnership has encouraged utilization of CHP once installed. Using nearest neighbor matching on data for electricity plants in the US, results find weak evidence that the program has helped CHP system spread, controlling for the selection of firms into the partnership.

Keywords: Voluntary Environmental Measures; Combined Heat and Power; Fossil Fuels
JEL Codes: Q58; Q48; L51; L94

Since the start of the first national voluntary programs in the early 1990s, governments have made increasingly more use of this type of policy tools to achieve abatement reductions, environmental awareness of firms or information provision to the public. A majority of the programs call on participating firms (known as partners) to commit to an action, such as a reduction in emissions. This trend has consequently led to a growing importance of measuring those programs' success (Brouhle et al. 2005, EPA 2007). A more rare 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

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Partnership (CHPP) was established in 2001 and represents this special application of voluntary programs. Designed as a multi-sector federal voluntary program, it aims to facilitate the diffusion of combined heat-and-power (CHP) by giving early-stage consulting support to firms, public recognition as well as by providing 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. The hypothesis to be tested is whether the partnership has encouraged the installation of CHP applications in electricity and manufacturing plants. In all of the estimates the coefficient on CHPP partnership is positive; however it is not always statistically significant. It would imply that the evidence points to a potentially successful program.

1 Introduction

The trend in environmental and energy policy over the past two decades has been to use market forces to ensure more efficient outcomes. While there have been many successes (the Acid Rain program and natural gas deregulation for example), more recent policy decisions are either not taken or they specify goals without specifying instruments. 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 et al. 2010). The UK Climate Change Act of 2008 sets emissions targets for firms but does not provide direct incentives (taxes or tradable permits) to meet these goals. The European Union 20-20-20 system calls for a 20% reduction in energy use through increases in energy efficiency. Most policies assume that meeting these targets will be facilitated with the use of new technologies which are either low 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, like learning-by-doing, incomplete information or network effects (Jaffe et al. 2005). Indeed, these issues are why a basket of policy instruments are shown to be more efficient at achieving an emissions goal than any single instrument (Fischer & Newell 2008). One potentially cost effective way to overcome these adoption externalities is with a voluntary program like CHPP. This type of program potentially complements policies that provide a goal but do not specify actions that need to be taken to achieve the goal. However, it must be shown that these voluntary programs are overcoming the externalities they are meant to correct for these arguments to hold.

Lyon & Maxwell (2007) argue that voluntary program goals imply that the diffusion of information should be as wide as possible across the economy[1]. A similar voluntary program to CHPP, in that it encouraged the diffusion of new technology, is the U.S. Green Lights program. DeCanio & Watkins (1998) find that the U.S. Green Lights program, which 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, although more often the evidence points to a lack of effectiveness. Boyd & Mason (2011) discuss a number of reasons why it is difficult to undertake rigorous evaluations of voluntary programs. Some examples of evaluations that find improved environmental outcomes are Khanna & Damon (1999), Innes & Sam (2008), and Lange (2009) for the 33/50, 33/50, and Coal Combustion Products Partnership programs, respectively. Gamper-Rabindran (2006), Vidovic & Khanna (2006), and Brouhle et al. (2008) find a lack of improvement in environmental outcomes for the programs they study (33/50, 33/50, and Strategic Goals Program for Metal Finishers, respectively).

CHPP was established in 2001 with the goal to promote the use of CHP as a means of reducing the environmental impact of power generation (EPA 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 come 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 organisations 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.

[1]Other theoretical analysis of voluntary programs can be found in Lyon & Maxwell (2003) and Segerson & Miceli (1998)

The CHPP utilizes a number of methods to encourage 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 finalise the project. CHPP runs a number of workshops and web-seminars (webinars) for partners to discuss their experience with CHP system. Finally, public recognition is granted by listing partners' names on the EPA's CHP website and 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. The data is annual and recorded at the plant level, which may contain more than one boiler. Only boilers in the electric utility or manufacturing sector are used in this analysis, North American Industrial Classification System (NAICS) 22 and 31-33 respectively.

The data contains information on plant specific characteristics like the primary fuel and the amount of fuel used, average total heat consumed, the location and industry code of the plant as well as indicators for the existence of a CHP system. Although the data start in 2001, the first year also includes all installations of unknown timing from previous years and therefore it cannot be determined how many CHP systems were installed in 2001. Figure 1 shows the number of new CHP systems installed over time. The dataset does not discuss which type of CHP system is installed. Firms join CHPP at different times thus there is variation over time and firm. No firms have quit the 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,

Further information on fuel and electricity prices, policy variables and indicators for participation in other voluntary programs was 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). If industrial prices were not available for the entire sample for either the gas or oil prices, commercial prices were used.

The policy variables contain information on state incentives to promote CHP which was gathered from U.S. EPA CHPP (2008), and emissions regulations. There are three indicators for the presence of a state environmental portfolio standard (EPS), which counts CHP as renewable energy source, the existence of financial state support schemes and for whether the state the plant is in has a restructured electricity market. An EPS dummy equals one all years after the state that a plant is located in passed EPS legislation, a Support dummy equals one in the year and all years after the state set up a program to promote CHP and a Deregulated Market dummy is one for the year and all years after has state has deregulated its electricity market. In the opposite outcome, the dummies are equal to zero. Information on electricity market status comes from the EIA (2003).

The emissions regulations effects are captured by using a NO_x regulation dummy that is equal to 1 if the state the plant is located in participates in the NO_x SIP Call and/or the NO_x Budget Program. The NO_x Budget Program replaced the NO_x SIP Call and expanded the number of states which require compliance with a tradable permit scheme for summer months NO_x 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 plants is subject to NSPS from either the 1970 or 1977 Clean Air Acts and is zero otherwise. Data on NSPS status

Gainesville Regional Utilites, Maui Electric Company Limited, Nebraska Public Power District, and Rochelle Municipal Utilites.

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 given in Table I.

3 Model

Under the neoclassical theory of the firm, the decision of technology adoption 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 & Watkins 1998). Previous attempts to model the installation of CHP have generally focused on particular sectors and use similar variables to determine installation (see Bonilla et al. 2003, Madlener & Wickart 2004). Here, the net benefits are a function of prices, plant size as well as other incentives or policies affecting the decision. In an ideal world without endogeneity one could model the probability of installation for partners and non-partners using a conditional panel logit model. Since this is mostly not true, the conditional logit model here serves as the benchmark and is described below.

The problem of endogeneity arises for several reasons. 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 & Alberini 2000, Brouhle et al. 2005). Firms with this predisposition to join the program will consequently lead to an upward bias of the conditional logit 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 which is a common problem of environmental voluntary programs (Delmas & Keller 2005). In this case of self-selection the estimates would be biased downwards and counter the previous effect, however it is hard to say which effect is larger or whether they cancel each other out. To overcome such issue we use nearest neighbor matching in order to recover the average causal effect of CHPP on CHP installations in the electricity and manufacturing sector since 2001. The matching estimator is described in more detail after the random effects conditional logit setting.

Secondly, we employ a utilization model to test whether the partnership has led partner plants with a CHP system to use it more compared to non-partner plants with a CHP system. The model is described after the nearest neighbor model.

3.1 Random Effects Conditional Logit

The installation of CHP is defined as a firm's decision to install at least one unit of CHP 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 for installation $I_{i,t}$ in a conditional probit model equals 1 if firm 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 a partnership dummy, 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 environmental portfolio standards 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 their observations in the sample is dropped as otherwise the model would be trying to predict installation of a CHP system given that the plant has already installed.

3.2 Matching Estimator

Another option for evaluating whether the 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. The causal effect of the partnership is then the difference between the installing partner and installing non-partner plants that share the same characteristics. The average causal effect of the partnership can then be estimated as $E(I) = E(I^1 - I^0)$, where the superscripts 1 and 0 denote partners and non-partners respectively. 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. 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 nearest neighbor matching estimator depends on the assumption that joining the partnership is random for like plants given the matching covariates (see Abadie et al. 2004). Since joining CHPP does not come at high costs as the only effort is to fill in a postcard sized agreement, this assumption is likely to be satisfied.

Data for the year 2008 is used to determine whether a plant changed from not having a CHP system in 2001 to having one in 2008 given plants which had the CHPP treatment. The number of nearest neighbors, m, used to construct a control is varied to ensure the robustness of the match. Due to the smaller number of manufacturing plants in the sample, only plants in the electricity sector are included. The variables used to match CHPP plants with non-CHPP plants are: Primary fuel type, Plant size, Utility size, PM Non-attainment status, New source performance standard, NO_x regulation, State environmental portfolio standard, State support, State and Grid Network Dummies.

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 which help them to use more recycled heat. CHPP runs a number of workshops and webinars for partners to discuss their experience with CHP system. To test for this type of attribution, a CHP utilization analysis is performed which compares plants with CHP system by their partner status. The CHP use decision is represented by the model:

$$R_{i,t} = \alpha_i + \beta_1 CHPP_{i,t} + \beta_2 S_{i,t} + \beta_3 PL_{i,t} + \beta_4 D_{i,t} + \varepsilon_{i,t} \tag{2}$$

where $R_{i,t}$ is the amount of heat recycled by plant i in year t, α_i is a plant fixed effect,

$CHPP_{i,t}$ is a partnership dummy, $PL_{i,t}$ 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[3]. 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

Table II gives the results of the random effects conditional logit model for installation of a CHP system. The first column shows the results for both sectors while column 2 and 3 show each sector separately. Overall, the sample includes over 2600 plants and 16,000 observations with a large portion of the observations coming from the electricity sector. Looking at column 1, the CHPP coefficient is positive and statistically significant, but Column 2 and 3 find that the coefficient is not statistically significant when each sector is estimated separately. Each CHPP partner coefficient is statistically significant at the 16% level when estimated separately. A similar pattern is found for the NOx regulation dummy, statistically significant at the 10% level when the sectors are combined but not significant when the sectors are estimated separately. Column 1 finds that manufacturing plants are statistically more likely to install CHP systems than electric utilities. A number of reasons could be causing this, such as the smaller scale and the differential environmental regulations for small versus large boilers. Oil-fired plants and smaller plants are less likely to install CHP systems across all there estimations.

The nearest neighbor matching estimates are listed in Table III. These results are for both sectors and the electric utilities sector only. There are not enough observations to use a matching estimator with the manufacturing sector data only. The table shows how the average treatment effect for the treated is affected by introducing a regression-based bias adjustment and controlling for heteroskedastic error terms. The bias adjustment controls for bias that could be introduced due to a low quality match (Abadie & Imbens 2006). All estimates in Table II match on the one nearest neighbor match. When the bias adjustment

[3]Hausman specification test favor fixed effects over random effects. Results available from author by request.

and hetroskedasticity is controlled for, firms joining the CHPP are statistically more likely to install CHP systems. The coefficient implies that joining CHPP increases the likelihood of installing a CHP system by 5% across both sectors and 3% in the electricity sector. This result is not robust to removing the heteroskedasticity control though it is to removing the bias adjustment.

Table IV 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. 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. 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 8% level with one neighbor while the statistical significance increases as more neighbors are added.

A second outcome metric to evaluate CHPP is the utilization of CHP systems at plants which have already installed one. The results of this analysis are given in Table V. The first column shows the fixed effects results and the second column the random effects results. Both models find no statistical relationship between firms in the CHPP and the utilization of their CHP systems. A deregulated market is statistically associated with less utilization of CHP systems in the fixed effect model. The result is surprising given that deregulated markets have been shown to bring about the use of more efficient generation (Douglas 2006).

The results across the two models of CHP installation give a cautiously favorable impression of CHPP. The installation of CHP systems is statistically more likely in CHPP partner plants than in the non-partner plants for the nearest neighbor estimates and for conditional logit model with both sectors. However the statistical significance of the nearest neighbor estimates are not robust to changes in the specification of the error term. In addition, splitting the sample by sectors for the conditional logit finds that neither is statistically significant at the 10 % level. There is no statistical evidence that CHPP knowledge transfer has led to increased utilization of CHP systems at partner plants.

5 Conclusion

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, voluntary programs can improve the performance of industries. This analysis evaluates whether CHPP has encouraged the diffusion of CHP systems and whether CHPP plants have utilized their CHP system more than non-CHPP plants. CHP systems improve efficiency of a boiler in converting energy in a fuel to heat and electricity. Two methods, a conditional logit and nearest neighbor matching, are used to test whether CHPP partners are more likely to install CHP systems than non-partners. Results provide some evidence that the program has helped CHP system spread, however it is not definitive.

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Appendix A

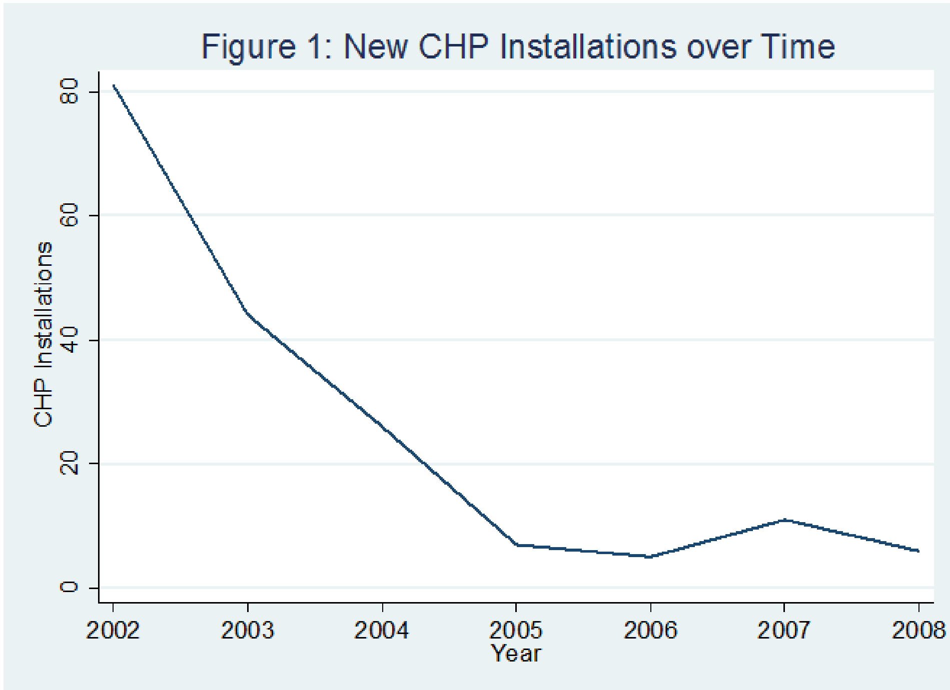

Figure 1: New CHP Installations over Time

Note: Year 2001 includes installations of unknown timing from previous years and is therefore omitted from the graph

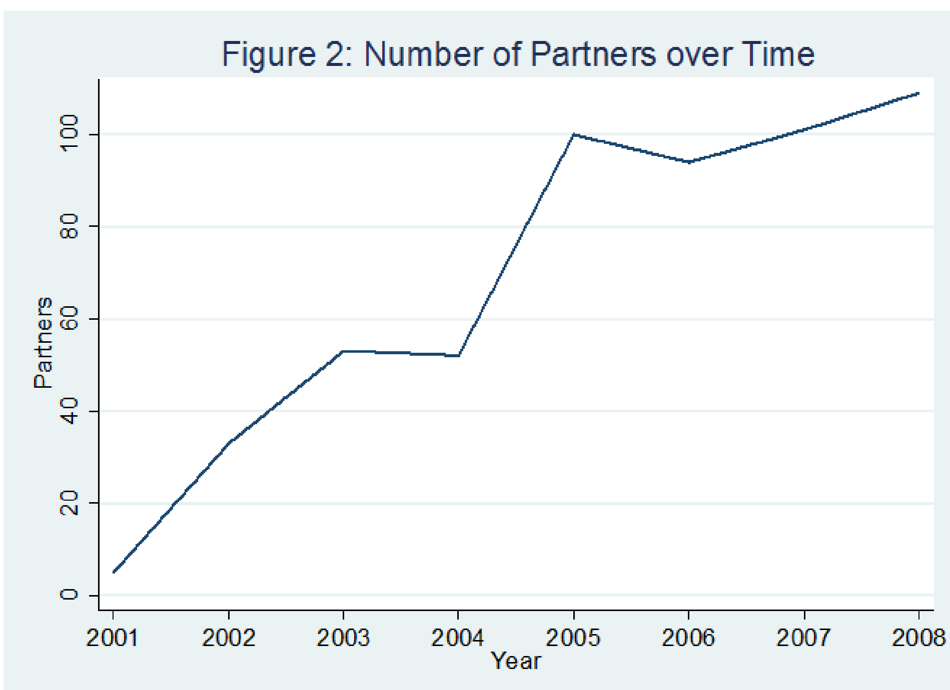

Figure 2: Number of Partners over Time

Appendix B

Table 1 - Sample Summary Statistics

Sample	Electricity & Manufacturing Sector		Electricity Sector		Manufacturing Sector	
Variable	Mean	S.D	Mean	S.D	Mean	S.D
CHP Plant	0.04	0.20	0.02	0.14	0.51	0.50
CHPP Partner Plant	0.03	0.18	0.03	0.17	0.06	0.23
Natural Gas Price (\$ per 1000Ft^3)	8.16	2.68	8.16	2.67	8.28	2.46
Fuel Oil Price (Cents per gallon)	168.24	78.22	168.12	79.17	170.90	76.64
Electricity Price (\$ per MWh)	6.14	2.41	6.14	2.38	6.07	2.07
NOx Regulation	0.29	0.45	0.28	0.45	0.28	0.45
State Envir. Performance Stnd	0.08	0.27	0.08	0.27	0.04	0.20
State Subsidy for CHP	0.20	0.40	0.19	0.27	0.19	0.39
PM Non-attainment			0.05	0.22		
NSPS			0.06	0.22		
Manufacturing Sector	0.04	0.15				
Utility Sector	0.96	0.15				
Oil Plant	0.32	0.46	0.32	0.46	0.21	0.41
Gas Plant	0.46	0.49	0.46	0.49	0.55	0.49
Coal Plant	0.20	0.40	0.21	0.41	0.22	0.41
Size (Heat in billion Btu)	11900	28300	13800	33610	2929	7070

Table 2 - Installation Conditional Logit Results

Dependent Variable: Year CHP System Installed						
Sample	Electricity & Manufacturing Sector		Electricity Sector		Manufacturing Sector	
Variable	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
CHPP Partner	1.15**	0.47	0.68	0.49	3.59	2.41
NOx Regulation	0.71*	0.38	0.52	0.42	1.01	1.25
Envir. Performance Stnd	0.11	0.55	-0.08	0.57	3.33	2.16
PM Non-attainment			-0.29	0.47		
NSPS			-4.89	4.33		
State Subsidy for CHP	-0.01	0.41	-0.44	0.4	1.98	2.34
Natural Gas Price	0.09	0.09	0.11	0.08	-0.32	0.42
Fuel Oil Price	-0.01	0.02	-0.01	0.02	-0.09	0.08
Electricity Price	0.02	0.09	0.09	0.09	-0.23	0.48
Oil Plant	-2.87***	0.54	-1.62***	0.62	-9.28***	2.29
Gas Plant	-0.68	0.45	-0.01	0.51	-4.38**	2.16
Size	-1.2E-07**	4.2E-08	-5.8E-8**	3.40E-08	-1.1E-6**	5.1E-07
Oil Plant Size Interaction	-9.89E-08	-1.0E-07	2.9E-08	9.8E-08	1.6E-06	4.5E-06
Gas Plant Size Interaction	1.2E-07**	4.4E-08	5.4E-08	3.7E-08	1.8E-06**	5.5E-07
Manufacturing Sector	4.81***	0.31				
Observations	16647		16229		418	
Plants	2636		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 3 - Nearest Neighbor Matching 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 & Manufact. Sector	Electricity & Manufact. Sector	Electricity & Manufact. Sector	Electricity & Manufact. Sector
Average Treatment Effect on the Treated	0.05** (0.02)	0.05** (0.03)	0.03** (0.02)	0.03 (0.03)
Bias Adjustment	Yes	Yes	No	No
Heteroskedasticity-Correction	Yes	No	Yes	No
Sample	Electricity Sector	Electricity Sector	Electricity Sector	Electricity Sector
Average Treatment Effect on the Treated	0.03** (0.01)	0.03 (0.03)	0.03* (0.01)	0.03 (0.03)
Bias Adjustment	Yes	Yes	No	No
Heteroskedasticity-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, NO_x Budget Program, State Environmental Portfolio Standard, State Support, Sector, State and Grid Network Dummies. Exact matching is on Fuel Type, Sector, and State. All estimates are for 1:1 nearest neighbor matching.

Table IV: Matching Estimator Robustness

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.)
Average Treatment 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