Re-evaluating the impact of voluntary programs with information spillovers*

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Abstract

Lyon and Maxwell (2007) argue that the traditional program evaluation method is not appropriate for evaluating voluntary programs with strong treatment spillovers. However, to date there exists little empirical evidence supporting their argument. This paper studies the role of information diffusion in the Combined Heat and Power Partnership (CHPP) program, a voluntary program to promote adoption of the CHP technology. Based on the traditional method used in the VA literature, the result indicates that the program has had little impact. After incorporating national information diffusion, the new results show that, although the program has had little effect on increasing participants' adoption rate, it increases adoption by non-participants, providing empirical support for the Lyon and Maxwell's (2007) argument. In addition, information diffusion impacts provide one explanation for the low participation rate by electric utilities in this program.

Keywords: Voluntary program with information diffusion, energy-efficient technology

1 Introduction

Since the first national voluntary programs started in the U.S. in the early 1990s, this policy instrument has been widely used in a variety of areas, such as agriculture, energy efficiency, climate change, technology adoption, product labeling, transportation, waste management and

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water. There is a substantial empirical literature on voluntary programs. While some studies focus on incentives to join a program (Arora and Cason 1995, 1996; Videras and Alberini 2000), our interest here is in papers studying the impact of these programs on the performance of firms (Bi and Khanna 2012; Gamper-Rabindran 2006; Innes and Sam 2008; Khanna and Damon 1999; Vidovic and Khanna 2007, 2012).

Among the voluntary environmental programs that have been implemented in the U.S., several have been widely studied, e.g., the 33/50 program, Climate Challenge, Climate Wise, Energy Star, Green Lights and so on. On the whole, the empirical literature finds mixed evidence of the impact of voluntary programs on the behavior of participants. For example, while a few papers find significant impacts of these programs (Bi and Khanna 2012; Khanna and Damon 1999), many studies suggest that the programs are ineffective (Brouhle et al. 2009; Delmas and Keller 2005; Delmas and Montes 2007; Welch et al. 2000; Vidovic and Khanna 2007, 2012), or that the impact exists only in some industries or in the early phases of the programs (Gamper-Rabindran 2006; Innes and Sam 2008; Morgenstern and Pizer 2007).[1]

However, most of the empirical studies have not considered possible information dissemination effects of voluntary programs. The information about different technologies (e.g., cost-effective abatement techniques, or energy-efficient technologies) that participants obtain from the program may also be received by non-participants. The traditional program evaluation method that regards programs as successful if participants achieve significantly better outcomes than non-participants is not appropriate to evaluate programs with strong treatment spillovers or treatment externalities. This is especially true for voluntary programs that seek to diffuse information about technologies as widely as possible throughout the country to encourage adoption of technologies that improve overall environmental outcomes (Lange 2009; Lyon and Maxwell 2007). If a diffusion effect exists and is large, we can expect little observed difference in performance between participants and non-participants, i.e., there will be little or no observed impact of joining the program (de Vries et al. 2012; Lyon and Maxwell 2007). In this context, there is a critical distinction between the impact of *participation* in the voluntary programs (which captures only the difference between the effect on performance of participants

[1] Alberini and Segerson (2002), de Vries et al. (2012) and Lyon and Maxwell (2007) provide detailed reviews of these empirical studies.

and non-participants) and the effect of the *existence* of the programs (which captures the effect on performance of both groups). The evaluation of the latter is more valuable to policy makers seeking to diffuse information widely throughout the industry to improve aggregate environmental outcomes. However, it is typically not included in the previous literature evaluating voluntary programs.

To our knowledge, there have been three papers studying treatment spillover or information diffusion effects in the context of voluntary programs. To investigate how the adoption of a pollution prevention technology is influenced by information spillovers in the context of the 33/50 Program, Bi et al. (2011) use the lagged number of pollution prevention technologies adopted as proxies for the information effect. Since this measure is not related to the existence or extent of the program, what they study is actually a general technology diffusion effect, rather than an information dissemination effect due to the voluntary program.[2] Based on data from the voluntary Coal Combustion Products Partnership program, Lange (2009) studies the treatment spillover from participants to non-participants, more precisely, from participants who demand Coal Combustion Products (CCP) to non-participants who supply CCP. He divides states into two groups: those with a small number of participants demanding CCP (low spillover effect) and those with a large number of participants demanding CCP (high spillover effect). However, he does not simultaneously examining the impact of the program on participants or the overall effect of the program. Finally, Bui and Kapon (2012) examine the overall information spillover of all state voluntary pollution prevention programs. As proxies for the spillover to a certain state, they use the fraction of all facilities in the U.S. (excluding this state) that are located in the states with voluntary pollution prevention programs and in the same industry, or the fraction of all the facilities in the same industry and in the bordering states, where the bordering states have voluntary pollution prevention programs. However, they do not study a specific program. Therefore, they cannot examine the impact of a program on either participants or non-participants. In summary, among the papers that examine spillover effects in the context of voluntary programs, we are not aware of any that have analyzed the overall impact of the program on both participants and non-participants simultaneously. More importantly, the

[2] By "information dissemination effect of the program", we mean the specific information flow from program participants to non-participants, rather than any general information diffusion about the technology.

existing studies have not examined the role of including information diffusion in the estimation.

The purpose of this paper is to study whether incorporating program information diffusion effects into the widely used estimation method in the literature affects conclusions regarding the effectiveness of the program. In particular, we test Lyon and Maxwell's (2007) argument that, because of spillover effects, voluntary programs that diffuse information about a technology widely throughout the country might have a beneficial overall environmental impact, even though there is little impact from participation. We base our analysis on the Combined Heat and Power Partnership (CHPP) program, which is a voluntary program that aims to promote the energy-efficient combined heat and power (CHP) technology to reduce fossil fuel use and the environmental impact of power generation.

The dynamic panel data GMM method pioneered by Arellano and Bond (1991) is applied to an unbalanced panel dataset of 23,921 electric utilities between 1998 and 2011. This method has been used in previous studies of voluntary programs (see, e.g., Bi and Khanna 2012; Vidovic and Khanna 2012). To compare with the previous studies and to investigate whether accounting for information diffusion in the estimation makes a difference, we start by estimating program impacts without considering information diffusion effects. The estimates suggest that the program has had little impact, which is similar to the conclusions in many previous empirical studies of other programs. However, when we incorporate national information diffusion effects in the estimation, the results show that, compared with the outcomes that would arise without the program, although the program has a low participation rate and is ineffective in increasing participants' rate of adoption of the CHP technology, it statistically significantly increases non-participants' fraction of CHP plants, on average, by 0.006 to 0.10 points from 2003 to 2011. Ignoring the program diffusion effect in the estimation cannot capture the impact of the program on non-participants via information diffusion, and might suggest the incorrect conclusion that the program has had little overall impact. On the other hand, the estimates are consistent with the reality that the program does not change electric utility participants' behavior much. This indicates that the program has had little participation impact in terms of the adoption rate of the technology. On the whole, our findings support the argument by Lyon and Maxwell (2007) that the traditional program evaluation method may be inappropriate for voluntary programs with strong spillover effects. In addition, information diffusion provides one explanation for the low participation rate of electric utilities in the program.

The paper is organized as follows. In section 2, we provide a brief description of the CHPP program. In section 3 we describe our data, and then in section 4 we describe the econometric models and the estimation method. Section 5 presents the estimated results and section 6 concludes.

2 Background of Combined Heat and Power Partnership program

The CHPP program is a voluntary program launched in 2001 that aims to reduce total fossil fuel use and the environmental impact of power generation by promoting the energy-efficient CHP technology. The CHP technology generates electricity and useful thermal output simultaneously from a single fuel source, which leads to increased fuel efficiency and hence reduced greenhouse gas emissions. There are basically five types of CHP technologies: gas turbines, microturbines, reciprocating engines, steam turbines and fuel cells. The installation costs range from $430/KW to $6500KW (EPA CHPP 2008). The CHP systems can use a variety of fuels, e.g., coal, oil, natural gas and other alternatives. The thermal output from the CHP systems can be used in either direct process application or indirectly to produce steam, hot water, hot air for drying, or cold water for cooling processes. For example, gas turbines can produce high-pressure thermal output to be used directly for heating and drying processes (EPA CHPP 2008).

In 2013, there were 492 participants in the CHPP program. Partners in the program are organizations that have committed to improving energy efficiency in the U.S., including governments and private organizations such as CHP project developers, consultants/engineers, end users, equipment manufacturers, energy service companies, financiers and utilities (EPA CHPP 2013). The CHPP program does not require adoption of the CHP technology once an organization joins. However, participants are required to report to EPA annually about existing CHP projects, new project development, and other CHP-related activities. This is the main cost participants incur after joining the program.

The main incentives that induce organizations to join the CHPP program are public recognition and technical assistance. For example, the CHPP program lists the names of its partners online, provides partners with the CHPP logo for use in sales and advertising, and issues an Energy Star CHP award based on annual performance. In addition, the CHPP program provides direct project assistance. Some energy projects may not be suitable for CHP systems. The program helps partners identify opportunities for cost-effective CHP adoption at a particular facility, assesses goals and potential barriers for a project, directs partners to the available tools and resources, and calculates energy saving and emission reduction of a CHP system compared to a separate heat and power system. This technical support is provided exclusively to participants.

However, the CHPP program also advances information diffusion regarding the CHP technology to non-participants through education and outreach. For instance, the CHPP program holds a number of national meetings, workshops and web-seminars for participants to share their experience using the CHP technology. It also encourages participants to share their experience with non-participants in other conferences and industry events. Therefore, as a result of the program, information about the CHP technology can also be received by non-participants.

While a majority of voluntary programs require participants to commit to an action once they join, e.g., a reduction of toxic releases in the 33/50 program, the main goal of the CHPP program is to accelerate diffusion of the CHP technology. This makes it easier to explicitly measure the impact of the program by investigating the utilization of the new technology across plants. Based on the data available, we limit our analysis to the impact on the electric utilities that engage in electric power generation. Through 2013, twenty utilities have participated in the program, among which ten operate electric power generation plants (EPA CHPP 2013), as shown in Table 1. We hypothesize that one reason for this low participation rate among electric utilities is the information diffusion impact of the program. Specifically, electric utilities anticipate that they can learn about the technology even as non-participants via information diffusion of the program. The benefit of joining the program is small in terms of learning about the technology. Therefore, they have less incentive to join the program. We will later discuss whether this hypothesis is supported by the estimates.

3 Data description

We obtain information from several data sources. The main data source used is the EIA860 form report, which covers all existing and proposed plants that have a total generator nameplate capacity no less than 1 megawatt (MW), are connected to the local or regional electric power grid, and have the ability to deliver power to the grid or draw power from the grid (EIA 2013). As mentioned above, we limit our sample to electric power plants whose primary purpose is generating electricity for sale and have at least one operating generator.[3] We refer to their operators as electric power generation utilities (hereafter, electric utilities for short). We use data from 1998 to 2011, which covers both the years before the CHPP program and years when the program is in place. This data source contains information on plant-specific characteristics, such as the primary energy source of each plant, the nameplate capacity of its generators, the location, the regulatory status (either regulated or unregulated) of each plant and an indicator for the existence of a CHP system. We group plant-level data to derive utility-level information, including the number of plants each electric utility operates, each electric utility's percentage of CHP plants, the fraction of each electric utility's plants using different types of energy, the fraction of its plants that are regulated and total nameplate capacity of its generators. Our unbalanced panel data consists of 23,921 electric utility-year observations between 1998 and 2011.

Moreover, expected cost saving from adopting the CHP technology might be affected by fuel costs. Therefore, we also include information on fuel costs. FERC-423 form collected monthly plant-level fuel cost data prior to 2008 and has been superseded by EIA-923 form since 2008. We combine 1998-2007 data from FERC-423 and 2008-2011 data from EIA-923 to obtain plant-level fuel cost information. Annual plant-level, state-level and national average

[3]The EIA-860 form requires that electric utility plants whose primary purpose is generating electricity for sale use code 22, while those generators whose primary purpose is for industrial or commercial business (e.g., paper mills, refineries, etc.) or for which generating electricity is only a secondary purpose use a code other than 22. Note that some of the electric power plants included in EIA-860 form whose primary purpose is electricity generation for sale also transmit and/or distribute electricity (e.g., Connecticut Light & Power Company). However, the EIA-860 form does not include electric utilities that only engage in transmission or distribution activities (e.g., Bozrah Light & Power Company in CT). The majority of plants in EIA-860 form are generating electricity for sale, with an overall fraction equal to 85% from 1998 to 2011. We are interested in examining the impact of the program on this large group, i.e., we include plants with code equal to 22 in EIA-860 form in our sample.

fuel costs are derived by averaging monthly data across the same plants, the plants in the same states and all the plants in the U.S. in a specific year, respectively. For those plants missing plant-level information, we use state-level average fuel costs instead or national data if state-level information is also unavailable.[4] We further derive the utility-level fuel costs by averaging the costs of its plants.

To avoid confounding effects of other programs, we control for the existence of other financial incentives or regulations that also promote the CHP technology. This information is taken from the Database of State Incentives for Renewables & Efficiency (DSIRE) supported by the Department of Energy, which is the most comprehensive source of information on incentives and policies that support renewables and energy efficiency in the U.S. We mainly focus on state policies related to the CHP technology and applicable to the utility sector. There are basically three types of policies, including financial incentive programs (e.g., tax incentives, grants and loans), the Energy Portfolio Standard (which includes the CHP technology as an eligible technology), and the Public Benefit Fund (which supports energy efficiency programs or technologies, including CHP technology).[5,6] We use either weighted or binary policy dummies in the different model specifications. More specifically, because some utilities have plants distributed in different states, we derive weighted state policy dummies for each electric utility based on the weighted average of the policy dummies of its plants, with weights equal to the percentage of its plants in different states. In contrast, the binary state policy dummies are defined as one, if the electric utility has at least one plant faced with a certain state policy, and zero otherwise.

Finally, although the EPA CHPP program provides the list of its partners online, it does not provide the specific information on when each of them joined the program. We obtain the detailed information on the joining date of each participant through personal communication with the CHPP program (Sneeden 2014).

[4] EIA-923 form only collects fuel cost information on regulated plants. A small number of states lack data for regulated plants in certain years and hence lack the average fuel cost information.

[5] These three types of state policies support different kinds of energy efficient technologies, apart from the CHP technology. For example, the Connecticut Public Benefit Fund for clean energy is authorized to invest in solar-electric energy, solar-thermal energy, wind energy, ocean-thermal energy, usable electricity from combined heat and power (CHP) systems with waste-heat recovery systems, and so on.

[6] Here, we use the dates when the policies became effective as the beginning time. However, the estimates that use the dates when the policies were enacted as the beginning point are similar.

Table 2 summarizes our data at the electric utility level before the influence of the program (year 2002) and for the most recent year in the sample (2011).[7] In 2011, on average, each participating electric utility's number of plants and number of CHP plants were greater than the average levels in 2002, while those of each non-participating electric utility were almost the same as those in 2002. The average level of individual participating and non-participating electric utility's fraction of CHP plants in 2011 were lower than that in 2002. The participating electric utilities have a higher, but non-participating ones have a lower, average nameplate capacity than that in 2002. Both groups face higher fuel costs in 2011 than 2002. In addition, participating electric utilities have a much higher fraction of regulated plants than non-participating ones. On average in 2011, participating utilities had a higher fraction of plants using coal, petroleum and gas, but a lower fraction using renewable fuels and other fuels as their primary energy source than non-participating utilities. The other state-level policies related to the CHP technology are almost the same between electric utility participants and non-participants.

Table 3 compares the overall adoption rate of the CHP technology among electric utility participants and non-participants across years. We find participants' total number of plants and number of CHP plants are increasing across years. Their overall fraction of CHP plants first increases and then declines. Overall, non-participants' total plants and CHP plants have an increasing trend, and their total fraction of CHP plants fluctuates slightly across years.

4 Empirical model and estimation method

Consistent with previous studies of technology adoption, we examine the impact of the program on the adoption rate of the CHP technology, measured as each utility's percentage of plants that are CHP (see, e.g., Besley and Case 1993; Griliches 1957; Kok et al. 2011; Mansfield 1961). In addition, from the perspective of EPA, the fraction of plants adopting the CHP technology is likely to be a more relevant indicator of the program's impact than the total number of CHP plants. Denote utility i's percentage of plants using the CHP technology at time t as y_{it}, which

[7] We assume the program's impact is two years lagged in the outcome equation. Therefore, it did not start to influence outcomes in 2002. The outcome in 2011 was actually affected by the program in 2009.

is determined by the following dynamic panel data model:[8]

$$y_{it} = \beta_1 y_{i,t-1} + \beta_2 X_{1i,t-2} + \delta D_{i,t-2} + \gamma \left(1 - D_{i,t-2}\right) * \Phi_{t-2} + \alpha_i + \lambda_t + u_{it}, \tag{1}$$

where β_1, δ and γ are scalar coefficients, β_2 is a vector of coefficients, α_i is the electric utility fixed effects, and λ_t captures the year fixed effects. We assume there is no serial correlation in u_{it}, i.e., $E\left(u_{it}\right) = 0$ and $E\left(u_{it}u_{is}\right) = 0$, for $t \neq s$. $X_{1i,t-2}$ includes electric utility i's own characteristics in $(t-2)$ (such as nameplate capacity and its fraction of plants using different types of primary energy sources), fuel costs and other state policies that also promote the CHP technology. We use two-year lagged explanatory variables to account for the time lag to adopt a new technology (see, e.g., Kok et al. 2011).The binary participation variable, $D_{i,t-2}$, equals 1 if the electric utility participated in the program in year $(t-2)$, and 0 otherwise.

$\left[\delta D_{i,t-2} + \gamma \left(1 - D_{i,t-2}\right) * \Phi_{t-2}\right]$ is a general expression of the impact of the program on electric utility i either as a participant or as a non-participant. It implies that $E\left[y_{it}|D_{i,t-2} = 1\right] - E\left[y_{it}|\text{no program}\right] = \delta$, i.e., δ measures the impact of the CHPP program on the participants' fraction of CHP plants. On the other hand, $E\left[y_{it}|D_{i,t-2} = 0\right] - E\left[y_{it}|\text{no program}\right] = \gamma\Phi_{t-2}$, i.e., $\gamma\Phi_{t-2}$ measures the impact of the program on non-participants' fraction of CHP plants. Φ_{t-2} is a proxy for the information diffusion effects of the program. In the main analysis, we define it as the total number of participants in the CHPP program in all sectors in the U.S. in $(t-2)$, including both utility and non-utility participants. As noted above, participants in the CHPP program are encouraged to share their experience with non-participants in national meetings, presentations and web seminars held by the program, or in other conferences and industry events. Information flow of the program increases with an increase in the number of participants. On the other hand, the impact of participation is measured by $E\left[y_{it}|D_{i,t-2} = 1\right] - E\left[y_{it}|D_{i,t-2} = 0\right] = \delta - \gamma\Phi_{t-2}$.

In addition, note that the specification in equation (1) also distinguishes between information spillover from the program and general information diffusion or technology diffusion. General

[8] A dynamic panel data model is more appropriate for our analysis than the standard fixed effects or random effects panel data model. Because investment in the new technologies is a gradual process, the stock of each electric utility's equipment builds on its previous stock. In addition, other factors such as managerial and organizational features are unobservable. Their effects can be captured by including lags of the dependent variable (see, e.g., Bi and Khanna 2012; Vidovic and Khanna 2012).

information spillover throughout the country that is the same for each utility can be captured in the year fixed effects. In contrast, the program information diffusion effect, when multiplied by utility's participation status, is utility-specific. Moreover, the magnitude is determined by the number of participants. Therefore, Φ_{t-2} measures the program information spillover rather than general information diffusion.

Because each electric utility's fraction of plants adopting the CHP technology might also be affected by some factors that simultaneously determine the utility's participation decision (such as fuel costs), the endogenous treatment problem identified by Heckman (1978) arises. We correct the resulting selection bias by including an augmented inverse Mills ratio in the performance equation (1). This method has been used in previous studies of voluntary programs (see, e.g., Innes and Sam 2008). Specifically, in the first stage, we estimate a probit model (as described in equation (2) below) and construct the augmented inverse Mills ratio based on the estimated coefficients. In the second stage, we include the inverse Mills ratio in equation (1) to evaluate the effectiveness of the program.

Electric utility i's participation decision is determined by the expected net benefit from participation in the CHPP program, D^*_{it}, which is given by

$$D^*_{it} = \beta_3 X_{2i,t-1} + \kappa_t + \varepsilon_{it}, \tag{2}$$

where β_3 is a vector of coefficients, κ_t captures the year fixed effects and $\varepsilon_{it} \sim N(0,1)$. The latent variable D^*_{it} cannot be observed. We can only observe the participation status, D_{it}, equal to 1 if the expected net benefit is positive ($D^*_{it} > 0$) and 0 otherwise. Following Khanna and Damon (1999) and others, we lag all explanatory variables by one year to avoid the simultaneity problem.

The variables in $X_{2i,t-1}$ are not exactly what are included in $X_{1i,t-2}$ (or equivalently, $X_{1i,t-1}$). To satisfy the exclusion restriction condition, we need to include at least one variable in the participation equation (2) that is not in the performance equation (1). As mentioned above, one incentive that induces firms to join the program is public recognition. For example, some studies in the literature use an instrument variable that captures whether a firm sells final goods as a proxy for its closeness to final consumers to capture the importance of public recognition for that firm (see, e.g., Khanna and Damon 1999; Vidovic and Khanna 2007). However, the electric power market has its unique characteristics. Specifically, the electric industry is comprised of some companies controlling the entire market in a local region. Demand is generally inelastic, and electric companies are more concerned about price. For regulated utilities, electric rates (prices) are approved by the utility commission through rate-of-return regulation (see, e.g., Regulatory Assistance Project 2011; Virginia State Corporation Commission 2007). In contrast, for unregulated utilities, the rates are determined by the competitive market.[9] We might expect that regulated and unregulated utilities value public recognition differently, and hence that utilities with a higher fraction of regulated plants would have a greater incentive to join voluntary programs that contribute to a positive public image to regulators and hence potentially more favorable treatment in rate-of-return regulation. However, the impact of the regulatory status on the adoption rate of the CHP technology is not apparent. The adoption rate is more likely based on the feasibility and cost-benefit analysis of installing the new systems.[10] Therefore, a variable measuring each electric utility's fraction of regulated plants is included in the participation equation but not in the performance equation. Following Khanna and Damon (1999), we confirm the validity of excluding this variable from the performance equation by computing the F-test statistics (see F-test in Tables 5-7).

Based on the estimates from the probit model, $\widehat{\beta}_3$ and $\widehat{\kappa}_t$, we construct the augmented inverse Mills ratio

$$IMR_{it} = D_{it}\left[\frac{\phi\left(\widehat{\beta}_3 X_{2i,t-1}+\widehat{\kappa}_t\right)}{\Phi\left(\widehat{\beta}_3 X_{2i,t-1}+\widehat{\kappa}_t\right)}\right] + (1-D_{it})\left[\frac{-\phi\left(\widehat{\beta}_3 X_{2i,t-1}+\widehat{\kappa}_t\right)}{1-\Phi\left(\widehat{\beta}_3 X_{2i,t-1}+\widehat{\kappa}_t\right)}\right], \tag{3}$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are normal density and distribution functions, respectively. We then

[9] A utility might have some of its plants regulated and others unregulated.

[10] Although the regulated utilities are allowed to recover their costs of new investment by adding the additional costs into the rate base (which needs to be approved by the utility commission), most states have not included the investment in CHP in the rate base (Chittum 2013). Through 2012, only two states (California and Connecticut) have appropriately designed utility rates to allow utility cost recovery and to support the clean projects (EPA CHPP 2014). Therefore, regulated utilities have no cost advantage over unregulated utilities in investing in the CHP technology.

include this in the performance equation:[11]

$$y_{it} = \beta_1 y_{i,t-1} + \beta_2 X_{1i,t-2} + \delta D_{i,t-2} + \gamma\left(1 - D_{i,t-2}\right) * \Phi_{t-2} + \beta_4 IMR_{i,t-2} + \alpha_i + \lambda_t + u_{it}. \quad (4)$$

To disentangle the impact of national diffusion from the year fixed effects, we rewrite equation (4) as

$$y_{it} = \beta_1 y_{i,t-1} + \beta_2 X_{1i,t-2} + \delta D_{i,t-2} + \gamma\left(-D_{i,t-2}\Phi_{t-2}\right) + \beta_4 IMR_{i,t-2} + \alpha_i + \omega_t + u_{it}, \quad (5)$$

where $\omega_t = (\gamma\Phi_{t-2} + \lambda_t)$. Applying a standard fixed effects or random effects estimation method to equation (5) would result in inconsistent estimates, because $y_{i,t-1}$ is correlated with the error term u_{it}. Following Arellano and Bond (1991), we first transform it into a first-difference model to eliminate the individual fixed effects, and then estimate using the panel data generalized method of moments (GMM) method, with two year and earlier lags of dependent variables ($y_{i,t-s}$, $s \geq 2$) as GMM instruments for $\triangle y_{i,t-1}$ and the first differences of other explanatory variables as instruments for themselves.[12]

The consistency of the above GMM estimator hinges on the assumption that the instruments are valid (i.e., uncorrelated with the error terms) and there is no second-order serial correlation in the first-difference residuals (Arellano and Bond 1991). We will use the Arellano-Bond test to check for serial correlation in the errors, and Hansen's J-statistics to test for orthogonality of the instruments, i.e., validity of the over-identification restrictions. Furthermore, Kleibergen-Papp rk statistics will be used to test whether these instruments are weak instruments (Kleibergen and Paap 2006).

[11] The correction term $IMR_{i,t-2}$ should be in the same period as $D_{i,t-2}$.

[12] The first differences of explanatory variables can be used as instruments for themselves when they are exogenous. In our model, the explanatory variables in equation (5) are treated as exogenous.

5 Results and discussion

5.1 Determinants of participation decision

We first study the determinants of electric utility participation in the CHPP program based on the data from 2001 to 2011, which consists of 20,971 electric utility-year observations. Because participants are free to quit after they join, they actually make decisions on whether to be in the program each period. Therefore, we do not drop a utility from the samples once it has joined the program. The estimates obtained from the pooled probit models are presented in Table 4.

As mentioned above, to control for the confounding effects of other state policies, we include variables indicating the existence of state policies that also promote the CHP technology. We explore alternative specifications. Models 1 and 3 use weighted state policy dummies, while binary state policy dummies are used in Models 2 and 4. In addition, Models 1 and 2 exclude the year fixed effects, while Models 3 and 4 include them. We find the results are similar across these four models.

The electric utility size, as measured by total nameplate capacity of generators, is an important determinant of participation in the program. Specifically, larger electric utilities are more likely to join the program. One explanation is that small electric utilities might generally be more uncertain about the benefits of participation in the program than larger ones and hence less likely to join without learning from the experience of previous participating utilities. Moreover, electric utilities with a higher fraction of regulated plants are also more likely to participate in the program. This supports our hypothesis that the regulated electric utilities have a larger incentive to join the program in an effort to project a positive public image to regulators. However, there is little evidence that an electric utility's participation decision is driven by its previous fraction of CHP plants.

Furthermore, the estimates indicate that utilities are more likely to join when faced with higher fuel costs. This supports the hypothesis that the expected cost saving by utilizing the energy-efficient CHP technology induces firms to join the program, although this cost savings is also available to non-participants who learn about the technology via information diffusion and adopt it. Nonetheless, the percentages of its plants using different sources of energy are generally not good predictors of each electric utility's participation decision. This is because the CHP systems can use a variety of fuel sources (EPA CHPP 2008), which implies that the decision on whether or not to join the program would not be driven by a specific fuel type. In addition, there is little evidence suggesting that the existence of other state policies affects firms' decision to join the CHPP program. Because these state policies support different types of energy-efficient technologies apart from the CHP technology, they have had little impact on the participation decision in a program only targeting the CHP technology. Although not shown in Table 4, the estimates of year fixed effects are significantly positive, which implies that the increase in participation probability is partly attributed to an increasing time trend.[13]

5.2 Evaluation of the CHPP program

In this section, we evaluate the effectiveness of the CHPP program in increasing the adoption rate of the CHP technology. In the main analysis, we use the sample over the whole time period (1998 to 2011), including the years before the program started.

The results of the Arellano-Bond panel GMM estimates are presented in Table 5. We match the utilities across years by their utility IDs defined in the EIA form and drop the observations without two-year lagged information, which leaves 16,551 electric utility-year observations. Table 5 uses weighted state policy dummies. Vidovic and Khanna (2007) find that controlling for year fixed effects has a large impact. Therefore, we employ alternative specifications to see whether including year fixed effects affects the conclusions implied by the results. Specifically, Models 1 and 3 exclude the year fixed effects, while Models 2 and 4 include them. (Note that excluding the year fixed effects would not allow us to capture a general information or technology diffusion effect.) In all models, Hansen tests show that the instruments in the estimation are valid at the 1% level.[14] Arellano-Bond tests confirm lack of second-order serial correlation in the first-differenced residuals. In addition, Kleibergen-Papp rk statistics reject the hypothesis that the instruments are weak.

To compare with the previous voluntary program literature and to investigate whether in-

[13] Year dummy 2001 is omitted in the participation decision regression. Therefore, the estimates measure the time trend compared with year 2001.

[14] Based on the Hansen test, we use three to five year lags of the dependent variable as instruments for $\triangle y_{i,t-1}$. The Hansen test fails if the model is estimated using a two-year lag of the dependent variable as an instrument.

corporating information diffusion in the estimation makes a difference, Models 1 and 2 follow the widely used method in the voluntary program evaluation literature of ignoring information diffusion effects, i.e., not including the term $\gamma\,(1 - D_{i,t-2}) * \Phi_{t-2}$ in equation (4) or equivalently, not including the term $\gamma\,(-D_{i,t-2}\Phi_{t-2})$ in equation (5) (see, e.g., Bi and Khanna 2012). Specifically, we first derive the inverse Mills ratio based on the results from Model 3 in Table 4, which has the greatest log-likelihood value. We assign zero to the inverse Mills ratio of observations from 1998 to 2000 before the program launched (Khanna and Damon 1999). We then include the inverse Mills ratio in the performance equation. Similar to the conclusion in many previous studies, the statistically insignificant coefficients on the participation variable in Models 1 and 2 in Table 5 suggest that the program is ineffective if we ignore information diffusion of the program in the estimation, regardless of whether we control for year fixed effects or not.[15]

In Models 3 and 4, we incorporate a national information dissemination effect in the estimation, i.e., assuming participants throughout the country diffuse information about the technology to non-participants. We find that, even after including the national information diffusion variable in the estimation, the coefficient on the participation variable (δ) is still insignificant, regardless of whether we control for year fixed effects, as shown in Models 3 and 4. This implies that the program has had little impact on increasing electric utility participants' fraction of CHP plants. This is consistent with what we observe. The program does not change electric utility participants' behavior much. Specifically, among the eight electric utility participants that had joined the program by 2009, only one participant (Austin Energy) had increased two CHP plants since two years after it joined the program. The other seven participants had not changed their CHP plant numbers. However, when we control for the year fixed effects simultaneously, the coefficient of the diffusion variable (γ) is positive and statistically significant at the 10% level, which indicates that the program is effective in increasing the adoption rate of the CHP technology among non-participants via information diffusion.[16] For instance, γ equal to 0.0004 in Model 4 means that the program increases non-participants' fraction of CHP plants by $0.0004\Phi_{t-2}$, which ranges from 0.006 in 2003 to 0.10 in 2011 (corresponding to the impact

[15] We report Windmeijer-corrected robust standard errors based on the xtabond2 command in Stata (Roodman 2009). However, using robust standard errors without the Windmeijer correction does not change the basic conclusions.

[16] Note that the information spillover is from all participants, not just from electric utility participants.

of the program from 2001 to 2009, given the two-year lag).

To see the impact of the program more clearly, we derive the outcomes with and without the impact of the program based on equation (5) in first-difference form.[17] The comparison is shown in Figure 1, which is based on the estimates in Model 4 in Table 5. (We also include the actual outcome under the program as a benchmark.) The vertical axis is the average change in utilities' fraction of CHP plants between two adjacent years, i.e., the change in the utilities' adoption rate of the CHP technology. The difference between the two curves measures the impact of the program. Since the participation rate is so low, this primarily reflects the impact on non-participants via information diffusion. We can see that the estimated change is negative without the program, which means that on average, each utility's adoption rate would have declined without the program. The estimated change under the program fluctuates around the zero line. This indicates that the program actually offsets a declining trend, and keeps the estimated adoption rate almost the same across years.

In summary, the estimates based on models incorporating national information diffusion show that, although the program has had little impact on participants' adoption rate of the CHP technology, it has had a significant impact on non-participants' adoption rate via information dissemination. In other words, overall the program has been effective in increasing the adoption rate of the CHP technology, although participation has been low and the program has had little impact on the technology adoption rate of participants. The main incentive for electric utilities to join the program might be to obtain public recognition, rather than direct technical assistance. This supports the argument by Lyon and Maxwell (2007) that voluntary programs that aim to spread information widely might have beneficial environmental impacts in the aggregate, even though there is little impact through participation. This further supports our hypothesis that electric utilities have less incentive to join the program because they anticipate that they can obtain information about the technology even as non-participants through

[17] Because the utility fixed effects are unidentified in equation (4) or (5), we first transform (5) into a first-difference model to eliminate the individual fixed effects:

$$\triangle y_{it} = \beta_1 \triangle y_{i,t-1} + \beta_2 \triangle X_{1i,t-2} + \delta \triangle D_{i,t-2} + \gamma \triangle \left(-D_{i,t-2}\Phi_{t-2}\right) + \beta_4 \triangle IMR_{i,t-2} + \triangle\omega_t + \triangle u_{it},$$

where $\triangle\omega_t = (\gamma\triangle\Phi_{t-2} + \triangle\lambda_t)$. Therefore, more precisely, what we present is the impact of the program on the average change in individual utility's fraction of CHP plants across years. We deduct the terms related to the program, i.e., $[\delta\triangle D_{i,t-2} + \gamma\triangle\left(-D_{i,t-2}\Phi_{t-2}\right) + \beta_4\triangle IMR_{i,t-2} + \gamma\triangle\Phi_{t-2}]$ to derive the estimated average change in individual utility's fraction of CHP plants without the program.

information diffusion, and hence the benefit of joining the program is small in terms of learning about the technology. Thus, the information diffusion impact of the program provides one explanation for why electric utilities' participation rate in the program is so low. In addition, comparing the estimates in Model 4 with those in Model 2 indicates that ignoring the program diffusion effect in the estimation cannot capture the impact of the program on non-participants via information diffusion, which in turn leads to an incorrect conclusion that the program has had little (overall) impact. Furthermore, comparing the results in Models 3 and 4 supports the argument that controlling for year fixed effects makes a difference. Including the year fixed effects allows us to separately identify the impact of general information dissemination and the information spillover effects of the program.

Apart from the direct influence of the program, we also find a strong correlation between the individual electric utility's fraction of CHP plants in this period and that in the previous period. However, the size of the utility, as measured by nameplate capacity, has little influence on the utility's decision to adopt the energy-efficient CHP technology. In general, there is little evidence on the correlation between the type of energy sources and electric utilities' adoption rate of CHP technology. Surprisingly, fuel cost is no longer a significant determinant of each electric utility's fraction of CHP plants.

In addition, there is little evidence that the other state policies and regulations included here encourage the utilization of CHP technology. One explanation is that these state polices support the CHP technology along with other energy-efficient technologies. It is possible the utilities replace old technology by some alternatives rather than the CHP technology based on the consideration of feasibility or cost-effectiveness. If so, we might expect no correlation between each electric utility's utilization of CHP technology and these state policies. In general, the coefficients on the inverse Mills ratio are insignificant, implying that selection bias is not a concern in our context.

5.3 Robustness checks

The above evaluation of the impact of the CHPP program uses weighted state policy dummies in the estimation. As a first robustness check, we employ an alternative specification using binary state policy dummies. As shown in Table 6, the estimates are very similar to those in Table 5.

Specifically, ignoring information dissemination in the estimation suggests that the program has had little impact of participation (Models 1 and 2 in Table 6). In contrast, after incorporating national information diffusion, the estimates imply that, although the program has had little impact on the adoption rate of electric utility participants, it has been effective in promoting the CHP technology among non-participants through information diffusion, increasing non-participants' fraction of CHP plants by 0.006 to 0.10 across years (Model 4 in Table 6). On the whole, the model controlling for information diffusion finds that the program has had significant overall impact on promoting CHP technology, regardless of whether weighted or binary state policy dummies are used in the estimation.

As a second robustness check, we estimate the model with information dissemination assumed to be limited to each state. We would expect this diffusion effect to be lower than with national diffusion. We replace Φ_{t-2} by state-level program information diffusion, $\Phi_{i,t-2}$, in equation (4), which is defined as the number of participants in all sectors in each state.[18] Then we can directly estimate equation (4) based on the Arellano-Bond GMM estimation procedure. The results are shown in Table 7. Models 1 and 2 use weighted state policy dummies, while Models 3 and 4 use binary state policy dummies. In addition, Models 1 and 3 exclude year fixed effects, while Models 2 and 4 include them. In general, we find that, when the information diffusion is assumed to be limited to each state, the estimates indicate that the program has had little impact, similar to that under models without controlling for information dissemination.

Furthermore, some studies in the literature suggest that it is better to estimate based on the sample during the time when the program has existed, which excludes the pre-program trend (see, e.g., Vidovic and Khanna 2007). Therefore, we also analyze based on the sample from 2001 to 2011 when the CHPP program exists to further check the robustness of our results. The results are shown in Table 8. Panel I and II use weighted and binary state policy dummies, respectively. We find the basic conclusion still holds based on this subsample. Specifically, models ignoring information diffusion effects find little impact of participation, consistent with many studies in the previous literature. Models controlling for national information diffusion find that, although the program has had little impact on participant's adoption rate of CHP

[18] If a utility has plants distributed in different states, we calculate weighted average of state-level information diffusion of the program, with weights equal to the fraction of its plants in different states.

technology, it has been effective in promoting the technology among non-participants and hence has had a significant overall impact. The significance levels are improved based on this sub-sample, compared to those based on the sample from 1998 to 2011. The estimates imply that the program increased non-participants' fraction of CHP plants by 0.006 to 0.11 across years. However, if we confine the diffusion effect to within individual states in the estimation, the results indicate that the program has been ineffective, similar to that under models ignoring information diffusion.

6 Conclusion

Most of the empirical studies in the voluntary program literature are based on the traditional program evaluation method that ignores the information diffusion impact of programs and considers a program as successful if participants achieve significantly better outcomes than non-participants. However, Lyon and Maxwell (2007) argue that it is possible that voluntary programs improve environmental outcomes overall, even though there is little impact of participation. This highlights the importance of distinguishing between the impact of *participation* in a voluntary program (which captures only the difference between the effects on the performance of participants and non-participants) and the effect of the *existence* of the program (which captures the effects on the performance of both groups). The evaluation of the latter is more valuable to policy makers seeking to diffuse information widely to improve aggregate environmental outcomes, but has not been included in previous empirical studies of voluntary programs.

In this paper, we explore the role of incorporating information diffusion in the estimation of the impact of a voluntary program to test the argument by Lyon and Maxwell (2007) that the traditional program evaluation method is not appropriate for voluntary programs with the potential for strong treatment spillovers. We base our analysis on the Combined Heat and Power Partnership (CHPP) program, which is a voluntary program that aims to promote the energy-efficient combined heat and power (CHP) technology to reduce fossil fuel use and the environmental impacts of power generation.

We apply the dynamic panel data GMM method pioneered by Arellano and Bond (1991) to an unbalanced panel dataset of electric utilities between 1998 and 2011. To be comparable with the previous studies and to explore whether incorporating information diffusion in the estimation makes a difference, we start with the widely used method in the voluntary program evaluation literature, ignoring information diffusion. Similar to many previous studies, the estimates indicate that the program has had little impact.

However, when we incorporate national information diffusion impacts of the program in the estimation, the results imply that, although the program is ineffective in increasing participants' adoption rate of the CHP technology, it statistically significantly increases non-participants' fraction of CHP plants, on average by 0.006 to 0.10 points from 2003 to 2011. In other words, the program has had a significant overall impact on increasing the adoption rate of the CHP technology, mainly through the information dissemination effect on non-participants. Ignoring the program diffusion effect in the estimation cannot capture the impact of the program on non-participants via information diffusion, which might lead to the wrong conclusion that the program has had little (overall) impact. On the other hand, the estimates are consistent with the reality that the program does not change electric utility participants' behavior much. This implies that the program has had little impact through participation. Our finding supports the argument by Lyon and Maxwell (2007) that the traditional program evaluation method may not be appropriate for voluntary programs with strong treatment externalities. In addition, the information diffusion impact provides one explanation for the low participation rate of electric utilities in this program. Specifically, electric utilities may have less incentive to join the program because they anticipate that they can obtain information about the technology even as non-participants through information diffusion, and hence the benefit of joining the program is small in terms of learning about the technology.

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Table 1: Utility participants in the CHPP program

Name (Business name)	Partnership join date	State	Operating electric power generation plants	Utility ID
Austin Energy	1/17/2003	TX	Yes	1015
Chesapeake Utilities	6/7/2013	DE	No	
City of Palo Alto Utilities	11/30/2005	CA	No	
Connecticut Natural Gas Corp /Southern Connecticut Gas	11/4/2005	CT	No	
Efficiency Vermont/Vermont Energy Investment Corporation	11/2/2012	VT	No	
Fort Wayne City Utilities	4/27/2009	IN	No	
Gainesville Regional Utilities	1/25/2008	FL	Yes	6909
Great River Energy	1/11/2007	MN	Yes	7570
HBH Gas Systems	11/21/2006	TX	No	
Lakehaven Utility District	9/21/2010	WA	No	
Massachusetts Water Resources Authority[a]	7/29/2011	MA	Yes	11426
Maui Electric Company Limited	12/13/2002	HI	Yes	11843
National Grid	10/16/2009	NY	Yes	56505
Nebraska Public Power District	2/12/2008	NE	Yes	13337
Oglethorpe Power Company	12/7/2010	GA	Yes	13994
Orange Water and Sewer Authority	12/8/2011	NC	No	
Philadelphia Gas Works	5/7/2013	PA	No	
Rochelle Municipal Utilities (RMU)	1/26/2004	IL	Yes	16179
Sacramento Municipal Utility District (SMUD)	1/25/2005	CA	Yes	16534
Southern California Gas Company	7/18/2006	CA	No	

[a] EIA860 form shows Massachusetts Water Resources Authority has two operating plants that are coded with 22, i.e., with primary purpose to generate electricity for sale.

Table 2: Descriptive Statistics (electric utility-level)[a,b]

Variables	Before the impact of the program (2002)[c]	During the program (2011)[d]		
	Full sample	Full sample	Participants	Non-participants
Number of plants	2.34	2.38	8.25	2.35
	(4.75)	(4.96)	(5.15)	(4.94)
Number of CHP plants	0.16	0.15	0.75	0.15
	(0.42)	(0.60)	(1.16)	(0.60)
Fraction of CHP plants[e]	0.13	0.10	0.11	0.10
	(0.34)	(0.30)	(0.20)	(0.30)
Nameplate capacity (MW)	536.61	529.33	1861.10	524.11
	(1959.99)	(1927.25)	(1498.99)	(1927.21)
Fuel costs (cents/MMBtu)	271.12	623.50	827.62	622.70
	(86.80)	(281.28)	(565.36)	(279.59)
Fraction of each utility's regulated plants	0.45	0.35	1.00	0.35
	(0.50)	(0.48)	(0.00)	(0.47)
Fraction of each utility's plants that use the following fuels as primary energy sources				
Coal	0.10	0.07	0.09	0.07
	(0.27)	(0.23)	(0.13)	(0.23)
Petroleum products	0.19	0.14	0.28	0.14
	(0.38)	(0.34)	(0.36)	(0.33)
Natural gas and other gases	0.33	0.28	0.50	0.28
	(0.45)	(0.43)	(0.37)	(0.43)
Renewable fuels	0.16	0.32	0.03	0.32
	(0.36)	(0.46)	(0.05)	(0.46)
Other fuels	0.22	0.19	0.11	0.19
	(0.40)	(0.38)	(0.20)	(0.38)
State policies related to CHP technology				
Weighted policy dummies				
Financial incentive	0.05	0.11	0.10	0.11
	(0.22)	(0.31)	(0.27)	(0.31)
PBF	0.38	0.36	0.35	0.36
	(0.48)	(0.48)	(0.48)	(0.48)
EPS	0.05	0.36	0.25	0.27
	(0.22)	(0.48)	(0.46)	(0.43)
Binary Policy dummies				
Financial incentive	0.06	0.13	0.13	0.13
	(0.24)	(0.33)	(0.35)	(0.33)
PBF	0.39	0.37	0.38	0.37
	(0.49)	(0.48)	(0.52)	(0.48)
EPS	0.06	0.27	0.25	0.29
	(0.23)	(0.43)	(0.46)	(0.45)
Observations	1684	2049	8	2041

[a] Standard deviations are in parentheses.

[b] This table reports the mean of each variable across utilities.

[c] We assume the program impact is two years lagged in the outcome equation. Therefore, it did not influence the outcome in 2002.

[d] The outcome in 2011 was actually influenced by the program in 2009. Thus, for the last two columns, participation status is based on 2009.

[e] For utility i, fraction of CHP plants = (i's number of CHP plants)/(i's number of plants).

Table 3: CHP plant number, total plant number and adoption rates of electric utility participants and non-participants[a]

Year	2002		2003		2004		2005		2006		2007		2008		2009		2010		2011	
	CHP	total	CHP	total	CHP	total	CHP	total	CHP	total	CHP	total	CHP	total	CHP	total	CHP	total	CHP	total
Participant Utility ID (joining year)																				
1015 (2003)	-	-	-	-	-	-	1	4	2	5	2	4	2	4	2	4	2	4	2	4
6909 (2008)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	1	3	1	3
7570 (2007)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	9	0	9	0	9
11843 (2002)	-	-	-	-	0	4	0	4	0	4	0	4	0	4	0	4	0	5	0	5
13337 (2008)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	13	0	13
16179 (2004)	-	-	-	-	-	-	-	-	0	3	0	3	0	3	0	3	0	3	0	3
16534 (2005)	-	-	-	-	-	-	-	-	-	-	3	15	3	15	3	15	3	15	3	15
56505 (2009)	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	14
Participants' aggregate	-	-	-	-	0	4	1	8	2	12	5	26	5	26	5	35	6	52	6	66
Fraction of CHP plants		-		-		0		0.125		0.167		0.192		0.192		0.143		0.115		0.091
Non-participants' aggregate	268	3929	301	4086	295	4041	295	4073	296	4130	291	4218	313	4399	319	4538	314	4646	307	4800
Fraction of CHP plants		0.068		0.074		0.073		0.072		0.072		0.069		0.071		0.070		0.068		0.064
Total number of participants two years ago		-		14		38		68		90		114		131		149		177		257

[a] Given that it is assumed that there is a two-year lag in the impact of the program in the outcome equation, here for example, the outcome in 2004 was due to the influence of the program in 2002. The utilities affected by the program as a participant is two years after they join the program.

Table 4: Determinants of participation status in the CHPP program[a]

Dependent variable: participation status (the explanatory variables are lagged one year)				
Variable	Model 1	Model 2	Model 3	Model 4
Nameplate capacity (MW)	3.14e-05**	2.92e-05**	3.02e-05**	2.85e-05**
	(1.3e-05)	(1.33e-05)	(1.33e-05)	(1.36e-05)
Fraction of CHP plants	0.487	0.469	0.482	0.461
	(0.372)	(0.369)	(0.374)	(0.370)
Fraction of regulated plants	1.345***	1.327***	1.349***	1.330***
	(0.418)	(0.415)	(0.404)	(0.399)
Fraction of each utility's plants that use the following fuels as primary energy sources				
Coal	-0.218	-0.215	-0.205	-0.201
	(0.453)	(0.458)	(0.463)	(0.467)
Petroleum products	0.080	0.078	0.096	0.090
	(0.363)	(0.360)	(0.358)	(0.356)
Natural gas and other gases	0.446	0.442	0.450	0.443
	(0.304)	(0.307)	(0.309)	(0.311)
Renewable fuels	0.119	0.113	0.076	0.071
	(0.310)	(0.313)	(0.313)	(0.315)
Fuel costs (cents/MMBtu)	6.97e-04***	7.16e-04***	6.79e-04***	6.99e-04***
	(1.08e-04)	(1.05e-04)	(1.59e-04)	(1.56e-04)
Policies related to CHP technology				
Weighted policy dummies				
Financial incentive	-0.216		-0.264	
	(0.391)		(0.393)	
PBF	0.024		0.027	
	(0.275)		(0.274)	
EPS	0.290		0.238	
	(0.244)		(0.257)	
Binary policy dummies				
Financial incentive		-0.133		-0.173
		(0.378)		(0.381)
PBF		0.031		0.035
		(0.264)		(0.263)
EPS		0.218		0.166
		(0.244)		(0.261)
Constant	-4.445***	-4.429***	-7.532***	-7.503***
	(0.501)	(0.502)	(0.577)	(0.571)
Year fixed effects included	No	No	Yes	Yes
Number of observations	20971	20971	20971	20971
χ^2 (p-value)	244.51 (0.00)	250.83 (0.00)	730.52 (0.00)	740.67 (0.00)
Log likelihood	-353.60	-354.70	-345.26	-346.29

[a] Robust standard errors clustered on utilities are in parentheses.

*** Statistical significance at the 1% level, ** Statistical significance at the 5% level, * Statistical significance at the 10% level.

Table 5: Determinants of each electric utility's fraction of CHP plants[a]
(1998 to 2011, using weighted state policy dummies)

Dependent variable: each utility's fraction of CHP plants				
	Without diffusion		National diffusion	
Variable	Model 1	Model 2	Model 3	Model 4
Participation (δ)	0.074	0.068	0.064	0.203
	(0.137)	(0.123)	(0.134)	(0.176)
Diffusion (γ)			1.11e-05	4.00e-04*
			(6.78e-06)	(2.34e-04)
Lagged fraction of CHP plants	0.467***	0.495***	0.472***	0.496***
	(0.090)	(0.094)	(0.089)	(0.094)
Nameplate capacity (MW)	2.05e-06	1.95e-06	1.93e-06	1.95e-06
	(1.80e-06)	(1.90e-06)	(1.87e-06)	(1.90e-06)
Fraction of each utility's plants that use the following fuels as primary energy sources				
Coal	-0.003	0.007	-0.004	0.007
	(0.004)	(0.006)	(0.004)	(0.006)
Petroleum products	-0.003	0.002	-0.004	0.002
	(0.010)	(0.010)	(0.010)	(0.010)
Natural gas and other gases	5.53e-06	0.008	2.33e-04	0.008
	(0.010)	(0.011)	(0.010)	(0.011)
Renewable fuels	0.006	0.004	-1.12e-04	0.004
	(0.012)	(0.012)	(0.011)	(0.012)
Fuel costs (cents/MMBtu)	1.44e-06	-3.02e-06	-1.08e-07	-2.64e-06
	(2.24e-06)	(4.19e-06)	(2.19e-06)	(4.21e-06)
Other policies related to CHP technology (Weighted policy dummies)				
Financial incentive	-0.026	-0.022	-0.023	-0.022
	(0.017)	(0.018)	(0.017)	(0.018)
PBF	0.004	0.003	0.008	0.003
	(0.008)	(0.008)	(0.007)	(0.008)
EPS	-1.40e-04	3.09e-04	1.10e-04	4.10e-04
	(0.001)	(0.001)	(0.001)	(0.001)
Inverse Mill Ratio	-0.020	-0.017	-0.017	-0.047
	(0.036)	(0.029)	(0.032)	(0.042)
Year fixed effects included	No	Yes	No	Yes
Number of observations	16551	16551	16551	16551
χ^2 (p-value)	33.83 (0.00)	85.41 (0.00)	36.11 (0.00)	85.67 (0.00)
F[1, N-K-1] (p-value)[b]	1.45 (0.23)	1.73 (0.19)	1.54 (0.21)	1.76 (0.19)
AR(1) p-value[c]	0.000	0.000	0.000	0.000
AR(2) p-value[c]	0.342	0.322	0.336	0.326
Hansen test (df)[d]	36.13 (23)	36.28 (23)	38.64 (23)	36.40 (23)
Kleibergen-Papp rk statistics[e]	25.214***	24.831***	25.203***	24.839***

[a] The GMM estimates reported are all two step. Windmeijer-corrected robust standard errors are in parentheses.

[b] F[1, N-K-1] is F-test statistics for the validity of excluding the fraction of regulated plants as an explanatory variable.

[c] AR(1) and AR(2) are tests for first-order and second-order serial correlation in the first-differenced residuals. The AR(2) show that assumption of no serial correlation errors cannot be rejected.

[d] Hansen test is a test of the over-identifying restrictions, asymptotically distributed χ^2 as under the null hypothesis of valid instrument. The degrees of freedom are reported in parentheses. The Hansen test shows that the over-identifying restrictions are valid at 1% level for all models.

[e] Kleibergen-Papp rk statistics is used to detect the correlation between the instruments and endogenous variable.

*** Statistical significance at the 1% level, ** Statistical significance at the 5% level, * Statistical significance at the 10% level.

Figure 1: Impact of the program on the change in individual utility's fraction of CHP plants across years

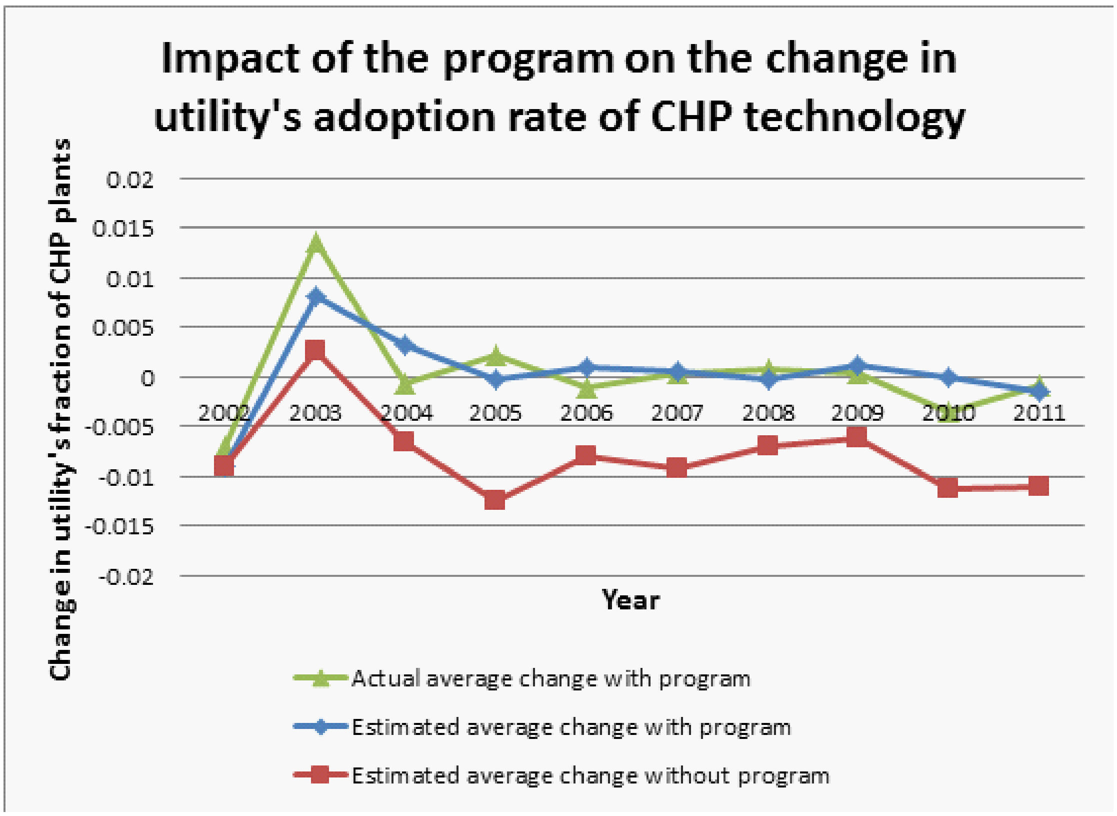

Table 6: Determinants of each electric utility's fraction of CHP plants[a]
(1998 to 2011, using binary state policy dummies)

Dependent variable: each utility's fraction of CHP plants				
	Without diffusion		National diffusion	
Variable	Model 1	Model 2	Model 3	Model 4
Participation (δ)	0.072	0.069	0.065	0.203
	(0.138)	(0.123)	(0.136)	(0.176)
Diffusion (γ)			1.04e-05	4.00e-04*
			(6.74e-06)	(2.34e-04)
Lagged fraction of CHP plants	0.469***	0.495***	0.474***	0.496***
	(0.090)	(0.094)	(0.089)	(0.094)
Nameplate capacity (MW)	2.11e-06	2.01e-06	1.96e-06	2.01e-06
	(1.76e-06)	(1.93e-06)	(1.78e-06)	(1.93e-06)
Fraction of each utility's plants that use the following fuels as primary energy sources				
Coal	-0.003	0.007	-0.004	0.007
	(0.004)	(0.006)	(0.004)	(0.006)
Petroleum products	-0.004	0.002	-0.005	0.002
	(0.010)	(0.010)	(0.010)	(0.010)
Natural gas and other gases	-6.71e-05	0.008	2.02e-04	0.008
	(0.010)	(0.011)	(0.010)	(0.011)
Renewable fuels	0.005	0.005	2.32e-04	0.005
	(0.012)	(0.012)	(0.011)	(0.012)
Fuel costs (cents/MMBtu)	1.34e-06	-2.97e-06	-2.79e-07	-2.59e-06
	(2.24e-06)	(4.19e-06)	(2.17e-06)	(4.20e-06)
Other policies related to CHP technology (Binary policy dummies)				
Financial incentive	-0.026	-0.021	-0.023	-0.022
	(0.016)	(0.016)	(0.016)	(0.016)
PBF	0.005	0.002	0.007	0.002
	(0.007)	(0.008)	(0.007)	(0.008)
EPS	-1.23e-04	1.83e-04	1.03e-04	2.73e-04
	(0.001)	(0.001)	(0.001)	(0.001)
Inverse Mill Ratio	-0.019	-0.017	-0.018	-0.047
	(0.036)	(0.029)	(0.032)	(0.042)
Year fixed effects included	No	Yes	No	Yes
Number of observations	16551	16551	16551	16551
χ^2 (p-value)	32.04 (0.00)	81.45 (0.00)	33.90 (0.00)	79.90 (0.00)
F[1, N-K-1] (p-value)[b]	1.47 (0.23)	1.73 (0.19)	1.53 (0.22)	1.75 (0.19)
AR(1) p-value[c]	0.000	0.000	0.000	0.000
AR(2) p-value[c]	0.34	0.322	0.335	0.326
Hansen test (df)[d]	35.91 (23)	36.36 (23)	38.90 (23)	36.48 (23)
Kleibergen-Papp rk statistics[e]	25.220***	24.838***	25.210***	24.846***

[a] The GMM estimates reported are all two step. Windmeijer-corrected robust standard errors are in parentheses.

[b] F[1, N-K-1] is F-test statistics for the validity of excluding the fraction of regulated plants as an explanatory variable.

[c] AR(1) and AR(2) are tests for first-order and second-order serial correlation in the first-differenced residuals. The AR(2) show that assumption of no serial correlation errors cannot be rejected.

[d] Hansen test is a test of the over-identifying restrictions, asymptotically distributed χ^2 as under the null hypothesis of valid instrument. The degrees of freedom are reported in parentheses. The Hansen test shows that the over-identifying restrictions are valid at 1% level for all models.

[e] Kleibergen-Papp rk statistics is used to detect the correlation between the instruments and endogenous variable.

*** Statistical significance at the 1% level, ** Statistical significance at the 5% level, * Statistical significance at the 10% level.

Table 7: Determinants of each electric utility's fraction of CHP plants[a]
(1998 to 2011, State-level diffusion)

Dependent variable: each utility's fraction of CHP plants				
Variable	Model 1	Model 2	Model 3	Model 4
Participation (δ)	0.066	0.073	0.066	0.073
	(0.133)	(0.123)	(0.133)	(0.123)
Diffusion (γ)	1.30e-04	1.64e-04	1.09e-04	1.58e-04
	(1.68e-04)	(3.61e-04)	(1.64e-04)	(3.62e-04)
Lagged fraction of CHP plants	0.465***	0.494***	0.467***	0.494***
	(0.092)	(0.094)	(0.092)	(0.094)
Nameplate capacity (MW)	1.88e-06	1.95e-06	1.94e-06	2.00e-06
	(1.77e-06)	(1.90e-06)	(1.72e-06)	(1.92e-06)
Fraction of each utility's plants that use the following fuels as primary energy sources				
Coal	-0.003	0.007	-0.004	0.007
	(0.004)	(0.006)	(0.004)	(0.006)
Petroleum products	-0.004	0.001	-0.004	0.002
	(0.010)	(0.010)	(0.010)	(0.010)
Natural gas and other gases	4.94e-05	0.008	6.50e-06	0.008
	(0.010)	(0.011)	(0.010)	(0.011)
Renewable fuels	0.002	0.004	0.002	0.005
	(0.012)	(0.012)	(0.011)	(0.012)
Fuel costs (cents/MMBtu)	9.19e-07	-2.71e-06	8.79e-07	-2.65e-06
	(2.32e-06)	(4.19e-06)	(2.32e-06)	(4.19e-06)
Other policies related to CHP technology				
Weighted policy dummies				
Financial incentive	-0.024	-0.021		
	(0.017)	(0.018)		
PBF	0.007	0.004		
	(0.007)	(0.008)		
EPS	-1.82e-05	3.29e-04		
	(0.001)	(0.001)		
Binary policy dummies				
Financial incentive			-0.024	-0.021
			(0.016)	(0.016)
PBF			0.006	0.003
			(0.007)	(0.008)
EPS			-1.69e-05	2.13e-04
			(0.001)	(0.001)
Inverse Mill Ratio	-0.018	-0.018	-0.018	-0.018
	(0.034)	(0.029)	(0.034)	(0.029)
Year fixed effects included	No	Yes	No	Yes
Number of observations	16551	16551	16551	16551
χ^2 (p-value)	31.86 (0.00)	81.34 (0.00)	30.46 (0.00)	77.63 (0.00)
F[1, N-K-1] (p-value)	1.33 (0.25)	1.68 (0.20)	1.31 (0.25)	1.67 (0.20)
AR(1) p-value	0.000	0.000	0.000	0.000
AR(2) p-value	0.341	0.322	0.34	0.322
Hansen test (df)	37.80 (23)	36.93 (23)	37.82 (23)	37.02 (23)
Kleibergen-Papp rk statistics	25.237***	24.572***	24.912***	24.576***

[a] The notes for the table are the same as in Tables 5 and 6.

Table 8: Determinants of each electric utility's fraction of CHP plants (2001 to 2011)[a,b,c]

Dependent variable: each utility's fraction of CHP plants			
Variable	Without diffusion	National diffusion	State-level diffusion
Panel I. Weighted policy dummies			
Participation (δ)	0.035	0.182	0.034
	(0.239)	(0.157)	(0.242)
Diffusion (γ)		4.57e-04**	2.28e-04
		(2.32e-04)	(4.57e-04)
Number of observations	12925	12925	12925
Panel II. Binary policy dummies			
Participation (δ)	0.034	0.179	0.034
	(0.239)	(0.156)	(0.242)
Diffusion (γ)		4.51e-04**	2.31e-04
		(2.30e-04)	(4.56e-04)
Number of observations	12925	12925	12925

[a] The GMM estimates reported are all two step. Windmeijer-corrected robust standard errors are in parentheses.

[b] The other variables included in the models in Table 8 are similar to those in Tables 5-7. Here, we only show the estimates of the coefficients of most interest.

[c] All models in this table include year fixed effects. As before, models excluding year fixed effects find that the program has little impact even controlling for national information diffusion of the program.

*** Statistical significance at the 1% level, ** Statistical significance at the 5% level, * Statistical significance at the 10% level.