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Why Do Firms Participate in Voluntary Environmental Programs?: The Case of DOE's Greenhouse Gas Reporting Program

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1. Introduction

This paper tries to answer the question, 'Why do firms participate in the Department of Energy (DOE)'s voluntary reporting of greenhouse gases program?' Over the last decade voluntary programs have risen as popular tools to address environmental issues. This is especially true of issues related to climate change and pollution prevention (Lyon and Maxwell, 2004). The increase in voluntary programs has prompted a large body of academic literature in these areas (Lyon and Maxwell, 2002). This literature ranges from theoretical evaluations of their welfare implications to empirical examinations of firms' participation in the programs.

Despite the vast coverage, however, most of the rigorous firm-level participation decision studies are limited to pollution prevention-related issues. Climate change-related issues have not been explored as rigorously. This is probably due to the difficulty in obtaining the relevant data for firm-level analysis. The analysis of climate change-related voluntary programs often requires examining the electric utility sector because it is the largest industrial emitter of greenhouse gases. Collecting financial and operational data for electric operating companies, especially those of investor-owned, has become very difficult since the mid-1990s when the Energy Information Administration (EIA), the statistical agency of DOE, stopped organizing in a convenient format the raw data that electric operating companies report to the Federal Energy Regulatory Commission (FERC). More recently the Environmental Protection Agency (EPA) has made publicly available an integrated database that provides emissions and generation data. A problem with the EPA database is that there is a considerable time lag. For example, the database now available covers only from 1996 to 2000. Also, there are no financial variables.

Fortunately, thanks to the financial support of the Horace H. Rackham School of Graduate Studies at the University of Michgan, we are purchasing the necessary firm-level data. We managed to make an agreement with Platts, a company specializing in energy industry data, that we purchase an annual operating company-level financial and customer-related database for 1990-2004 at a reasonable price. At this point, we are in the middle of negotiating with Platts for a further agreement to purchase some additional data including investment, environmental performance, and fuel mix data. A full-fledged study of electric operating companies' participation decisions in the 1605(b) program will have to wait until a comprehensive dataset is available.

This paper presents a preliminary analysis of this forthcoming study. It analyzes the same topic, 'Why do firms counter-intuitively participate in the 1605(b) program?' Participation in the program is likely to increase the costs of the participating firms. It is puzzling why firms voluntarily incur extra costs. This paper tries to answer the question by examining firm-specific characteristics that affect participation decisions. Since the ideal dataset is not yet available, my analysis relies on a very limited database, the EPA database, covering 1996-2000. The 1605(b) program started in 1994, so we examine approximately the first half of the program period. Because of the lack of some essential data, especially those related to financial performance, our econometric estimation suffers from omitted variable bias. Despite this problem this paper presents the results and interpret them.

2. Conceptual Framework

This paper adopts the analytical framework of Khanna and Damon (1999), in which firms' participation decisions are determined by observed exogenous firm-specific variables.

$$D_{it}^{*} = \mathbf{X_{it}\beta} + \varepsilon_{it}, \quad (1)$$

where D_{it}^{*} is a latent variable that measures the propensity to participate in the 1605(b) program, and $\mathbf{X_{it}}$ is a vector of firm-specific variables for the *i*th firm. Since we do not observe D_{it}^{*}, a binary probit model is derived from the latent variable model, assuming ε_{it} is independent of $\mathbf{X_{it}}$ and has the standard normal distribution.

$$\begin{aligned} D_{it} &= \mathrm{P}(D_{it}=1|\mathbf{X}) = \mathrm{P}(D_{it}^{*}>0|\mathbf{X}) = \mathrm{P}(\mathbf{X_{it}\beta} + \varepsilon_{it}>0|\mathbf{X}) \\ &= \mathrm{P}(\varepsilon_{it} > -\mathbf{X_{it}\beta}\,|\mathbf{X}) = 1-F(-\mathbf{X_{it}\beta}) = F(\mathbf{X_{it}\beta}) \quad (2) \\ D_{it} &= 1 \text{ if } D_{it}^{*} > 0 \text{ and } D_{it} = 0 \text{ otherwise,} \end{aligned}$$

where F is the standard normal cumulative distribution function. Firms' participation decisions are observed as discrete outcomes, equal to 1 if participate and 0 otherwise. The probit model is the basis of my analysis. This section discusses what variables to include in $\mathbf{X}$ and why.

What kinds of firm-specific factors might affect the participation decision in the 1605(b) program? Assuming the factors that motivate firms to join voluntary environmental programs are not too different across various programs, I summarize the firm-specific factors examined in previous studies along with their choice of variables. Relevant hypotheses are also displayed.

Table I
Summary of variables used in previous studies

Relevant factors	Hypotheses	Previous studies (choice of variables)
Size	• The larger the company, the greater the likelihood of participation due to a greater reputation effect. • The larger the company, the greater the likelihood of participation due to larger avoided environment-related costs. • The greater the number of subsidiaries, the greater the likelihood of participation of a holding company.	• Arora & Cason, 1995 (no. of employees) • Arora & Cason, 1996 (no. of employees, no. of facilities) • Karamanos, 1999 (total sales in mwhs) • Khanna & Damon, 1999 (no. of facilities) • Videras & Alberini, 2000 (no. of employees)
Growth	• The higher the growth rate, the greater the likelihood of participation due to the availability of extra resources.	• Videras & Alberini, 2000 (past period increase in sales)

Profitability	• The higher the profitability, the greater the likelihood of participation due to the availability of extra resources.	• Arora & Cason, 1995 (5-year (86-90)average of return on assets) • Karamanos, 1999 (electric fixed asset turnover)
Debt	• The larger the debt, the lower the likelihood of participation.	• Arora & Cason, 1995 (debt to asset ratio)
Company culture	• The greater the environmental awareness, the greater the likelihood of participation.	• Videras & Alberini, 2000 (whether env performance is a factor in compensation, firm publishes env report, conducts internal env auditing, and considers env risks)
Customer	• The larger the residential customer base, the greater the reputation effect.	• Arora & Cason, 1995, 1996 (industry expenditure on advertising/industry sales) • Khanna & Damon, 1999 (firm produces final good or not) • Karamanos, 1999 (fraction of revenues from retail customers) • Videras & Alberini,2000 (firm produces consumer goods)
Past Environmental Performance (general)	• The lower the past environmental performance, the greater the effort to fix the bad reputation. • In case reduction is measured in percentage reduction terms, reporting bad past performance could be beneficial.	• Arora & Cason, 1995 (Clean Air Act compliance) • Khanna & Damon, 1999 (no. of superfund sites) • Videras & Alberini, 2000 (past period Clean Air Act fines ($ per employee), PRP notifications)
Emissions Reduction prior to Participation (program-specific)	• The greater the past cleanup effort, the greater the likelihood of participation (firms with a good past cleanup history may want to publicize their effort).	• Arora & Cason, 1996 (percentage reduction in 33/50 toxic releases and transfers from 1988 to 1990) • Khanna & Damon, 1999 (percentage prior reduction in 33/50 releases)
Emissions/ Emissions Intensity (program-specific)	• The larger the emissions (emissions intensity), the greater the avoided environment-related costs.	• Arora & Cason, 1995, 1996 (total release, total release divided by firm sales) • Khanna & Damon, 1999 (33/50 releases)
Fuel Mix (carbon-weighted)	• In the case of climate change-related programs, the larger the use of coal (or fossil fuels), the greater the likelihood of participation.	• Karamanos, 1999 (fraction of electricity generated from fossil fuel)
Age of Assets	• The older the assets, the greater the likelihood of participation. (In case reduction is measured in percentage reduction terms, reporting bad past performance could be beneficial.)	• Khanna & Damon, 1999 (age of assets)
R&D Expenditure	• The larger the R&D expenditure, the greater the likelihood of participation due to the availability of extra resources.	• Arora & Cason, 1995, 1996 (industry expenditure on R&D/industry sales) • Khanna & Damon, 1999 (R&D/sales)

Industry Concentration	• The higher the industry concentration, the greater the likelihood of participation	• Arora & Cason, 1995, 1996 (Herfindahl index for industry)
State-level regulation	• The stronger the state-level environmental regulations, the greater the likelihood of participation.	• Karamanos, 1999 (number of state env group members per 1000 capita)
Membership in pro- or anti-environment organizations	• Membership in pro- (anti-) environment organizations increases (decreases) the likelihood of participation.	• Khanna & Damon, 1999 (CMA member)
Participation in other voluntary programs	• The greater the participation in other voluntary programs, the greater the likelihood of participation.	• Arora & Cason, 1996 (Green lights program participation)

Among the variables described, three variables show consistent and statistically significant results across studies. Both firm size and poor environmental performance increase the likelihood of participation in voluntary programs. These findings are consistent with the hypotheses shown in Table 1. However, the effect of program-specific emissions reduction prior to participation is contrary to our expectation. A good emissions reduction history decreases the likelihood of participation. Since this finding is based only on the analysis of the EPA's 33/50 program, the counterintuitive effect may be explained by the nature of the voluntary program examined. Firms' progress in this program is monitored through a public record. It is possible that firms with a good abatement history fear bad publicity that may arise in case they fail to keep up their good records after participation in the program (Lyon and Maxwell, 2002). All the other variables used in more than two studies show mixed results.

This paper examines firms' participation decisions in DOE's voluntary reporting of greenhouse gases program. The 1605(b) program is a voluntary registry program for greenhouse gas emissions and emissions reductions. In the US, more than 95% of carbon dioxide, the most abundant greenhouse gas, is emitted as the result of the combustion of fossil fuels (EIA, 2004). Consequently, greenhouse gas emissions and fossil fuel-based energy use are highly correlated. It is not surprising that the electric power sector accounts for the majority of participation in the 1605(b) program. In 2003, for example, the electric power sector accounted for 68% of project-level reports and 42% of entity level reports (EIA, 2005).

The high correlation between greenhouse gas emissions and fossil fuel-based energy use raises some questions. Does fossil fuel consumption increase the likelihood of participation in the 1605(b) program? How does the association between other explanatory variables and participation probability change with the type of fuel used? For example, how does the effect of firm size on participation probability differ between fossil fuel and nuclear use? Karamanos (1999) examined the effect of fossil fuel consumption on the likelihood of participation in the climate challenge program. He measured fossil fuel consumption as the fraction of electricity generated from fossil fuels, and found that the higher the fraction, the greater the likelihood of participation in the climate challenge program. It will be interesting to see whether this finding holds true for the 1605(b) program as well. No study so far has examined how the association between other explanatory variables and participation probability changes across different fuel types. This paper examines these issues.

3. Econometric Model

The probit model in (2) estimates the probability of participation based on explanatory variables. For this study the main variable of interest is fuel type category. I control for other factors that may affect the participation decision in the 1605(b) program. Based on the results from previous studies and the characteristics of the 1605(b) program, the factors that need to be controlled are firm size, profitability, customer base, past environmental performance, program-specific emissions/emissions intensity, and state-level regulation. Because firm-specific variables can affect firms in deciding whether to participate in the program, the explanatory variables might be endogenous with the participation decision. To avoid this problem I use lagged values (t-1) for all time-dependent explanatory variables (Khanna and Damon, 1999 and Arora and Cason, 1995).

$$\begin{aligned} P(D_{it}=1|\mathbf{X}) = F(&\beta_0 + \beta_1\, \textit{fuel type category}_{it-1} + \beta_2\, \textit{size}_{it-1} + \beta_3\, \textit{profitability}_{it-1} + \\ &\beta_4\, \textit{efficiency}_{it-1} + \beta_5\, \textit{past environmental performance}_{it-1} + \\ &\beta_6\, \textit{emissions/intensity}_{it-1} + \beta_7\, \textit{customer base}_{it-1} + \\ &\beta_8\, \textit{state-level regulations}_{it-1}) \end{aligned} \tag{3}$$

The main variable, fuel type category, is generated as follows. Data on net generation by fuel type are available as continuous variables at an electric operating company-level. I convert the continuous variables to a multinomial variable with four categories: fossil fuel, nuclear, renewable, and mixed. The classification is based on the fraction of total generation coming from the four fuel types for each company. If for a particular fuel type the fraction is greater than 1/2, I define the company as that fuel type. If no fuel type accounts for more than half of total generation, the company is defined as a mixed type. Fossil fuel includes coal, oil, and gas. Renewables includes hydro. For example, assume an electric operating company generates 100MWh: 30MWh from coal, 20MWh from oil, 10MWh from gas, and 40MWh from nuclear. The total fossil fuel generation is 60MWh, accounting for 2/3 of the total generation, so I define this company as a fossil fuel type. Although nuclear accounts for 2/5 of the total generation, it is less than 1/2. Coal is the major fuel used by the company.

Efficiency of electric operating companies, one of the control variables, can be measured using capacity factor and the inverse of heatrate. Capacity factor is the ratio of actual energy generated to the maximum possible energy that could have been generated during a period of time. The inverse of heatrate measures efficiency for fossil fuel power plants. Heatrate is the ratio of heat input to net energy generated, thus to maximize efficiency, heatrate should be minimized. I use capacity factor and heatrate to control for efficiency. This is because taking the inverse of heatrate generates too many missing variables since heatinput is zero for those power plants that use non-fossil fuels.

State-level regulations are the most difficult to quantify. The League of Conservation Voters (LCV)'s scorecard may be used. LCV is a nonprofit organization for a pro-environment Congress and White House. It publishes an annual national environmental scorecard, which scores Members of Congress based on their environmental voting records (www.lcv.org/scorecard/past-scorecards). The data is publicly available but, unfortunately, not in a convenient format. This paper instead uses a dummy variable for state-level regulations.

4. Data

This paper uses the generation and environmental performance-related data for the electric operating companies from EPA's eGRID 2002.[1] This database provides information on both investor-owned utilities (IOUs) and publicly-owned utilities (POUs) from 1996 to 2000. I use only the IOU data since the IOUs accounts for most energy generation in the US. Table II provides a list of explanatory variables used in this study.

Table II
Explanatory variables and their definitions

Variable (relevant factor)	Definition (unit of measurement)
Fuel type (fuel type category)	A dummy with four categories: fossil fuel, nuclear, renewable, and mixed
Capacity (size)	The amount of electric power that can be delivered at one time (GW)
Electric fixed asset turnover (profitability)*	A ratio of electric operating revenue to net electric utility plant value
Capacity factor (efficiency)	A ratio of energy actually generated to maximum that could have been generated (%)
Heatrate (efficiency)	A ratio of heat input to net energy generated (Btu/MWh)
SO_2 emissions (past environmental performance)	Sulfur dioxide emissions (Mtons)
CO_2 emissions (program-specific emissions)	Carbon dioxide emissions (Mtons)
Fraction of sales to residential customer (customer base)*	A ratio of sales to residential customer to total sales, where sales are measured in MWh
State-level regulation	A dummy for 50 states**

* Data for these variables are not available yet, so excluded in this study.
** LCV's scorecard will replace the dummy variable in my forthcoming study.

Data across different years are merged using EPA's Electric Generating Company (EGC) ID. This paper uses the data of only those companies that existed throughout 1996-2000.[2] Table III shows the number of the IOUs in eGRID during 1996-2000 and of those IOUs which existed throughout the period.

Table III
Number of IOUs

Year	1996	1997	1998	1999	2000
Number of IOUs	N/A*	171	154	129	127
IOUs existed throughout			116		

* Data for electric operating company type is not available for 1996.

[1] The database is available at http://www.epa.gov/cleanenergy/egrid/download.htm.
[2] Since the passage of the Energy Policy Act of 1992, which opened the US electricity market for competition, there have been mergers, acquisitions, and divestitures amongst the IOUs to increase their competency. The number of the IOUs changes accordingly from year to year (EIA, 1999).

This paper examines the determinants of the participation decisions of the IOUs over the period 1997-2000, using a probit model with lagged explanatory variables based on pooled panel data. Pooled panel data is chosen because the 1605(b) program does not require any short- or long-term commitment. The IOUs can choose every year whether to participate or not. The number of the total observations in the pooled dataset is 464 (=116×4 years). This approach is different from how Khanna and Damon (1999) analyzed their data for the 33/50 program. Noticing that once a firm participates, it stays in, they dropped those observations for which one-year lag participation dummy is 1.

Table IV provides summary statistics for the explanatory variables used in this study, both in aggregate and by participation category.

Table IV
Descriptive statistics for explanatory variables

Variable	Entire Sample (N=462)*	Non-participants (N=235)	Participants (N=227)
Fuel type			
Mean	1.463	1.706	1.211
Standard Deviation	0.826	0.949	0.579
Min	1	1	1
Max	4	3	4
Capacity			
Mean	3.244	1.120	5.444
Standard Deviation	4.212	1.712	4.859
Min	0.00045	0.00045	0.00461
Max	20.824	8.304	20.824
Capacity factor			
Mean	0.457	0.400	0.516
Standard Deviation	0.207	0.243	0.140
Min	0.00299	0.00299	0.115
Max	1	1	0.899
Heatrate			
Mean	9.611	10.403	8.791
Standard Deviation	24.187	33.778	3.258
Min	0	0	0
Max	505.113	505.113	13.730
SO_2 emissions			
Mean	0.06566	0.02449	0.108
Standard Deviation	0.09496	0.04106	0.114
Min	0	0	0
Max	0.525	0.140	0.525
CO_2 emissions			
Mean	11.894	4.569	19.477
Standard Deviation	14.248	7.220	15.702
Min	0	0	0
Max	76.715	29.289	76.715
State-level regulation			
Mean	23.258	23.877	22.617
Standard Deviation	13.383	14.637	11.947
Min	1	1	2
Max	44	43	44

* The sample size, 462, is smaller than 464. Two observations with a negative or missing total generation value are dropped.

5. Results

Table V presents the results for the participation decision study in the 1605(b) program. Model I is the econometric model in section 3. Model II replaces the fuel type category in Model I with five categorical variables: coal, oil, gas, nuclear and hydro. As described in section 3 the fuel type category in Model I is generated from the originally continuous variables, generation by fuel. This categorization does

Table V
Estimation results from probit models

Variable	Model I	Model II
Fuel type	-0.761*** (0.218)	
Coal		-0.142 (0.253)
Oil		0.189** (0.085)
Gas		0.202** (0.099)
Hydro		-0.094 (0.082)
Nuclear		0.535 (0.500)
Capacity	0.237*** (0.054)	0.139* (0.082)
Capacity factor	0.557 (0.408)	1.193 (0.418)
Heatrate	-0.096** (0.039)	-0.015*** (0.020)
SO_2 emissions	1.643 (1.893)	3.609* (2.120)
CO_2 emissions	0.0042 (0.0178)	0.021 (0.028)
State-level regulation	0.0016 (0.0059)	-0.0003 (0.0062)
Intercept	0.809 (0.709)	-2.078*** (0.702)
N	462	462
Count R^2	0.751	0.760
Adjusted count R^2	0.493	0.511
Log likelihood	-213.36	-213.78
χ^2 [7]	213.61 {0}	
χ^2 [11]		212.77 {0}

Note. All explanatory variables are lagged by one year. Standard errors are in parentheses. Degrees of freedom are in square brackets. P values are in curly brackets. χ^2 is a chi-square test of the assumption that all coefficients are jointly equal to zero.

*** Statistically significant at the 1% level

** Statistically significant at the 5% level

* Statistically significant at the 10% level (all two-tailed tests).

represent the major fuel type consumed by each IOU, but results in asymmetric categories: fossil fuel (344), nuclear (26), renewable (88), and mixed (4). To mitigate any problems that might arise from the unproportional distribution of the IOUs across the fuel categories, I generate five categorical variables for each company based on the percentile of generation by each fuel type. For coal, oil, gas and hydro, I generate four categories (<50, 50~75, 75~90, and >90). For nuclear, I generate only two categories (<90, and >90) because nuclear generation has highly rightly skewed distribution. This way of categorization allows a company to belong to more than two high-percentile fuel type categories.[3] In addition, a cutoff point of the 90th percentile brings an even distribution of the IOUs across the five fuel types: coal (47), oil (47), gas (47), nuclear (48), and hydro (47). For model II these above the 90th percentile IOU data are used to compare the effects of the explanatory variables on the participation decisions across the fuel categories.

Model I correctly specifies 75% of the participation decisions. Model II correctly specifies 76% of the participation decisions. Consistent with the previous studies, firm size, as measured by capacity, and poor environmental performance, as measured by SO_2 emissions, have positive effects on the probability of participation. The effect of firm size is significant in both models, but the effect of poor environmental performance is significant only in model II.

Efficiency of power plants, as measured by capacity factor and the inverse of heatrate, has positive effect on the probability of participation. However, the effect is significant only for heatrate. It is important to note that this is not due to high correlation between capacity factor and the inverse of heatrate. For 427 out of 462 observations for which heatrate is not zero, the correlation between the two variables is only 0.1314. Rather, it may be the result of the omitted variable bias mentioned in the introduction section.

The effect of program-specific emissions, as measured by CO_2 emissions, is positive but not significant. This is different from the previous findings on the 33/50 program. As pointed out in section 2, the previous findings may be due to the particular nature of the 33/50 program that firms' progress is monitored through a public record. The effect of state-level regulation is also not significant. This is different from expected. In case of greenhouse gas emissions, it is understandably argued that state-level regulations become more important than almost non-existent federal-level regulations (Rabe, 2004). The significance of this effect may change if the state dummy variable is replace by LCV's scorecard described in section 3.

The fuel type category in Model I has a negative significant effect. The oil and gas categories in Model II have positive significant effects. These results are consistent with Karamanos's finding that the probability of participation in the climate challenge program increases with the amount of fossil fuel consumption. As explained in section 3, the fuel type category in Model I has four categories: fossil fuel (344), nuclear (26), renewable (88), and mixed (4). These categories are coded for probit analysis: fossil fuel=1, nuclear=2, renewable=3 and mixed=4. Thus, the

[3] I again try to categorize the continuous variables because one of the objectives of this study is to examine how the effects of other explanatory variables on participation probability change across different fuel types. I intend to do this graphically, so I convert them to categorical variables.

negative coefficient indicates that the probability of participation in the 1605(b) program decreases as we go from fossil fuel types to non-fossil fuels types. Due to the categorical nature of the fuel type variable, however, interpreting the magnitude of this negative effect is not meaningful.

In case of the oil and gas categories in Model II, there are four categories according to the percentile of generation by each fuel type: <50=1, 50~75=2, 75~90=3, and >90=4. Thus, the positive significant coefficients for oil and gas indicate that the probability of participation in the 1605(b) program increases with the consumption of oil and gas, respectively. It is interesting to note that, although not significant, the coefficients for coal and hydro are negative, and the coefficient for nuclear is positive. With the exception of the hydro category, these findings are not consistent with the previous study. The results may reflect the omitted variable bias problem, or indicate some inherent differences between the companies whose major fuels are coal and those whose major fuels are oil or gas.

Table VI shows changes in predicted probabilities as explanatory variables change from their minimums to maximums and from 1/2 standard deviation below their means to 1/2 standard deviation above, and for marginal changes from their means. In case of discrete changes, changes in capacity and heatrate change the probability of participation in the 1605(b) program by large degrees. According to Model I, an increase in capacity from its minimum to maximum increases the

Table VI
Changes in predicted probabilities

Variable	Model I			Model II		
	Min→Max	-+SD/2	Marginal effect	Min→Max	-+SD/2	Marginal effect
Fuel type	-0.6072	-0.2468	-0.3035			
Coal				-0.1684	-0.0571	-0.0561
Oil				0.2166	0.0761	0.0749
Gas				0.2302	0.0812	0.0799
Hydro				-0.1117	-0.0378	-0.0371
Nuclear				0.1989	0.0645	0.2115
Capacity	0.7820	0.3816	0.0943	0.6182	0.2277	0.0548
Capacity Factor	0.2187	0.0460	0.222	0.4410	0.0976	0.4717
Heatrate	-0.8191	-0.7550	-0.0384	-0.6094	-0.1405	-0.0058
SO_2 emissions	0.3187	0.0622	0.6552	0.5038	0.1348	1.4265*
CO_2 emissions	0.1261	0.0236	0.0017	0.4807	0.1189	0.0084
State-level regulation	0.0274	0.0085	0.0006	-0.0056	-0.0017	-0.0001

*A marginal effect is a derivative at a point, so can be greater than 1.
(source:http://www.stata.com/support/faqs/stat/mfx_size.html)

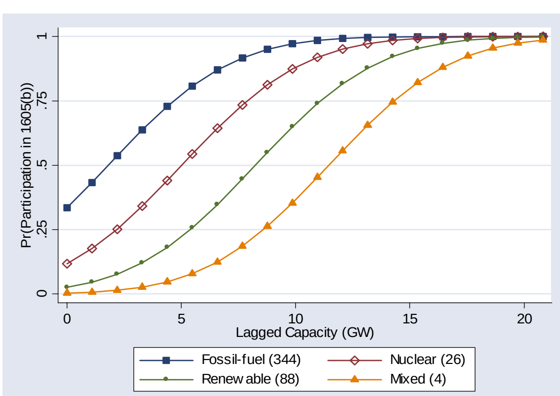
probability by 78%, holding all other variables constant at their means. A corresponding increase in heatrate decreases the probability by 82%. A standard deviation increase in capacity centered on its mean increases the probability by 38%, holding all other variables constant at their means. A corresponding increase in heatrate decreases the probability by 76%. The change in probability due to a marginal change is the largest for SO_2 emissions. A marginal change in SO_2 emissions from its mean changes the probability of participation by 66%.

Figure I shows how the association between the continuous explanatory variables and the participation probability changes across different fuel types. The graphs on the left are the results from Model I and those on the right are from Model II. Overall, as firm size increases the probability of participation increases at a decreasing rate. However, Model I and Model II show somewhat different results similar to those found in the above probit analysis. Whereas Model I shows that among firms of the same size the fossil fuel-using firms (coal, oil and gas in aggregate) are more likely to participate in the 1605(b) program than the nuclear-using firms, Model II shows that this is true only for the oil and gas categories. The coal-using firms are less likely to participate than their nuclear counterparts. The discrepancy between the coal types and the oil and gas types are also apparent in the case of the effect of other explanatory variables on the participation decisions. Again, it is not clear at this point whether this indicates any differences between companies that use different fossil fuel types, requiring sub-categorization of the fossil fuel category, or simply reflects the omitted variable bias. This issue warrants further examination.

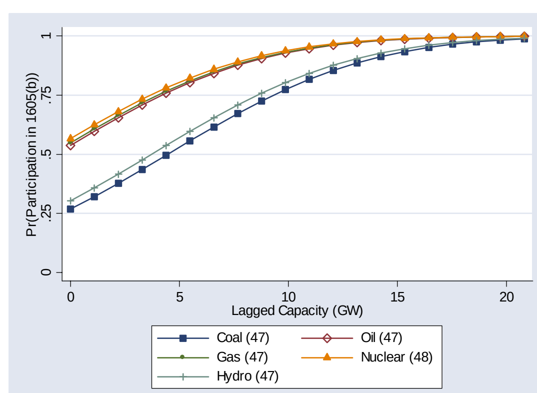
Capacity factor, a proxy for efficiency, linearly increases the probability of participation in both models. Heatrate, the inverse of efficiency for fossil fueled power plants, decreases the probability of participation. The magnitude of this effect decreases as heatrate increases. Past environmental performance, as measured by SO_2 emissions, increases the probability of participation. Model I shows that the effect is approximately linear. Model II shows that the magnitude of the effect decreases as SO_2 emissions increase. The similar trend is observed for program-specific emissions measured as CO_2 emissions.

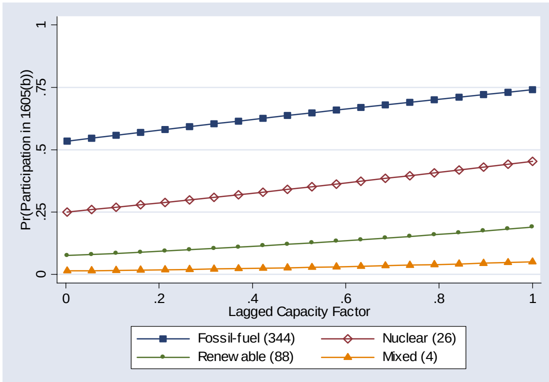
Figure I
Effects of explanatory variables on the participation decisions

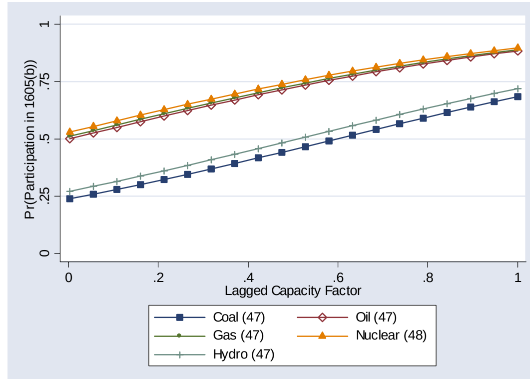
Model I

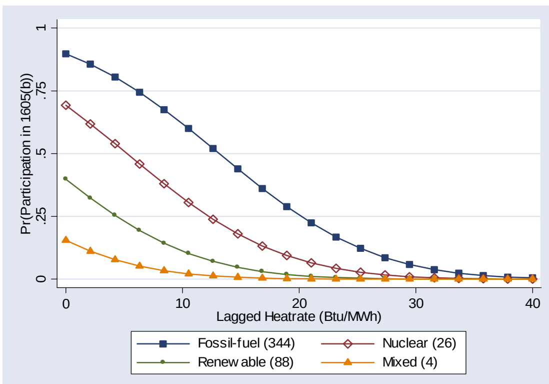


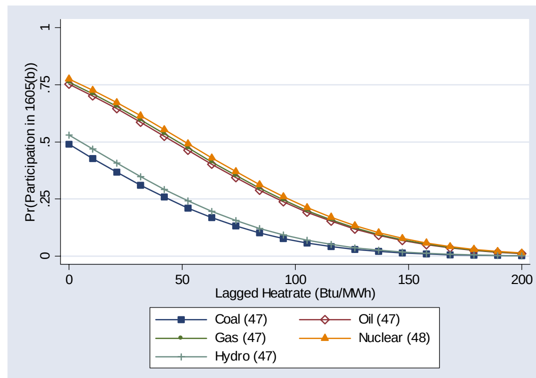
Model II

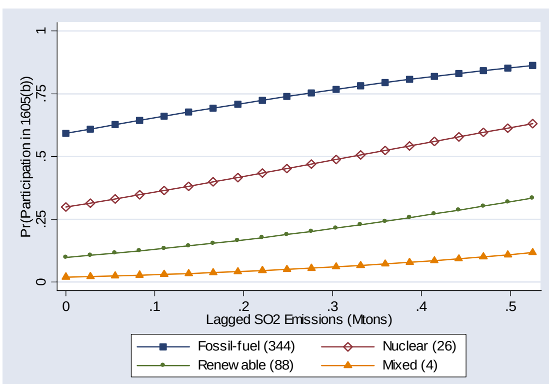


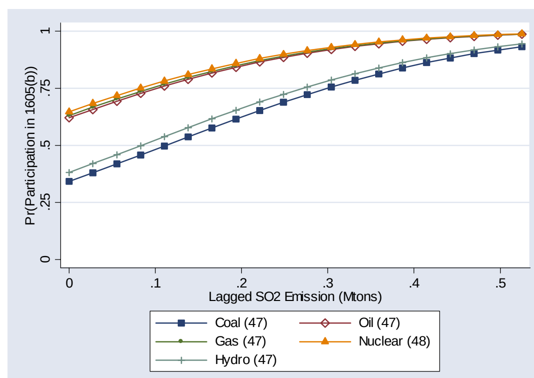

Pr(Participation in 1605(b))
0
.25
.5
.75
1
0
.2
.4
.6
.8
1
Lagged Capacity Factor
Fossil-fuel (344)
Nuclear (26)
Renew able (88)
Mixed (4)

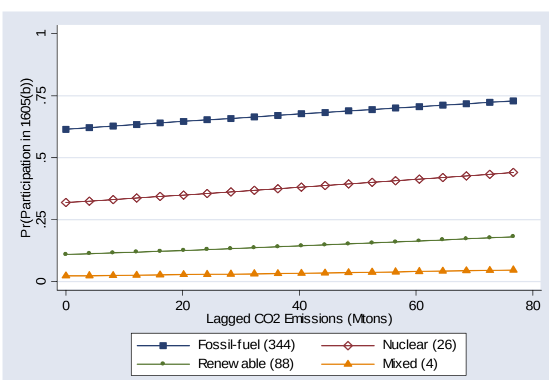

Pr(Participation in 1605(b))
0
.25
.5
.75
1
0
.2
.4
.6
.8
1
Lagged Capacity Factor
Coal (47)
Oil (47)
Gas (47)
Nuclear (48)
Hydro (47)

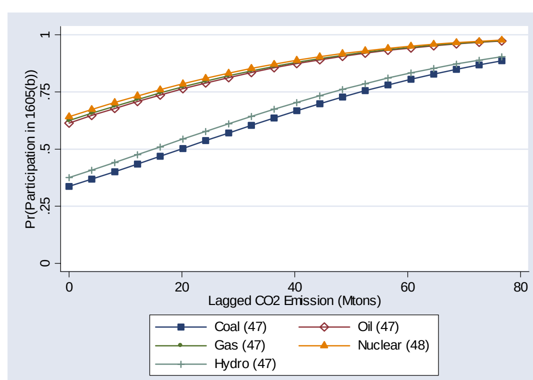

Pr(Participation in 1605(b))
0
.25
.5
.75
1
0
10
20
30
40
Lagged Heatrate (Btu/MWh)
Fossil-fuel (344)
Nuclear (26)
Renew able (88)
Mixed (4)


Pr(Participation in 1605(b))
0
.25
.5
.75
1
0
50
100
150
200
Lagged Heatrate (Btu/MWh)
Coal (47)
Oil (47)
Gas (47)
Nuclear (48)
Hydro (47)


Pr(Participation in 1605(b))
0
.25
.5
.75
1
0
.1
.2
.3
.4
.5
Lagged SO2 Emissions (Mtons)
Fossil-fuel (344)
Nuclear (26)
Renew able (88)
Mixed (4)


Pr(Participation in 1605(b))
0
.25
.5
.75
1
0
.1
.2
.3
.4
.5
Lagged SO2 Emission (Mtons)
Coal (47)
Oil (47)
Gas (47)
Nuclear (48)
Hydro (47)


Pr(Participation in 1605(b))
0
.25
.5
.75
1
0
20
40
60
80
Lagged CO2 Emissions (Mtons)
Fossil-fuel (344)
Nuclear (26)
Renew able (88)
Mixed (4)


Pr(Participation in 1605(b))
0
.25
.5
.75
1
0
20
40
60
80
Lagged CO2 Emission (Mtons)
Coal (47)
Oil (47)
Gas (47)
Nuclear (48)
Hydro (47)

6. Conclusion

This paper examines what firm-specific characteristics determine the participation decisions of the electric operating companies in the 1605(b) program. Consistent with the previous studies, I found significant positive effects of firm size, poor environmental performance, and fossil fuel consumptions. Subdividing the fossil fuel category, however, shows an interesting result. The probability of participation increases with the oil and gas consumptions, but not with the coal consumptions. The discrepancy is also apparent from the comparisons of the graphs that show how the effects of the explanatory variables on the participation decisions change across different fuel categories. This issue will be further examined when more comprehensive data is available.

REFERENCES

1. S. Arora and T. N. Cason, An experiment in voluntary environmental regulation: Participation in EPA's 33/50 Program, *J. Environ. Econom. Management*, **28**, 271-286 (1995).
2. S. Arora and T. N. Cason, Why do firms volunteer to exceed environmental regulations? Understanding participation in EPA's 33/50 program, *Land Econom*., **72**, 413-432 (1996).
3. P. Karamanos, "Voluntary Environmental Agreements for the Reduction of Greenhouse Gas Emissions: Incentives and Characteristics of Electric Utility Participants in the Climate Challenge Program" working paper, School of Public and Environmental Affairs, Indiana University, Bloomington (1999).
4. M. Khanna and L. A. Damon, EPA's voluntary 33/50 program: Impact on Toxic Releases and Economic Performance of firms, *J. Environ. Econom. Management*, **37**, 1-25 (1999).
5. T. P. Lyon and J. W. Maxwell, "Voluntary approaches to environmental regulation," in Maurizio Franzini and Antonio Nicita (eds.), *Economic Institutions and Environmental Policy*, Ashgate Publishing Company, Aldershot (2002).
6. T. P. Lyon and J. W. Maxwell, "Corporate Environmentalism and Public Policy," Cambridge Univ. Press, Cambridge (2004).
7. B. G. Rabe, "Statehouse and greenhouse: the Emerging Politics of American Climate Change Policy," Broookings Institution Press, Washington, D.C. (2004).
8. U.S. Energy Information Administration, "The Changing Structure of the Electric Power Industry 1999: Mergers and Other Corporate Combinations," DOE/EIA-0562(99), Office of Coal, Nuclear, Electric and Alternate Fuels (December 1999).
9. U.S. Energy Information Administration, "Emissions of Greenhouse Gases in the United States 2003," DOE/EIA-0573(2003), Office of Integrated Analysis and Forecasting (December 2004).
10. U.S. Energy Information Administration, "Voluntary Reporting of Greenhouse Gases 2003", DOE/EIA-0608(2003), Office of Integrated Analysis and Forecasting (February 2005).
11. J. Videras and A. Alberini, The appeal of voluntary environmental programs: which firms participate and why?, *Contemporary Economic Policy*, **18**, 449-461 (2000).