20 Apr 2017

Three Essays on the Efficiency of Carbon Emission Trading Programs

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University of Connecticut, 2017

Using individual level data from electricity generators, my dissertation empirically investigates the effectiveness of existing regional environmental policies in the U.S. electricity wholesale markets aiming to reduce CO_2 emissions. Big drop of natural gas price and limited magnitude and variation of CO_2 allowance prices make the contribution of CO_2 cap and trade programs questionable. Given the complexity of the electricity markets, the central of my research is to decompose the co-existing various effects on individual firms' emissions and evaluate the performance of current regional regulations. I particularly study the Regional Greenhouse Gas Initiative (RGGI), which regulates power plants in nine northeastern states of the U.S.. The first chapter measures the impact of carbon emission regulation on U.S. power plants' technical efficiency. No evidence of technical efficiency changes due to the RGGI regime in the RGGI area is found. Using a difference-in-difference framework in chapter two, we find that overall the RGGI program leads to 7.72 million short tons of CO_2 reduction per year in Delaware and Maryland, or about 34.36% of the average total annual emissions in these two states. All utilities respond to the program by decreasing their heat input per capacity even including natural gas utilities. Chapter 3 studies electricity generators' production behavior and how the decisions are altered with CO_2 emission regulations. The results show that the RGGI policy has helped to decrease the total CO_2 emissions by at least 4.73% during the sample period. All other things equal, an additional \$1/ton increase in permit price reduce the total CO_2 emissions by 1.85%.

Three Essays on the Efficiency of Carbon Emission Trading Programs

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A Dissertation

Submitted in Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

at the

University of Connecticut

2017

APPROVAL PAGE

Doctor of Philosophy Dissertation

Three Essays on the Efficiency of Carbon Emission Trading Programs

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Overview

Market-based emission trading programs have been widely adopted around the world since 1990s. The first national emissions cap and trade program in the U.S. is the Acid Rain Program (ARP), established under Title IV of the 1990 Clean Air Act (CAA) Amendments. It requires power plants to reduce emissions of sulfur dioxide (SO_2) and nitrogen oxides (NO_x), the primary precursors of acid rain. However, similar programs for greenhouse gas (GHG) emissions were not established until rather recently. European Union Emissions Trading Scheme (EU ETS) is the first and largest GHG emissions trading scheme in the world. In the U.S., although lacking of regulations at national level, some regional programs have been formed, such as the Regional Greenhouse Gas Initiative (RGGI) and the Western Climate Initiative (WCI). On June 2, 2014, United States Environmental Protection Agency (EPA) proposed a nationwide plan to cut carbon pollution from power plants in all states. The study of existing regional GHG emission trading programs can provide important guidelines for future regulations, at both regional and federal levels.

The focus of my dissertation is on RGGI. RGGI is a cooperative effort to reduce CO_2 emissions among the states of Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont specifically in the electric power sector.[1] Regulated sources are fossil fuel-fired power plants with a capacity of 25 MW or greater located within the RGGI States. RGGI aims to stabilize and then reduce CO_2 emissions within the signatory states. The effort was formally initiated in 2003 and the compliance started on January 1st, 2009. Every control period lasts three years, at the end of the third year of a control period, each regulated plant is required to hold one allowance for each ton of CO_2 emitted. During a control period, unused allowances will not expire and can be banked for future years. If a plant violates the rule, it needs to surrender a number of allowances equal to three times the number of its excess emissions. More

[1] New Jersey withdrew from the program at the end of year 2011.

than 90% of the allowances are sold at RGGI quarterly auctions. Through the end of 2013, RGGI has conducted 22 successful auctions, selling a total of 651 million CO_2 allowances for $1.6 billion. Proceeds from the auctions are returned to states and invested in consumer benefit programs such as energy efficiency and renewable resources. The annual emission cap, which is the total allowances allocated each year, is decreasing over time.

According to RGGI (2014), average CO_2 emissions from 2010-2012 in RGGI states decreased by 25.4%, compared with the average from 2006-2008. In addition, the CO_2 emission rate (pounds of CO_2 per megawatt hour) dropped by 16.7% during the same period. There are four major methods to reduce CO_2 emissions: The first is to reduce demand of electricity generated by fossil fuel plants, such as energy efficiency programs and increase use of renewable resources in electricity generation. The second is to use more natural gas and less coal (fuel switching), given that burning coal generates twice as much CO_2 as burning natural gas when producing the same amount of heat. The third method is to increase the efficiency in electricity generation, i.e., generate more electricity with the same set of inputs. Last but not least, The development of carbon capture and sequestration allows firms to store CO_2 underground, which prevents the release of CO_2 into the atmosphere.

In this dissertation I explore several issues related with RGGI. First, the effectiveness of RGGI has been criticized due to its low CO_2 allowance price. The CO_2 price was around only $2 per short ton from 2009 to 2013, it was at or very close to the price floor set by the program. The low permit price was the result of excess supply of CO_2 permits for the first several years of the program. From 2006 to 2008, the average annual CO_2 emissions are 163 million short tons. However, the emissions cap set by RGGI was 188 million short tons per year from 2009-2011 and 165 million short tons per year from 2012-2013. To make the carbon policy more effective, the regulator adjusted cap by decreasing the number of permits issued each year. For example, the adjusted cap was only 83 million short tons in 2014 and 62 million short tons in 2017. Therefore, it is important to understand how fossil fuel generation and CO_2 emissions respond to various allowance price levels, especially when the price is high.

Second, although CO_2 emissions decreased significantly after 2009 in regulated states, it is still unclear whether the emission reduction is due to the RGGI program. Starting from 2009, the price of natural gas has plummeted with the development of shale gas extraction. Decrease of demand or increase of renewable capacity could also lead to CO_2 emission reduction. These effects all drive emissions down. As an evidence, CO_2 emissions in both regulated and unregulated states have declined after 2009. In addition, a general concern of all regional emission trading programs is emission leakage, which is the increase in emissions in neighboring unregulated states. Last but not least, environmental regulations provide power plants with extra incentives to increase production efficiency, i.e., producing more electricity with less heat. However, RGGI could undermine power plants' production efficiency as it is an additional constraint imposed on production process. If this is true, the decrease in production efficiency cannot be ignored and it attenuates the effectiveness of the RGGI program. Studies on these topics shed light on the real impact of RGGI on CO_2 emissions and provide important guidelines and caveat for future regulations at both the state and federal level.

Summary

This dissertation is organized as follows: Chapter 1 estimates power plants' production efficiency and evaluates the impact of RGGI policy on the efficiency of coal and natural gas plants located within both RGGI regulated area and neighboring states. By using the directional distance function, we find that overall the power sector is highly efficient: The average technical efficiency scores for coal and natural gas plants are 88.70% and 83.14% respectively. The results show that overtime all power plants become more efficient. There is no clear evidence of RGGI undermining technical efficiency for both fuel types of plants in the RGGI area. However, the policy decreases the technical efficiency for coal plants within neighboring states. A likely explanation is that since the neighboring states are not regulated by the RGGI policy, plants with lower production cost in neighboring states, such as coal plants, could produce more than usual due to a spillover effect. Increased production activities may result in more malfunctions and less frequency of maintenance, leading to a decreased level of technical efficiency. In RGGI regulated area, less efficient coal plants exited and more efficient natural gas plants entered after 2009.

Chapter 2 uses difference in difference (DID) estimation to analyze RGGI's impact on the electric sector's fuel switching behavior at both plant and firm levels. We find that overall the RGGI program leads to 7.72 million short tons of CO_2 reduction per year in Delaware and Maryland, or about 34.36% of the average total annual emissions in these two states from 2009 to 2013. We find little evidence that utilities adjust their capacities within five years after program implementation except natural gas-only utilities. All utilities respond to the program by decreasing the utilization rate even including natural gas utilities. However, the emission reduction achieved through less coal and natural gas generation in RGGI area is covered by emission leakage instead of fuel switching from dirtier to cleaner energy sources. The results suggest that the power utilities do respond to the emission trading program with current carbon prices, but tremendous fuel switching did not occur before 2013 due to the program as it is less costly to leak the emissions under the regional regime.

In Chapter 3, I take advantage of the detailed hourly data to investigate how much of the emission reduction can be attributed to the RGGI policy and how individual firms respond to more stringent carbon policies. By accounting for the intertemporal production constraints across hours, I find that the RGGI policy has helped to decrease the total CO_2 emissions by at least 4.73% from 2009 to 2013. the relationship between each generator's production and the price-cost markup at hourly level and how the producers respond as CO_2 price changes. CO_2 can be reduced by 23.50% if carbon is priced at $15/ton.

Future Work

The average annual total CO2 emissions of Delaware and Maryland are 42.4 and 29 million short tons from 2006-2008 and 2009-2013 respectively, i.e., after 2009 the annual emissions have decreased by 46.21% of the average level from 2009-2013. Using different methods, Chapter 2 and Chapter 3 both examine the effectiveness of the RGGI policy: How much of the observed emission reduction is attributed to RGGI rather than the price drop of natural gas? The data used in Chapter 2 are year-round from 2002 to 2013, while chapter 3 only include the data from every September and October of each year due to the computation burden with detailed hourly data. In both chapters, the data include the major states in the PJM market, in which only Delaware and Maryland are regulated by the RGGI program. The treatment group includes power plants in Delaware and Maryland, while the control group consists of all other plants in the PJM.

Both chapters conclude that the RGGI policy was effective during the sample period 2009-2013. However, there is notable discrepancy in estimates from two models. In Chapter 2, we find that on average the RGGI program leads to about 34.36% of the average total annual emissions in Delaware and Maryland from 2009 to 2013, compared to the conterfactual scenario if there was no RGGI policy. In Chapter 3 I investigate the same issue with another approach and the emission reduction caused by RGGI in the two regulated states is only 4.73% from 2009 to 2013. Although the choices of both data and model differ in the two chapters, this discrepancy is large and deserves more concerns. Possible explanations for the wide range of estimates need to be further investigated in the future.

I also plan to adjust the current model in Chapter 3 to accommodate more features in the electricity markets. Chapter 3 examines how individual firms change production and emission decisions in response to higher CO_2 prices, while keeping other factors constant.

An reasonable interpretation is that less profit caused by the extra cost of CO_2 permits provides the electricity industry with more incentives to switch to cleaner fuels. However, this incentive is weakened if the electricity prices rises along with the CO_2 permit prices, and leaves firms' profit unchanged. Therefore, the pass-through rate, which measures how much of the additional emissions cost is passed-through to electricity prices, is an important part that needs to be added to the existing model (Fabra and Reguant, 2014).

Electricity prices could also be affected by market power. Although Chapter 3 illustrates the detailed market power mitigation actions taken by the market regulator and argues the market is very close to perfect competition, market power is generally an important concern in many electricity markets. If some big firms are manipulators of the market clearing prices rather than price takers, then the level of non-fossil fuel generation would also influence firms fossil-fuel production decisions and market prices. There are important aspects to explore in the future.

Chapter One

Have U.S. Power Plants Become Less Technically Efficient? The Impact of Carbon Emission Regulation

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Abstract

We estimate directional distance functions to measure the impact of carbon emission regulation, the Regional Greenhouse Gas Initiative (RGGI) in particular, on U.S. power plants' technical efficiency. The model shows that the average technical efficiency scores for coal and natural gas plants are 88.70% and 83.14% respectively, indicating a very technically efficient industry. We find no evidence of technical efficiency changes due to the RGGI regime in the RGGI area. In the same area, relatively less efficient coal plants exited the market and slightly more efficient natural gas plants entered, compared to the incumbent plants. In addition, some evidence of a spillover effect is found. Using a counterfactual analysis, the RGGI regulation leads to a 1.48% decline in the average technical efficiency for coal plants within neighboring states of RGGI during 2009-2013.

Keywords: Carbon Emission Regulations; RGGI; Technical Efficiency

Introduction

The economic burden of environmental regulations has been debated among economists and U.S. policy-makers since the beginning of stringent pollution restrictions in the 1970s (Jaffe et al., 1995). The conventional wisdom is that as partial inputs are diverted to produce extra environmental goods, environmental regulations can reduce firms' productivity, operating efficiency and competitiveness, while other scholars argue a net positive impact for some industries (Gollop and Roberts, 1983; Jaffe et al., 1995; Berman and Bui, 2001; Greenstone et al., 2012; Chan et al., 2013). For example, Greenstone et al. (2012) found that ozone regulations have large negative effects on total factor productivity (TFP) while carbon monoxide regulations can increase TFP among refineries. The Clean Power Plan, announced by President Obama and the Environmental Protection Agency (EPA) on August 3, 2015 , requires power plants to cut the carbon pollution at the national level. This new federal regime symbolizes a historic step and will have tremendous impacts on the electricity industry. The purpose of this paper is to understand the impact of carbon emission regulations on power plants' operating efficiency, more specifically, their technical efficiency.

Technical efficiency is measured by the distance to the technologically possible minimum input (or technologically possible maximum output) given the output (or input). A higher distance indicates a lower technical efficiency level. As with other SO_2 or NO_x regulations, carbon emission regulations might alter the efficiency level (van der Vlist et al., 2007; Fleishman et al., 2009). In the U.S., programs for carbon emissions were not established until rather recently. Such existing carbon programs make it possible to examine the impact and provide useful guidelines for the Clean Power Plan. In this paper, we focus on the Regional Greenhouse Gas Initiative (RGGI) program and investigate how power plants' technical efficiency is affected by the RGGI regulations.

Effective on January 1, 2009, the RGGI program regulates fossil fuel-fired power plants with a capacity of 25 MW or greater, located within the states of Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont.[2] The RGGI program sets an annual cap on the number of available CO_2 allowances that can be bought or sold in quarterly auctions and secondary markets. [3] After the implementation of RGGI, average CO_2 emissions from 2010-2012, in regulated states, decreased by 25.4% compared to the average from 2006-2008 (RGGI, 2014). However, very little is known about the impact of regulatory change on plants' operating efficiency. We fill this gap by using plant-level data to measure the technical efficiency changes due to the implementation of RGGI. More specifically, we estimate directional distance functions and use the distance to the output frontier to measure the technical efficiency of power plants. Because the RGGI program offers data variations across time and space, it provides a perfect natural experimental setting to study this issue.

As a market-based emission trading program, the RGGI creates incentives for power plants to reduce emissions or sell allowances to others who have a higher marginal cost of abatement. However, such regulations may result in substantial loss in terms of technical efficiency. A growing literature has examined the relevant issues with one strand leading to negative impacts. Multiple mechanisms are found. First, the operating of emissions reduction equipment directly reduces production efficiency. For example, Moullec (2012) found that the most mature technology of carbon capture, which can greatly reduce the emissions of CO_2, caused a significant loss in efficiency. Second, the investment due to environmental regulations could crowd out other investments, causing efficiency reduction. For example, the extra cost of CO_2 permits economically limits available funds to improve thermal efficiency (Adair et al., 2014). Last but not least, extra regulations place constraints on production so that some technologies cannot be flexibly applied, leading to lower technical efficiency. For example, Burtraw and Woerman (2013) examined

[2] New Jersey withdrew from the program at the end of year 2011.

[3] Regulated plants must surrender one allowance for each ton of CO_2 emitted at the end of each three-year control period. Unused permits will not expire and can be banked for future years.

the relationship between flexibility and stringency of tradable performance standards for Greenhouse Gas Regulations.

In addition to negative impacts, the environmental regulation could cause some ambiguous impacts. Huang and Zhou (2015) found that fuel switching to natural gas is one of the most important methods currently used by fossil fuel power plants to reduce CO_2. Whether the fuel switching decreases technical efficiency is, in fact, unclear. If power plants increase energy efficiency to reduce CO_2 emissions, as discussed in Burtraw et al. (2014) and Sargent & Lundy (2009), the impacts might be positive. Furthermore, more stringent environmental regulations could cause exit of less efficient plants, thus increasing the average industry technical efficiency. [4] With the above mixed effects, it is debatable whether the carbon emission regulation reduces efficiency. We will empirically measure the impact.

As stated above, we estimate directional distance functions (DDF) to measure technical efficiency, accommodating both a stochastic frontier for good and bad outputs and technical inefficiency simultaneously in one empirical model. A similar estimation method is used in Färe et al. (2005, 2012). We estimate the directional distance functions with detailed plant-level data from 1191 U.S. fossil fuel plants between 2002 and 2013. The comprehensive data allow us to analyze the determinants of plant efficiency levels, such as ownership, plant size, as well as the RGGI cap and trade program. We focus on coal and natural gas plants only, as they account for more than 98.7% of the heat input among fossil fuel power plants in our sample. Because plants using alternative fuels are very likely to have different production functions, we estimate separate directional distance functions for coal and natural gas plants.

According to our model estimates, on average, the technical efficiency scores for coal and natural gas plants are 88.70% and 83.14%, respectively, indicating a very efficient industry. We do not find any evidence that RGGI regulations cause a change in the technical

[4] Huang et al. (2015) found that less efficient vessels exited the fisheries when a new rights-based policy was implemented.

efficiency in the RGGI area. Over time, coal plants became more technically efficient in all areas. Compared to coal plants in neighboring states of RGGI and other areas, those in the RGGI area were the least efficient, but their efficiency levels increased the fastest. Relatively, natural gas plants in the RGGI area and neighboring states became slightly less efficient over time, while the plants in other areas became slightly more efficient.

We also examine the issue of entry and exit. The extra environmental cost of the RGGI program might force less efficient plants to exit and also affect plants' entry decisions. We find that, at the national level, the number of coal plants decreases slightly, while there are many new entries of natural gas plants. In the RGGI area only, very few coal plants entered and very few natural gas plants exited after 2009. Relatively less efficient coal plants exited the market and slightly more efficient natural gas plants entered.

Another important concern of regional regulations is the spillover effect. The interconnected grid network makes electricity transmission possible between the RGGI and adjacent areas, which makes it possible for the RGGI policy to affect neighboring states. Burtraw et al. (2015) examined the geographic shift in generation and investment due to carbon emission regulations. We also consider this spillover effect of production in our model. We do find some evidence that RGGI leads to a decrease in technical efficiency levels of coal plants in the neighboring states. Using a counterfactual analysis, we find that the technical efficiency of coal plants in the RGGI area decreased by 1.48%, on average, during the period of 2009-2013 due to the RGGI program.

The rest of the paper is organized as follows: Section 2 describes the model specification. Section 3 introduces the data. Results of the DDF model are presented in Sections 4 and 5. Section 6 concludes.

Methodology

When generating electricity as a good output, plants also jointly produce bad outputs such as CO_2, SO_2, and NO_x. In theory, we need to account for undesirable outputs: disposing bad outputs (abatement) is costly, affecting a plant's ability to produce good outputs. Therefore, we apply a DDF method to our data due to its approving feature of accommodating bad outputs. DDF models have been applied in the literature to incorporate bad outputs (e.g. Färe et al. (2005)). Zhang and Choi (2014) and Zhou et al. (2008) provided surveys on estimation methods of DDF. The production technology of power plants including bad outputs can be represented by the output set $P(x)$:

$$P(x) = \{(y, b) : x \; can \; produce \; (y, b)\},$$

where (y, b) denotes the set of good and bad outputs. In our context, y is electricity generation and b is the set of pollutants CO_2, SO_2, and NO_x. The vector of inputs is denoted as x. For fossil-fuel plants, the inputs are capital and heat [5]. The capital is approximated by a plant's input capacity. Let g=($g_y, -g_b$) be a directional vector, the directional distance is defined as

$$\vec{D_0}(x, y, b; g_y, -g_b) = max\{\beta : (y + \beta g_y, b - \beta g_b) \in P(x)\}. \quad (1)$$

It measures the maximum possible simultaneous increase in good outputs and decrease in bad outputs at a certain level of inputs. A higher value of distance means the plant's current production profile is further from the frontier, indicating a lower efficiency level. The directional distance function has to satisfy a few properties from the output possibility set (Färe et al., 2005). These properties are that the distance, $\vec{D_0}(x, y, b; g_y, -g_b)$, has to be: (i) non-negative if and only if $(y, b) \in P(x)$, and the directional distance takes value

[5] We do not have labor input information, so it is omitted. Empirically, it is highly correlated with capital.

zero for production levels of y and b on the frontier; (ii) monotone in good and bad outputs but with opposite directions; (iii) of weak disposability in good and bad outputs; and (iv) concave in (y, b). Furthermore, the DDF also satisfies the translation property (Färe et al., 2005; Matsushita and Yamane, 2012), which is denoted as:

$$\vec{D_0}(x, y + \alpha g_y, b - \alpha g_b; g_y, -g_b) = \vec{D_0}(x, y, b; g_y, -g_b) - \alpha. \tag{2}$$

In the above notation, we omit the subscript i and t for simplicity. DDF models can be estimated by using either a non-parametric or a parametric method. The popular non-parametric method is Data Envelopment Analysis (e.g. Färe et al. (1989, 2014)). In this paper, we employ the parametric estimation. Following Färe et al. (2005, 2012), we parameterize the DDF with $g_y = g_b = 1$ and a quadratic function:[6]

$$\begin{aligned}
\vec{D_{0it}}(x_{it}, y_{it}, b_{it}; 1, -1) &= \alpha'_0 + \sum_{n=1}^{2} \alpha'_n x_{nit} + \frac{1}{2} \sum_{n=1}^{2} \sum_{n'=1}^{2} \alpha'_{nn'} x_{nit} x_{n'it} + \beta'_1 y_{it} \\
&+ \frac{1}{2}\beta'_2 y_{it}^2 + \sum_{j=1}^{2} \gamma'_j b_{jit} + \frac{1}{2} \sum_{j=1}^{2} \sum_{j'=1}^{2} \gamma'_{jj'} b_{jit} b_{j'it} + \sum_{n=1}^{2} \delta'_n x_{nit} y_{it} + \sum_{n=1}^{2} \sum_{j=1}^{2} \eta'_{nj} x_{nit} b_{jit} \\
&+ \sum_{j=1}^{2} \eta'_j y_{it} b_{jit} + \sum_{l=1}^{M} d'_l D_{lit} + \mu'_1 After_t + \mu'_2 RGGI_i + \mu'_3 Neighbor_i \\
&+ \mu'_4 After_t * RGGI_i + \mu'_5 After_t * Neighbor_i
\end{aligned} \tag{3}$$

where x_1 and x_2 are heat input and input capacity respectively, and y is the electricity generation. Bad outputs, b_1 and b_2 are the amount of SO_2 and NO_x, respectively. In addition, the model also includes a set of control variables, D, to account for other factors affecting electricity generation, including dummy variables for the North American Electric Reliability Corporation (NERC) area, ownership, prime mover types and time trend. Because the RGGI regulations can also affect production, we add a RGGI policy year dummy, a RGGI region dummy (whether the power plants are in the RGGI area), a neighboring region dummy (whether the power plants are in the neighboring states of RGGI), and their inter-

[6] In the literature, the quadratic function is chosen since it satisfies the translation property.

actions. By utilizing the translation property shown in Equation 2, and adding a random error v $\sim N(0,\sigma_v^2)$, we have

$$
\begin{aligned}
&\vec{D_0}_{it}(x_{it}, y_{it}, b_{it}; 1, -1) - \alpha_{it} = \alpha'_0 + \sum_{n=1}^{2} \alpha'_n x_{nit} + \frac{1}{2}\sum_{n=1}^{2}\sum_{n'=1}^{2} \alpha'_{nn'} x_{nit} x_{n'it} + \beta'_1 (y_{it} + \alpha_{it}) \\
&+ \frac{1}{2}\beta'_2 (y_{it} + \alpha_{it})^2 + \sum_{j=1}^{2} \gamma'_j (b_{jit} - \alpha_{it}) + \frac{1}{2}\sum_{j=1}^{2}\sum_{j'=1}^{2} \gamma'_{jj'} (b_{jit} - \alpha_{it})(b_{j'it} - \alpha_{it}) \\
&+ \sum_{n=1}^{2} \delta'_n x_{nit} (y_{it} + \alpha_{it}) + \sum_{n=1}^{2}\sum_{j=1}^{2} \eta'_{nj} x_{nit} (b_{jit} - \alpha_{it}) + \sum_{j=1}^{2} \eta'_j (y_{it} + \alpha_{it})(b_{jit} - \alpha_{it}) \\
&+ \sum_{l=1}^{M} d'_l D_{lit} + \mu'_1 After_t + \mu'_2 RGGI_i + \mu'_3 Neighbor_i + \mu'_4 After_t * RGGI_i \\
&+ \mu'_5 After_t * Neighbor_i + v_{it}
\end{aligned}
\tag{4}
$$

If we subtract $\vec{D_0}_{it}(x_{it}, y_{it}, b_{it}; 1, -1)$ on both sides and denote it by u on the right side, the above equation can be written as

$$
\begin{aligned}
&- \alpha_{it} = \alpha'_0 + \sum_{n=1}^{2} \alpha'_n x_{nit} + \frac{1}{2}\sum_{n=1}^{2}\sum_{n'=1}^{2} \alpha'_{nn'} x_{nit} x_{n'it} + \beta'_1 (y_{it} + \alpha_{it}) \\
&+ \frac{1}{2}\beta'_2 (y_{it} + \alpha_{it})^2 + \sum_{j=1}^{2} \gamma'_j (b_{jit} - \alpha_{it}) + \frac{1}{2}\sum_{j=1}^{2}\sum_{j'=1}^{2} \gamma'_{jj'} (b_{jit} - \alpha_{it})(b_{j'it} - \alpha_{it}) \\
&+ \sum_{n=1}^{2} \delta'_n x_{nit} (y_{it} + \alpha_{it}) + \sum_{n=1}^{2}\sum_{j=1}^{2} \eta'_{nj} x_{nit} (b_{jit} - \alpha_{it}) + \sum_{j=1}^{2} \eta'_j (y_{it} + \alpha_{it})(b_{jit} - \alpha_{it}) \\
&+ \sum_{l=1}^{M} d'_l D_{lit} + \mu'_1 After_t + \mu'_2 RGGI_i + \mu'_3 Neighbor_i + \mu'_4 After_t * RGGI_i \\
&+ \mu'_5 After_t * Neighbor_i + v_{it} - u_{it}
\end{aligned}
\tag{5}
$$

where $u = \vec{D_0}_{it}(x_{it}, y_{it}, b_{it}; 1, -1)$. It is the distance between a plant's actual production and the frontier. According to its definition, u is a non-negative term, when it is zero, the plant is already producing at the most efficient level. We assume it follows the half normal distribution: u $\sim N^{+}(0,\sigma_u^2)$. We estimate the DDF using the stochastic method similar to Färe et al. (2012), and choose the value of α to be the logarithm of CO_2 emissions.

Note that we exclude CO_2 emissions from the model's bad output set b. The emission abatement technologies for CO_2, SO_2, and NO_x are different. The pollutants of SO_2, and NO_x can be scrubbed using scrubber systems. However, CO_2 can be only reduced through reducing inputs, fuel switching, or very expensive carbon sequestration. Unlike SO_2 and NO_x, there is no convincing successful end of pipe treatment to effectively abate CO_2. Our data show that CO_2 and heat input are correlated with the correlation equal to 99%, indicating that CO_2 is fully determined by heat input within both coal and natural gas groups.

After estimating the model, we can calculate the plant-level technical efficiency value. Following Battese and Coelli (1993), we define the technical efficiency of the i^{th} plant in year t as:

$$TE_{it} = E(e^{-u_{it}} | v_{it} - u_{it}) \tag{6}$$

The calculation formula can be found in Gronberg et al. (2005); note that the calculated TE is always within $[0, 1]$.

Data Sources

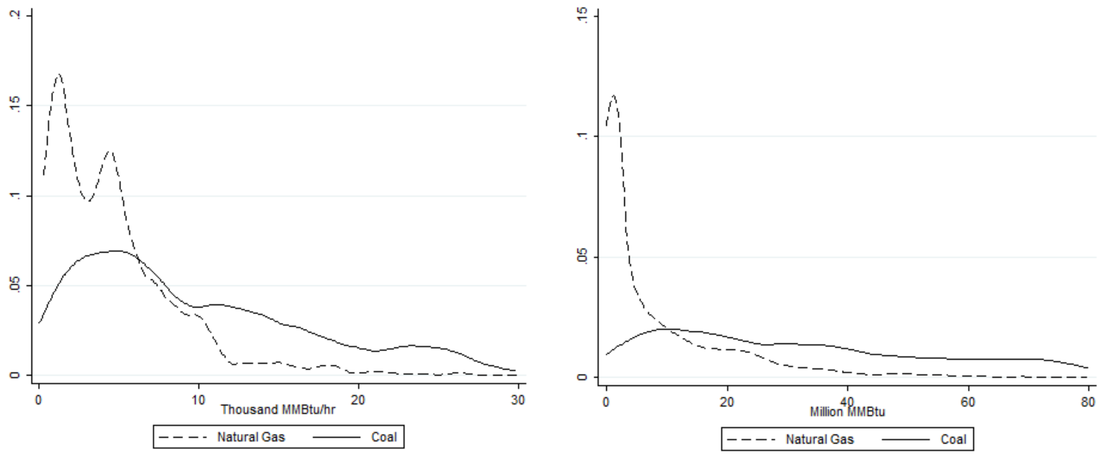
We use detailed plant-level data from U.S. Environmental Protection Agency (EPA) and Energy Information Administration (EIA) to estimate the DDF. EPA's Air Market Program Data (AMPD) provides information on each power plant's input capacity, heat input for electricity generation, gross generation, and air emissions. EIA survey form EIA-860 collects information on individual plant's location, ownership type, regulatory status and NERC region code. Form EIA-923 collects data on CHP (Combined Heat and Power) availability, prime mover type and primary fuel type. Merging all these data, we obtain an unbalanced panel dataset that consists of 1191 fossil-fuel power plants operating in the U.S. over a 12-year period from 2002-2013, for a total of 10,742 observations. Among them, 3649 observations are from plants that use coal as the primary fuel, 7093 are from natural gas plants.

Table 1 reports the descriptive statistics for variables used in the estimation. We focus only on coal and natural gas plants and exclude petroleum plants from the analysis. Petroleum is usually used in electricity generation as a supplemental fuel to coal and natural gas in order to cover demand spikes. In addition, petroleum plants only account for 4% of the observations, and the impact of regulations will be small in magnitude. We only include relatively purer coal (natural gas) plants which is defined as having more than 98% of electricity output generated by coal (natural gas). Plants in New Jersey are special in the sense that they participated RGGI in 2009 and withdrew at the end of year 2012. To avoid any confusion, we drop these plants.

Table 1 shows that natural gas plants are generally much smaller in capacity than coal plants. The average input capacity for natural gas plants is less than half of the average for coal plants. In addition, the gross generation and heat input of a coal plant are more than five times greater than those of a natural gas plant.

The distributions of input capacity and heat input for each fuel-type plants are shown in Figure 1. Panel (a) shows that the input capacity for a majority of natural gas plants is smaller than coal plants. Panel (b) shows that most natural gas plants have small heat input.

Figure 1: Distribution of Input Capacity and Heat Input



(a) Input Capacity

(b) Heat Input

Table 1: Plant-level Summary Statistics

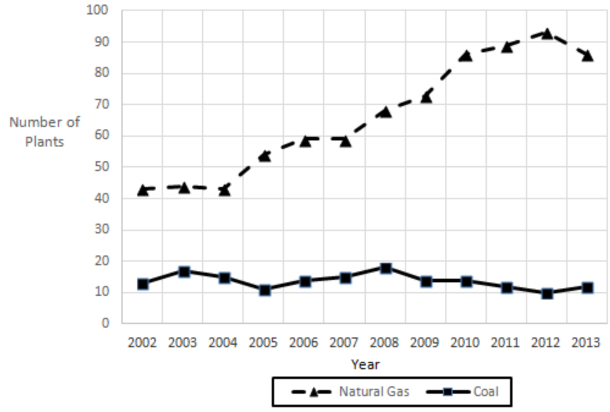
Variable	Unit	Notation	Coal: Mean or Percentage	Coal: Std. Dev.	Natural gas: Mean or Percentage	Natural gas: Std. Dev.	Source
Gross generation	Million MWh	y	5.61	5.04	1.01	1.59	AMPD
Heat input	Million MMBtu	x_1	55.25	48.34	8.99	13.14	AMPD
Input capacity	Thousand MMBtu/hr	x_2	10.84	9.01	4.69	4.23	AMPD
CO_2	Thousand Tons	α	5183.82	4534.62	481.69	709.32	AMPD
SO_2	Thousand Tons	b_1	20.37	26.86	0.05	0.30	AMPD
NO_x	Thousand Tons	b_2	7.72	7.84	0.21	0.56	AMPD
Regulatory status	Binary	$regulate$	76.76%		46.85%		EIA 860
Ownership type:							
Cooperative	Binary	$owner1$	9.43%		6.98%		EIA 860
Federally-owned	Binary	$owner2$	0.66%		0.62%		EIA 860
Investor-owned	Binary	$owner3$	47.22%		25.70%		EIA 860
Municipally-owned	Binary	$owner4$	8.00%		11.24%		EIA 860
Political Subdivision	Binary	$owner5$	1.67%		2.41%		EIA 860
Independent Power Producer	Binary	$owner6$	1.48%		1.10%		EIA 860
State-owned	Binary	$owner7$	11.87%		31.59%		EIA 860
Other	Binary	$owner8$	19.67%		20.36%		EIA 860
NERC region:							
Florida Reliability Coordinating Council	Binary	$nerc1$	1.23%		4.38%		EIA 860
Midwest Reliability Organization	Binary	$nerc2$	13.07%		4.26%		EIA 860
Northeast Power Coordinating Council	Binary	$nerc3$	2.82%		10.53%		EIA 860
ReliabilityFirst Corporation	Binary	$nerc4$	32.34%		14.80%		EIA 860
SERC Reliability Corporation	Binary	$nerc5$	27.05%		18.16%		EIA 860
Southwest Power Pool, RE	Binary	$nerc6$	7.40%		10.55%		EIA 860
Texas Regional Entity	Binary	$nerc7$	4.41%		11.76%		EIA 860
Western Electricity Coordinating Council	Binary	$nerc8$	11.67%		25.56%		EIA 860
Year 2009 and beyond	Binary	$after$	40.83%		48.06%		EIA 860
RGGI states	Binary	$rggi$	4.52%		11.24%		EIA 860
Neighboring states	Binary	$neighbor$	11.40%		4.27%		EIA 860
CHP	Binary	chp	0.93%		10.63%		EIA 923
Prime mover type:							
Combined cycle-steam part	Binary	$prime1$	0.00%		0.47%		EIA 923
Combined cycle combustion-turbine part	Binary	$prime2$	0.00%		41.38%		EIA 923
Combustion (gas) turbine	Binary	$prime3$	0.00%		34.25%		EIA 923
Steam turbine	Binary	$prime4$	91.86%		15.87%		EIA 923
Other	Binary	$prime5$	8.14%		8.03%		EIA 923
No. of observations			3649		7093		

About 76.76% of coal plants are regulated by local public utilities commissions, while only less than half of natural gas plants are so regulated. We define Pennsylvania, Virginia, West Virginia, and District of Columbia as "neighboring states" of RGGI states. In our sample, 8.96% of total observations are from plants within RGGI states, while 6.69% are from plants located in neighboring states. RGGI states have more natural gas plants, while neighboring states have more coal plants. Among natural gas plants, 10.63% have at least one CHP generator, but this number is only 0.93% for coal plants. We also include dummy variables that indicate ownership types, NERC regions, and prime mover types of the generator with the highest generation in one power plant. In Table 1, we list all the notations for the variables that will be used in the model.

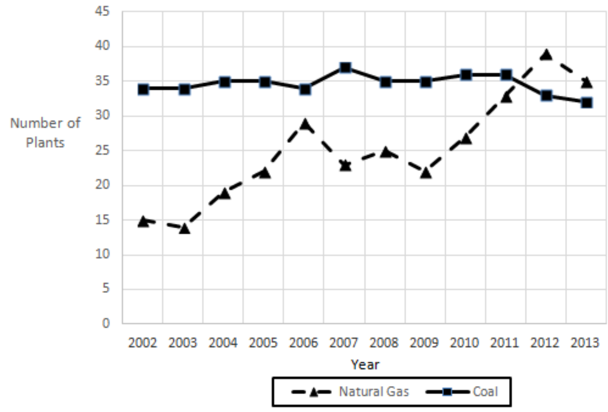
Figure 2 plots the number of plants over time. For the RGGI area, neighboring states and other areas, the number of coal plants is relatively stable, and has slightly declined in recent years, while the number of natural gas plants is increasing. It shows that, in recent years, the newly built plants are mostly natural gas plants for all areas. Compared to other areas, the gap between number of natural gas plants and number of coal plants is much bigger in RGGI, indicating that RGGI relies more heavily on the cleaner energy.

Figure 3 further examines gross electricity generation by fuel type and area. The three panels in the left column illustrate the aggregate generation and show that the use of natural gas in all three areas increases during the sample period. Generation by natural gas is even higher than by coal in the RGGI area after 2006, while it is much lower than coal generation in other two areas. Over time, the aggregate gross generation from coal plants has declined in all three areas. The three panels in the right column plot the average gross generation over plants. In the RGGI area, although the aggregate generation by natural gas plants is much higher than that of coal plants, the average generation by natural gas plants is still lower than that of coal plants, with a slight increase over years because there are many more natural gas power plants. Average generation by natural gas plants increases slightly in neighboring states and other areas as well. The

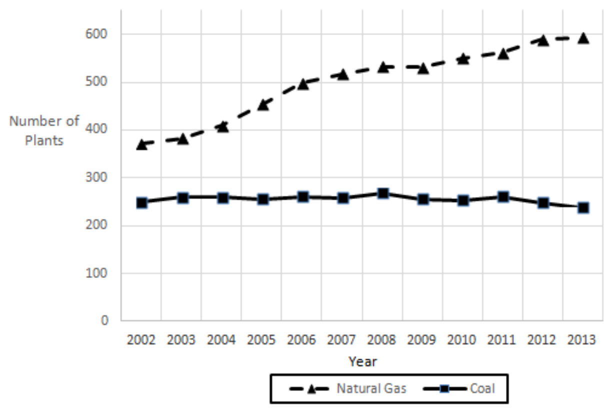
Figure 2: Number of Plants



(a) RGGI

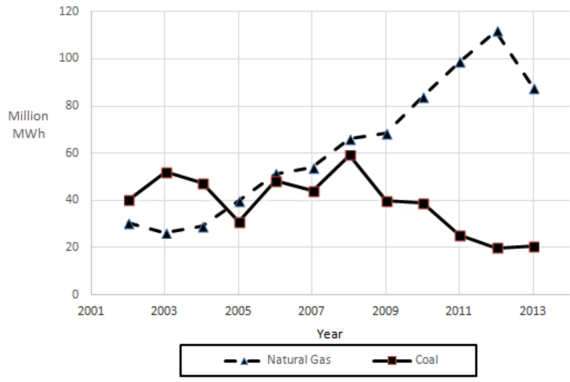


(b) Neighbor

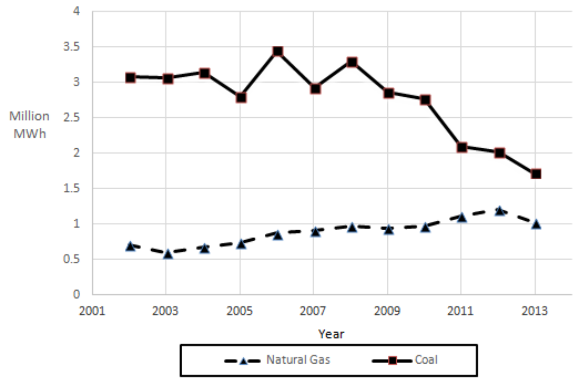


(c) Other

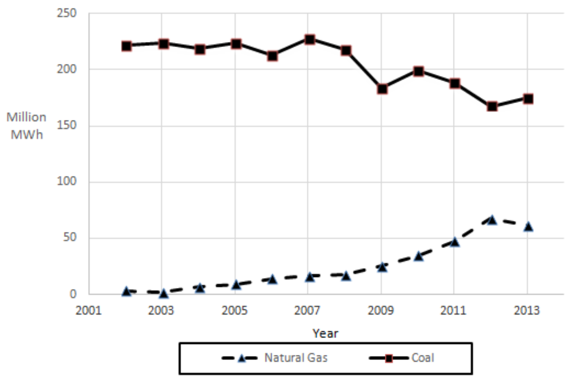
Figure 3: Gross Generation by Fuel Type and Area



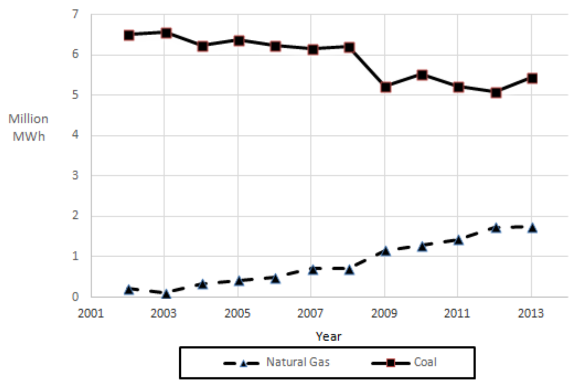
(a) Aggregate - RGGI



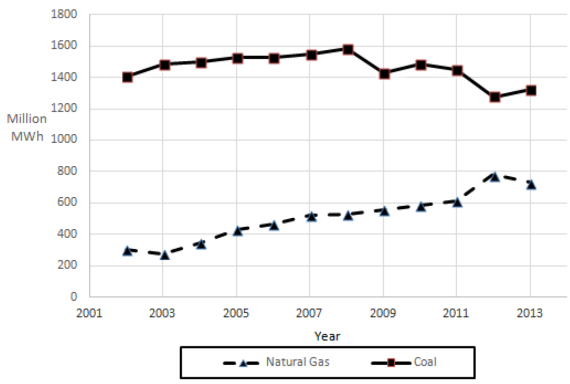
(b) Average - RGGI



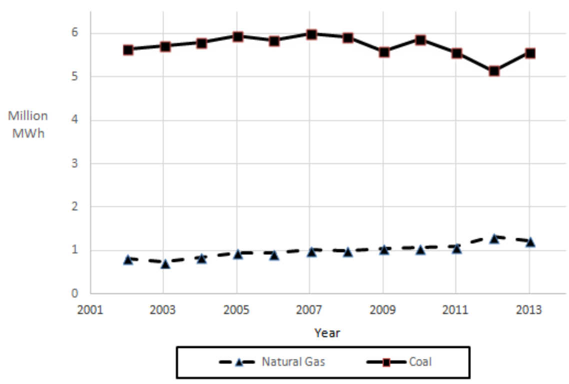
(c) Aggregate - Neighbor



(d) Average - Neighbor



(e) Aggregate - Other



(f) Average - Other

average generation by coal plants shows a declining trend in the RGGI and neighboring area, but remains stable in other areas. As natural gas plants are very different from coal plants, in the next section, we divide all plants into coal plants and natural gas plants, and then estimate each group's DDF model.

Determinants of Plant-level Technical Efficiency

We estimate the DDF model (Equation 1) using Equation 5 for coal and natural gas plants separately. In Equation 5, u_{it} measures the distance to the production frontier, which is the maximum possible simultaneous increase in good outputs and decrease in bad outputs given the amount of inputs. A negative coefficient indicates a positive impact on efficiency.

The estimates are presented in Table 2. Using the notation in Table 1, y is the electricity generation, and x_1 and x_2 are heat input and input capacity, respectively. The bad outputs, b_1 and b_2 are the amount of SO_2 and NO_x, respectively. Note that we exclude SO_2 when estimating the model for natural gas plants due to the extremely low sulfur content of natural gas.[7] The variable "$after$" indicates the year dummy for the RGGI policy. For year 2009 and beyond, $after$ = 1, otherwise 0. It captures any change that occurred in 2009 over all geographic areas. If the plants are RGGI power plants, $rggi$ = 1, and if they are in the states neighboring the RGGI area, $neighbor$ = 1. We also include $after * rggi$ and $after * neighbor$ to measure the impact of RGGI policies on distance for plants located in RGGI and neighboring states. Table 2 shows that the coefficients for $after$ are statistically significant and negative for natural gas plants, but not significant for coal plants. This indicates that natural gas plants became more efficient after year 2009 due to reasons other than RGGI policies, and no such change is found for coal plants. The significant coefficient for $RGGI$ in the result implies that the efficiency of coal plants in the RGGI area is lower than plants in other areas.

[7] In 2012, the average SO2 emission intensity of a natural gas power plant with combined cycle was 0.2% of that of a coal power plant.

Table 2: Estimates of the Directional Distance Function Model

Variable	Coal	Natural gas	Variable	Coal	Natural gas
y	-0.921***	-0.844***	$owner1$	0.004	-0.016**
	(0.015)	(0.010)		(0.012)	(0.007)
x_1	0.069***	0.058***	$owner2$	0.072*	0.031*
	(0.002)	(0.006)		(0.039)	(0.020)
x_2	-0.044***	-0.011***	$owner3$	0.003	-0.006
	(0.007)	(0.002)		(0.008)	(0.006)
b_1	2.530^{b}		$owner4$	-0.009	-0.023***
	(1.730)			(0.012)	(0.007)
b_2	-2.340^{b}	-0.274^{***a}	$owner5$	-0.025	-0.021*
	(6.430)	(0.028)		(0.020)	(0.011)
y^2	0.039***	0.038***	$owner6$	-0.011	-0.013
	(0.005)	(0.003)		(0.019)	(0.009)
x_1^2	0.229^{***a}	-0.691^{***a}	$owner7$	-0.032***	0.019***
	(0.075)	(0.142)		(0.012)	(0.006)
x_2^2	6.660^{b}	0.243^{*a}	$nerc1$	0.063***	-0.014
	(36.600)	(0.133)		(0.020)	(0.015)
b_1^2	0.002^{c}		$nerc2$	0.014	0.015***
	(0.005)			(0.011)	(0.005)
b_2^2	-0.109^{c}	5.160^{c}	$nerc3$	0.011	-0.016
	(0.076)	(4.770)		(0.025)	(0.019)
x_1x_2	-1.565^{***a}	1.128^{***a}	$nerc4$	0.059***	-0.011
	(0.286)	(0.294)		(0.011)	(0.007)
b_1b_2	0.037^{c}		$nerc5$	0.056***	0.003
	(0.029)			(0.009)	(0.006)
x_1b_1	-0.050^{b}		$nerc6$	-0.011	0.012**
	(0.055)			(0.010)	(0.006)
x_1b_2	0.210^{b}	-2.760^{b}	$nerc7$	0.053***	-0.017**
	(0.164)	(1.900)		(0.015)	(0.008)
x_2b_1	-0.118^{***b}		$prime1$		-0.046**
	(0.040)				(0.021)
x_2b_2	0.100^{b}	-1.400^{b}	$prime2$		0.001
	(0.168)	(1.480)			(0.008)
yx_1	-0.006***	0.080^{a}	$prime3$		-0.008
	(0.001)	(1.155)			(0.009)
yx_2	0.014***	-0.005***	$prime4$	-0.009	-0.044***
	(0.002)	(0.001)		(0.015)	(0.011)
yb_1	0.294^{b}		$after$	0.009	-0.013**
	(0.468)			0.010	(0.007)
yb_2	-1.170^{b}	0.045^{***a}	$rggi$	0.054***	0.005
	(1.430)	(0.011)		(0.021)	(0.018)
t	-0.001	0.016***	$neighbor$	0.028**	0.024*
	(0.004)	(0.003)		(0.013)	(0.013)
chp	-0.159***	-0.030***	$after * rggi$	0.013	-0.011
	(0.025)	(0.010)		(0.023)	(0.012)
$regulate$	0.014	0.009*	$after * neighbor$	0.037**	0.055
	(0.010)	(0.006)		(0.015)	(0.039)
t^2	0.443^{a}	-0.669^{***a}	$constant$	-0.071***	0.179***
	(0.302)	(0.196)		(0.024)	(0.013)
			No. of observations	3649	7093

[a b c] Coefficients are multiplied by $10^3, 10^6, 10^9$, respectively.
Robust standard errors in parentheses. ***: $p < 1\%$, **: $p < 5\%$, *: $p < 10\%$.

We are particularly interested in the coefficient of $after * rggi$ as it is the diff-in-diff estimator representing the impact of RGGI policies on the directional distance. The results show that the coefficients of $after * rggi$ are statistically insignificant for both fuel groups, meaning there is no clear evidence of RGGI undermining technical efficiency for both fuel types of plants in the RGGI area. The coefficients for $after * neighbor$ show that there is no policy impact on natural gas plants' technical efficiency within neighboring states. However, the policy decreases the technical efficiency for coal plants within neighboring states. A likely explanation is that since the neighboring states are not regulated by the RGGI policy, less efficient plants in neighboring states could produce more than usual due to a spillover effect, then leading to a decreased level of technical efficiency.

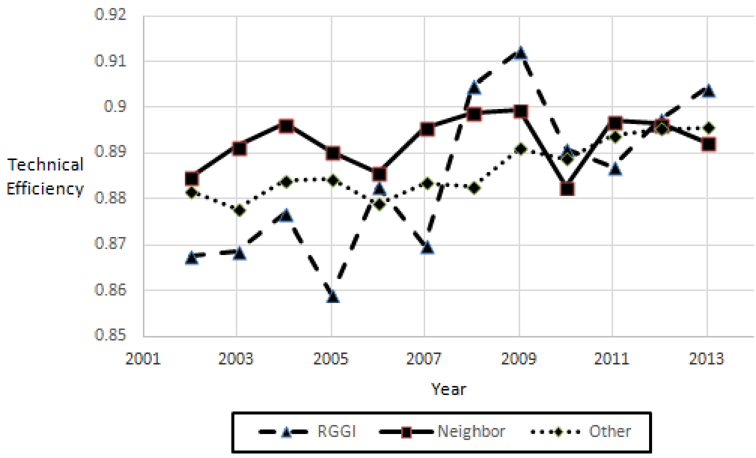
However, the magnitude of the spillover effect is found quite small. After estimating the DDF model, we can calculate TE according to Equation 6. We can then calculate the average TE for the coal plants within neighboring states and compare it to the TE value of setting the coefficient for $after * neighbor$ to be zero (no policy scenario). We find that with policy enforcement, the average TE for the coal plants in the neighboring states after 2009 is 89.35%, while the average without RGGI policy is 90.67%. Therefore the RGGI policy reduces the technical efficiency for the coal plants in the neighboring states with a very small amount (1.48%).

Industry Dynamics

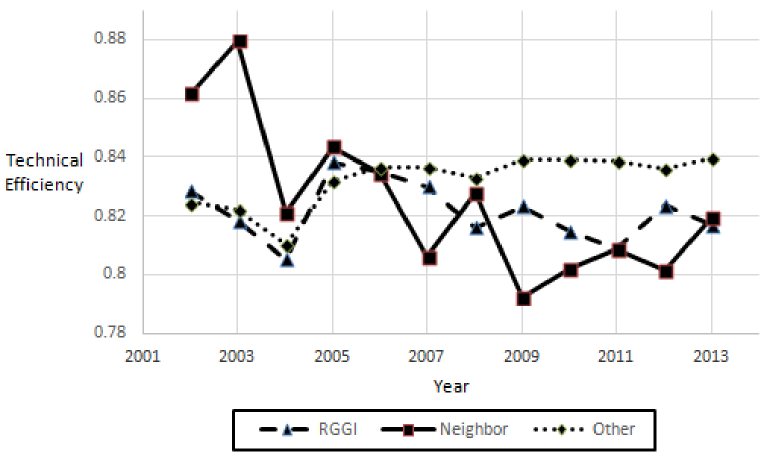
Our major finding in the previous section is that RGGI policies reduce TE of neighboring coal plants, and no such impact is found for both types of RGGI plants and natural gas plants in neighboring states. Note that the analysis is at the plant level. In this section, we analyze the change of efficiency at the industry level.

We start by comparing TE averages. Across all areas and years, the average TE for coal and natural gas plants are 88.70% and 83.14%, respectively. These values suggest that, overall, the power plants are quite efficient. These values are also very similar to the findings in Hiebert (2002). To examine more details of industrial TE, Figure 4 plots the average TE scores by year and area. Panel (a) shows that the average TE for coal plants increases slightly for both RGGI and other areas over time. However, the change in TE for neighboring coal plants is minimal. Overall, efficiency is very stable and similar in all three areas. It is between 85% and 92% across all areas and in all years. Like we have pointed out in the previous section, although the RGGI policy lowers TE of neighboring coal plants as indicated by Table 1, the change is small and not obvious by examining the graph.

Figure 4: Average Technical Efficiency by Fuel Type



(a) Coal



(b) Natural Gas

Panel (b) in Figure 4 illustrates the changes in TE for natural gas plants. In general, natural gas plants are less efficient than coal plants. Over time, the average technical efficiency of natural gas plants in RGGI states and other areas is stable. In contrast, neighboring natural gas plants show a slight decline in technical efficiency after 2009. The impact might be due to factors other than RGGI policies, for example, other production process changes or a structural change through entry or exit, which will be analyzed later.

To clearly show the magnitude of the change, we calculate the average TE for two periods: 2002-2008 and 2009-2013. The result is reported in Table 3. We find that, compared to the 2002-2008 average, the 2009-2013 average TE for coal plants increases by 2.45% in the RGGI area, 0.17% in neighboring states and 1.26% in other areas. Unlike coal plants in RGGI and other areas, coal plants in neighboring states do not experience a clear increase in TE. For natural gas plants, the changes vary across areas. The 2009-2013 average TE increases by 1.18% in other areas, but decreases by 0.93% and 3.57% in RGGI and neighboring states, respectively. Although the TE of neighboring natural gas plants decreases more than natural gas plants in other two areas, it is not attributed to RGGI as indicated in Table 2.

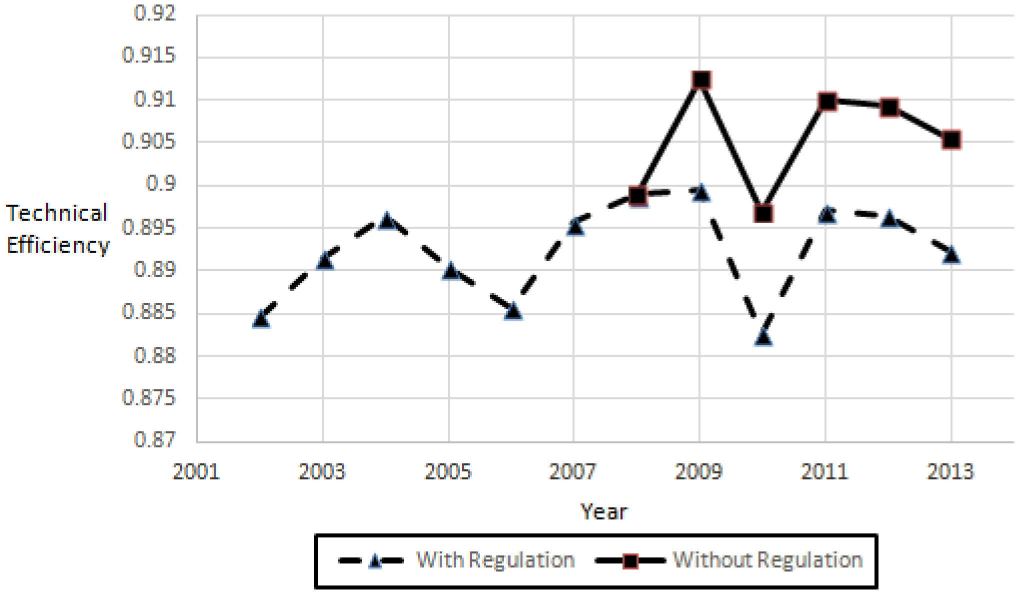
Table 3: Change of Industrial Technical Efficiency

Fuel Type	Area	Average TE (2002-2008)	Average TE (2009-2013)	Change
Coal	RGGI	0.8771	0.8986	+2.45%
Coal	Neighbor	0.8920	0.8935	+0.17%
Coal	Other	0.8818	0.8929	+1.26%
Natural Gas	RGGI	0.8250	0.8173	-0.93%
Natural Gas	Neighbor	0.8356	0.8058	-3.57%
Natural Gas	Other	0.8288	0.8386	+1.18%

Fuel Type	Area	With Policy Average TE (2009-2013)	No Policy Average TE (2009-2013)	Change
Coal	Neighbor	0.8935	0.9067	+1.48%

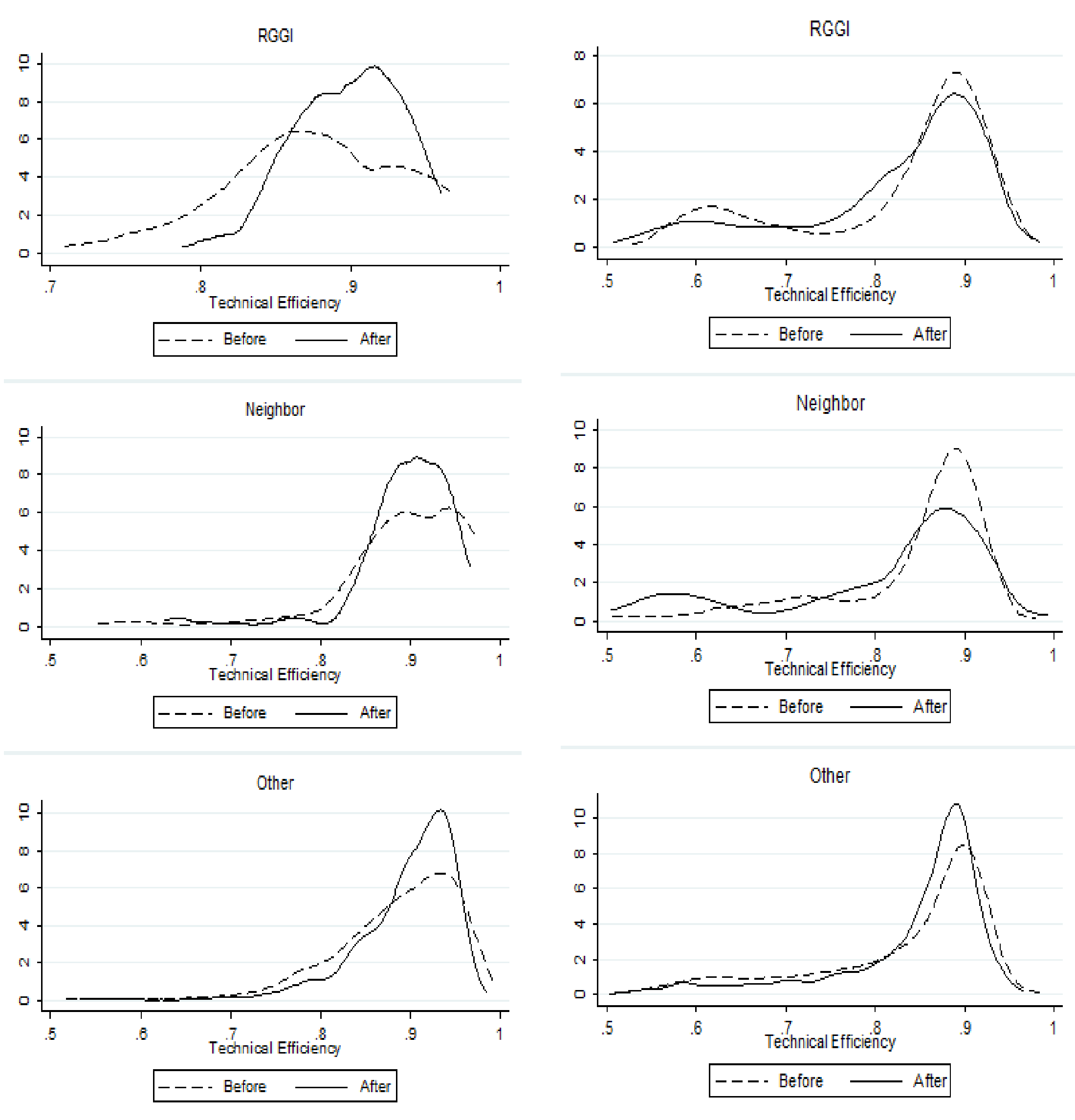
The impact of RGGI regulations on TE is of particular interest. As the impact is included in the DDF model (Table 2), we are able to calculate the TE level when there is no RGGI program. The results from the DDF show that the RGGI program affects only neighboring coal plants (which we call it a spillover effect in the previous section), so we compare the TE with and without RGGI regulations for this group. We have already calculated the TE values for the scenario with the RGGI program. For the scenario without RGGI, we set the coefficient of $after * neighbor$ to be 0 for natural gas plants, and recompute TE. Figure 5 illustrates the counterfactual analysis. The dashed line is with policy in reality, while the solid line represents the counterfactual scenario when there is no regulation. The trend clearly shows that without policy, the TE level for neighboring coal plants is higher than it is with the policy. In fact, the RGGI policy enforcement leads to a 1.48% decline in the 2009-2013 average TE for coal plants in neighboring states. This has been mentioned in the previous section and also reported in Table 3.

Figure 5: Neighbor Coal Plants: With and Without Regulation



To explore how the plant-level TE changes structurally, we plot the distributions of TE in Figure 6. As shown in Panel (a) of this figure, for coal plants in the RGGI area, the distribution shifts rightwards after year 2009, with thinner tails in the neighborhood of low technical efficiency scores. Coal plants in neighboring states and other areas have higher peaks after 2009, but the overall increase is not as significant as that of RGGI coal plants. Panel (b) shows that the average TE of natural gas plants in neighboring states has a notable decrease after 2009, no such evidence is found for the other two groups. All features found in Figure 6 are consistent with those in Figure 4 and Table 3.

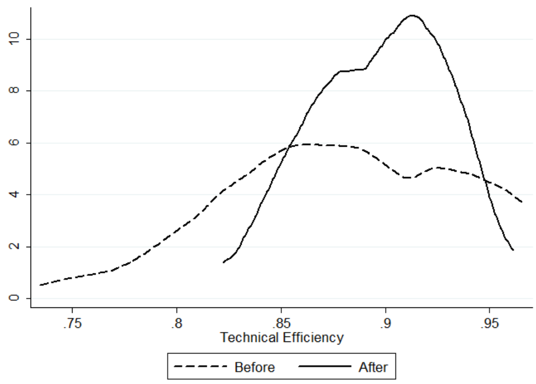
Figure 6: Kernel Density of TE: Before and After 2009



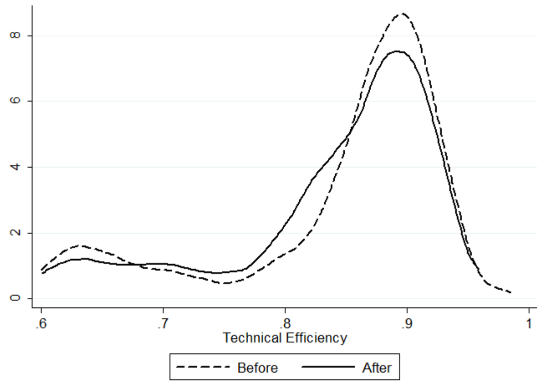
(a) Coal (b) Natural Gas

Two potential mechanisms can explain the changes of the average TE. One is a plant-level technical efficiency change through a change in production process, e.g. changes in energy efficiency, extra input for reducing emissions or less flexibility in production. The other is a structural change through plants' entry and exit. To isolate these two mechanisms, we separate the entry and exit plants from other plants and examine their TE separately. In our data, the number of coal plants declined over time, while the number of natural gas plants increased tremendously in the RGGI area. In fact, there was rarely entry of coal plants and rarely exit of natural gas power plants. In the RGGI area, only one coal plant entered and one natural gas plant exited after 2009. Therefore, for coal plants, we compare TE of exiting and remaining plants, while for natural gas plants, we compare entry and remaining plants. Figure 7 presents the comparison for RGGI plants.

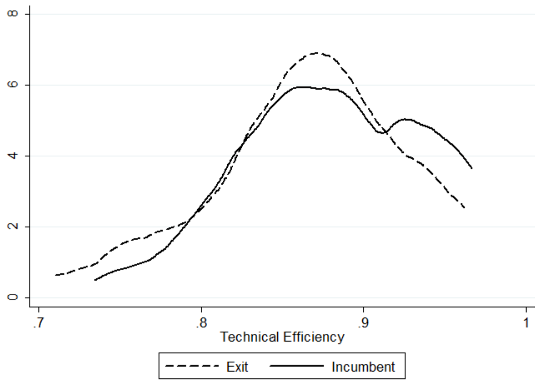
Figure 7: Kernel Density of TE for RGGI Plants: Change of Incumbent Plants and Entry and Exit



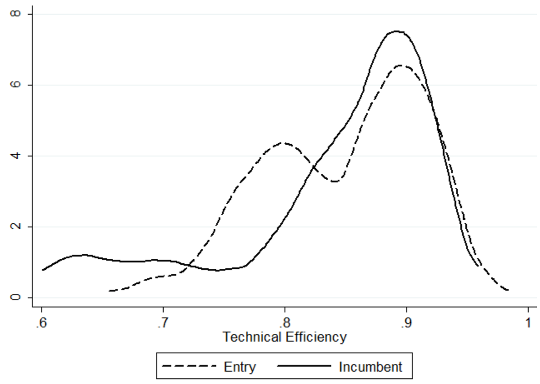
(a) Incumbent Coal Plants: Before and After 2009



(b) Incumbent Natural Gas Plants: Before and After 2009



(c) Exit and Incumbent Coal Plants: Before 2009



(d) Entry and Incumbent Natural Gas Plants: After 2009

For coal plants, we define exit plants as those that produced before 2009, and shut down after 2009. We call the remaining plants incumbent plants. Panel (a) illustrates the TE change excluding exit plants and only for incumbent ones, and Panel (c) compares the incumbent and exit plants. According to Panel (a), incumbent plants became more efficient after 2009. For exit plants, we can only see their TE value before the RGGI program. Panel (c) shows that exit plants are relatively less efficient than incumbent ones. Before 2009, the average TE for exit coal plants in the RGGI area is 86.68%, which is lower than that of the incumbent ones (88.25%). Combining these two effects from Panel (a) and (c), the coal plants became more efficient after 2009, which is consistent with the result in Panel (a) of Figure 6.

With regard to natural gas plants, we define entry plants as those that operated after 2009. As shown in Panel (b), incumbent plants have a similar TE distribution before and after 2009. Panel (d) plots the comparison of entry and incumbent plants, which again shows similarity in TE between new entry plants and incumbent ones. But in fact, the entry plants are slightly more efficient (TE is 84.54%) than the incumbent ones (TE is 80.70%) after 2009. Again, these two effects together contribute to the outcome that technical efficiency levels of RGGI natural gas plants did not change much after 2009.

So far, we have presented three interrelated terms: 1) average TE, 2) entry or exit of power plants, and 3) RGGI policy impact captured in the DDF model. As the RGGI policy impact captured in the DDF is at the plant level, it does not capture the effect of entry or exit of power plants. Therefore 1) is a combination of 2) and 3) and other factors, and is not necessarily caused by RGGI policies. The before and after increase is due to multiple reasons. For example, it could be due to many other variables in the DDF model including time trend, other policies etc. (Table 2) and the RGGI regime is only one of the causes. It could also be due to entry or exit of power plants.

Concluding Remarks

In this paper, we employ DDF estimation to investigate changes in technical efficiency of fossil fuel plants due to the implementation of the RGGI program. With detailed plant-level data from coal and natural gas plants in all states, we find no evidence that the RGGI program changes the technical efficiency of both fuel types of power plants in the RGGI area. For RGGI coal plants, less efficient plants exited the market, while more efficient natural gas plants entered compared to the incumbent plants. We also consider the possibility that the RGGI policy might affect plants in neighboring states through interconnected market, and find that the RGGI regulation leads to a 1.48% decline in the average technical efficiency for coal plants within neighboring states during 2009-2013 using a counterfactual analysis.

Although we find minor impacts of carbon emission regulation on the technical efficiency of power plants, they do not undermine the value of our study. The findings remove the policymakers' concern about a sudden drop of technical efficiency at least at the current stage. However, our results should be viewed as being short run and they do not necessarily eliminate the impacts in the long run. As climate change becomes a more and more important international issue, and the concern over the economic burdens becomes one of the biggest hurdles that prevent countries from taking aggressive actions, more research is called for in this area.

Chapter Two

Carbon Prices and Fuel Switching: A Quasi-experiment in Electricity Markets

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Abstract

Within the Pennsylvania-New Jersey-Maryland (PJM) electricity market, Delaware and Maryland participate in the Regional Greenhouse Gas Initiative (RGGI) but other states do not, providing a quasi-experiment setting to study the effectiveness of the RGGI program. Using a difference-in-difference framework, we find that overall the RGGI program leads to 7.72 million short tons of CO_2 reduction per year in Delaware and Maryland, or about 34.36% of the average total annual emissions in these two states from 2009 to 2013. We find little evidence that utilities adjust their capacities within five years after program implementation except natural gas-only utilities. All utilities respond to the program by decreasing their heat input per capacity even including natural gas utilities. Counter-intuitively, the reduction is mainly achieved through reduction of coal and natural gas input and emission leakage instead of fuel switching from coal to natural gas or from fossil fuel (coal and natural gas) to non-fossil fuel. The results suggest that the power utilities do respond to the emission trading program with current carbon prices, but tremendous fuel switching did not occur before 2013 due to the program as it is less costly to leak the emissions under the regional regime.

Keywords: Carbon Emission Market, RGGI

Introduction

The U.S. Electric power sector accounts for 2,122 million short tons of carbon dioxide (CO_2) emissions in 2015, or about 37% of the total U.S. energy-related CO_2 emissions. [8] To address the climate change issues, the power sector is critical. However, the power sector appears to have a limited option to reduce CO_2: phasing out coal power plants and replacing with cleaner plants, i.e. fuel switching in a general sense. It is far from easy, though, since emission reduction could force heavy economic burden on the existing fossil-duel power plants. Therefore, the Clean Power Plan, as the first-ever national standard to reduce CO_2 from power plants, has encountered very strong opposition since its announcement on August 3, 2015. [9] Understanding fuel switching for fossil-duel power plants is essential to the success of any future program targeting at reducing CO_2.

The Regional Greenhouse Gas Initiative (RGGI) is the first cooperative effort in the U.S. to reduce CO_2 emissions among the states of Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont, specifically in the electric power sector. [10] RGGI aims to stabilize and then reduce CO_2 emissions within the signatory states. Regulated sources of emissions are fossil fuel-fired power plants with a capacity of 25 MW or greater, located within the RGGI states. RGGI was formally initiated in 2003 and compliance started on January 1, 2009. [11] According to RGGI

[8] EIA data: http://www.eia.gov/tools/faqs/faq.cfm?id=77&t=11.

[9] The U.S. Supreme Court granted a stay on the implementation of Clean Power Plan because of cases filed by more than two dozen states and numerous industry groups.

[10] Globally, the carbon emission trading market has been increasing in recent years. After the implementation of the European Union Emissions Trading Scheme (EU ETS), several domestic and regional initiatives emerged in developed and developing countries including the RGGI (Kossoy and Guigon, 2012). Currently, the United States has altogether three systems related to GHG emission trading: the RGGI, the California, Qubec and the Western Climate Initiative, and the Chicago Climate Exchange (CCX). The first two are mandatory schemes, while the CCX is operated on a voluntary base.Unlike traditional harmful pollutants explicitly regulated by the Clean Air Act (SO_2 and NO_x), CO_2 emissions are a new pollution source that raises many new questions. Reduction of CO_2 is regulated under section 111(d) of Clean Air Act which covers other unnamed potential pollutants. These pioneering programs can provide very helpful guidelines for the future carbon markets in the U.S.

[11] Every control period lasts three years, and, at the end of the third year of a control period, each regulated plant is required to hold one allowance for each ton of CO_2 emitted. Unused allowances do not expire and can be banked for future years. If a plant violates the rule, it needs to surrender a number of allowances equal to three times the number of its excess emissions.

(2014), average CO_2 emissions from 2010-2012 in RGGI states decreased by 25.4%, compared with the average from 2006-2008. In addition, the CO_2 emission rate (pounds of CO_2 per megawatt hour) dropped by 16.7% during the same period. However, multiple factors could have triggered the emission decrease. Lower natural gas prices, decrease of demand or increase of renewable capacity could all lead to CO_2 emission reduction. This paper studies whether the RGGI program leads to the emission reduction.

There are five major ways for fossil-fuel power plants under the system of RGGI to reduce CO_2. The first one is switching to fuel with lower carbon content. [12] Changing from coal to natural gas, for instance, can reduces a power plant's carbon emissions by 40-60% per megawatt hour (Mwh) taking into consideration of efficiency loss (CCES, 2013). The second option is to switch from fossil fuel to non-fossil fuel. The third option is to improve energy efficiency during electricity generation. This would include using more efficient electrical appliances and improvement of technology (e.g. switching to a combined heat and power system). The fourth method is to sponsor CO_2 offset projects, including carbon capture and sequestration, emission reduction in the building and agriculture sector, etc. [13] The fifth method is to shift the production to non-RGGI areas. Consequently, it causes emission leakage. Among all these five methods, energy efficiency improvement and offset projects require much more technological advancement, therefore fuel switching and emission leakage are the main focus of this paper.

The RGGI program in the Pennsylvania-New Jersey-Maryland (PJM) electricity market provides a perfect quasi-experiment to study the fuel switching behavior. Within the PJM territory, Delaware and Maryland participate in the RGGI. Electric utilities from these two states form the treatment group in the quasi-experiment. [14] Ohio, Pennsylvania, Virginia and West Virginia, part of Illinois, Indiana, North Carolina and Kentucky are in the PJM

[12] Per million BTU of energy, coal emits around 215 pounds, oil emits 160 pounds and natural gas emits 117 pounds of CO_2.

[13] See http://www.rggi.org/market/offsets.

[14] An electric utility is the operating power generation unit, which can have multiple power plants and a power plant can have multiple generators.

market but do not participate in the RGGI. The electric utilities from these states are treated as the control group. Using a panel data from 2002-2013, we use a difference-in-difference (DID) framework to isolate the impact of the RGGI program.

Our empirical results show that the RGGI program leads to 7.72 million short tons of CO_2 reduction per year in Delaware and Maryland, or about 34.36% of the average total annual emissions in these two states from 2009 to 2013. Natural gas-only utilities increase 5.01% emissions of their own total emissions due to the program through long-term capacity investment, and decrease emissions by 42.26% through reducing short-term heat input per capacity (hereafter, called utilization rate). Coal-only utilities, natural gas capacities within the flexible utilities (with both natural gas and coal capacities) and coal capacities within the flexible utilities decrease CO_2 reduction by 20.34%, 27.14% and 38.69% of their own emissions due to the program respectively, all through reduction in utilization rate. The results suggest that the compliance strategies adopted by the flexible and non-flexible utilities are similar. We implement multiple robustness checks and confirm that our results hold under different specifications.

Another key concern we need to consider is emission leakage. Emission leakage refers to emissions shifting outside the jurisdictional area, driven by the enforced emission costs, which could be substantial and misleading when evaluating the effectiveness of carbon trading programs (Cullenward and Wara, 2014; Newell et al., 2014). Interconnected grid network makes electricity transmission (import and/or export) possible between RGGI and adjacent areas. Potentially, it is possible that RGGI increases the import of electricity from non-RGGI areas. In this case, it would appear that emissions in the RGGI area are reduced, while national emissions stay the same or even increase. We consolidate the import data for Maryland and Delaware and find that the import did increase significantly after 2009. In addition, the power generation excluding natural gas and coal generation in Maryland and Delaware did not change after 2009. The results suggest that the reduction of coal input has not been replaced by non-fossil sources. Instead, it was covered by leaking the emissions to non-RGGI areas.

We compare our results to studies in the literature. Swinton (1998) estimates the shadow price of SO_2 emissions by modeling the joint production of electricity and sulfur dioxide. He finds that fuel-switching can also significantly reduce emissions in the short run. Linn et al. (2014a) examine the operation of coal-fired generating units and find that a 10% increase in coal prices leads to a 0.2 to 0.5% decrease in heat rate. McKibbin et al. (2014) compare the effects of emission reduction programs imposed on the power sector only and economy-wide, and find that the power-sector-only approach requires a carbon price that is almost twice the economy-wide carbon price to achieve the same cumulative emission reduction. There is no clear evidence that pollution controls on the electric power sector will drive up CO_2 emissions outside this sector. Hitaj and Stocking (2014) find that the U.S. SO_2 allowance prices did not reflect marginal abatement costs in the early years after implementation. In terms of reduction reasons, Ellerman and Montero (1998) find that rail rates for shipping low-sulfur coal, rather than the 1990 Clean Air Act Amendments, are the principal reason why sulfur dioxide emissions by electric utilities declined from 1985 to 1993. Murray et al. (2014) specifically examine the RGGI impact on CO_2 reduction and find that the emissions in the whole RGGI region would have been 24% higher without the program. Our study contributes to the literature by specifically estimating the fuel switching behavior to carbon price signals and examining how emissions are reduced at a micro-level. In addition, our studies trace the emission reduction back to individual utility level and take advantage of the quasi-experiment setting.

This paper also contributes to the literature on emission trading programs. A well-designed emission trading program has been learnt that it can effectively reduce air pollution (Joskow et al., 1998; Stavins, 1998; Ellerman et al., 2000; Stavins, 2003; Sterner, 2003). Many studies examine these programs from different perspectives. For example, Bovenberg et al. (2005) examine the efficiency costs of choosing particular environmental permits and taxes. Rubin (1996) develops a framework for modeling emission trading, banking, and borrowing, and uses optimal control theory to derive optimal time paths for emissions by firms. Subramanian et al. (2007) characterize firms' compliance strategies under an emission cap and trade program with a three-stage model of structural decisions on abatement, permit auction, and production. Hart and Ahuja (1996) and Smale et al. (2006) examine the impact of emission regulations on firm performance. Joskow et al. (1998) evaluate the economic impacts of the RGGI on ten Northeast and Mid-Atlantic States and find that the program expenditures benefit the region's economy. Ruth et al. (2008) study the economic impact of participation in RGGI on the state of Maryland and find little net impact. Our paper examines the effectiveness of emission trading programs from the perspective of firm production decisions.

In addition to the literature on cap and trade program evaluation, our study also contributes to the literature investigating which factors can determine emissions. Vollebergh et al. (2009) and Holtz-Eakin and Selden (1995) use country-level panel data to regress the amount of CO_2 or/and SO_2 emissions on variables such as income and per capita GDP. Auffhammer and Carson (2008) forecast China's CO_2 emissions using province-level data, and concluded that emissions in China are unlikely to decrease in the near future unless substantial changes in energy policies occur. Cole et al. (2013) explore the factors influencing firms' CO_2 emissions with firm-level data from Japan and found emissions among firms are spatially correlated. Our study takes the perspective of firm production and focuses on the input function and examines what factors determine CO_2 emissions.

The rest of the paper is organized as follows. Section 2 describes the methodology, followed by Section 3, which presents the data. Model results and robustness check are in Section 4 and 5. Section 6 presents the emission reduction quantification and Our conclusions are finally presented in Section 7.

Methodology

There are three fossil fuel types of utilities: coal, natural gas and Petroleum. Since petroleum is not frequently used and counts only a very small fraction of total heat generated from fossil fuel combustion, we hence focus on fuel switching between natural gas and coal among fossil fuel utilities. We define fuel switching between natural gas and coal as replacing coal heat input by natural gas. It can take multiple hypothetical forms. At the industry level, if natural gas utilities increase capacity and inputs, while coal utilities decrease capacity and inputs, the relative fuel inputs structure of the industry can change. It is also possible that more natural gas utilities enter the market and more coal utilities exit. At the utility level, a utility can directly increase their natural gas inputs relative to coal inputs in the short term. In the long term, they can invest more natural gas capacity. As different types of utilities have different forms of fuel switching, we divide the utilities into three excludable categories: 1) non-flexible always-staying utilities; 2) flexible always-staying utilities; and 3) entry and exit utilities. Entry and exit of utilities can alter the capacity structure in terms of fuel types. Those utilities who do not enter or exit the market are always-staying utilities. Among the always-staying utilities, we define flexible utilities as those having both coal and natural gas power plants. In fact, fuel switching can occur even at the generator level: some generators can use multiple types of fuel. [15] Non-flexible utilities are natural gas-only and coal-only utilities. [16] In the following, we analyze response to the RGGI program by each category separately.

For a non-flexible always-staying utility, its heat input can be written as:

$$I_{itx} = Z_{itx} * \frac{I_{itx}}{Z_{itx}} \quad for \;\; x = c, n \tag{7}$$

[15] See http://www.eia.gov/tools/faqs/faq.cfm?id=65&t=3. For a generator that can use both fuel types, we double count its capacity for natural gas capacity and coal capacity, but count only once for the total capacity.

[16] In our data, some utilities are non-flexible always-staying utilities in some years and flexible always-staying utilities in other years. We categorize them into flexible always-staying utilities.

in which I_{itx} is utility i's heat input at time t and Z is its capacity. The notation x indicates its fuel type. While $x = n$ indicates a natural gas utility, $x = c$ indicates a coal utility. Therefore, the change of heat input can be written as:

$$\begin{aligned} \triangle I_{itx} &= \triangle Z_{itx} * \frac{I_{itx}}{Z_{itx}} + Z_{itx} * \triangle \frac{I_{itx}}{Z_{itx}} \\ &= \triangle Z_{itx} * U_{itx} + Z_{itx} * \triangle U_{itx} \end{aligned} \tag{8}$$

Equation 8 states that the change of heat input can be decomposed into a long-term capacity adjustment $\triangle Z_{itx}$ and a change in the utilization rate U_{itx}. Later, we need to examine whether the RGGI program has led to changes in these two terms.

For a flexible always-staying utility, since it has both natural gas and coal power plants, a direct way is to treat its natural gas and coal capacities as two separate units and examine their capacity adjustment and heat input decisions separately. However, within one single utility, the decisions of capacity adjustment and input decisions of natural gas and coal are inter-correlated and not independent. Therefore, we write its inputs of natural gas and coal as the following:

$$\begin{cases} I_{itc} = (Z_{itn} + Z_{itc}) * \frac{Z_{itc}}{Z_{itn}+Z_{itc}} * \frac{I_{itc}}{Z_{itc}} \\ I_{itn} = (Z_{itn} + Z_{itc}) * \frac{Z_{itn}}{Z_{itn}+Z_{itc}} * \frac{I_{itn}}{Z_{itn}} \end{cases} \tag{9}$$

in which

$$Z_{itx}\% = \frac{Z_{itx}}{Z_{itc} + Z_{itn}} \qquad for\ \ x = c, n$$

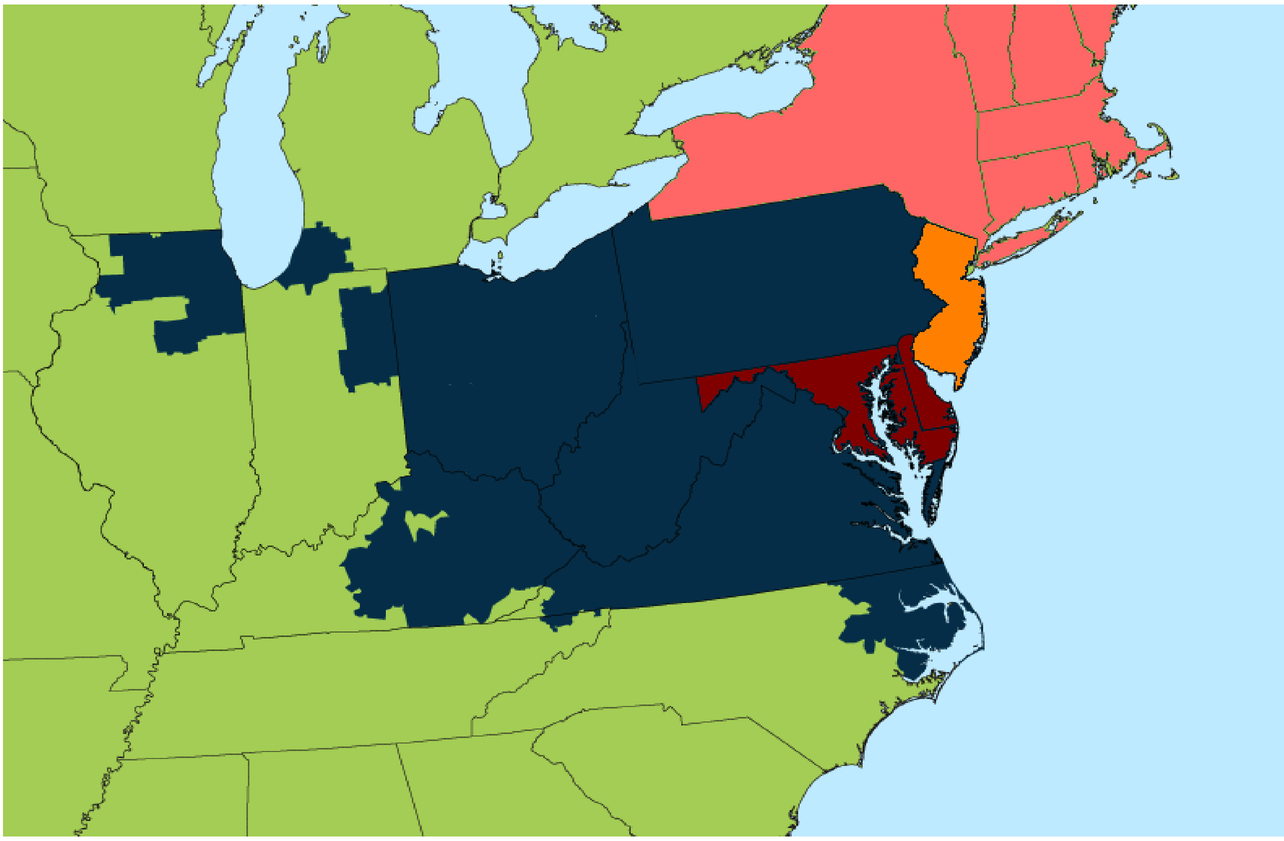
Again, we call $\frac{I_{itc}}{Z_{itc}}$ as U_{itc}. Then we can write down the change of heat inputs as:

$$\begin{cases} \triangle I_{itc} = \triangle(Z_{itn} + Z_{itc}) * Z_{itc}\% U_{itc} + (Z_{itn} + Z_{itc}) * \triangle Z_{itc}\% U_{itc} + (Z_{itn} + Z_{itc}) * Z_{itc}\% \triangle U_{itc} \\ \triangle I_{itn} = \triangle(Z_{itn} + Z_{itc}) * Z_{itn}\% U_{itn} + (Z_{itn} + Z_{itc}) * \triangle Z_{itn}\% U_{itn} + (Z_{itn} + Z_{itc}) * Z_{itn}\% \triangle U_{itn} \end{cases} \tag{10}$$

Differently from coal-only and natural gas-only utilities, change of inputs can be decomposed to change of total capacity, percentange change of each fuel type of capacity and utilization rate. Using this method, we examine four key changes: $\triangle(Z_{itc} + Z_{itc})$, $\triangle Z_{itn}\%$, $\triangle U_{itc}$ and $\triangle U_{itn}$.

For entry and exit utilities, we also start with examining their capacity change. We find that their capacity change is a very small amount. We therefore ignore the impact of the RGGI program on this category of utilities.

Figure 8: PJM territory served and RGGI



Note: Currently, Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont are in RGGI, in which Delaware and Maryland are in the PJM territory. Other states in PJM but not regulated by PJM that we include in our analysis are Ohio, Pennsylvania, Virginia and West Virginia, part of Illinois, Indiana, North Carolina and Kentucky.

As noted in the Introduction, we take the advantage of a quasi-experimental setting. Figure 8 describes the quasi-experiment. Currently, Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont participate in the RGGI. Within the PJM territory, Delaware and Maryland are regulated by the program. Utilities from these two states serve as the treatment group. Other states in the PJM market but not regulated by the RGGI that we include in our analysis are Ohio, Pennsylvania, Virginia and West Virginia, part of Illinois, Indiana, North Carolina and Kentucky. Utilities from these states serve as the control group. In other words, within the Pennsylvania-New Jersey-Maryland (PJM) market, power utilities in Maryland and Delaware have to purchase CO2 allowances after 2009 under RGGI, while utilities in other states are free to emit CO2. New Jersey is also in PJM, but they withdrew from the program at the end of year 2011. So we exclude New Jersey from our analysis.

With the quasi-experimental setting and panel data, we apply a simple DID method to isolate the impact of RGGI program on each category of utilites. For the non-flexible always-staying utilities, the corresponding reduced DID regression can be written as:

$$\begin{aligned} Y_{itx} =& \beta_0 + \beta_1 P_{itx} + \beta_2 P_{et} + \beta_3 trend_{year} + \beta_4 Demand_t + \beta_5 S_{it} \\ &+ \beta_6 After_{year} + \beta_7 After_{year} * RGGI_i + \alpha_i + \varepsilon_{it} \quad for \ x = c, n \end{aligned} \tag{11}$$

in which

$$Y_{itx} = Z_{itx} \ or \ U_{itx}$$

where Y_{itx} is the dependent variable and it could be Z_{itx} or U_{itx}. Z_{itx} is the capacity of natural gas or coal of i^{th} utility in time t and U_{itx} is the utilization rate. When estimating the capacity model, the data is yearly, and when estimating the utilization rate model, the data is monthly. So the time t is different for these two models. For the utilization rate model, monthly dummies from January to December are added to control for seasonal patterns. The term P_{itx} is fuel price across individual utility and time and P_{et} is electricity price at time t. The term $trend$ is the yearly time trend. We also include PJM area's total demand and regard it exogenous. With higher electricity demand, more natural gas plants need to be brought up online, to serve the peak demand along with the base load coal plants, thus increasing natural gas usage. The term α_i is the time-invariant individual utility fixed effect and S_{it} is time-variant characteristics of utilities including capacity, combined heat and power (CHP) availability and age. $After$ is a dummy variable, which equals to 1 for the years after 2009 and 0 otherwise. It captures any change before and after 2009 for the whole PJM area. Dummy of $RGGI$ captures regional differences of natural gas usage percentage. If the utility is located in the RGGI area, $RGGI$ is equal to 1, 0 otherwise. The term $After_{it} * RGGI_i$ is the treatment. After controlling for year 2009 and individual fixed effects, the coefficient, β_7, is expected to reflect the impact of the RGGI program on Y_{itx}.

For the flexible always-staying utilities, a few things need to be altered:

$$\begin{aligned} Y_{itx} = &\beta_0 + \beta_1 P_{itn} + \beta_2 P_{itc} + \beta_3 P_{et} + \beta_4 trend_{year} + \beta_5 Demand_t + \beta_6 S_{it} \\ &+ \beta_7 After_{year} + \beta_8 After_{year} * RGGI_i + \alpha_i + \varepsilon_{it} \quad for \;\; x = c, n \end{aligned} \tag{12}$$

in which

$$Y_{itx} = Z_{itc} + Z_{itc}, \;\; logit(Z_{itc}\%), \;\; U_{itc} \;\; or \;\; U_{itn}$$

The dependent variables are $Z_{itc} + Z_{itc}$, $logit(Z_{itc}\%)$, U_{itc} and U_{itn}. $Z_{itc} + Z_{itc}$ is the total capacity including natural gas and coal. $Z_{itc}\%$ is the percentage of capacity from natural gas. Since it is a percentage value ranging from 0 to 1, we use its logit transformation. U_{itc} and U_{itn} are the utilization rate of natural gas and coal, respectively. In Equation 12, we use both fuel prices p_{itn} and p_{itc} as the explanatory variables, which can be considered by a flexible utility simultaneously.

Data

Three major datasets are used. The first one is EIA 860, which collects generator-level information, including whether the generator has a co-fire function, its capacity, operation age, fuel type, whether it has a combined heat and power system, region, etc. The second dataset is EIA 923, which contains detailed electricity generation data, including heat content of fuels, quantity of fuels, prime mover, net generation, heat content/fuel cost by contract, contract type, contract expiration date, fuel cost, abatement expense and abatement investment for all pollution, etc. The third dataset is the Emissions & Generation Resource Integrated Database (eGRID), provided by the U.S. Environmental Protection Agency (EPA), which is the main data source on CO_2 emissions. Plant identification information from PJM's website is used to match PJM plants with the above three datasets.[17] We also acquire state-level fuel costs, demand and generation from EIA's Electric Power Monthly issues.[18] The data consist of 196 fossil fuel electric facilities from 124 utilities operating in the PJM area over the 144-month period from 2002-2013, for a total of 14940 observations.[19] Because of entry and exit, not every utility appears in all the 144 months. The average number of observations per utility is 120.5.

Table 4 reports summary statistics of variables used in regressions and data sources. Fuel prices are averaged over monthly transactions, thus vary across utilities and time. If a utility's fuel prices are missing, we replace them with the monthly average state fuel prices reported in EIA's Electric Power Monthly issues. Figure 9 plots the average monthly natural gas price and coal price. Comparing to coal, natural gas has a much higher price per unit of heat input, about three times as expensive as coal on average. Our data also show that coal is the dominant fossil fuel in this industry: heat input by coal is about 9 times as high as heat input by natural gas. This is due to the reason that coal plants are

[17] See http://www.pjm.com/documents/reports/eia-reports.aspx.

[18] See http://www.eia.gov/electricity/monthly/.

[19] If an utility has plants in multiple states, we treat them as separate utilities, as they face distinct state-level regulation policies.

often used to serve base load and operate almost constantly. The average coal capacity is only 240 MW more than the natural gas capacity, indicating a significant potential for fuel switching even without new investment. We weight the age of generators from the same utility by capacity to get a utility's weighted age, and the average is 20 years. For the utilities we include in our sample, the RGGI regulated areas are Delaware and Maryland, which encompasses 11.49% of the total electricity generation by natural gas and coal.

Table 4: Summary Statistics

Variables	Mean	Std. Dev.	Source
Natural gas price (¢/MMBtu)	630.23	247.61	EIA 923
Coal price (¢/MMBtu)	208.12	70.99	EIA 923
Heat input by coal (Million MMBtu)	2.76	5.70	EIA 923
Heat input by natural gas (Million MMBtu)	0.32	0.90	EIA 923
Dummy of CHP availability (%)	25.62		EIA 923
Dummy of after policy year 2009 (%)	42.17		EIA 923
Age (year)	20.44	14.49	EIA 860
Coal Capacity (MW)	628.70	1256.03	EIA 860
Natural gas Capacity (MW)	390.28	619.68	EIA 860
Ownership-Joint (%)	7.95		EIA 860
Ownership-Single (%)	74.78		EIA 860
Ownership-Other (%)	17.27		EIA 860
Dummy of within RGGI area (%)	11.48		EIA 860
PJM monthly load (Million MWh)	53.20	14.80	PJM
Delaware (%)	4.66		PJM
Illinois (%)	15.68		PJM
Indiana (%)	4.58		PJM
Kentucky (%)	1.93		PJM
Maryland (%)	6.83		PJM
North Carolina (%)	1.93		PJM
Ohio (%)	8.84		PJM
Pennsylvania (%)	37.17		PJM
Virginia (%)	10.60		PJM
West Virginia (%)	7.79		PJM

Figure 9: Monthly Fuel Prices

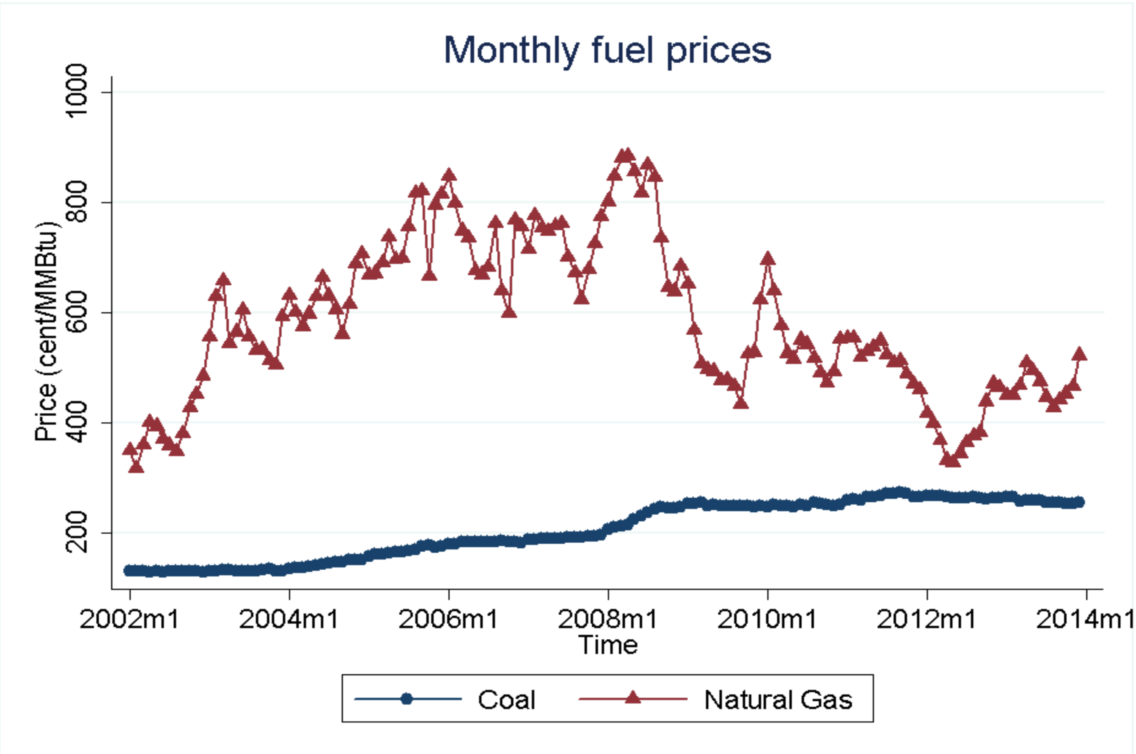
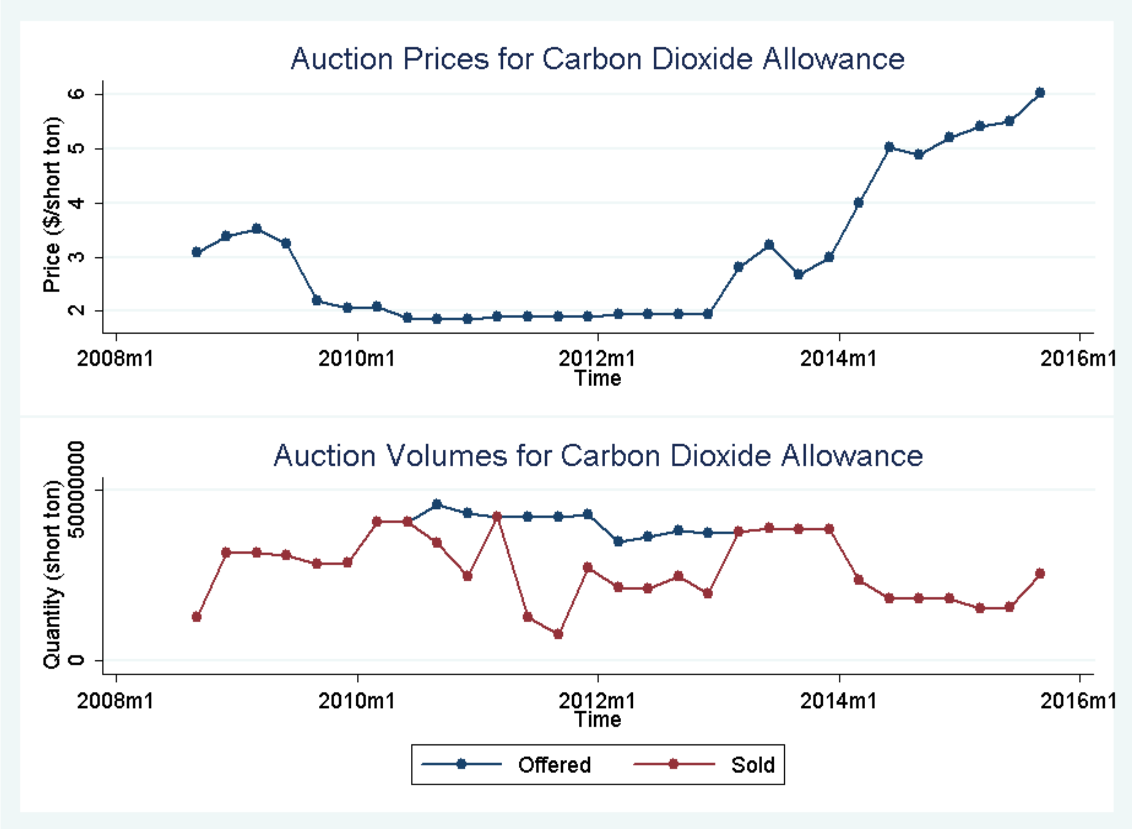


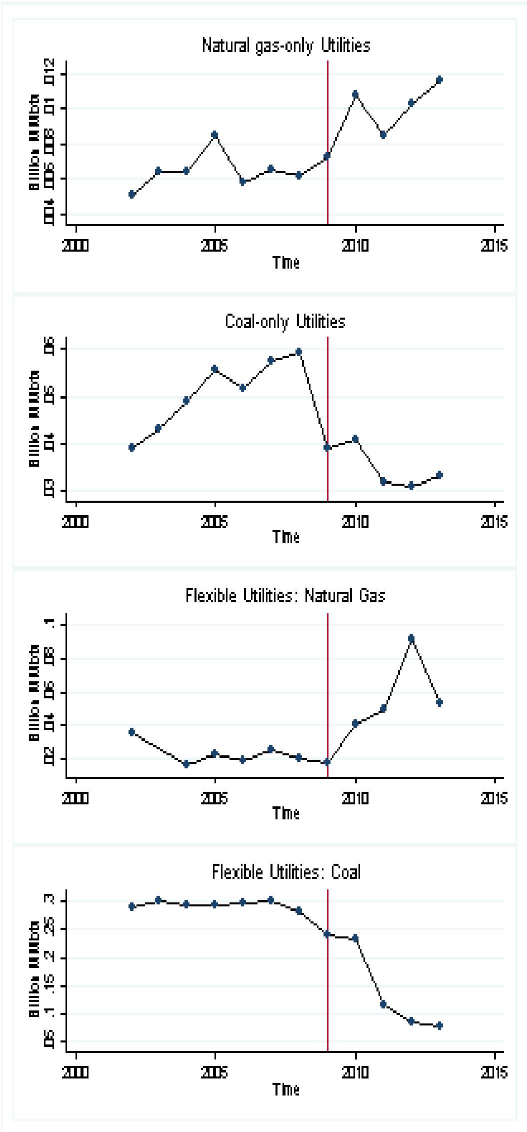
Figure 10: Carbon Prices



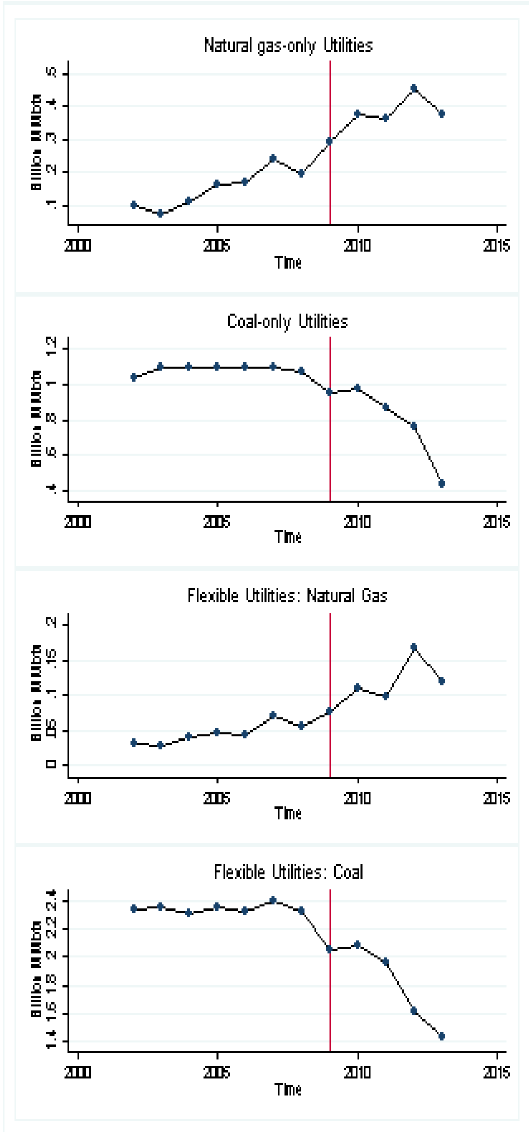
The CO_2 auction related information is shown in Figure 10. The top panel plots the quarterly auction prices for CO_2 from the end of 2008 to 2015 (two years later than our analysis). The bottom panel compares the offered and actually sold auction volumes. The flat price from 2010 to 2013 is the reserve price as the supply of volumes is greater than the demand.

Figure 11 plots the total annual heat input for RGGI and non-RGGI areas. Each column contain natural gas-only, coal-only, natural gas of flexible and coal of flexible utilities. The figure shows that RGGI and non-RGGI regions have similar patterns. Natural gas inputs increase for all types and areas over time, while coal inputs decrease except that coal from RGGI coal-only utilities increase before 2008 and then decrease after 2008. Figure 12 shows the corresponding capacity. Coal-only utilities show stable capacity before 2012, but have a relatively huge decrease in 2013 for both RGGI and non-RGGI area.

Figure 11: Total Annual Heat



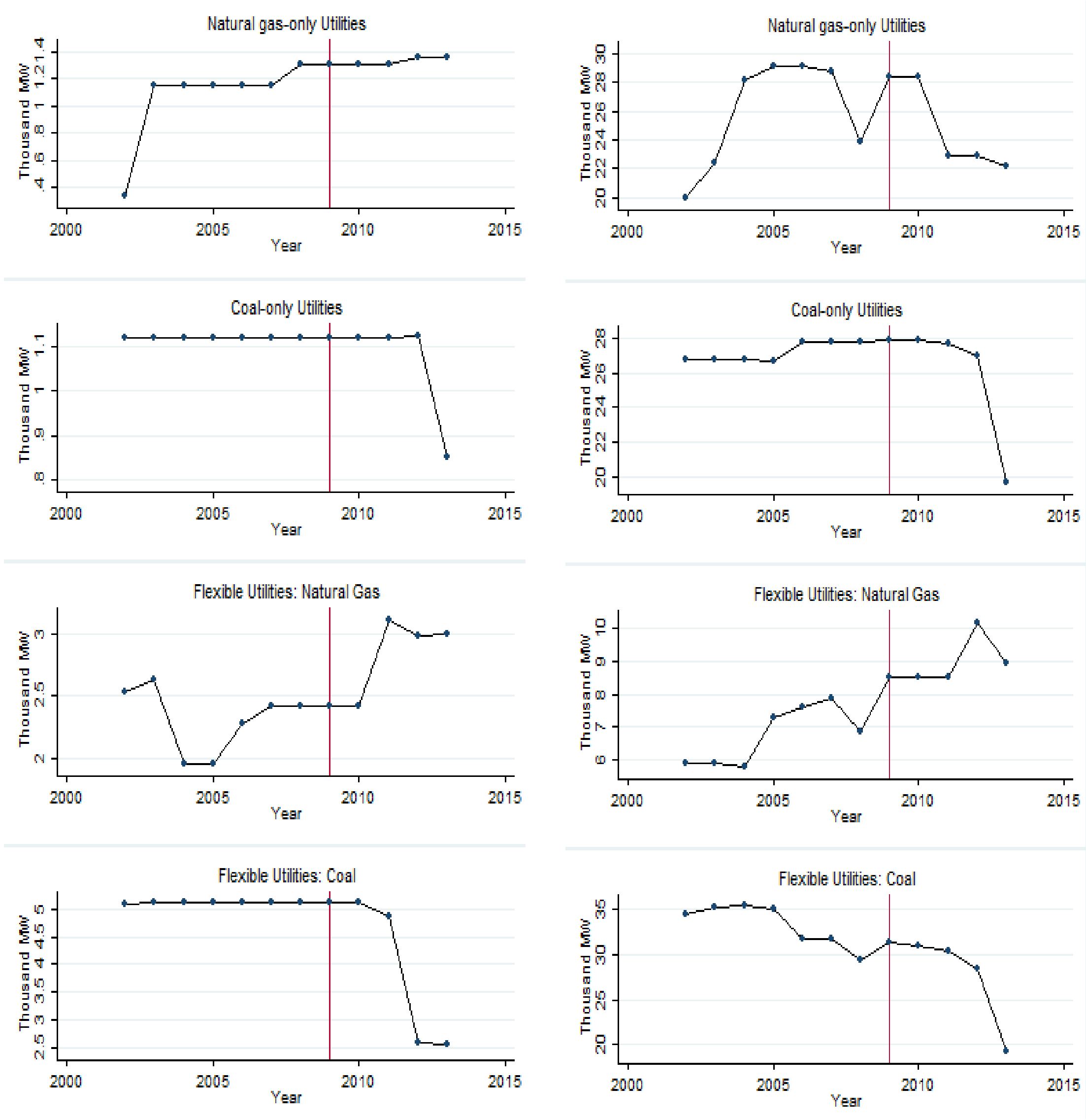
(a) RGGI



(b) Non-RGGI

Coal capacity from flexible utilities decreases significantly after 2012. Natural gas capacity show a increase over years for both RGGI and non-RGGI areas. We furthermore show the pattern of utilization rate in Figure 13. We present the average monthly utilization rate over individual utilities. The coal utilization rate is much higher than the natural gas utilization rate for all areas. For the non-RGGI areas, the utilization rate of natural gas has an increasing pattern and coal has a decreasing pattern. The RGGI area has more noise as it has fewer number of utilities, so the pattern is less clear. We will rely on the DID setting to compare RGGI and non-RGGI regions and estimate if the RGGI region has extra fuel switching due to the RGGI program.

Figure 12: Capacity

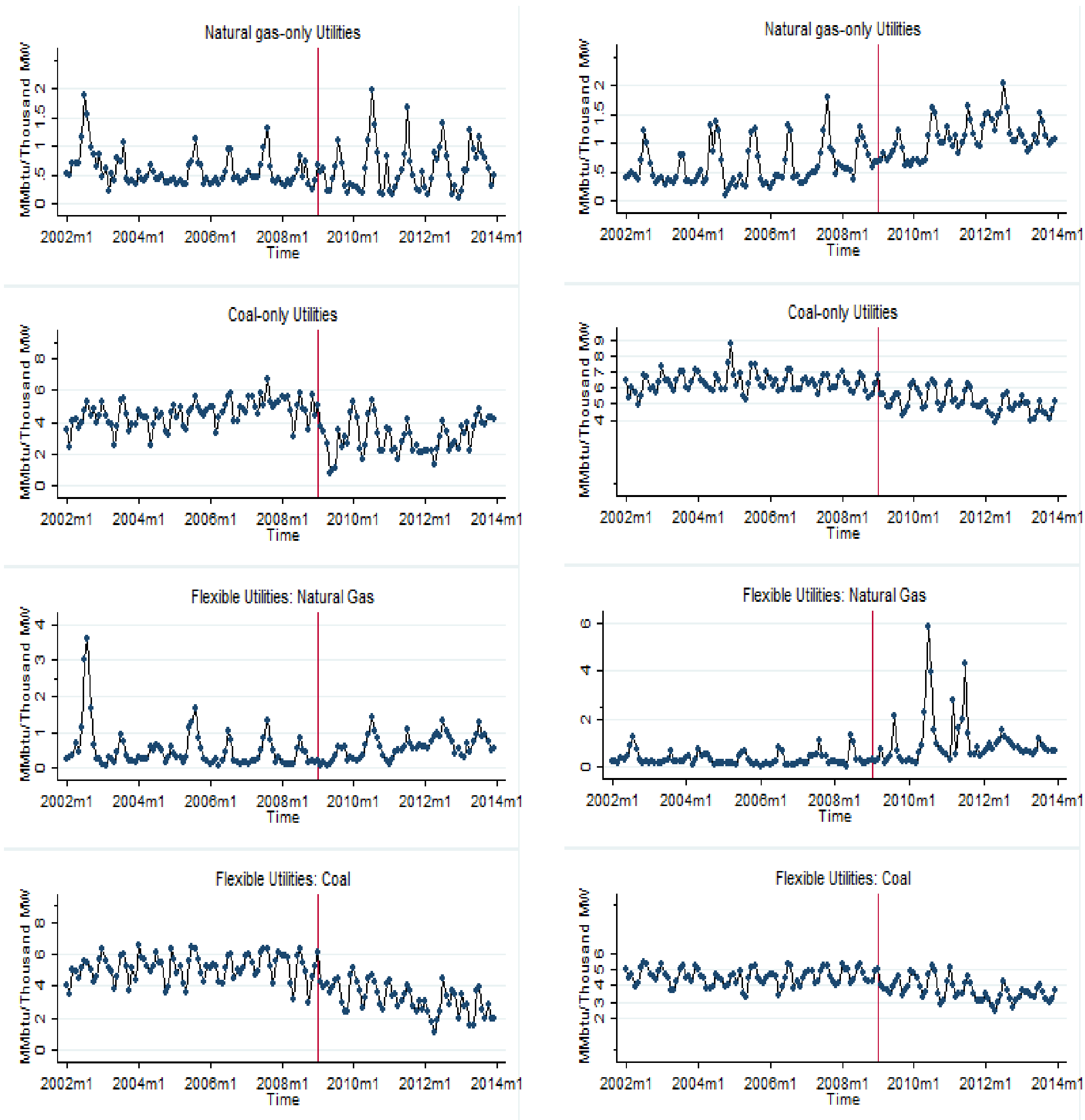


(a) RGGI

(b) Non-RGGI

As we state above, the non-flexible and flexible always-staying utilities can adjust their own capacity and utilization rate, which changes the the fuel structure of the industry. Entry of new natural gas utilities and exit of old coal utilities can also change the struc-

Figure 13: Average Utilization Rate



(a) RGGI

(b) Non-RGGI

ture. For each category, adjusting utilization rate is regarded as a short-term change, while capacity adjustment by investing in natural gas plants and divesting in coal plants is a long-term change. In the following, we divide electricity utilities into three exclusive categories and evaluate their fuel switching behavior separately.

Estimation Results: the Baseline Model

Non-flexible Always-staying Utilities

We first examine the factors that can influence the long-term fuel-switching behavior of non-flexible always utilities. As seen from our data, natural gas power plants are newly built and coal plants are retired. According to American Electric Power (AEP), “Simple cycle natural gas plants are typically constructed in 18 to 30 months and combined cycle natural gas plants are constructed in about 36 months. These lead times are significantly less than the average for solid fuel plants (i.e. coal plants), about 72 months.”[20] As natural gas power plants require multiple years to construct, the capacity adjustment cannot occur instantaneously. Therefore, we estimate lag models by forwarding capacity two years or three years. Two years might be the minimum year that the capacity can respond to the emission market. Coal plants require even longer time to construct. Retiring a coal plant also takes a very long time as it has to be planned ahead for electricity reliability concerns and approved by regulatory commissions. Our data time frame is not long enough, so we assume that the coal capacity is not able to be adjusted due to the RGGI program for simplicity.

Table 5 reports the results for the natural gas capacity adjustment model using yearly data. The dependent variable for the first two columns is two-year lead capacity. In Column (1), many variables are insignificant, but the coefficient for the treatment effect $After * RGGI$ is positive and significant at 1% level. Column (2) and Column (1) are identical except that it replaces the DID variable $After * RGGI$ with the weighted yearly CO_2 allowance price from transactions recorded by RGGI. For observations of utilities located in non-RGGI area and year before 2009, we set the CO_2 allowance price to be 0. Compared with Column (1), all other variables are quite similar and the coefficient of CO_2 price also positive and significant. The third and fourth columns report the same

[20] See https://www.aep.com/about/IssuesAndPositions/Generation/Technologies/NaturalGas.aspx.

two models but with three-year lead capacity as the dependent variable. Column (3) also shows that the RGGI program can increase the natural gas capacity for the natural gas-only always-staying utilities three years later. The CO_2 price in Column (4), again, shows a positive and significant effect. Therefore, the natural gas-only always-staying utilities respond to the program by increasing their capacity more than non-RGGI corresponding utilities. We use the three-year lag model as the baseline result. Note that for all the models, we add time-invariant fixed effect to control for unobserved heterogeneity.

Table 5: Natural Gas-Only Utilities: Total Capacity

Variable	**Two-year lead Z_{itn}**		**Three-year lead Z_{itn}**	
	(1)	(2)	(3)	(4)
Natural gas price	0.087	0.086	0.042	0.041
	(0.061)	(0.061)	(0.047)	(0.047)
Electricity price	-1.487	-1.472	-0.831	-0.799
	(1.294)	(1.300)	(0.865)	(0.869)
After	2.478	2.672	-3.610	-3.160
	(21.191)	(21.221)	(15.124)	(15.098)
After*RGGI	43.137***		38.876***	
	(15.086)		(13.876)	
CO_2 price		15.780**		14.659**
		(6.977)		(5.756)
Trend	0.284	0.381	0.746	0.746
	(4.363)	(4.361)	(3.005)	(2.998)
CHP	20.710***	14.728**	16.755**	13.256**
	(7.992)	(7.403)	(6.985)	(6.051)
Age	-1.219*	-1.170*	-0.931	-0.909
	(0.700)	(0.694)	(0.631)	(0.627)
Ownership-Single	-17.793**	-17.204**	-12.619*	-12.296*
	(7.865)	(7.769)	(7.354)	(7.276)
Ownership-Other	-12.670	-11.913	-11.768	-11.405
	(9.369)	(9.270)	(8.005)	(7.889)
PJM annual load [a]	-0.246	-0.258	-0.294	-0.304
	(0.492)	(0.492)	(0.444)	(0.444)
Constant	1292.754***	1292.565***	1286.386***	1285.513***
	(60.926)	(60.879)	(46.375)	(46.233)
Utility fixed effects	Yes	Yes	Yes	Yes
R^2	0.9853	0.9853	0.9873	0.9873
Observations	421	421	379	379

[a] Coefficients are multiplied by 10^7.
Robust standard errors in parentheses. ***: $p < 1\%$, **: $p < 5\%$, *: $p < 10\%$.

In the short-term, utilities can adjust their heat inputs per capacity (utilization rate). Table 6 reports the results for both natural gas-only and coal-only utilities using monthly data. For natural gas-only utilities, the fuel price variable is natural gas price, while for coal-only utilities, it is coal price. Again, Column (2) and (4) are identical to Column (1) and (3), respectively, except replacing dummy variables $After * RGGI$ with CO_2 price.

For natural gas-only models, the coefficient for fuel price is negative and significant as expected, suggesting that a higher fuel price decreases inputs. A higher electricity price also increases heat input. Larger utilities (those with higher capacity) have a higher utilization rate than smaller utilities. From year to year, the utilization rate has an increasing trend. We also include monthly dummies and find a significant seasonal pattern: the utilization rate is higher from May to September and December when temperature is high or low.

We are particularly interested in the variables that are policy relevant. The variable $After$ captures any change before and after 2009 for all areas. Column (1) shows that there is a statistically insignificant decrease from pre-2009 to post-2009 controlling other factors. The coefficients of $After * RGGI$ and CO_2 price are the DID estimates of RGGI's impact on regulated utilities located in Delaware and Maryland. They are negative and statistically significant for both models, suggesting that the RGGI program does decrease the natural gas-only utilities' utilization rate, surprisingly. There are two possible explanations. One is that there is an emission leakage problem that RGGI utilities shift the production to non-RGGI utilities. The other is that more non-fossil fuel replaces the fossil fuel in the RGGI area.

For coal-only models, the signs for many coefficients are similar to the results of the natural gas-only models. The seasonal pattern of coal use is similar that there are a much higher utilization rate in summer and winter. The coefficients of $After * RGGI$ and CO_2 prices are both significant, suggesting that coal-only utilities also decrease their utilization rate responding to the RGGI program.

Flexible Always-staying Utilities

From the above analysis, we find that the RGGI program increases natural gas capacity investment among natural gas-only always-staying utilities, which is a relatively longer-term adjustment. We also find short-term adjustment that both types of non-flexible

Table 6: Natural Gas-Only and Coal-Only Utilities: Utilization Rate

Variable	Natural gas-only U_{itn}		Coal-only U_{itc}	
	(1)	(2)	(3)	(4)
Natural gas price	-1.014***	-1.014***		
	(0.087)	(0.087)		
Coal price			-3.412***	-3.545***
			(0.751)	(0.752)
Electricity price	12.647***	12.651***	20.858***	20.897***
	(1.429)	(1.431)	(2.105)	(2.105)
After	-16.068	-20.841	209.104**	210.613**
	(45.307)	(45.279)	(102.860)	(103.004)
After*RGGI	-256.228***		-578.418***	
	(52.137)		(135.512)	
CO_2 price		-83.997***		-213.408***
		(20.383)		(56.514)
Capacity	0.260***	0.250***	-5.781***	-5.795***
	(0.059)	(0.058)	(0.369)	(0.370)
Trend	44.710***	44.760***	-418.170***	-415.124***
	(10.198)	(10.197)	(44.848)	(44.942)
CHP	185.483	218.853	1900.774***	1894.540***
	(163.732)	(159.440)	(171.776)	(171.540)
Age	17.851***	17.957***	274.036***	271.664***
	(3.676)	(3.671)	(38.285)	(38.369)
Ownership-Single	69.618	74.183	-811.729***	-813.074***
	(56.206)	(55.401)	(152.208)	(152.210)
Ownership-Other	-67.944	-63.901	-1297.950***	-1293.342***
	(81.643)	(81.060)	(178.775)	(178.729)
PJM monthly load [a]	-4.810***	-4.840***	20.100***	20.200***
	(1.860)	(1.860)	(3.750)	(3.750)
Feb.	-39.740	-39.101	-507.743***	-505.268***
	(45.712)	(45.771)	(84.844)	(84.924)
Mar.	-11.749	-11.492	-379.041***	-377.299***
	(44.627)	(44.678)	(93.006)	(93.088)
Apr.	-78.585	-77.968	-839.121***	-835.974***
	(49.224)	(49.259)	(99.679)	(99.755)
May.	78.553	79.175	-1009.563***	-1006.760***
	(60.389)	(60.392)	(102.342)	(102.327)
Jun.	220.159***	220.476***	-694.894***	-694.223***
	(46.049)	(46.075)	(94.085)	(94.080)
Jul.	560.257***	560.750***	-286.148***	-286.315***
	(71.386)	(71.403)	(85.263)	(85.247)
Aug.	529.754***	530.028***	-272.006***	-272.086***
	(62.006)	(62.020)	(90.735)	(90.806)
Sept.	162.528***	161.738***	-747.984***	-747.940***
	(43.380)	(43.411)	(94.161)	(94.231)
Oct.	8.283	7.680	-838.813***	-838.116***
	(45.409)	(45.451)	(99.598)	(99.660)
Nov.	-18.073	-16.863	-512.871***	-508.321***
	(45.809)	(45.847)	(101.640)	(101.708)
Dec.	120.940***	120.544***	-121.495	-121.976
	(44.781)	(44.824)	(103.355)	(103.447)
Constant	539.705***	549.781***	2018.082***	2054.572***
	(195.720)	(195.307)	(600.673)	(602.289)
Utility fixed effects	Yes	Yes	Yes	Yes
R^2	0.6036	0.6034	0.6605	0.6604
Observations	6240	6240	5364	5364

[a] Coefficients are multiplied by 10^6.
Robust standard errors in parentheses. ***: $p < 1\%$, **: $p < 5\%$, *: $p < 10\%$.

utilities decrease their utilization rate. In this subsection, we investigate whether there is evidence of short-term or long-term fuel switching for flexible always-staying utilities. We first examine the total capacity and the percentage of natural gas capacity.

Table 7 reports the regression results using yearly data. We also estimate two-year and three-year lagged models. Columns (1) to (4) are for the total capacity and Column (5) to (8) are for the percentage of natural gas capacity. For the capacity percentage of natural gas, we take logit transformation of the dependent variable. In the table, again, Columns with even numbers replace the DID estimator $After * RGGI$ with weighted yearly CO_2 price. As shown in the table, the coefficients for $After * RGGI$ and CO_2 price are all insignificant, suggesting that the RGGI program does not induce flexible always-staying utilities to invest more on natural gas plants than before and other areas.

Although we find no significant change in total capacity and natural gas capacity percentage caused by RGGI, with the existence of the program, regulated utilities may use natural gas plants more often even with the same natural gas capacity. We hence examine the factors that influence the utilization of capacity. The regression results are shown in Table 8 using monthly data. The dependent variable is U_{itn} for Column (1) and (2), U_{itc} for Column (3) and (4). The results show that a lower natural gas price leads to more natural gas heat input per capacity. Coal heat input is not sensitive either coal or natural gas prices. Utilities with higher total capacity have a lower utilization rate in coal than those with lower total capacity. Higher monthly total demand in the PJM market leads to an insignificant change in usage of natural gas but increase in coal use. Again, there is a clear seasonal pattern. From June to September, natural gas plants are used more often than other months during a year. Coal plants are used more often in both winter and summer time. The coefficients for the treatment effects in four models are all significant, indicating that the RGGI program leads to a lower utilization rate of natural gas and coal, which is consistent to the response from natural gas-only and coal-only utilities. More specifically, one unit increase in the CO_2 allowance price causes the natural gas utiliza-

Table 7: Flexible Utilities: Total Capacity and Natural Gas Capacity Percentage

Variable	$Z_{itn} + Z_{itc}$				**logit($Z_{itn}\%$)**			
	Two-year lead		Three-year lead		Two-year lead		Three-year lead	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Natural gas price [a]	-8.340	-8.530	7.780	-7.364	-0.002	-0.000	-0.003	-0.004
	(6.010)	(6.080)	(6.100)	(6.132)	(0.041)	(0.041)	(0.036)	(0.036)
Coal price	2.567	2.014	5.507*	5.295*	0.004	0.006	0.003	0.004
	(2.749)	(2.784)	(2.782)	(2.744)	(0.011)	(0.011)	(0.009)	(0.010)
Electricity price	17.241	18.089	4.542	3.438	-0.040	-0.045	0.057	0.061
	(15.239)	(15.464)	(13.536)	(13.649)	(0.067)	(0.067)	(0.065)	(0.065)
After	347.934	324.417	-372.760	-393.224	-1.069	-0.954	1.820	1.907
	(379.153)	(383.439)	(342.877)	(342.424)	(1.766)	(1.772)	(1.564)	(1.567)
After*RGGI	-362.780		-459.759		0.673		1.821	
	(298.353)		(376.320)		(1.280)		(1.558)	
CO_2 price		-94.387		-166.902		0.070		0.653
		(117.520)		(152.865)		(0.502)		(0.635)
Capacity [b]					0.007	0.008	-0.461	-0.465
					(0.585)	(0.584)	(0.577)	(0.577)
t	-60.784	-55.535	-30.941	-27.545	0.739	0.716	0.255	0.241
	(101.830)	(102.573)	(83.710)	(83.851)	(0.525)	(0.525)	(0.440)	(0.442)
CHP	223.594	188.782	234.752	222.422	1.622*	1.739*	1.820*	1.871*
	(161.188)	(150.647)	(179.168)	(175.633)	(0.971)	(0.981)	(0.981)	(0.970)
Age	-61.818**	-59.855**	-49.584**	-49.010**	-0.235	-0.241	-0.182	-0.185
	(28.145)	(27.820)	(22.839)	(22.608)	(0.147)	(0.147)	(0.118)	(0.118)
Ownership-Single	-478.658	-465.856	290.180	294.601	-2.942*	-2.987*	-2.985*	-3.007*
	(626.057)	(626.548)	(322.451)	(322.564)	(1.695)	(1.703)	(1.598)	(1.594)
Ownership-Other	-827.349	-801.592	69.451	77.312	-3.130	-3.213	-3.682*	-3.720*
	(725.976)	(723.795)	(300.860)	(296.499)	(2.143)	(2.156)	(1.931)	(1.935)
PJM annual load [c]	186.000	169.000	145.000	173.000	1.300	1.450	-0.092	-0.197
	(866.000)	(875.000)	(811.000)	(817.000)	(4.340)	(4.340)	(4.010)	(4.000)
Constant	7829.006***	7860.583***	6870.464***	6913.343***	11.094	10.943	7.390	7.250
	(2022.899)	(2024.064)	(1198.228)	(1195.583)	(11.697)	(11.685)	(9.837)	(9.880)
Utility fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.9370	0.9366	0.9443	0.9441	0.7360	0.7355	0.7786	0.7779
Observations	163	163	147	147	163	163	147	147

[a] Coefficients are multiplied by 10.
[b] Coefficients are multiplied by 10^3.
[c] Coefficients are multiplied by 10^9.
Robust standard errors in parentheses. ***: $p < 1\%$, **: $p < 5\%$, *: $p < 10\%$.

tion rate to decrease by about 120 MMtbu/thousand MW, and causes the coal utilization rate to decrease by 423 MMtbu/thousand MW. Overall, we find that flexible utilities and non-flexible utilities have similar emission reduction strategies. They all tend to use the short-term method by reducing heat input. Only the natural gas-only utilities have been found also adjusting their capacity, which is a long-term method.

Entry and Exit of Utilities

The last fuel switching behavior between natural gas and fuel we intend to examine is through entry and exit of fossil fuel utilities. Coal utilities usually exit and natural gas utilities enter. In our data, there are altogether 124 utilities, 13 of them are located in

Table 8: Flexible Utilities: Natural Gas and Coal Utilization Rate

Variable	U_{itn}		U_{itc}	
	(1)	(2)	(3)	(4)
Natural gas price	-0.783***	-0.770***	-0.148	-0.135
	(0.145)	(0.144)	(0.197)	(0.200)
Coal price	0.184	-0.041	0.250	-0.887
	(0.449)	(0.423)	(0.874)	(0.870)
Electricity price	14.628***	14.616***	22.983***	23.545***
	(4.274)	(4.294)	(3.367)	(3.417)
After	569.424***	568.477***	649.493***	610.896***
	(211.988)	(209.851)	(147.779)	(149.534)
After*RGGI	-323.897***		-1291.242***	
	(94.290)		(136.905)	
CO_2 price		-119.942***		-422.861***
		(31.510)		(60.233)
Capacity	-0.056	-0.055	-0.339***	-0.335***
	(0.041)	(0.041)	(0.050)	(0.051)
t	37.330	40.325*	-348.802***	-333.831***
	(25.036)	(24.401)	(36.559)	(36.490)
CHP	80.346	71.126	-902.782***	-971.068***
	(71.658)	(70.802)	(135.293)	(140.889)
Age	-76.025***	-76.054***	27.677	26.887
	(6.777)	(6.809)	(18.445)	(18.359)
Ownership-Single	256.398***	257.702***	239.336*	249.856*
	(85.801)	(86.179)	(131.959)	(132.637)
Ownership-Other	166.013*	172.303*	480.604***	531.963***
	(92.374)	(91.364)	(171.700)	(172.318)
PJM monthly load [a]	-0.001	-0.001	0.017***	0.017***
	(0.003)	(0.003)	(0.005)	(0.005)
Feb.	-15.172	-10.838	-297.028**	-280.721**
	(51.745)	(51.811)	(135.168)	(136.856)
Mar.	112.258	115.546	-342.326**	-328.719**
	(96.748)	(97.070)	(143.835)	(145.242)
Apr.	63.978	69.473	-859.920***	-837.603***
	(60.202)	(60.533)	(146.024)	(148.394)
May.	153.410**	159.125**	-896.442***	-872.332***
	(70.883)	(71.344)	(137.427)	(138.854)
Jun.	272.021***	275.713***	-444.492***	-432.488***
	(93.874)	(93.927)	(131.756)	(133.480)
Jul.	590.324***	595.351***	-217.770	-205.818
	(188.126)	(188.544)	(138.535)	(140.661)
Aug.	484.206***	488.432***	-295.183**	-284.113**
	(144.380)	(144.598)	(135.747)	(137.424)
Sept.	214.095***	214.136***	-603.077***	-600.031***
	(64.974)	(64.974)	(128.189)	(129.553)
Oct.	126.073**	126.516**	-853.334***	-847.067***
	(58.641)	(58.657)	(137.790)	(138.561)
Nov.	109.359*	117.663*	-708.855***	-673.701***
	(61.051)	(61.981)	(135.867)	(137.275)
Dec.	72.715	72.627	-418.524***	-414.514***
	(49.773)	(49.756)	(144.282)	(145.375)
Constant	2482.944***	2526.304***	2932.554***	3166.971***
	(279.526)	(284.185)	(1036.922)	(1031.896)
Utility fixed effects	Yes	Yes	Yes	Yes
R^2	0.1801	0.1801	0.6172	0.6134
Observations	2376	2376	2376	2376

[a] Coefficients are multiplied by 10^3.
Robust standard errors in parentheses. ***: $p < 1\%$, **: $p < 5\%$, *: $p < 10\%$.

Delaware and Maryland. During the sample period the exit at utility level is minimal: Only one utility located in Pennsylvania exited the market before 2009.[21] Among the 124 utilities, 9 entered after 2009, and only one of them is within the RGGI region. From 2009 to 2013, the entering capacity counts for 4.43% of the total capacity in the whole PJM area. Therefore, the RGGI policy impact on utilities' entry & exit decisions is minimal.

Robustness Check and Causality

The previous baseline models test whether the RGGI program is effective in inducing fuel switching and how utilities respond. In this section we apply multiple tests to check the robustness of previous results.

11.1 Specification Check

We first repeat all the previous analyses with logged dependent variables. Since the utilization rate could be equal to zero, we add 1 to the rate and then take the logarithm format. All the regression results are reported in Appendix A. We find that with logged format of dependent variables, all the results are robust to the specification except that the treatment effect becomes weakly significant for the natural gas utilization rate in the flexible utilities. We will discuss this more later.

11.2 Falsification Tests

Next we use falsification tests to check if our model specification produces spurious results. In the tests, we include only utilities in unregulated states (the control group in previous analysis) in the PJM area, and then create "fake" treatment groups by randomly assign treatment to half of the sample. Under this scenario, the treatment effects are

[21] Moreover, it exited after year 2004, which was well before the proposition of RGGI.

Table 9: Falsification Tests: Random Treatment

	Natural gas-only		Coal-only	Flexible-natural gas	Flexible-coal
Variable	**Three-year lead** Z_{itn}	U_{itn}	U_{itc}	U_{itn}	U_{itc}
	(1)	(2)	(3)	(4)	(5)
Natural gas price	0.049	-1.046***		-0.719**	-0.533**
	(0.062)	(0.094)		(0.298)	(0.242)
Coal price			-4.193***	3.089*	-2.914*
			(0.865)	(1.859)	(1.509)
Electricity price	-0.850	12.917***	20.048***	16.341***	20.171***
	(1.149)	(1.558)	(2.211)	(5.151)	(4.180)
After	1.152	-60.184	324.005***	548.609**	133.950
	(21.275)	(50.676)	(113.693)	(216.882)	(175.981)
After*RGGI	9.613	-2.703	-38.471	48.212	74.844
	(10.558)	(34.379)	(70.186)	(118.135)	(95.856)
Capacity		0.339***	-5.634***	-0.103**	-0.410***
		(0.060)	(0.387)	(0.052)	(0.042)
t	-0.781	56.199***	-438.178***	1.017	-238.176***
	(4.136)	(11.044)	(48.845)	(43.881)	(35.606)
CHP	26.656	588.679**	1878.771***	-377.040	-442.126**
	(16.346)	(272.946)	(171.852)	(247.242)	(200.615)
Age	-1.195	16.139***	285.549***	-73.213***	29.788***
	(0.809)	(3.759)	(41.319)	(13.186)	(10.699)
Ownership-Single	-15.020	104.406*	-818.577***	199.523	227.245
	(10.369)	(60.552)	(152.462)	(185.081)	(150.177)
Ownership-Other	-15.696	-32.750	-1267.488***	53.565	385.614*
	(11.907)	(84.825)	(179.270)	(262.088)	(212.662)
PJM load [a]	-6.590	-614.000***	2180.000***	-329.000	1370.000**
	(6.640)	(204.000)	(401.000)	(676.000)	(549.000)
Feb.		-49.693	-513.533***	-20.393	-295.746**
		(49.641)	(88.748)	(185.151)	(150.234)
Mar.		-18.597	-368.761***	130.409	-359.042**
		(48.611)	(96.440)	(185.548)	(150.556)
Apr.		-107.690**	-830.267***	49.621	-899.192***
		(53.020)	(105.398)	(193.923)	(157.351)
May.		66.038	-991.679***	147.974	-826.576***
		(65.789)	(107.905)	(187.278)	(151.960)
Jun.		213.757***	-712.164***	263.373	-422.208***
		(49.883)	(99.256)	(183.561)	(148.943)
Jul.		569.332***	-304.771***	601.445***	-198.154
		(77.573)	(88.275)	(195.993)	(159.031)
Aug.		541.684***	-306.789***	449.173**	-257.456*
		(67.495)	(95.939)	(192.029)	(155.815)
Sept.		153.920***	-773.711***	154.954	-626.552***
		(47.154)	(99.418)	(184.959)	(150.078)
Oct.		3.519	-856.026***	94.245	-727.887***
		(49.280)	(104.604)	(186.441)	(151.280)
Nov.		-20.250	-518.579***	113.988	-686.264***
		(49.898)	(107.515)	(186.942)	(151.687)
Dec.		129.565***	-102.618	53.893	-337.826**
		(48.592)	(109.412)	(183.398)	(148.811)
Constant	1313.903***	533.555***	-1082.363	2009.734**	4930.363***
	(49.269)	(204.117)	(1071.766)	(830.980)	(674.267)
Utility fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.9841	0.6028	0.6503	0.1616	0.6211
Observations	267	5688	4944	1668	1668

[a] Coefficients are multiplied by 10^8.
Robust standard errors in parentheses. ***: $p < 1\%$, **: $p < 5\%$, *: $p < 10\%$.

supposed to be zero. If the treatment effects for the "fake" treatment groups are different from 0, then our previous results are likely to be biased. Table 9 reports the results of falsification tests for the previous regression models with significant results. As shown in the table, the coefficients of $After * RGGI$ are all not statistically significant. The results show that since no significant impact of RGGI is found, it is a good sign that our significant results are not spurious.

11.3 Event Study-Style Model

In the previous DID framework, we have a single coefficient for treatment effect. It does not allow for heterogeneous effects varying before and after the policy year. In the following, we re-estimate event study-style models allowing for heterogeneous effects, the new model can be written as:

$$\begin{aligned} Y_{itx} =& \beta_0 + \beta_1 P_{itx} + \beta_2 P_{et} + \beta_3 trend_{year} + \beta_4 Demand_t + \beta_5 S_{it} \\ &+ \sum_{year=1}^{T} d_{year} D_{year} + \sum_{year=1}^{T} \gamma_{year} D_{year} * RGGI_i + \alpha_i + \varepsilon_{it} \quad for\ x = c, n \end{aligned} \tag{13}$$

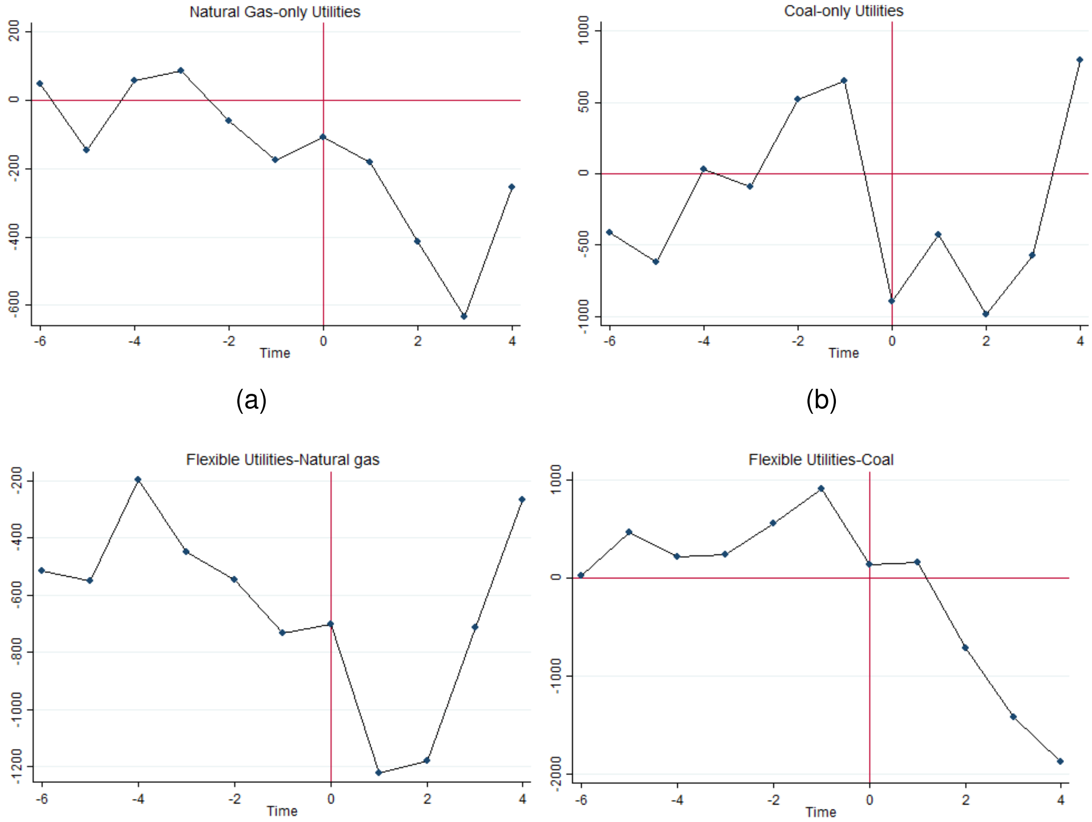
The difference between this framework and the previous one is that instead of using $After_{year}$, we use dummy variables for each year (D_{year}), and instead of using $After_{year} * RGGI_i$, we use $D_{year} * RGGI_i$. Therefore, there is a different coefficient each year for the effect. After obtaining the yearly effect, we test whether there is a break in the yearly effect due to the policy using the following model:

$$\gamma_{year} = r_0 + r_1 After_{year} + r_2 trend_{year} + r_3 After_{year} * trend_{year} + \zeta_{year} \tag{14}$$

Figure 14 presents the event study graphs of the yearly effect, γ_{year}, from estimating Equation 13. Panel (a) to (d) show yearly effects on the utilization rate of natural gas-only utilities, coal-only utilities, flexible utilities-natural gas and flexible utilities-coal respectively. The year of policy year, 2009, is denoted by zero and marked with a vertical line in all panels. The Zero effect is noted by a horizontal line.

These figures visually reveal the possible pattern of the policy impact. Except the

Figure 14:



(a) (b) (c) (d)

flexible utilities-natural gas, other utilities have a close to zero impact before policy year, suggesting that the impact on utilization rate in the RGGI area are similar to non-RGGI utilities. For the flexible utilities-natural gas, the impact does not start with zero, but with some negative value meaning that such RGGI utilities have a lower value before 2009 compared to non-RGGI utilities.

Among all utilities, flexible utilities-coal are more likely to have a clear break in the policy year just by visually examining the graph. More formal tests are reported in Table 10. Column (3) is the full model for Equation 14, while Column (1) only contains a dummy for $After$ and Column (2) allows for a dummy for $After$ and a time trend. The full model is more flexible and additionally allows for different trend after 2009. We list the results, again, by the order of natural gas-only utilities, coal-only utilities, flexible utilities-natural gas and flexible utilities-coal. The results show that if allowing for the maximum flexibility (Column (3)), natural gas utilities for both flexible and non-flexible utilities do not have a break in the policy year because both coefficients for $After$ and $After * t$ are not significant, suggesting that the RGGI policy impact is not significant. However, the tests for coal utilities show that there is a clear significant policy impact. Concerning that there are only 11 observations, the evidence is strong that coal utilities respond to the RGGI policy by reducing their utilization rate.

Table 10: Break Tests For Yearly Effects

Generating Utilities	(1)	(2)	(3)
Natural Gas Only Utilities			
After	-280.336**	-53.471	-45.579
	(102.679)	(118.890)	(113.697)
Trend		-42.539*	-25.236
		(22.742)	(22.622)
After*Trend			-53.154
			(66.487)
Constant	-28.935	-175.633*	-115.961
	(46.423)	(79.453)	(86.673)
Coal Only Utilities			
After	-409.771	-1933.216***	-1942.225***
	(378.913)	(286.958)	(330.957)
Trend		273.466***	245.821***
		(67.377)	(47.247)
After*Trend			80.522
			(173.017)
Constant	2.446	972.268***	874.229***
	(205.322)	(228.994)	(140.207)
Flexible Utilities- Natural Gas			
After	-250.348	-354.653	-383.146
	(179.598)	(301.934)	(338.584)
Trend		18.601	-37.170
		(50.188)	(35.093)
After*Trend			162.720
			(114.475)
Constant	-498.233***	-432.935*	-628.715***
	(70.612)	(216.270)	(129.856)
Flexible Utilities- Coal			
After	-1054.226**	-462.933	-485.917
	(419.054)	(891.236)	(306.703)
Trend		-110.300	132.006**
		(148.970)	(46.446)
After*Trend			-688.427***
			(88.998)
Constant	397.250***	10.394	860.236***
	(121.438)	(589.792)	(180.232)
Observations	11	11	11

11.4 Pre-policy Effects

Although the RGGI program is effective on January 1, 2009, the history of the initiative goes back to 2003 when nine states start the discussion. Early in December of 2005, a Memorandum of Understanding (MOU) is signed to implement the Regional Greenhouse Gas Initiative. Delaware signed it in December, 2005, joined by Maryland in 2007. Therefore, utilities in Delaware and Maryland were aware of their obligation before 2009. So it is possible for them to respond to the program before 2009. In order to understand the pre-policy effects, we restrict the year of observations to 2002-2008 only, and set 2006 to be the first year of agreement (the middle year for Delaware and Maryland) and rerun the basic analyses for policy impact on utilization rate.

Table 11 reports the results. Column (1) to (4) are models of utilization rate for natural gas-only utilities, coal-only utilities, flexible utilities-natural gas and flexible utilities-coal respectively. The results show that the policy announcement does not affect the natural gas-only utilities while affect others. Specifically, the announcement decreases the utilization rate for flexible utilities-natural gas by 203.73 MMtbu/thousand MW, which is lower than the policy implementation effect (323.90 MMtbu/thousand MW) but with the same direction. Opposite to the policy impact of implementation, the announcement increases the utilization rate for coal in both flexible and non-flexible utilities. This suggests that coal utilities are aware that they need to pay for CO_2 emission after 2009 and will reduce coal use after 2009, so they in fact increase coal use before 2009 and after announcement.

Such evidence of pre-policy effect raises an issue that the impact of policy implementation identified in the baseline model might be over-estimated for the coal utilities as they deliberately increased the coal use right before 2009. In the other hand, the estimation for flexible utilities-natural gas might be under-stated. Unfortunately, we are not able to isolate the bias, but just document the caveat here.

Table 11: Pre-policy: 2002-2008 with 2006 as Policy Year

	Natural gas-only	Coal-only	Flexible-natural gas	Flexible-coal
Variable	U_{itn}	U_{itc}	U_{itn}	U_{itc}
	(1)	(2)	(3)	(4)
Natural gas price	-0.728***		-0.317***	-0.956***
	(0.088)		(0.087)	(0.217)
Coal price		-2.955***	0.170	-1.023
		(1.020)	(0.465)	(1.156)
Electricity price	11.923***	9.755***	8.784***	22.351***
	(2.008)	(2.625)	(1.552)	(3.860)
After	-11.319	128.883	199.752***	170.273
	(55.512)	(111.303)	(54.814)	(136.307)
After*RGGI	-46.536	507.539***	-203.725***	334.954**
	(46.234)	(153.034)	(53.105)	(132.056)
Capacity	-0.002	-2.884**	0.029	-0.912***
	(0.065)	(1.464)	(0.023)	(0.057)
t	29.138	-687.693***	-73.706***	-25.237
	(22.094)	(192.946)	(23.376)	(58.129)
CHP	1376.381***	97.690	-325.109***	-118.300
	(472.727)	(241.311)	(65.967)	(164.040)
Age	-1.630	661.547***	-8.590	-122.630***
	(4.562)	(184.019)	(6.860)	(17.060)
Ownership-Single	-81.282	-976.745***	12.414	113.992
	(88.849)	(175.839)	(64.211)	(159.674)
Ownership-Other	-154.372	-530.122**	114.018	484.940*
	(125.880)	(216.744)	(103.953)	(258.502)
PJM monthly load [a]	-3.160*	11.900***	0.135	0.267
	(1.830)	(4.150)	(1.900)	(4.740)
Feb.	-29.910	-569.010***	-14.309	-389.564***
	(39.264)	(99.460)	(56.439)	(140.346)
Mar.	21.963	-340.512***	-15.753	-294.383**
	(37.888)	(107.848)	(56.366)	(140.165)
Apr.	-3.639	-777.326***	18.189	-1127.569***
	(44.056)	(113.960)	(57.772)	(143.661)
May.	167.015**	-1102.642***	75.060	-1124.148***
	(75.503)	(123.461)	(56.482)	(140.454)
June.	308.231***	-691.955***	180.808***	-498.417***
	(50.643)	(116.605)	(56.783)	(141.203)
Jul.	639.443***	-16.945	316.349***	-77.462
	(97.129)	(97.148)	(60.999)	(151.687)
Aug.	639.326***	-71.307	354.647***	-213.593
	(88.306)	(112.337)	(61.677)	(153.372)
Sept.	255.102***	-682.962***	162.387***	-599.323***
	(40.206)	(110.041)	(56.184)	(139.715)
Oct.	105.529***	-824.244***	49.573	-905.544***
	(40.655)	(115.013)	(56.180)	(139.702)
Nov.	4.347	-504.556***	18.439	-786.092***
	(39.121)	(125.790)	(56.313)	(140.034)
Dec.	96.232**	69.726	12.167	-238.162*
	(38.008)	(137.273)	(57.091)	(141.969)
Constant	288.692	-420.756	-568.945	14635.215***
	(257.025)	(2454.871)	(425.820)	(1058.892)
Utility fixed effects	Yes	Yes	Yes	Yes
R^2	0.5871	0.6522	0.3666	0.6193
Observations	3660	3192	1404	1404

[a] Coefficients are multiplied by 10^6.
Robust standard errors in parentheses. ***: $p < 1\%$, **: $p < 5\%$, *: $p < 10\%$.

Emission Reduction

12.1 Emission Reduction and Fuel Switching

In the previous sections, we have examined how the RGGI could potentially induce the fuel switching behavior and conducted multiple robustness tests. However, only with regression results, we are not clear about the magnitude of emission reduction. In this section, we will calculate counterfactuals to quantify the emission reduction.

The counterfactual change can be calculated according to the regression results in Column (3) of Table 5, and Columns (1) and (3) of Table 6 and 8. In fact for the natural gas-only utilities, the RGGI program effectively increases the capacity by 38.88 MW on average three years later. The utilization rate decreases by 256.23 MMbtu/thousand MW for natural-gas only utilities, and 578.42 MMbtu/thousand MW for coal-only utilities. We can calculate the counterfactuals with and without policy according to Equation 8. For the flexible utilities, the program induces an average utility to decrease the natural gas utilization rate by 323.90 MMbtu/thousand MW, and decrease the coal utilization rate by 1291.24 MMbtu/thousand MW. Given the total fossil capacity ($Z_{itn} + Z_{itc}$) for a regulated flexible utility, we can calculate its change of fuel use using Equation 10. In the counterfactual scenario when there is no RGGI program, the treatment coefficient is set to zero.

The changes due to the RGGI program can be read from Table 12. It reports the annual heat input with and without the RGGI program in Delaware and Maryland. For the natural gas-only utilities, we consider the capacity adjustment after 2012 (three years after 2009) and consider the adjustment of utilization rate after 2009. The total natural gas heat input is 48.15 million MMBtu with policy for the period of 2009 to 2013, while if without policy the input increases by 17.94 million MMBtu. The capacity increase accounts for 2.41 million MMBtu increase in natural gas heat input, while the utilization rate adjustment accounts for 20.35 million MMBtu decrease in natural gas heat input. So overall the

the RGGI program leads to 17.94 million MMBtu reduction in natural gas input, which is 37.26% of their total heat input. In contrast, the natural gas heat input of flexible always-staying utilities decreases by 49.30 million MMBtu over the period 2009 to 2013, which is 27.14% of their own total input. The coal heat input of coal-only utilities decreases by 37.05 million MMBtu from 2009 to 2013 in total, or about 20.34% of their total coal input, while the coal heat input of flexible utilities decreases by 285.40 million MMBtu which is 38.69% of their total coal input.

Table 12: Emission Reduction in RGGI Area : 2009-2013

Generating Utilities	2009	2010	2011	2012	2013	Total
Natural Gas Only Utilities						
With policy	7.18	10.74	8.41	10.22	11.60	48.15
Without policy change-capacity				-1.06	-1.35	-2.41
Without policy change-utilization	+4.01	+4.01	+4.01	+4.16	+4.16	+20.35
Without policy change-overall	+4.01	+4.01	+4.01	+3.10	+2.81	+17.94
Emission Change (Thousand Short Tons)	-234.59	-234.59	-234.59	-181.35	-164.39	-1049.49
Coal Only Utilities						
With policy	40.61	43.84	32.78	31.94	33.00	182.17
Without policy change	+7.78	+7.78	+7.78	+7.81	+5.90	+37.05
Emission Change (Thousand Short Tons)	-836.35	-836.35	-836.35	-839.58	-634.25	-3982.88
Flexible Utilities- Natural Gas						
With policy	12.73	26.55	40.69	57.17	44.49	181.63
Without policy change	+9.39	+9.39	+12.10	+11.59	+11.66	+54.13
Emission Change (Thousand Short Tons)	-549.32	-549.32	-707.85	-678.02	-682.11	-3166.61
Flexible Utilities- Coal						
With policy	236.76	229.35	112.83	82.37	76.34	737.65
Without policy change	+79.06	+79.06	+75.16	+40.07	+39.79	+313.04
Emission Change (Thousand Short Tons)	-8498.95	-8498.95	-8079.70	-4307.53	-4277.43	-33651.80
Natural gas heat input percentage	2009	2010	2011	2012	2013	Average
With policy	6.70%	12.01%	25.22%	37.09%	33.91%	22.98%
The Baseline Model						
Change due to policy	-1.64%	-0.36%	+2.80%	+3.27%	+2.45%	+1.30%
The Event Study-style Model						
Change due to policy	+1.42%	+2.46%	+7.10%	+7.27%	+6.89%	+5.03%

Given the information of heat input change, we can directly calculate the emission change. [22] Overall, the RGGI program leads to 7.72 million short tons of CO_2 reduction per year in Delaware and Maryland, which is about 34.36% of the average total annual emissions in these two states from 2009 to 2013. However, as discussed in the sections of "Specification Check" and "Event Study-style Model", models for natural gas are not

[22] In our data, the correlation between CO2 and heat input is 0.99.

as robust as coal models. To be conservative, if we only calculate the emission reduction through coal utilities only, the fuel switching under the RGGI program causes 6.93 million short tons of CO_2 reduction per year, or about 35.06% of the average total annual emissions.

Table 12 also reports the natural gas input rate change due to the program implementation. With the baseline model, the program implementation changes the rate from 21.68% to 22.98% on average between 2009 and 2013. If using the results from the event study-style model, the implementation increases the percentage from 17.96% to 22.98%. For both cases, natural gas heat input rate increases due to the program.

12.2 Replacement for Reduced Coal in RGGI

In Delaware and Maryland, we observe that coal heat input has decreased and natural gas input has increased, but the decreased coal input cannot be covered by the increased coal input. We then need to examine what replaced the gap left by coal reduction. One potential way is to increase the non-fossil fuel input within the RGGI area. The other way is simply to shift the production to non-RGGI areas. We use two tests to test these two hypotheses, which are reported in Table 13. In the first column, we regress the total power generation in each state of Delaware and Maryland excluding generation from natural gas and coal[23] on the $After$ dummy and other monthly dummies, and find that non-fossil fuel generation did not increase as the coefficient for $After$ is insignificant. In the second column, we first define the import of electricity of one state as total consumption minus total power generation by the utilities located in the state, and then regress the monthly import on the $After$ dummy and other monthly dummies. We find that the import increased significantly after 2009. This is, in fact, an evidence for the emission leakage problem. Two tests combined show that emission reduction in Delaware and Maryland due to the RGGI program is not achieved by replacing fossil fuel (natural gas and coal) by

[23] The power generation from petroleum is very small.

non-fossil, but by leaking emissions to non-RGGI areas. It reveals an important fact that leaking emissions to other non-RGGI areas is less costly than fuel switching.

Table 13: Replacement for Reduced Coal in RGGI

	RGGI States		**Neighboring States**	
	Other Generation	Import	Other Generation	Import
After	-249.631***	543.888***	258.645*	3285.331***
	(33.525)	(64.558)	(137.058)	(1112.796)
Feb.	-506.000***	290.833	-1955.250***	1041.500*
	(106.432)	(210.635)	(324.738)	(593.693)
Mar.	-562.250***	81.333	-2052.250***	-1157.333
	(114.010)	(181.464)	(352.750)	(2407.507)
Apr.	-354.083***	-350.583*	-3476.083***	-387.333
	(104.038)	(188.435)	(268.032)	(2277.857)
May.	-276.917**	-326.667	-2260.667***	314.250
	(116.695)	(219.579)	(288.443)	(543.904)
Jun.	-269.000***	-215.083	-1589.167***	-669.750
	(99.373)	(170.265)	(293.909)	(504.135)
Jul.	-202.333*	-52.917	-353.667	-4182.917*
	(103.313)	(165.280)	(447.545)	(2450.871)
Aug.	-198.083*	126.417	-609.000***	-6583.000**
	(107.338)	(175.692)	(215.857)	(3298.473)
Sept.	-328.417***	3.667	-2321.583***	1215.667*
	(94.616)	(170.104)	(289.774)	(630.818)
Oct.	-233.083**	-447.917**	-2988.667***	-6015.083
	(103.044)	(202.556)	(263.426)	(3788.471)
Nov.	-345.000***	-374.833**	-2497.333***	-1479.083
	(93.078)	(179.049)	(279.665)	(2225.681)
Dec.	-83.417	-126.667	-253.250	-890.833
	(106.167)	(190.829)	(299.333)	(643.641)
Constant	2018.763***	1835.297***	15898.231***	-6389.471***
	(90.082)	(156.320)	(197.540)	(625.450)
R_2	0.4663	0.4880	0.6636	0.1717
Observations	144	144	144	144

Discussion and Conclusion

In this paper, we empirically test the role of fuel switching in a carbon emission market under the context of the RGGI program. Fuel switching between natural gas and coal includes long-term capacity adjustment and short-term input adjustment. We find statistical evidence that the RGGI program is effective in reducing emissions, but mainly through reduction of coal and natural gas inputs. We find that the program is responsible for 7.72 million short tons of CO_2 reduction under the program, which is 34.36% of the average total annual emissions in Delaware and Maryland from 2009 to 2013. We also find that flexible and non-flexible utilities have adopted similar reduction strategies. All utilities tend to decrease utilization rate, except natural gas-only utilities adopt longer-term method through increasing capacity additionally.

Our major findings are based on comparing treatment and control groups. We have applied separate DID analyses to different utility categories: natural-gas only and coal-only utilities and flexible utilities. The separate analyses help prevent the endogeneity issue of the RGGI program, i.e. states who are easier to fuel switch are more likely to join the RGGI program. For example, a state with a higher capacity rate of natural gas may be easier to reduce CO_2 emissions. As the treatment and control groups are in the same category in terms of fuel type, we face a less severe problem.

Although our results show that utilities do respond to the not very high CO_2 price in the emission trading program, we find that the RGGI program leads to neither fuel switching from coal to natural gas nor from fossil fuel to non-fossil fuel. Instead, emission leakage occurred. It reveals an important fact that under the CO_2 emission trading program, it is less costly to reduce CO_2 by leaking emissions to non-RGGI areas than using more non-fossil fuel or more natural gas. In the other words, the CO_2 emission trading program can provide incentives for emission reduction. However, under the current regional program, shifting emissions to other areas is, unfortunately, the first option. Therefore, we need to be conservative about the CO_2 emission reduction due to the emission trading program if the program becomes national in the future.

There are a few caveats to our analyses that should be noted. First, our model does not control for vertical arrangement. To hedge risk, power plants often sign long-term contracts with electricity retailers to supply electricity. Such a fixed commitment can affect industry structure (Wolak, 2000) and change producers' behavior (Fabra and Toro, 2005). Bushnell et al. (2008a) emphasize the importance of accounting for the vertical arrangement in the electricity price equilibrium model. In addition, power plants also tend to sign long-term contracts with fuel suppliers (Jha, 2015). All these long-term contracts are constraints on power firms that are not taken into account in our model. Firm fixed effects may help alleviate the problem, however. Second, although we account for other types of pollutants in our profit maximization problem, we do not have sufficient information to isolate the empirical influence of regulations on other pollutants. Last but not least, the impact of the RGGI program may take a long time to fully emerge, and the equilibrium could change over time. Our results should be viewed as measuring the program's impact in the short run.

Chapter Three

Emission Responses to Carbon Pricing in Dynamic Electricity Markets

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Abstract

The Regional Greenhouse Gas Initiative (RGGI) regulates CO_2 emissions from the power sector in the nine northeastern states of the U.S.. The effectiveness of RGGI has long been criticized due to the low CO_2 allowance price and limited price variation. Using a model that accounts for intertemporal constraints, this paper studies electricity generators' production behavior and how the decisions are altered with CO_2 emission regulations. The results show that the RGGI policy has helped to decrease the total CO_2 emissions by at least 4.73% during the sample period. All other things equal, an additional $1/ton increase in permit price reduce the total CO_2 emissions by 1.85%. CO_2 can be reduced by 23.50% if carbon is priced at $15/ton. I also find slight evidence of fuel switching from coal to natural gas.

Keywords: Carbon Emission Market, RGGI, Emission Responses

Introduction

To regulate air pollution in the electricity industry, market-based emission trading programs have been widely adopted around the world since the 1990s. The first national emissions cap and trade program in the U.S. was the Acid Rain Program (ARP), established under Title IV of the 1990 Clean Air Act (CAA) Amendments. It requires power plants to reduce emissions of sulfur dioxide (SO_2) and nitrogen oxides (NO_x), the primary precursors of acid rain. However, similar programs for greenhouse gas (GHG) emissions were not established until rather recently. The European Union Emissions Trading Scheme (EU ETS) is the first and largest GHG emissions trading scheme in the world. In the U.S., although lacking of CO_2 regulations at the national level, some regional programs have been formed, such as the RGGI and the Western Climate Initiative (WCI). On June 2, 2014, the United States Environmental Protection Agency (EPA) proposed a nationwide plan to cut carbon pollution from power plants in all states. The study of existing regional GHG emission trading programs can provide important information for future regulations, at both regional and federal levels.

Using a model that accounts for intertemporal constraints, this paper studies electricity generators' production behavior and how the decisions are altered with CO_2 emission regulations. Unlike many other markets, the electricity market is highly complex with several notable features. Since it is extremely costly to store electricity on a large scale, and demand and wholesale electricity price fluctuate significantly within a day and across seasons, firms respond by making distinct production decisions from hour to hour. As a result, total capacity, which is the maximum electric output in an hour, is high in order to avoid power outage during peak load times. On the other hand, many generators are brought offline to match supply with lower demand during off-peak hours.

In this paper I study individual producers separately with hourly data. Many works studying emissions have been done at the aggregate level. Vollebergh et al. (2009) and

Holtz-Eakin and Selden (1995) use country-level panel data to investigate the relationship between emissions and variables such like income and per capita GDP. Auffhammer and Carson (2008) forecast China's CO_2 emissions by using province-level data. They conclude that emissions in China are unlikely to decrease in the near future unless substantial changes in energy policies occur. Using state-level data, Murray et al. (2014) quantify the emissions reduction due to RGGI with a three-stage model to estimate state demand, demand by fuel type and emission, respectively. However, aggregate data do not incorporate the important features of electricity markets into the analysis, and thus cannot fully explain and predict individual producers' detailed reaction to the complex market conditions which could vary from hour to hour.

As Mansur (2008) and Cullen (2015) point out, electricity generation cannot be smoothly adjusted from zero to full capacity at will due to technology limitations. Ramp rate, which is the maximum increase or decrease in output per hour, limits how fast a generator can make adjustment. Furthermore, when a generator is shut down, a start-up cost is incurred to bring it back online, which is significant and cannot be ignored (Reguant, 2014). Minimum load limits how little the production can be for a generator to remain operating in order to avoid paying the start-up cost. These intertemporal constraints impede output adjustment, and make current production depend heavily on the operating status in the previous period. Moreover, a generator aiming a high production in the future due to high expected price may need to start increasing production from now. Therefore, current production level is correlated with both past and future productions.

Very few studies recognize the importance of intertemporal constraints in the electricity markets. Mansur (2008) examines the welfare loss resulted from market power after restructuring in electricity markets. He finds that ignoring intertemporal constraints leads to overestimation of the welfare loss. Cullen (2015) structurally estimates production costs (including start-up cost), and then compute competitive equilibria under different environmental policies. Instead of causing immediate emission reduction, the results show that carbon pricing influences firms' profits and affects their long-run investment decisions.

A widely adopted "static" model in the literature ignores the features of electricity markets described above and assumes production decisions in each period are independent. For example, Linn et al. (2014b) estimate the marginal costs and potential magnitude of emissions reductions from improving the production efficiency. Mansur (2013) adds various regulation mechanisms to the static model and examines welfare implications of strategic behavior under different policy scenarios. Based on the static assumption, Godby et al. (2014) create a dispatch model to understand the effects caused by the development of wind power energy. However, failing to take dynamics and intertermporal constraints into consideration is likely to lead to biased conclusions. In this paper, I follow Mansur (2008) by incorporating constraints of production such as start-up cost, ramp rate, capacity and minimum load with an intertemporal model, and compare the predicted production decisions to those implicated by the static model.

The paper also adds contribution to the literature on producers' heterogeneity. Firms in the electricity market produce the same output (electricity) with different inputs and technologies, thus cannot be considered as identical. Among fossil-fuel plants, coal plants have least marginal costs but high start-up costs, thus are used to satisfy base load, while natural gas plants have higher marginal costs but are less costly to switch on and off. When a CO_2 emission trading program is introduced, it puts a price on carbon and increases the production costs of all fossil fuel power plants. However, the influence is not uniform. Compared to coal and oil plants, natural gas plants become more competitive due to the lower emission rate. Furthermore, prime mover (engine) types and production efficiency can vary even for plants using the same type of fuel. Therefore, it is important to consider individual producers' decisions separately and how much the production decisions change when adding carbon price to the picture.

I also contribute to the literature of measuring generation and emission responses to different market and policy conditions. Several studies have projected how firms respond to different levels of carbon prices (Cullen and Mansur, 2015; Chen, 2009). However, with limited variation in CO_2 permit prices of U.S. regional regulation programs, it is still unclear how much CO_2 emissions can be actually reduced if a more stringent policy is in place. The evaluation of ongoing regional programs is especially vital given the expectation that the national Clean Power Plan will effectively take place in the near future.

To the best knowledge of mine, this is the first paper studying how individual firms with intertemporal constraints react to various levels of CO_2 prices in RGGI regulated area. To conduct the analysis, I use data on the majority of firms operating in Pennsylvania-New Jersey-Maryland Interconnection LLC (PJM). PJM is a regional transmission organization (RTO) that coordinates the movement of wholesale electricity in all or parts of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia and the District of Columbia.[24] Electricity wholesalers bid in the day-ahead auction which decides the load allocation and hourly prices of the following day.[25] The data include individual characteristics as well as hourly detailed information of generation and emissions of all fossil fuel firms located in Delaware, Maryland, Ohio, Pennsylvania, Virginia and West Virginia. The sample contains 10 months, namely, every September and October from 2009 to 2013.

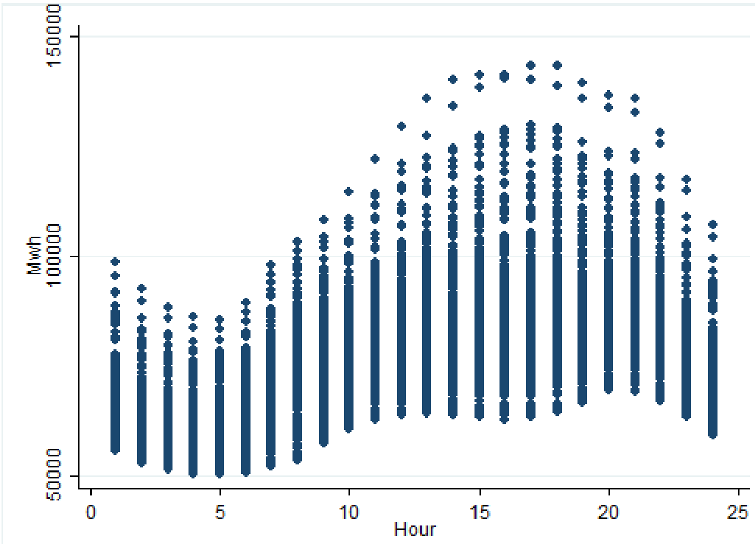
Figure 15 shows the aggregate load and price in the PJM market across hours of a day. Hour 1 is defined as the hour from midnight to 1 AM, and hour 24 is the last hour of a day. Within a day, both load and price experience high degree of fluctuations across hours. The volume for night hours is low and it can double in peak hours. For each hour, demand and price also vary significantly. Given this feature of significant variation during a day as well as across days/seasons, large capacity needs to be build in order to satisfy demand of peak hours, while much of it is then brought offline later in a day.

In the PJM area, only firms located in Delaware and Maryland are regulated by the

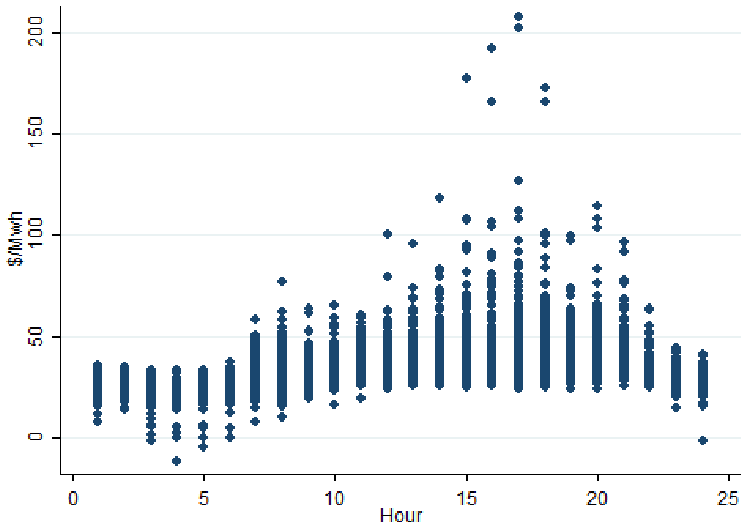
[24]See http://www.pjm.com/about-pjm/who-we-are.aspx.

[25]There is also a real-time market which supplements day-ahead auction, but most of the load is determined in day-ahead auction.

Figure 15: PJM Hourly Load and Price



(a) Load

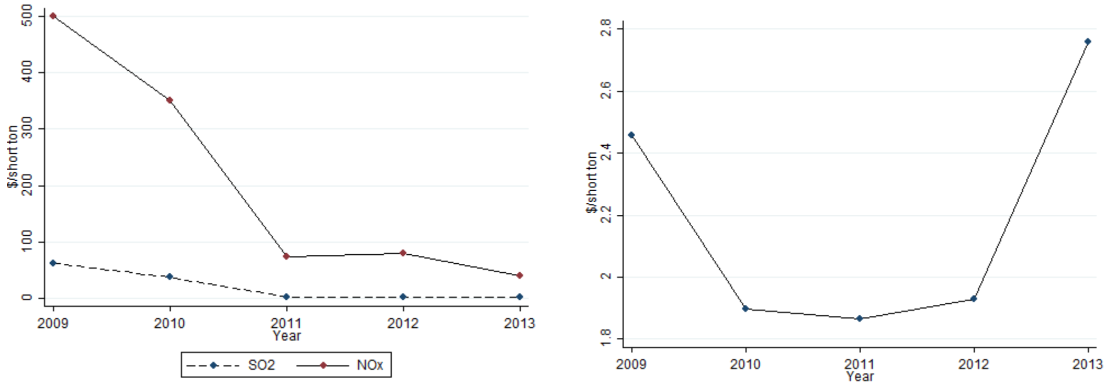


(b) Price

CO_2 emission trading program RGGI.[26] States of Ohio, Pennsylvania, Virginia and West Virginia in the sample are not regulated by RGGI and do not have extra costs for emitting CO_2. All firms are regulated by the long-existing ARP and thus need to purchase emission permits for SO_2 and NO_x emissions. During the sample period from 2009 to 2013, the CO_2 allowance price has been consistently low at around $2/ton and thus may not provide

[26]New Jersey withdrew from the program at the end of year 2011.

Figure 16: Emission Prices Over Time



(a) SO_2 and NO_x (b) CO_2

enough incentives for firms to make adjustment. The effectiveness of RGGI program has been long criticized due to its low allowance prices and limited price variation. As a matter of fact, the annual emission cap in the first control period was loose and allowance price was at the predetermined price floor (Figure 16). Therefore, whether the carbon price is sufficiently high and to what extent emissions can be reduced with tighter regulation is still underexplored. Motivated by this, the paper empirically estimates how individual firms adjust production (and thus emissions) to various levels of CO_2 allowance prices.

I estimate the intertemporal model proposed by Mansur (2008) for each producer separately. The results validate the findings in Mansur (2008) that both past and future markups are also related with output decision in the current period. The intertemporal model predicts actual production better than the static model does, which assumes current output only depends on current markup. With the estimated parameters from the intertemporal model, I examine how each producers' generation (and thus emissions) change if a more stringent carbon policy raise the cost of production. The results show that all other things remain the same, the CO_2 emissions decrease as allowance price increases, but the emission reduction slows down as the permit price of CO_2 approaches \$15/ton. For generators located in Delaware and Maryland, the RGGI policy has helped to decrease the total CO_2 emissions by at least 4.73% during the sample period. When the permit price is within the neighborhood of actual data, the reduction in CO_2 emissions due to a $1/ton increase in permit price is 0.304 million tons, or 1.85% of the total CO_2 emissions. Emissions can be reduced by 23.50% if carbon is priced at $15/ton.

Fuel switching from coal to natural gas arises as CO_2 price increases, i.e., generation from coal generators decreases and generation from natural gas generators increases. However, the scale of fuel switching is small due to the limited capacity and generation of natural gas generators within Delaware and Maryland. I also compare producers' reactions to higher carbon prices during peak and off-peak hours. When carbon price is relative low (below $10/ton), the reductions in generation and CO_2 are comparable between peak and off-peak hours. However, as carbon price continues raising, the abatement of CO_2 slows down more in off-peak hours.

The rest of the paper is organized as follows. I introduce the background of RGGI program in the next section. Section 3 describes a theoretical model of the electricity market with intertemporal constraints such as start-up cost, ramp rate, capacity and minimum load. Section 4 presents the reduced form regression used to empirically estimate individual generators' production decisions. Section 5 summarizes the data, and section 6 presents regression results of the intertemporal model and predicts generation and emission responses to different levels of carbon prices. Section 7 concludes.

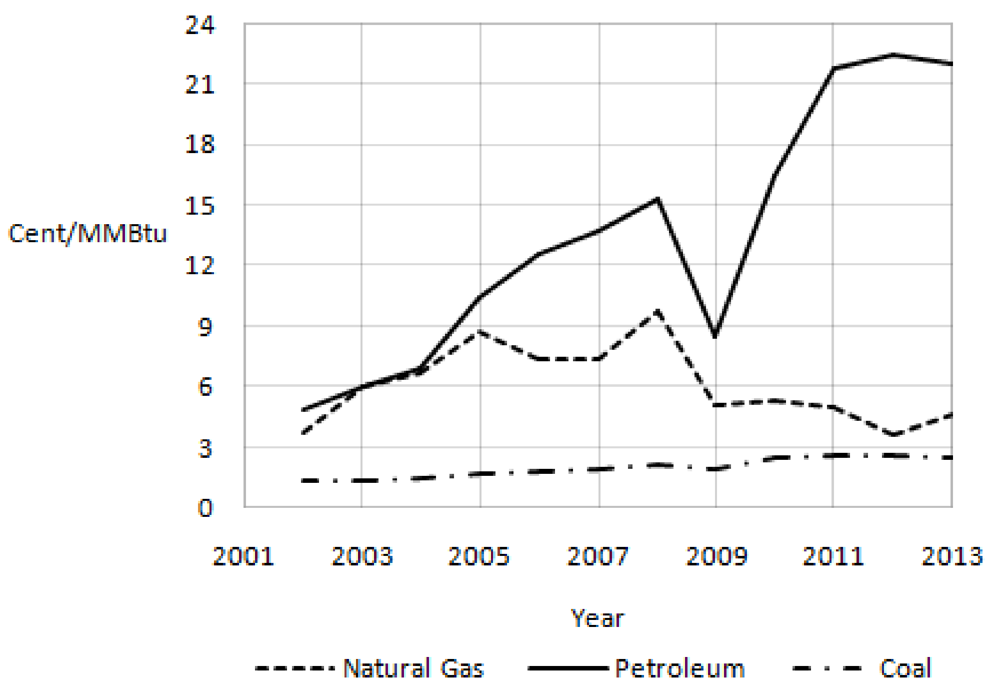
The RGGI Program

RGGI is a cooperative effort to reduce CO_2 emissions among the states of Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New York, Rhode Island, and Vermont specifically in the electric power sector.[27] Regulated sources are fossil fuel-fired power plants with a capacity of 25 MW or greater located within the RGGI States. RGGI aims to stabilize and then reduce CO_2 emissions within the signatory states. The

[27] See http://rggi.org/rggi.

effort was formally initiated in 2003 and the compliance started on January 1st, 2009. Every control period lasts three years, at the end of the third year of a control period, each regulated plant is required to hold one allowance for each ton of CO_2 emitted. During a control period, unused allowances will not expire and can be banked for future years. If a plant violates the rule, it needs to surrender a number of allowances equal to three times the number of its excess emissions. More than 90% of the allowances are sold at RGGI quarterly auctions. Through the end of 2013, RGGI has conducted 22 successful auctions, selling a total of 651 million CO_2 allowances for $1.6 billion. Proceeds from the auctions are returned to states and invested in consumer benefit programs such as energy efficiency and renewable resources. The annual CO_2 emission cap, which is the total allowances allocated each year, is decreasing over time.

Figure 17: Fuel Price: 2002-2013



According to RGGI (2014), average CO_2 emissions from 2010-2012 in RGGI states decreased by 25.4%, compared with the average from 2006-2008. In addition, the CO_2

emission rate (pounds of CO_2 per megawatt hour) dropped by 16.7%. However, as shown in Figure 17, natural gas price in the U.S. plummeted during the same period due to the rapid development of shale gas extraction, led by new applications of hydraulic fracturing technology and horizontal drilling. This makes natural gas generators more competitive compared to coal generators, and is a major contributor to the CO_2 emission reduction. Therefore, the effectiveness of RGGI remains questionable and needs to be further explored.

Although important, RGGI policy is not studied extensively yet. Chen (2009) uses simulation based on a transmission-constrained electricity market model to address two issues related to RGGI: CO_2 leakage and NO_x and SO_2 emissions spillover. Shawhan et al. (2014) model the RGGI regulated plants with a detailed electricity grid. They consider three grid models that have different numbers of transmission nodes. The simulation results show that impact predictions produced by the model with most nodes differ from those of the simplified models. Wing and Kolodziej (2009) employ general equilibrium models to analyze the effectiveness of RGGI. They conclude that RGGI induce power plants in unconstrained states to generate more electricity and export it to RGGI area, which results in emission leakage rate of more than 50%. Zhou and Huang (2016) estimate directional distance functions to measure the impact of RGGI on U.S. power plants' technical efficiency. Ruth et al. (2008) study the impact of participation on the state of Maryland.

Given that the decrease in natural gas price leads to more use of natural gas generators which also results in less CO_2 emissions, this paper answers the question whether RGGI is currently effective by analyzing the portion of emission reduction that is attributed to RGGI carbon pricing with the consideration of intertemporal constraints. In addition, this paper also contributes to the literature of RGGI by predicting the potential of CO_2 reduction given the characteristics of current regulated fossil fuel generators. The exploration of both generation and emission responses of individual producers to CO_2 allowance price levels not observed in reality also provides insights for policymakers when deciding the ideal emission cap level.

Electricity Market with Intertemporal Constraints

To illustrate the dynamic decisions in the electricity market, I Follow Mansur (2008) and Cullen (2015) to construct a profit-maximizing model. The model incorporates dynamic features of the electricity market into firms' production decisions. In each hour, firms maximize the profit given price, cost and intertemporal constraints. I assume firms in PJM area are price-takers, i.e., they do not strategically manipulate price by altering quantity of electricity produced, in order to raise profit.

Price taking in electricity market is an important and potentially restrictive assumption, especially given the extensive studies on market power in electricity markets (Bushnell et al., 2008b; Holland, 2009; Mansur, 2008; Puller, 2007). However, market power mitigation actions taken by PJM make this assumption less of a concern, if not perfect. More than 80% of the load is sold in the day-head market, leaving less incentive for firms to raise price in real-time market. The bids are capped at the reference level to prevent potential extreme prices. Moreover, a structural screen is performed after bids are submitted in the day-ahead and real-time markets. PJM implements automatic mitigation of bids from generating units dispatched for congestion relief if the structural screen is not passed (Reitzes et al., 2007). In addition, PJM also takes market power mitigation actions in other markets such as capacity market and ancillary services market. Although there is occasional local market power as a result of transmission congestion, the overall market performance is evaluated as competitive (Monitoring Analytics, 2015). The choice of data also alleviates the concern of market power. I avoid the summer time when demand is at its peak and firms have the most incentives to exercise market power. Instead, I use data of each September and October from 2009 to 2013, which approximately represents the average level of demand and generation throughout a year. During the sample period, the total generation of the firm with the highest aggregate production is only 7.94% of the total generation of full sample, and the capacity of the largest firm is 4.85% of the aggregate capacity. [28]

With the assumption of price taking, competitive firms maximize profit by maximizing profit at each generator separately. This is not the case when firms are able to exercise market power. With market power a firm would consider total production from all generators that have distinct cost structures. Therefore, throughout the analysis each generator is regarded as an independent unit maximizing its own profit.

As stated above, Intertemporal constraints such as capacity (CAP), start-up cost ($START$), ramp rate (R), minimum load (MIN) impede output adjustment, and make production decisions in different periods interdependent. These features make the intertemporal model distinct from a "static" model, where generators only care about current price, and operate at full capacity if price exceeds marginal cost, completely shut down otherwise. In the "static" model, generators can quickly adjust production with no cost, the corresponding optimization problem is

$$\underset{q_{it}\in\{0,CAP_i\}}{\text{Max}} (P_t - mc_{it}) \cdot q_{it}. \tag{15}$$

where P_t is the electricity price in PJM at time t, and mc_{it} is the marginal cost of production.

I assume each generator has constant marginal cost in each hour, i.e., independent of production. While the assumption of constant marginal cost might not hold for a firm or plant that has multiple generators with different characteristics, the marginal generation cost for a specific physical generating unit is stable. Generator i's marginal cost of

[28] A firm's capacity is defined as the largest observed production in an hour.

production at time t can be constructed as:

$$\begin{aligned} mc_{it} =& FuelPrice * HeatRate_{it} + SO_2Price * SO_2Rate_{it} \\ &+ NO_xPrice * NO_xRate_{it} + CO_2Price * CO_2Rate_{it} \end{aligned} \tag{16}$$

where heat and emission rate are defined as the amount of heat used and pollution emitted in order to produce one megawatt hour (Mwh) of electricity.

By contrast, generating units with non-negligible start-up cost, ramp rate and minimum load solve a discrete, dynamic decision model. The state variable for generator i in period t, S_{it}, is the production level of the previous period

$$S_{it} = q_{it-1}$$

I simplify the process of production adjustment between two periods to a sudden change at the beginning of each hour, and it is denoted as the choice variable x_{it}: $S_{it} + x_{it} = q_{it} = S_{it+1}$.

The value function $V(S_{it})$, proposed by Mansur (2008), depends on exogenous price P_t, marginal cost of production mc_{it}, as well as intertemporal variables such as capacity (CAP_i), start up cost ($START_i$), ramp rate (R_i) and minimum load (MIN_i). The Bellman equation of this dynamic problem can be written as

$$\begin{aligned} V(S_{it}) = & \underset{x_{it} \in [-R_i, R_i]}{\text{Max}} \Big\{ (P_t - mc_{it}) \cdot (S_{it} + x_{it}) - f(S_{it}, x_{it}) \cdot START_i + \beta V(S_{it} + x_{it}) \Big\} \\ & \text{s.t.} : S_{it} + x_{it} \geq MIN_i \quad \text{if} \quad S_{it} + x_{it} > 0 \\ & \text{and} \quad S_{it} + x_{it} \leq CAP_i, \end{aligned} \tag{17}$$

where $f(S_{it}, x_{it})$ is an indicator variable equals 1 if the generator is turned on from not operating, 0 otherwise:

$$
\begin{aligned}
f(S_{it}, x_{it}) &= 1 \quad \text{if} \quad x_{it} > 0 \quad \text{and} \quad S_{it} = 0, \\
&= 0 \quad \text{else.}
\end{aligned}
$$

Note that in the static model maximizing aggregate profit over time is equivalent to maximizing profit of each period separately, and the production is at full capacity whenever price exceeds marginal cost. This however is not the case with the intertemporal model. With intertemporal constraints generators aim to maximize profit over time by jointly determine production levels in each period. With a certain level of S_{it} determined by past price and limitation imposed by ramp rate, generators may not necessarily be able to adjust quantity to the level they would have done in the static scenario. Moreover, in order to achieve a target production level in future periods, they might need to start increasing or decreasing current output. Therefore, observed quantity of production with intertemporal constraints could be any number between minimum load and capacity.

Methodology

In the previous section I describe a dynamic model for price taking firms with intertemporal constraints. However, firms' expectation of the future path of price needs to be formed in order to structurally solve the problem (Cullen, 2015). In addition, the calculation of optimal solution involves extensive computational burden. Instead, this study employs a reduced form regression developed by Mansur (2008) to empirically investigate how firms' react to changes in electricity price and marginal cost of production.

With the assumption that firms in PJM behave competitively, each generator can be regarded as a independent single unit maximizing its own profit. In hour t, generator i's production, q_{it}, is positively correlated with the current price-cost markup

$$markup_{it} = P_t - mc_{it},$$

where each generator's marginal cost can be directly calculated from observed heat rate, fuel price and emission allowance prices. To compare with the static model, a dummy variable indicating whether the markup is positive ($markup\_pos$) is added to the model. If the static model fully explains output decisions, then $markup_{pos}$ should be the only variable which is statistically significant. In addition, as illustrated in the previous section, generators also take past and future markups into account when choosing q_{it}. This is mainly due to the existence of intertemporal constraints such as start-up cost and ramp rate. These constraints make a generator's production across periods interdependent.

High start-up cost makes generators less willing to change operating status from on to off, and vice versa. Past markup decides output in past periods, and the past output level further influences production in current period. For example, if the markup in past periods is high, the generator was more likely to be operating in the past, and remain running even with a low current markup, in order to avoid the start up cost. Similarly, future markup also has an impact on q_{it}. Generators that have a high expectation of future markup will operate in future periods for sure, thus in current period they might choose to continue to produce even facing a low current markup, as long as the the loss from production in current period is less than the start-up cost.

Ramp rate is another intertemporal constraint that makes past and future markups relevant in deciding current output. Past and future markups are likely to be positively correlated with past and future production, respectively. With ramp rate, generators' ability to adjust quantity is limited, thus how high or low the current production can be depends heavily on the production level in past periods. Moreover, high future markup provides incentives for a generator to raise future output. To achieve that target in the future, it might need to start raising production from current period, given that it takes time for a generator to make adjustment.

To account for these dynamic features, past and future markups are incorporated into the model. More specifically, I include markups for the past and following hours: $markup_{it-1}$ and $markup_{it+1}$. Furthermore, for generators which are slow to adjust, a high $markup_{it-1}$ or $markup_{it+1}$ itself may not be enough to induce production. For example, If a generator needs 3 hours to become fully operating from cold status, then it will not start up knowing that only markup in the following hour ($markup_{it+1}$) will be high. For this reason, the average markups of the current ($\overline{markup}_{it}$) , previous ($\overline{markup}_{it-24}$) and following days ($\overline{markup}_{it+24}$) are also included. It is worth noting that although actual future markup is not yet realized in current period, it is a good proxy for expected future markup if firms have good knowledge and information of the PJM market. Since the auctions are repeated on a daily basis, this seems to be a reasonable assumption.

Time-invariant variables such as start-up cost, ramp rate, capacity and minimum load vary across generators, but can not be separately identified from generator-specific fixed effects (α_i). Moreover, generators respond to various markups differently due to distinct characteristics. Similar to Mansur (2008), I model each generator's output decision separately. For generator i, the reduced form model is

$$\begin{aligned} q_{it} =& f(markup_{it}, markup_{it-1}, markup_{it+1}, \overline{markup}_{it}, \overline{markup}_{it-24}, \overline{markup}_{it+24}; \beta_i) \\ &+ \alpha_i + \gamma_i markup\_pos_{it} + \epsilon_{it} \qquad \text{if} \quad q_{it} > 0. \end{aligned} \tag{18}$$

where $f(\cdot)$ is the fifth-order polynomial function and β_i is a vector of corresponding coefficients. The sample included in this regression is a subset of the whole data, which only includes observations with positive output. The reasons are twofold. First, the comprehensive data include many inactive generators which barely operated during sample period. Moreover, generators with even high aggregate load are not necessarily always operating, they may switch on and off from hour to hour. Both of the above facts cause the number of observations with zero production to be high. As a matter of fact, the portion of observations with positive output is only 40.44% of the entire data (Table 14). Including many observations with dependent variable at 0 is problematic in an ordinary least squares regression. The second reason is specific to the electricity market. Due to the start-up cost, generators need a much higher incentive to raise output from zero to some positive level. In other words, the increase in markup which causes an output raise from 10 Mwh to 20 Mwh is comparable to that causes a movement from 20 Mwh to 30 Mwh, which should both be much lower than the markup raise needed to boost production from 0 Mwh to 10 Mwh. For this reason, including observations with zero generation leads to biased interpretation of the regression results.

Table 14: Number of Observations by Fuel Type

	Full Sample	$q_{it} > 0$	Ratio
Coal generators	1,090,656	620,556	56.90%
Natural gas generators	1,137,528	280,605	24.67%
All generators	2,228,184	901,161	40.44%

Another concern is the issue of endogeneity. Since markup is calculated as the gap between electricity price and marginal cost of production, if either price or marginal cost could be affected by then output decision, then the estimates are biased. Because of the assumption of competitive behavior, generators take price as given and cannot influence electricity price by altering quantities. Equation 18 is regressed at generator level, the marginal cost of a physical generating unit can be considered as constant in every period. Heat rate of a generator is also stable once heated up. Therefore, increasing or decreasing production is not likely to have a big impact on marginal cost of a generator. However, it is worth noting that the assumption of constant marginal cost may not hold at the utility level; The marginal cost of an utility that has multiple generators is a step function.

Data

The majority of generation in PJM Interconnection area is included. More specifically, the sample contains all firms burning coal or natural gas located in Delaware, Maryland, Ohio, Pennsylvania, Virginia and West Virginia. I exclude New Jersey from the analysis as it withdrew from the program at the end of year 2011. Generators using oil as the primary fuel source are dropped from the analysis due to the limited use. In the sample generation from oil counts for only 1% of the total fossil fuel generation. Moreover, the price-cost markup is almost always negative for oil generators due to the high oil price. Therefore, oil generators are only brought online occasionally to meet retail obligation during peak load or transmission congestion times.

Spanning from 2009 to 2013, I use hourly detailed data at generator level of every September and October. The reasons of picking this period rather than summer or winter are threefold. First, firms' production activities, such as choices of heat input, generation are close to year averages in September and October. Therefore, it is a good representation of firms' behavior throughout a year. Second, in summer when demand is high, fuel switching between coal and natural gas might be passive: Firms have to use natural gas more frequently as coal capacity is well used up. By contrast, the sample in this paper provides a better study of "voluntary" fuel switching, when demand is moderate and both coal and natural gas capacities are readily available. Last but not least, an important assumption of this analysis is that firms behave competitively. Firms have more incentives to raise price and exercise market power when demand is high in summer. This issue is mitigated with the chosen sample.

Three major datasets are used. The first one is Air Markets Program Data (AMPD) collected by EPA. AMPD provides hourly, generator-level on heat input, gross generation, fuel and generator type, location and CO_2, SO_2 and NO_x emissions. Net generation is then approximated as 95% of gross generation. Second, PJM reports hourly electricity wholesale price and demand.[29] The third data source is U.S. Energy Information Administration (EIA), which reports fuel prices of coal, natural gas. State-specific monthly coal and natural gas prices are obtained from EIA's Electric Power Monthly issues. Coal price is stable and does not have large variation (Figure 17), thus monthly coal price is a good proxy for daily coal price. Natural gas price varies across time and states, but daily spot natural gas price is only available at the Henry Hub in Louisiana. I estimate state-specific daily natural gas prices by comparing monthly average prices of other states to that reported at Henry Hub in Louisiana. Natural gas daily price is available for weekdays only, I acquire estimates of weekend price by calculating weekday average prices for each week.

Even for generators using the same type of fuel and the same generator operating in different years, heat rate and emission rate may vary. For this reason, generator-specific average heat rate and emission rate are calculated for each year. The Acid Rain Program of EPA regulates all firms in the sample and reports SO_2 and NO_x prices, while only firms located in Delaware and Maryland are regulated by RGGI and have extra cost of CO_2 emissions. The CO_2 allowance price is from RGGI quarterly auctions. The data consist of 344 generators from 78 utilities operating in the PJM area from 2009 to 2013, for a total of 2,228,184 observations.[30]

Table 15 reports summary statistics of variables used in regressions and data sources. During the period from 2009 to 2013, natural gas price has already fallen comparing with previous years. However, on average natural gas price is still higher than coal price. This explains why coal is still the dominant fuel choice even though it is dirtier. CO_2 emission rate is much higher than that of SO_2 and NO_x, but the allowance price is also much lower. The average hourly wholesale electricity price in PJM is 34.70 \$/Mwh. For the generators

[29]The wholesale price and demand from day-ahead and real-time markets are reported separately, I weight by quantity demanded to get average price.

[30]If an utility has plants in multiple states, I treat them as separate utilities, as they face distinct state-level regulation policies.

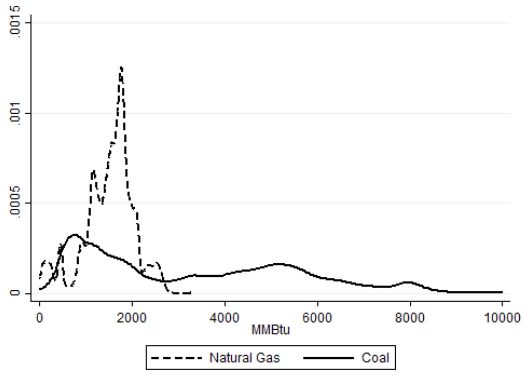
Table 15: Summary Statistics

Variables	Mean	Std. Dev.	Source
Coal price ($/MMBtu)	2.74	0.53	EIA
Natural gas price ($/MMBtu)	4.10	0.93	EIA
Heat input (MMBtu)	1178.41	2133.40	EPA
Gross generation (Mwh)	2.76	5.70	EPA
CO_2 (short ton)	113.67	220.17	EPA
SO_2 (short ton)	0.30	0.98	EPA
NO_x (short ton)	0.10	0.24	EPA
CO_2 price ($/short ton)	2.15	0.34	RGGI
SO_2 price ($/short ton)	21.03	25.17	EPA
NO_x price ($/short ton)	215.13	184.60	EPA
PJM hourly price ($/Mwh)	34.70	11.43	PJM
Delaware (%)	1.45		EPA
Maryland (%)	7.62		EPA
Ohio (%)	29.11		EPA
Pennsylvania (%)	29.11		EPA
Virginia (%)	19.05		EPA
West Virginia (%)	13.67		EPA

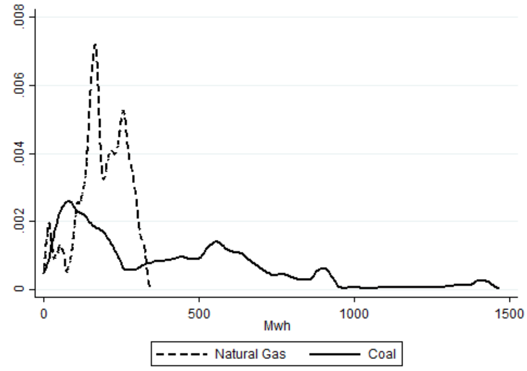
we include in our sample, the RGGI regulated areas are Delaware and Maryland, which encompasses 9.07% of the total observations.

Figure 18 plots the distribution of heat input, gross generation and emissions by fuel type for the observations when generators are operating. No graph for SO_2 is included due to the fact that the volume of SO_2 emissions from natural gas generators is almost negligible, thus the only source of SO_2 emissions is coal generators. The data show that currently coal is still the dominant fossil fuel in this industry: Comparing with coal generators, natural gas generators are much smaller, with much less heat input, generation and emissions. This is due to its lower cost so that coal generators are often used to serve base load and operate almost constantly. Figure 19 shows the total monthly heat input and gross generation for natural gas and coal generators. Consistent with Figure 18, the use of coal is about five times as high as the use of natural gas. However, over time there is fuel switching from coal to natural gas: More electricity is produced from natural gas

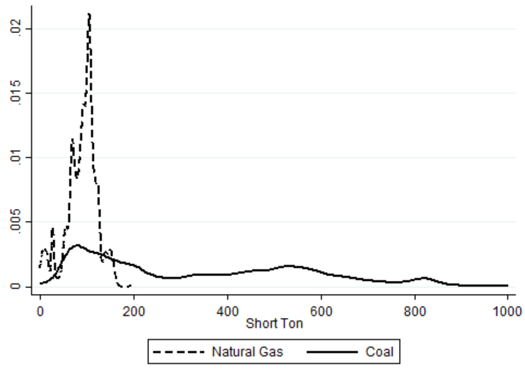
Figure 18: Distribution of Heat, Generation and Emissions



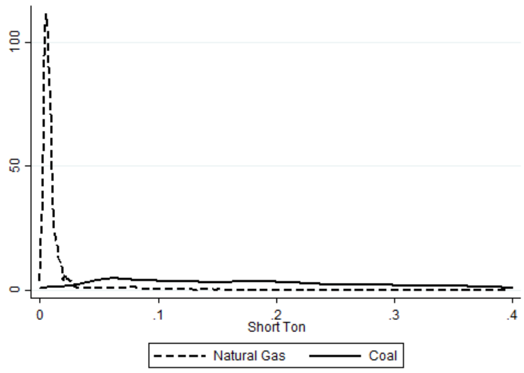
(a) Heat Input



(b) Gross Generation

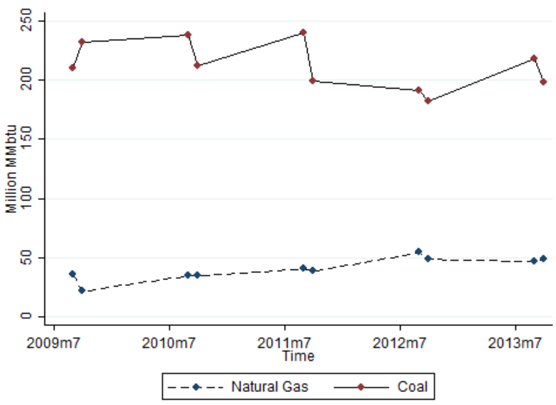


(c) CO_2

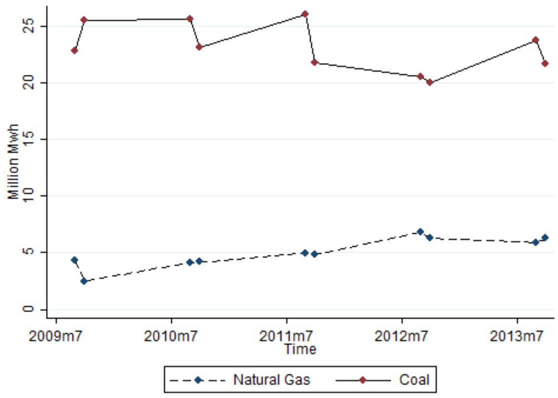


(d) NO_x

Figure 19: Total Heat and Generation



(a) Heat Input



(b) Gross Generation

generators instead of coal generators. The pattern of heat input and gross generation is similar for both coal and natural gas generators. This is strong evidence that heat rate is stable for both types of generators and the assumption of constant marginal cost is plausible.

Figure 16 illustrates emission allowance prices over time. The allowance prices of SO_2 and NO_x have declined significantly. The SO_2 price has decreased to a level which is almost negligible. The price of CO_2 allowance price was low and around minimum price ($1.86/ton) between 2010 and 2012, and has increased afterwards. However, the CO_2 price level remains low even with the recent increase. As a result, the effectiveness of RGGI has been widely questioned.

Empirical Analysis

19.1 Regression Results

This section presents the empirical estimation results of Equation 18. As stated above, only observations with positive outputs are included. Some generators were barely used during the sample period and are thus dropped from the analysis. In particular, I drop generators with less than 300 hours of active production. The remaining data consist of 256 generators, for a total of 854,940 observations.

Table 16 reports the summary of coefficients and corresponding standard errors from 256 generator-specific estimations. As expected, the average of coefficients of dummy variable $markup\_pos$ is positive, but only statistically significant for about half generators. Furthermore, other markups included in the model also have predictive power and the associated coefficients are significant for many generators. This is strong evidence that static model is insufficient in explaining production decisions. In practice, firms take markups in multiple periods into consideration. The average of marginal effects of the six markups are shown in the last column of Table 16. The marginal effects are calculated with the estimated parameters and each generator's specific markup levels. Current and

Table 16: Summary of 256 Generator-specific Estimations: Output Decision

Variables	Average of Coefficients	Average of Std. Dev.	# of Significant Coefficients	Marginal Effects
fixed effects	228.439	10.550	254	
$markup\_pos$	3.103	3.873	133	
$markup_t$	1.366	0.534	148	3.162
$markup_t 2$	-0.013	0.022	41	
$markup_t 3$[a]	-0.445	0.597	74	
$markup_t 4$[b]	7.522	8.280	84	
$markup_t 5$[c]	-2.581	4.464	94	
$markup_{t-1}$	0.627	0.348	122	0.728
$markup_{t-1} 2$[a]	0.678	15.868	69	
$markup_{t-1} 3$[a]	-0.436	0.456	98	
$markup_{t-1} 4$[b]	6.117	6.632	107	
$markup_{t-1} 5$[c]	-2.674	3.850	115	
$markup_{t+1}$	2.517	0.354	224	2.431
$markup_{t+1} 2$	-0.029	0.017	125	
$markup_{t+1} 3$[a]	-0.570	0.471	140	
$markup_{t+1} 4$[a]	0.011	0.007	147	
$markup_{t+1} 5$[c]	-4.824	3.860	146	
$\overline{markup}_t$	-0.324	2.369	155	0.573
$\overline{markup}_t 2$	0.335	0.397	126	
$\overline{markup}_t 3$	-0.053	0.035	143	
$\overline{markup}_t 4$[a]	2.172	1.597	140	
$\overline{markup}_t 5$[a]	0.018	0.061	147	
$\overline{markup}_{t-24}$	-4.851	2.849	154	0.416
$\overline{markup}_{t-24} 2$	0.988	0.470	124	
$\overline{markup}_{t-24} 3$	-0.087	0.040	130	
$\overline{markup}_{t-24} 4$[a]	1.846	1.627	121	
$\overline{markup}_{t-24} 5$[b]	59.146	57.419	123	
$\overline{markup}_{t+24}$	-1.370	1.143	141	-1.680
$\overline{markup}_{t+24} 2$	-0.715	0.278	128	
$\overline{markup}_{t+24} 3$	0.276	0.055	148	
$\overline{markup}_{t+24} 4$[a]	-30.239	5.846	130	
$\overline{markup}_{t+24} 5$[a]	1.128	0.224	146	

[a] Coefficients are multiplied by 10^3.
[b] Coefficients are multiplied by 10^6.
[c] Coefficients are multiplied by 10^8.
Robust standard errors.
Significant at 5% level.

the following hour markups have the highest marginal effects, and all the marginal effects are positive except that of the average markup of the following day, indicating past and future markups have strong impact on production.

Table 17 illustrates the estimation results by fuel type. Among the 256 generators, 164 are coal generators and 92 are natural gas generators. The coefficients for coal generators are generally larger than those for natural gas generators due to the larger size shown in Figure 18. For both groups, most markups have positive relationship with quantity of production, and current markup and markup in the next hour have the highest impact. The average markup of current day has a larger impact on coal generators, while natural gas generators rely more on average markup of the past day when choosing production level. The estimation results validate the use of intertemporal model over static model. In this particular industry, production decisions in each period cannot be regarded as independent, and both past and future periods matter because of the intertemporal constraints.

19.2 Static vs. Intertemporal

To compare the static and intertemporal model, I obtain utilization rate for each observation. Utilization rate is defined as the net generation divided by capacity. It measures to what degree a generator is utilized. The value of utilization is always between 0 and 1, and thus is comparable across generators with distinct sizes. For all observations, I compute conditional expectation of utilization rate at various markup levels, $E(utilization|markup)$, by using the kernel regression. Predicted utilization rate from both static and intertemporal models and actual utilization observed in data are all shown in Figure 20. For the rest of the paper, I include only variables with coefficients significant at 5% level when calculating fitted value of intertemporal model. To account for production constraints, I replace predicted output level above capacity by the capacity, and all negative outputs are replaced by zero.

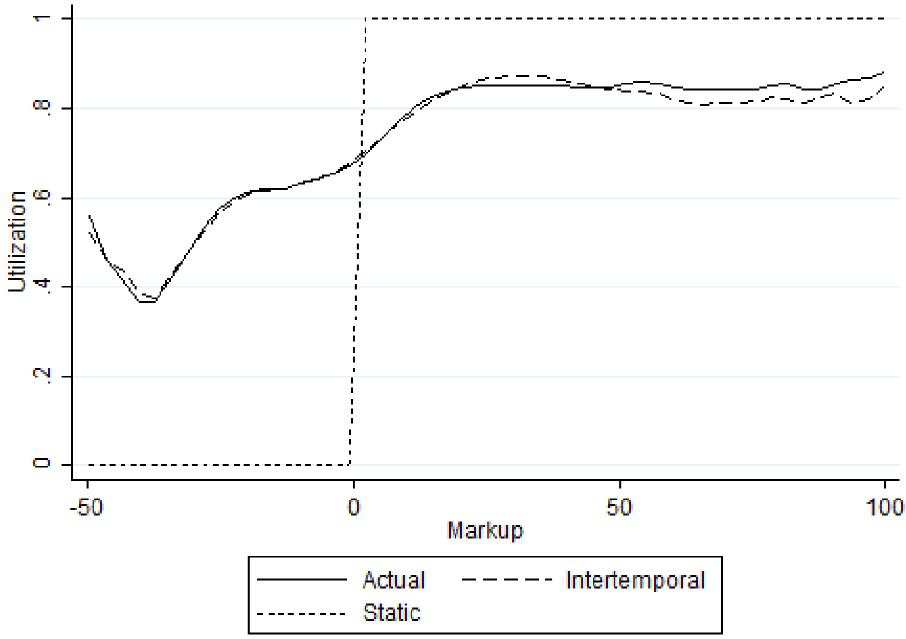
Table 17: Summary of 256 Generator-specific Estimations by Fuel Type: Output Decision

	164 Coal Generators				**92 Natural Gas Generators**			
Variables	Average of Coefficients	Average of Std. Dev.	# of Significant Coefficients	Marginal Effects	Average of Coefficients	Average of Std. Dev.	# of Significant Coefficients	Marginal Effects
fixed effects	278.269	10.550	162		139.605	3.892	92	
$markup\_pos$	4.220	3.873	92		1.111	2.666	41	
$markup_t$	1.816	0.534	109	4.190	0.565	0.338	39	1.329
$markup_t 2$	-0.017	0.022	23		-0.006	0.016	18	
$markup_t 3$[a]	-0.628	0.597	56		-0.119	0.352	18	
$markup_t 4$[b]	10.560	8.280	64		2.106	3.056	20	
$markup_t 5$[c]	-3.596	4.464	73		-0.770	0.867	21	
$markup_{t-1}$	0.905	0.348	86	0.892	0.132	0.220	36	0.436
$markup_{t-1} 2$[a]	2.562	15.870	44		-2.680		25	
$markup_{t-1} 3$[a]	-0.657	0.456	71		-0.040	0.286	27	
$markup_{t-1} 4$[b]	9.099	6.632	74		0.801	2.726	33	
$markup_{t-1} 5$[c]	-4.011	3.850	75		-0.290	0.821	40	
$markup_{t+1}$	3.181	0.354	153	3.071	1.335	0.220	71	1.291
$markup_{t+1} 2$	-0.029	0.017	73		-0.029	0.012	52	
$markup_{t+1} 3$[a]	-0.987	0.471	92		0.172	0.286	48	
$markup_{t+1} 4$[b]	17.000	7.000	109		0.042	2.520	38	
$markup_{t+1} 5$[c]	-7.307	3.860	110		-0.397	0.705	36	
$\overline{markup}_t$	0.111	2.369	105	1.270	-1.099	0.704	50	-0.670
$\overline{markup}_t 2$	0.487	0.397	94		0.064	0.097	32	
$\overline{markup}_t 3$	-0.085	0.035	115		0.003	0.009	28	
$\overline{markup}_t 4$[a]	3.641	1.597	113		-0.448	0.346	27	
$\overline{markup}_t 5$[a]	0.025	0.061	111		0.005	0.009	36	
$\overline{markup}_{t-24}$	-7.150	2.849	111	0.036	-0.752	0.701	43	1.094
$\overline{markup}_{t-24} 2$	1.504	0.470	93		0.067	0.097	31	
$\overline{markup}_{t-24} 3$	-0.135	0.040	98		-0.001	0.010	32	
$\overline{markup}_{t-24} 4$[a]	2.798	1.627	97		0.150	0.455	24	
$\overline{markup}_{t-24} 5$[b]	88.483	57.419	93		6.849	10.165	30	
$\overline{markup}_{t+24}$	-2.138	1.143	104	-0.898	-0.002	0.465	37	-3.073
$\overline{markup}_{t+24} 2$	-1.101	0.278	100		-0.027	0.067	28	
$\overline{markup}_{t+24} 3$	0.430	0.055	108		0.001	0.005	40	
$\overline{markup}_{t+24} 4$[a]	-47.173	5.846	100		-0.053	0.153	30	
$\overline{markup}_{t+24} 5$[a]	1.759	0.224	99		0.002	0.004	37	

[a] Coefficients are multiplied by 10^3.
[b] Coefficients are multiplied by 10^6.
[c] Coefficients are multiplied by 10^8.
Robust standard errors.
Significant at 5% level.

In the sample, 99% of the markups range from -\$50/Mwh to \$100/Mwh. As markup increases, the expectation of utilization rate increases from 0.4 to around 0.9. Note that

Figure 20: Utilization Rate by Model



the curves for actual data and intertemporal model are not strictly upward-sloping as current markup is not the only determinant of output decision. The curve for intertemporal model follows the pattern of actual data closely. By contrast, in the static model output and utilization are fully explained by whether the price-cost markup is positive. Generators completely shut down when markup is negative, and operate at full capacity whenever a positive markup is observed. This figure justifies the choice of intertemporal model over the static model. Ignoring intertemporal constraints cause issues in explaining observed production at negative markups, and leads to poor prediction of actual data.

19.3 Effects of Carbon Price

19.3.1 Fossil-fuel Generation and Emission Responses

The sample includes the majority of firms in PJM, among them firms located in Delaware and Maryland are regulated by RGGI program and have to surrender one CO_2 allowance for each ton of CO_2 emitted. The effectiveness of RGGI program has been long criticized due to its low allowance price. This issue is of particular concern during the sample period: As shown in Figure 16, from 2010 to 2012 the CO_2 allowance price was at the floor ($1.86/ton) due to the loose cap, and the average carbon price is around $2/ton from 2009 to 2013. Although the CO_2 price has increased to around $5/ton recently and peaked at $7.5/ton in 2015, whether it is sufficiently high and how much emissions can be reduced with tighter regulation is still underexplored.

To answer this question, I investigate how generators adjust production (and thus emissions) at various CO_2 price levels. Only the 22 generators located in Delaware and Maryland are included as others are not subject to RGGI regulations. Among the 22 generators, 17 are coal-fired and 5 are natural gas-fired generators. The total number of observations for RGGI generators is 73,886, which accounts for 8.64% of the full sample. Markup decreases as CO_2 price raises and eventually it is too low so that firms will not produce and exit in the long run. Therefore, it is unrealistic to set extreme CO_2 prices in practice. Furthermore, when making predictions with estimated parameters, one needs to be sure that the domain of markups used in the simulation is comparable to that in the data, otherwise the predictive power of the model is undermined. The relation between markup and CO_2 price is presented in Table 18. As discussed above, observed markups rage from -$50/Mwh to $100/Mwh, and the average markup is $5.872/Mwh. For the RGGI area, partly due to the extra cost on carbon, the average markup is -$3.161/Mwh. Therefore I restrict the range of CO_2 price to be under $18/ton, which makes the average markup to be between -$0.954/Mwh and -$19.521/Mwh for generators located in RGGI area.

Figure 21 plots how aggregate net generation and emissions respond to changes in CO_2 price. At each given CO_2 allowance price level, aggregate net generation is obtained by summing over fitted values of individual observations' outputs. Along with each generator's yearly-specific emission rate, the fitted values of individual outputs are used to construct individual emissions of CO_2, SO_2 and NO_x, respectively. The individual emissions are then aggregated to get total emissions at each CO_2 price level. Note that the response

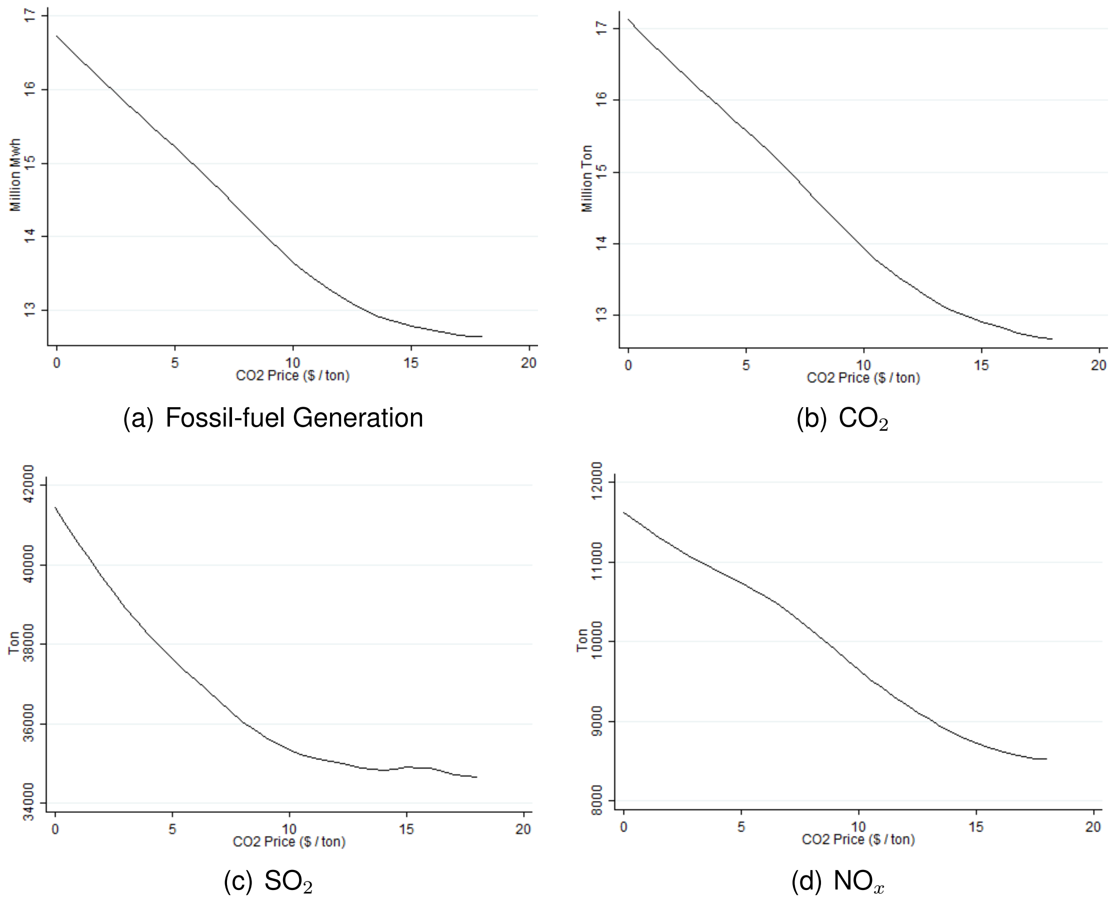
Table 18: Price-cost Markup Under Carbon Pricing in RGGI Area

	CO_2 Price ($/ton)	Average Markup ($/Mwh)
	0	-0.954
	1	-1.986
	2	-3.017
	3	-4.049
	4	-5.080
	5	-6.112
	10	-11.269
	15	-16.426
	20	-21.583
	30	-31.898
	40	-42.213
	50	-52.527
Actual Data		
Full Sample		5.872
RGGI Area		-3.161

is not perfectly linear due to the discrepancy of estimated parameters and emission rates among generators. Moreover, Equation 18 is estimated as fifth-order polynomial function, thus the marginal effects of carbon price depend on markup levels and vary even for the same generator across time.

As shown in Figure 21, aggregate net generation in Delaware and Maryland declines as carbon price raises. The decrease in generation slows down as the permit price of CO_2 approaches $15/ton. The response of CO_2 shares the similar pattern with the response of net generation due to the fact that coal is the dominant fuel in RGGI states. Comparison between coal and natural gas generators will be further explained in the next section. During the sample period, the average CO_2 price is at around $2/ton, and the level of total CO_2 emissions within RGGI area is 16.31 million tons. Without RGGI regulation, total CO_2 emissions would have been 17.12 million tons. It is worth noting that observations with zero production are excluded from the analysis. However, firms may choose to produce in more periods with the higher markups if there were no CO_2 price. Therefore, 17.12 million tons should be regarded as the lower bound of CO_2 emissions without RGGI regulation,

Figure 21: Responses to Carbon Pricing in RGGI



(a) Fossil-fuel Generation

(b) CO_2

(c) SO_2

(d) NO_x

i.e., the RGGI policy has helped to decrease the total CO_2 emissions from RGGI fossil fuel generators by at least 4.73% during the sample period. When the permit price is within the neighborhood of actual data, the reductions in net generation and CO_2 emissions due to a $1/ton increase in CO_2 price are 0.30 million Mwh and 0.31 million tons, or 1.86% and 1.85% of the total net generation and CO_2 emissions, respectively. Although not directly regulated by RGGI, along with the reduction in fossil fuel generation, the emissions of SO_2 and NO_x also decreases with more stringent carbon policy, as shown in Figure 21.

19.3.2 Coal vs. Natural Gas

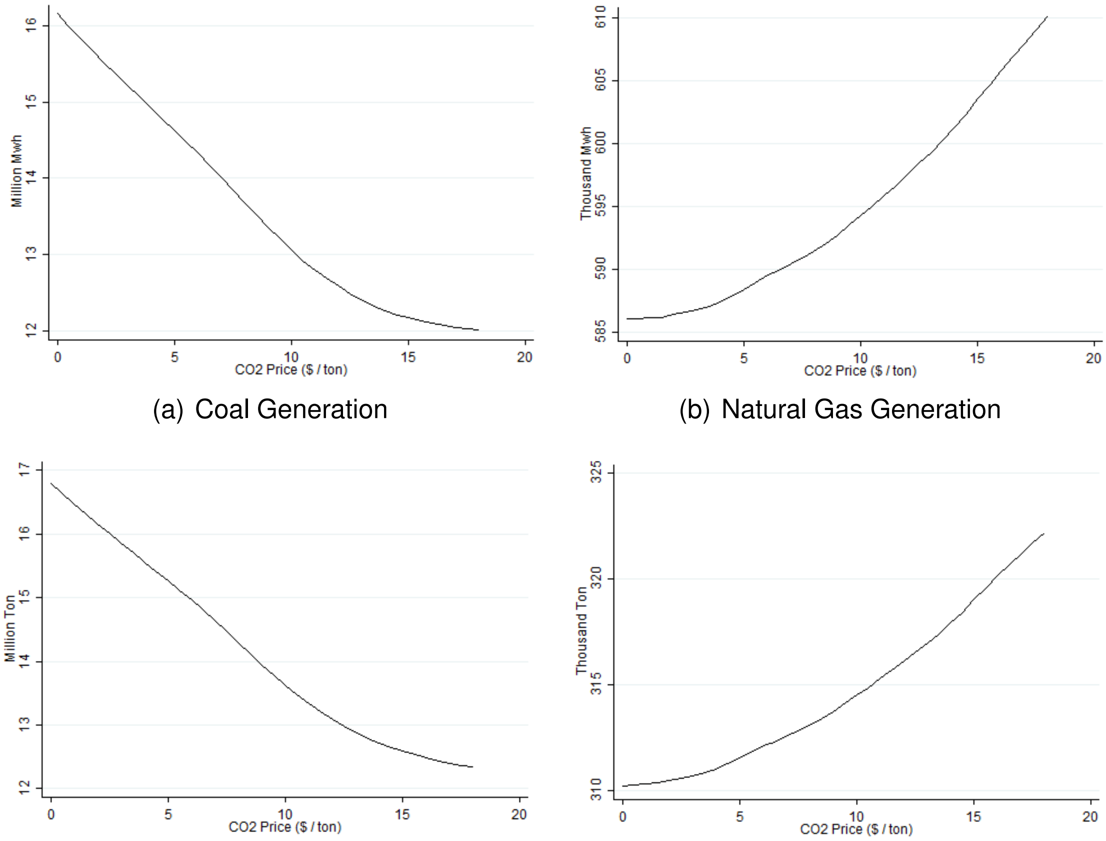
In the full sample, generation from natural gas is 21.64% of the generation from coal (Figure 19). However, natural gas generation is only 3.86% of coal generation in the two states regulated by RGGI (Delaware and Maryland). When CO_2 allowance price gets higher, marginal cost of production of both coal and natural gas generators raise, but coal generators become less competitive than natural gas generators due to the higher emission rates. As illustrated in Figure 22, generation and CO_2 from coal generators decrease with higher carbon price. However, generation and CO_2 from natural gas generators increase with more stringent RGGI policy. This is evidence of fuel switching from coal to natural gas among fossil-fuel generators. As stated above, coal is still the dominant fuel in the two states and the scale of fuel switching is small. On average, as the allowance price raises by $1/ton, CO_2 emissions from coal generators decrease by 247.61 thousand tons, or 1.47% of total CO_2 from coal generators. On the other hand, the emissions from natural generators increase by 0.67 thousand tons, or 0.21% of total CO_2 from natural gas generators.

Although fuel switching from coal to natural gas is observed during the sample period, the scale is too small to have any meaningful influence. This is primarily due to the limited natural gas capacity and generation in Delaware and Maryland. The gap between supply and demand of electricity caused by generation reduction from coal generators could be filled by generation from energy sources other than fossil fuels , energy efficiency programs, and import from non-regulated area. However, the estimates provided by this study are only short run effects. Higher utilization of natural gas generators due to higher carbon price will lead to new investment in natural gas capacity in the long run.

19.3.3 Peak vs. Off-peak Hours

As indicated by Figure 15, electricity load and price vary significantly during a day, and generators may respond to carbon pricing differently under distinct market conditions. I divide sample into two groups: peak hours and off-peak hours. Peak hours are defined as hour 14 to hour 21, i.e., from 1 PM to 9 PM of each day, and the rest are off-peak hours. In off-peak hours, only generators with lowest cost of production (usually coal and

Figure 22: Responses to Carbon Pricing in RGGI by Fuel Type



(a) Coal Generation

(b) Natural Gas Generation

(c) Coal CO_2

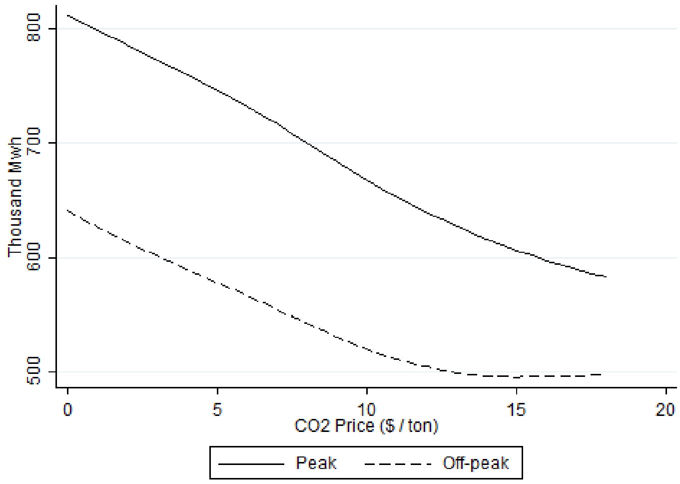
(d) Natural Gas CO_2

nuclear generators) are on to meet the base load. In contrast, generators with higher cost are also brought online in order to satisfy peak load during peak hours. To compute total generation and CO_2 emissions of a representative peak hour and a representative off-peak hour throughout the sample period, observation-specific predicted generation and CO_2 emissions are aggregated within each group, and then divided by the number of hours in a day (8 for peak hours and 16 for off-peak hours).

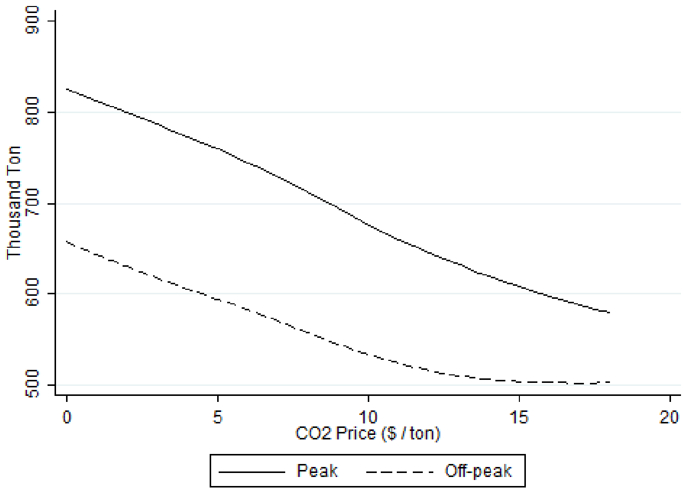
The responses of generation and CO_2 to carbon price in peak and off-peak hours are shown in Figure 23. When carbon price is relative low (below $10/ton), the reductions in generation and CO_2 are comparable between peak and off-peak hours. However, as carbon price continues raising, the abatement of CO_2 slows down more in off-peak hours. A likely explanation is the electricity price differential between peak and off-peak hours.

Producers other than coal and natural gas firms in PJM can be regarded as competitive fringe suppliers. Generators using other energy sources are likely to be willing to supply more given higher prices in peak hours, and supply less in off-peak hours when prices are low. To meet the load obligations, this leaves fossil-fuel generators, especially those using coal, less room to reduce generation and CO_2 emissions even with high carbon price in off-peak hours.

Figure 23: Fossil-fuel Generation and CO_2 in RGGI: Peak vs. Off-peak Hours



(a) Fossil-fuel Generation



(b) CO_2

19.3.4 Robustness Check

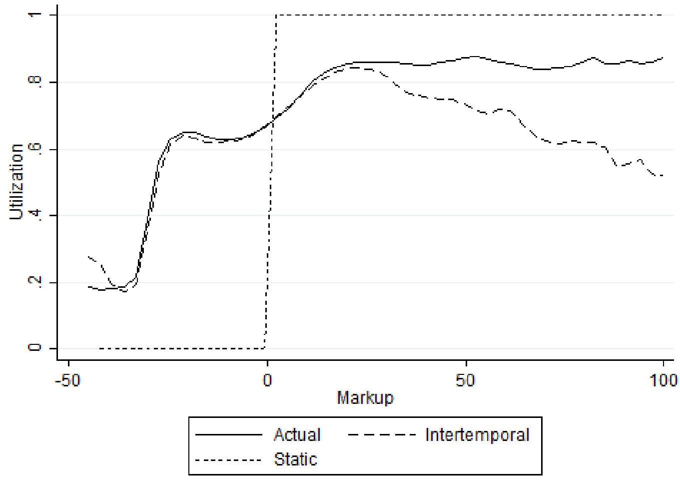
This section tests the robustness of the main results. I use partial data to run the regression Equation 18, then use the estimates to predict firms production in the rest of the observations. In particular, two robustness checks are performed, with the data of year 2009-2011 and the data of even days only. I examine the predictive power by applying the estimates to the data of year 2012-2013 and odd days, respectively.

For each regression, I drop observations from generators with less than 300 observations in the reduced sample. The results are shown in Table 19 and Table 20. Overall the results are similar to those presented in Table 16. It again validates the important correlation between production and past and future markups. All markups are statistically significant for many generators. Most marginal effects are consistent with the main results except those of average day markups. With the estimates, I compare the predicted kernel regression of utilization rate with that of the part of actual data not used in the estimation. As shown in Figure 24, the overall performance of the model is good in predicting utilization rate of observations out of the estimation sample. The prediction is very accurate for low markups ranging from -\$50/Mwh to \$30/Mwh, but underestimates utilization when markup gets high.

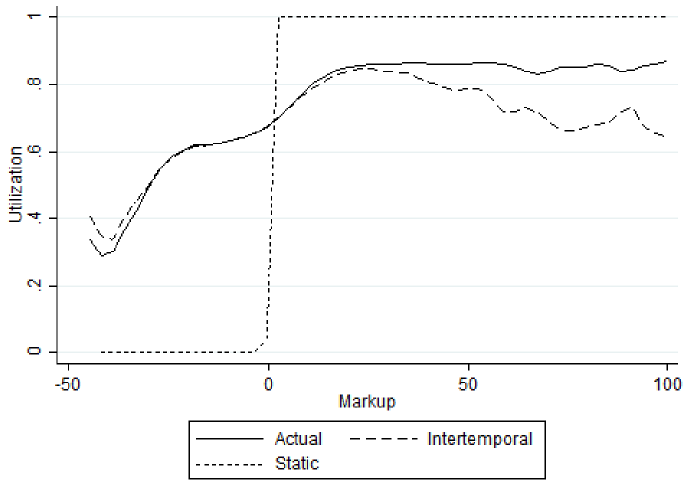
Conclusion

This paper studies the determinants of electricity firms' output decisions in a dynamic setting. Consistent with the existing literature, the results validate the use of an intertemporal model over the static model. Overlooking intertemporal constraints such as start-up cost and ramp rate leads to biased conclusion, and predicts actual data poorly. The technical limitations in electricity markets make firms' output decisions across periods interdependent. With the estimates of relationship between production and current, past and future price-cost markups, I investigate the CO_2 emission responses to carbon policy which is

Figure 24: Robustness Check: Utilization Rate



(a) Prediction for 2012-2013 with estimates from 2009-2011



(b) Prediction for odd days with estimates from even days

more stringent than the observed CO_2 allowance price during the sample period. The results show that CO_2 emissions decrease as carbon price raises, and the emission reduction slows down as the permit price of CO_2 approaches \$15/ton. The RGGI policy has helped to decrease the total CO_2 emissions from power sector of Delaware and Maryland by at least 4.73% during the sample period. The reduction in CO_2 emissions due to a \$1/ton increase in permit price is 0.304 million tons, or 1.85% of the total CO_2 emissions. Emissions can be reduced by 23.50% if CO_2 is priced at \$15/ton.

Table 19: Robustness Check: Summary of 203 Generator-specific Estimations for 2009-2011

Variables	Average of Coefficients	Average of Std. Dev.	# of Significant Coefficients	Marginal Effects
fixed effects	554.443	42.807	200	
$markup\_pos$	0.636	5.270	97	
$markup_t$	1.852	0.689	118	5.396
$markup_t 2$	-0.018	0.027	44	
$markup_t 3$[a]	-1.118	0.976	80	
$markup_t 4$[b]	0.024	21.500	61	
$markup_t 5$[c]	-0.131	15.400	58	
$markup_{t-1}$	0.853	0.465	97	0.700
$markup_{t-1} 2$[a]	-7.506	21.075	50	
$markup_{t-1} 3$[a]	-0.536	0.766	69	
$markup_{t-1} 4$[b]	11.700	18.200	57	
$markup_{t-1} 5$[c]	-6.840	14.100	59	
$markup_{t+1}$	2.888	0.462	173	2.747
$markup_{t+1} 2$	-0.032	0.021	108	
$markup_{t+1} 3$[a]	-1.635	0.815	129	
$markup_{t+1} 4$[a]	0.039	0.019	127	
$markup_{t+1} 5$[c]	-22.200	13.900	108	
$\overline{markup}_t$	-60.969	11.751	123	-6.640
$\overline{markup}_t 2$	9.594	1.919	96	
$\overline{markup}_t 3$	-0.741	0.160	106	
$\overline{markup}_t 4$[a]	25.047	6.657	120	
$\overline{markup}_t 5$[a]	-0.350	0.142	112	
$\overline{markup}_{t-24}$	-61.946	7.492	113	-0.803
$\overline{markup}_{t-24} 2$	10.035	1.235	109	
$\overline{markup}_{t-24} 3$	-0.787	0.105	109	
$\overline{markup}_{t-24} 4$[a]	29.279	4.523	105	
$\overline{markup}_{t-24} 5$[b]	382.500	91.000	105	
$\overline{markup}_{t+24}$	-5.556	3.325	127	-0.651
$\overline{markup}_{t+24} 2$	0.889	0.614	123	
$\overline{markup}_{t+24} 3$	-0.055	0.062	124	
$\overline{markup}_{t+24} 4$[a]	-0.735	4.100	124	
$\overline{markup}_{t+24} 5$[a]	-0.162	0.174	116	

[a] Coefficients are multiplied by 10^3.
[b] Coefficients are multiplied by 10^6.
[c] Coefficients are multiplied by 10^8.
Robust standard errors.
Significant at 5% level.

Table 20: Robustness Check: Summary of 224 Generator-specific Estimations for Even Days

Variables	Average of Coefficients	Average of Std. Dev.	# of Significant Coefficients	Marginal Effects
fixed effects	248.059	21.281	218	
$markup\_pos$	0.641	5.514	100	
$markup_t$	1.656	0.754	111	4.437
$markup_t2$	-0.003	0.029	38	
$markup_t3$[a]	-3.226	0.885	98	
$markup_t4$[b]	19.700	14.400	109	
$markup_t5$[c]	-4.760	9.320	111	
$markup_{t-1}$	0.707	0.471	87	0.708
$markup_{t-1}2$[a]	-1.773	19.680	44	
$markup_{t-1}3$[a]	-0.518	0.582	75	
$markup_{t-1}4$[b]	8.660	9.140	89	
$markup_{t-1}5$[c]	-3.140	6.520	100	
$markup_{t+1}$	2.788	0.483	198	2.723
$markup_{t+1}2$	-0.033	0.021	97	
$markup_{t+1}3$[a]	-0.645	0.604	121	
$markup_{t+1}4$[a]	0.013	0.009	132	
$markup_{t+1}5$[c]	-4.890	6.970	133	
$\overline{markup}_t$	0.382	19.430	115	-0.466
$\overline{markup}_t2$	-0.229	19.765	126	
$\overline{markup}_t3$	-0.014	0.067	124	
$\overline{markup}_t4$[a]	-0.561	265.121	123	
$\overline{markup}_t5$[a]	-0.047	8.411	127	
$\overline{markup}_{t-24}$	-2.607	1.971	122	-1.261
$\overline{markup}_{t-24}2$	0.378	9.997	128	
$\overline{markup}_{t-24}3$	-0.009	0.466	130	
$\overline{markup}_{t-24}4$[a]	0.602	0.516	126	
$\overline{markup}_{t-24}5$[b]	-27.700	0.046	124	
$\overline{markup}_{t+24}$	-0.010	11.202	118	-0.940
$\overline{markup}_{t+24}2$	-0.077	9.118	122	
$\overline{markup}_{t+24}3$	0.072	0.960	120	
$\overline{markup}_{t+24}4$[a]	-1.583	0.043	123	
$\overline{markup}_{t+24}5$[a]	-0.061	5.991	112	

[a] Coefficients are multiplied by 10^3.
[b] Coefficients are multiplied by 10^6.
[c] Coefficients are multiplied by 10^8.
Robust standard errors.
Significant at 5% level.

Fuel switching from coal to natural gas occurs with carbon pricing. However, the scale of fuel switching is small due to the limited capacity and generation of natural gas generators within Delaware and Maryland. When carbon price is relative low (below $10/ton), the reductions in generation and CO_2 are comparable between peak and off-peak hours. However, as carbon price continues raising, the abatement of CO_2 slows down more in off-peak hours.

There are a few caveats to the analysis that should be noted. First, this paper is a short run study of carbon effects on firms' production decisions. In the long run, if CO_2 price is persistently high, existing firms may make investment by adding natural gas capacity and retiring coal capacity. Carbon regulations can also induce entry/exit if dirtier firms find it is not profitable to produce and cleaner entrants become more competitive (Cullen, 2015; Ryan, 2012). Second, although the overall PJM market performance is evaluated as competitive (Monitoring Analytics, 2015), market power could potentially exist in certain periods. If that is the case, emission reduction resulting from fossil fuel firms strategically hold production should not be attributed to the carbon regulations. Third, the data used in the analysis are every September and October from 2009 to 2013. Therefore, one needs to be cautious when interpreting the estimates of emission response as it may not well represent firms' reactions to changes in carbon price during other months, especially given the fact that both demand and electricity price experience high degree of fluctuations throughout a year.

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Appendix A

Table A1: Natural Gas-Only Utilities: Total Capacity

Variable	Two-year lead log(Z_{itn})		Three-year lead log(Z_{itn})	
	(1)	(2)	(3)	(4)
Natural gas price [a]	0.131	0.123	0.098	0.086
	(0.115)	(0.114)	(0.098)	(0.097)
Electricity price	-0.003	-0.003	-0.002	-0.001
	(0.003)	(0.003)	(0.002)	(0.002)
After	-0.048	-0.048	-0.007	-0.004
	(0.054)	(0.055)	(0.045)	(0.045)
After*RGGI	0.381***		0.371***	
	(0.130)		(0.129)	
CO_2 price		0.143**		0.145***
		(0.060)		(0.054)
Trend [b]	0.104	0.113	-0.001	-0.003
	(0.113)	(0.115)	(0.098)	(0.096)
CHP	0.157*	0.107	0.107	0.076
	(0.093)	(0.072)	(0.089)	(0.068)
Age	-0.003	-0.002	-0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Ownership-Single	-0.038**	-0.033*	-0.022	-0.019
	(0.019)	(0.018)	(0.016)	(0.016)
Ownership-Other	-0.031	-0.025	-0.023	-0.020
	(0.021)	(0.021)	(0.017)	(0.017)
PJM annual load [c]	-0.029	-0.041	0.041	0.030
	(0.128)	(0.127)	(0.116)	(0.116)
Constant	7.198***	7.190***	7.139***	7.131***
	(0.071)	(0.071)	(0.067)	(0.067)
Utility fixed effects	Yes	Yes	Yes	Yes
R^2	0.9848	0.9844	0.9856	0.9855
Observations	421	421	379	379

[a] Coefficients are multiplied by 10^3.
[b] Coefficients are multiplied by 10.
[c] Coefficients are multiplied by 10^9.
Robust standard errors in parentheses. ***: $p < 1\%$, **: $p < 5\%$, *: $p < 10\%$.

Table A2: Natural Gas-Only and Coal-Only Utilities: Utilization Rate

Variable	**Natural gas-only log(U_{itn})**		**Coal-only log(U_{itc})**	
	(1)	(2)	(3)	(4)
Natural gas price	-0.002***	-0.002***		
	(0.000)	(0.000)		
Coal price			-0.000	-0.001
			(0.001)	(0.001)
Electricity price	0.029***	0.029***	0.011***	0.011***
	(0.003)	(0.003)	(0.001)	(0.001)
After	0.026	0.022	0.255***	0.257***
	(0.113)	(0.112)	(0.068)	(0.068)
After*RGGI	-0.574***		-0.813***	
	(0.133)		(0.166)	
CO_2 price		-0.217***		-0.298***
		(0.051)		(0.067)
Capacity	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Trend	0.000	0.000	-0.075***	-0.070**
	(0.026)	(0.026)	(0.029)	(0.029)
CHP	0.655**	0.705***	0.678***	0.669***
	(0.263)	(0.255)	(0.139)	(0.138)
Age	0.040***	0.040***	-0.050*	-0.053**
	(0.014)	(0.014)	(0.026)	(0.027)
Ownership-Single	0.041	0.047	-0.466***	-0.468***
	(0.236)	(0.235)	(0.120)	(0.120)
Ownership-Other	-0.474*	-0.468*	-0.259**	-0.253**
	(0.275)	(0.275)	(0.116)	(0.116)
PJM monthly load [a]	13.200***	13.100***	9.760***	9.930***
	(4.240)	(4.240)	(2.180)	(2.180)
Feb.	-0.030	-0.028	-0.076	-0.072
	(0.125)	(0.125)	(0.046)	(0.047)
Mar.	0.157	0.158	-0.128**	-0.126**
	(0.124)	(0.124)	(0.055)	(0.056)
Apr.	0.409***	0.411***	-0.226***	-0.222***
	(0.130)	(0.130)	(0.064)	(0.064)
May.	0.949***	0.950***	-0.310***	-0.306***
	(0.122)	(0.122)	(0.069)	(0.069)
Jun.	1.513***	1.514***	-0.248***	-0.247***
	(0.115)	(0.115)	(0.062)	(0.062)
Jul.	1.716***	1.719***	-0.158***	-0.158***
	(0.124)	(0.124)	(0.045)	(0.045)
Aug.	1.847***	1.849***	-0.154***	-0.154***
	(0.117)	(0.117)	(0.050)	(0.050)
Sept.	1.218***	1.216***	-0.226***	-0.226***
	(0.117)	(0.117)	(0.059)	(0.059)
Oct.	0.442***	0.440***	-0.351***	-0.350***
	(0.122)	(0.122)	(0.074)	(0.074)
Nov.	0.133	0.136	-0.228***	-0.221***
	(0.122)	(0.122)	(0.066)	(0.066)
Dec.	0.213*	0.211*	-0.186***	-0.187***
	(0.122)	(0.122)	(0.065)	(0.065)
Constant	4.034***	4.044***	8.481***	8.532***
	(0.623)	(0.623)	(0.442)	(0.447)
Utility fixed effects	Yes	Yes	Yes	Yes
R^2	0.5781	0.5781	0.2649	0.2640
Observations	6240	6240	5364	5364

[a] Coefficients are multiplied by 10^9.
Robust standard errors in parentheses. ***: $p < 1\%$, **: $p < 5\%$, *: $p < 10\%$.

Table A3: Flexible Utilities: Total Capacity

Variable	**log($Z_{itn} + Z_{itc}$)**			
	Two-year lead		Three-year lead	
	(1)	(2)	(3)	(4)
Natural gas price [a]	-0.219	-0.239	-0.465	-0.420
	(0.503)	(0.506)	(0.530)	(0.530)
Coal price	-0.000	-0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Electricity price	0.008	0.009	0.003	0.002
	(0.010)	(0.010)	(0.009)	(0.009)
After	0.169	0.153	-0.070	-0.082
	(0.227)	(0.228)	(0.245)	(0.243)
After*RGGI	-0.134		-0.360	
	(0.179)		(0.236)	
CO_2 price		-0.024		-0.136
		(0.068)		(0.096)
t	0.031	0.034	0.043	0.045
	(0.066)	(0.066)	(0.062)	(0.062)
CHP	0.112	0.094	0.180	0.173
	(0.094)	(0.085)	(0.109)	(0.106)
Age	-0.046**	-0.045**	-0.057**	-0.057**
	(0.022)	(0.022)	(0.023)	(0.023)
Ownership-Single	0.036	0.043	0.304	0.306
	(0.331)	(0.331)	(0.266)	(0.266)
Ownership-Other	-0.107	-0.093	0.221	0.226
	(0.339)	(0.339)	(0.250)	(0.248)
PJM annual load [b]	-0.317	-0.335	-0.181	-0.155
	(0.532)	(0.530)	(0.534)	(0.531)
Constant	10.470***	10.491***	10.639***	10.671***
	(1.225)	(1.224)	(1.077)	(1.082)
Utility fixed effects	Yes	Yes	Yes	Yes
R^2	0.9217	0.9214	0.9267	0.9264
Observations	163	163	147	147

[a] Coefficients are multiplied by 10^3.
[b] Coefficients are multiplied by 10^9.
Robust standard errors in parentheses. ***: $p < 1\%$, **: $p < 5\%$, *: $p < 10\%$.

Table A4: Flexible Utilities: Natural Gas and Coal Utilization Rate

Variable	$\log(U_{itn})$		$\log(U_{itc})$	
	(1)	(2)	(3)	(4)
Natural gas price [a]	-0.060***	-0.060***	0.002**	0.002**
	(0.010)	(0.010)	(0.001)	(0.001)
Coal price	0.020***	0.018***	0.001*	0.000
	(0.004)	(0.003)	(0.000)	(0.000)
Electricity price	0.052***	0.054***	0.004**	0.004**
	(0.014)	(0.014)	(0.002)	(0.002)
After	-0.391	-0.520	0.395***	0.377***
	(0.468)	(0.467)	(0.075)	(0.076)
After*RGGI	-2.486***		-0.625***	
	(0.437)		(0.076)	
CO_2 price		-0.727***		-0.206***
		(0.159)		(0.032)
Capacity [b]	0.243***	0.244***	-0.002	-0.001
	(0.016)	(0.016)	(0.028)	(0.003)
t	0.387***	0.420***	-0.230***	-0.222***
	(0.105)	(0.105)	(0.019)	(0.019)
CHP	-2.832***	-3.014***	-0.753***	-0.786***
	(0.704)	(0.686)	(0.077)	(0.080)
Age	-0.424***	-0.426***	0.036***	0.036***
	(0.038)	(0.038)	(0.009)	(0.009)
Ownership-Single	2.980***	3.009***	0.120	0.125
	(0.608)	(0.612)	(0.105)	(0.106)
Ownership-Other	5.880***	6.020***	0.429***	0.453***
	(0.825)	(0.828)	(0.115)	(0.116)
PJM monthly load [c]	-3.150*	-3.140*	1.420***	1.420***
	(1.750)	(1.750)	(0.225)	(0.225)
Feb.	-0.661	-0.631	0.006	0.014
	(0.475)	(0.477)	(0.068)	(0.068)
Mar.	-0.631	-0.604	-0.025	-0.018
	(0.471)	(0.473)	(0.068)	(0.069)
Apr.	-0.782	-0.738	-0.115	-0.104
	(0.506)	(0.509)	(0.070)	(0.071)
May.	-0.283	-0.235	-0.164**	-0.153**
	(0.489)	(0.491)	(0.068)	(0.068)
Jun.	0.459	0.478	-0.082	-0.076
	(0.459)	(0.461)	(0.065)	(0.066)
Jul.	0.343	0.353	-0.091	-0.085
	(0.500)	(0.502)	(0.070)	(0.071)
Aug.	0.449	0.461	-0.098	-0.093
	(0.475)	(0.477)	(0.069)	(0.070)
Sept.	-0.017	-0.007	-0.110*	-0.109*
	(0.464)	(0.465)	(0.065)	(0.065)
Oct.	-0.689	-0.670	-0.222***	-0.219***
	(0.480)	(0.481)	(0.071)	(0.071)
Nov.	-0.213	-0.142	-0.200***	-0.183***
	(0.461)	(0.464)	(0.070)	(0.070)
Dec.	0.157	0.172	-0.204***	-0.203***
	(0.451)	(0.453)	(0.074)	(0.075)
Constant	-4.987**	-4.438*	5.195***	5.307***
	(2.336)	(2.322)	(0.511)	(0.509)
Utility fixed effects	Yes	Yes	Yes	Yes
R^2	0.6935	0.6919	0.5581	0.5545
Observations	2376	2376	2376	2376

[a] Coefficients are multiplied by 10.
[b] Coefficients are multiplied by 100.
[c] Coefficients are multiplied by 10^8.
Robust standard errors in parentheses. ***: $p < 1\%$, **: $p < 5\%$, *: $p < 10\%$.