Emissions from Coal-Fired Power Plant Retirements

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Abstract

The coal-fired power plant industry is a major polluting source of various emissions, including greenhouse gas (CO_2), sulfur dioxide (SO_2) and nitrogen oxides (NO_x). Beginning in around 2012, many coal-fired power plants in the U.S. have started to retire, which creates a chance for evaluating their end-of-business-cycle polluting behavior. This paper examined the emission patterns of the coal-fired electric generating units (EGUs) when they approach retirement. I found a 4% efficiency drop in the last year of operation. The emission rates increase as EGUs approach retirement. As a result, in their final year of operation, each EGU on average emits 78.88 million lbs CO_2 (1.6%), 0.88 million lbs NOx (10.1%) and 5.01 million lbs SO_2(16.9%) more than the baseline level in 2012. Controlling for the start-up and shutdown frequency can explain about 43% of the efficiency lost. The efficiency lost explains almost all CO_2 emission rate increase but only 20% of the increase in the NOx and SO_2 emission rates. EGUs under fee-for-service regulation exhibit a sudden efficiency drop in the final year of operation, while their counterpart, the not regulated ones, show lower efficiency in the last three years of operation.

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Key words: emission leakage, nitrogen oxides, carbon dioxide, sulfur dioxide, energy efficiency, regulation

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1 Introduction

The coal-fired power plant industry is a major polluting source of various emissions, including greenhouse gas (CO_2), sulfur dioxide (SO_2) and nitrogen oxides (NO_x). The coal-fired power plants are aging and have started to retire. Most of the retirement comes from generators more than 50 years old. This creates a chance for evaluating their end-of-business-cycle polluting behavior. This paper examined the coal-fired power plants' emission patterns when they approach retirement. A better understanding of such emission patterns can guide the government in designing environmental regulations that reduce emissions efficiently.

The retirements have increased since 2010 and continued until it peaked in 2012, probably due to the decrease in natural gas prices driven by innovation in fracking technologies (Energy, 2013). Even more coal power generating units stopped operating in 2015 and beyond. Arguably one of the driving forces during this period is the Mercury and Air Toxics Standards (MATS). On December 21, 2011, the U.S. Environmental Protection Agency (EPA) announced MATS, the first national standard to reduce mercury emissions and other toxic air pollutants from coal- and oil-fired electric generating units (EGUs) with capacity more than 25MW. EGUs failing to meet the emission limits must retire by April 2015, or apply for a one-year extension and comply by April 2016. There has been a hot debate regarding this industry, from what drives the coal-fired power plants' retirement decisions to potential impacts of the closure.

This paper focuses on coal-fired power plants' emission behavior before the end of operation. Specifically, I documented the efficiency decrease and emission rates increase in coal-fired power plants during their last years of operation. In addition, I explored the underlying mechanism for the efficiency lost and extra emission rates. My research makes use of the studies of the driving forces of coal-fired power plant closure, contributes to the literature of emission leakage, and may provide implication to the market mechanism design and environmental regulation.

Many studies look into the driving forces of coal-fired power plant closures. There is no single reason for coal-fired power plants' retirement. However, researchers have identified many important driving forces. The findings suggest that the main threat to coal-fired power plants is the decrease in natural gas prices, the reduction in energy consumption and the increased profitability of renewable generators (Houser et al., 2017; Pratson et al., 2013). Using a commitment model for the eastern US electricity market, Linn and McCormack (2019) estimated that the aforementioned market shocks combined reduced 89% of the coal-fired power plants' profit from 2005 to 2015. Though they only included NO_x emission trading from the policy side in their model, their estimated impact from policies that limit pollution is very small. My research builds on these results to study the impact of these factors on the emission footprint in the last several years of operation.

Policies employ cost-effective mechanisms to regulate and reduce emissions. However, emission leakage can reduce the effectiveness of such policies (Böhringer et al., 2012). Studies about emission leakage mainly focus on across regulated areas. For example, Babiker (2005) assumes an oligopolistic structure with increasing returns to scale to study the 1997 Kyoto Protocol. The model suggests a significant relocation of energy-intensive industries away from OECD countries.

As a result, the leakage rate can be as high as 130% and the GHG control policies will in fact increase the global emission of CO_2. Holladay et al. (2018) use a computable general equilibrium (CGE) model to study the level of emission leakage between two sectors when one of the sectors has trade friction. Leakage may also happen across time due to anticipation of a stricter environmental policy. Lemoine (2017) finds evidence of extra CO_2 emissions leading up to the breakdown of a legislation in 2010 to reduce greenhouse gas emissions after 2013. My study contributes to the leakage literature from the aspect of the life cycle of coal-fired power plants. In anticipation of retirement, coal-fired power plants may pollute more than when they operate as business as usual. Besides, understanding the mechanism of increased emissions at the end of a coal-fired power plant's life cycle may help improve pollution control policies and reduce emissions more efficiently.

The end of operation behavior may be different for different types of coal-fired power plants. From the incentive perspective, coal-fired power plants with different cost structures may have diverse objective functions and thus implement distinct operational strategies. Regulated power plants are reimbursed by the government based on fee-for-service, while their counterpart, the not regulated ones, are independent private providers that operate on their own. Regulated and not regulated coal-fired power plants have been separated since 1997. The Averch-Johnson Effect (Averch and Johnson, 1962) predicts that firms under regulatory constraint which pays a rate of return that exceeds that cost of capital are prompt to adopt capital-intensive production techniques, which may not be economically efficient. Cicala (2015) showed that, due to the information asymmetry in the cost of coal purchase, regulated coal-fired power plants have less incentive to lower the cost of coal purchase, which results in a much higher cost of coal purchase. With different optimal operating strategies, these two groups experienced a disparate life track. Consequently, they may exhibit differential emitting behavior around the end of the operation. It is generally argued that not regulated power plants are more efficient in the short run (Davis and Hausman, 2016). My study provides a long-run comparison for regulated and not regulated power plants. In the long run, not regulated power plants have lower efficiency in their last three years of operation, which suggest they may be delaying exit.

From the expectation perspective, plants with better information regarding the future operational environment may do a better job in optimizing their total profit than those suffer from a sudden shock of an unfavorable operational environment. I apply a dispatch model to estimate the annual operational profit for each EGU and use it as an IV for the exit decision. I then use this IV to get the marginal treatment effect of the exit probability on the efficiency and emission rates. The marginal treatment effect shows different pattern under different regulatory status.

I found a significant emission rates increase in coal-fired power plant during their last several years of operation. Emission leakage may have an impact on social welfare by affecting people's health. There has been an increasing interest in studying environmental externality. Currie et al. (2015) study the effect of toxic emissions around the opening and closing of plants on housing value and infant birth weight. They found the opening and closing only affects a region within 1 mile of the plant. Only a small decrease in housing value is observed right after opening and no effect around closure is observed. Their study shows that markets react to the entry of a pollution source, but does not show much difference for the exit of a pollution source in the short run. However, this does not suggest that the exit of a plant has no abnormal emitting behavior, but rather the society may not be aware of such behavior. My study may bring this aspect to the public's attention.

Jotzo and Mazouz (2015) discuss the market mechanism for regulated closure of coal-fired power plants in Australia. My research can help advance the understanding of coal-fired power plants behavior before retirement and potentially bring unintended consequences into the attention of researchers.

The remainder of the paper is organized as follows. Section 2 introduces a model to explain the operation behavior of the coal power generating units. Section 3 describes the data and summarizes the characteristics of the U.S. coal power generating units. Section 4 discusses the empirical design to analyze the end-of-operation emission trends. Section 5 presents the estimation results. Section 6 concludes.

2 A Model for Decision Making

Assume each generating unit using coal as primary fuel use the following objective function to maximize their profit:

$$\begin{aligned} V_{it}(E_{it}) &= \max_{O_{it}, I_{it}, M_{it}} \pi_{it}(P_t, D_t - R_t, A_t, O_{it}, E_{it}) - I_{it} - M_{it} + \varepsilon_{it} \\ &\quad + \delta \mathbb{E}_{it}\{V_{i,t+1}(E_{i,t+1}) | E_{it}, O_{it}, I_{it}, M_{it}\} \end{aligned} \tag{1}$$

Let E_{it} denote the status of the machine i in period t, including the efficiency of converting heat input to electricity and the emission rates for all pollutants. Let $E_{i,t+1}$ denote the status of the machine in the next period, which is a function of the current machine status (E_{it}), maintenance (M_{it}) and operation frequency (O_{it}). P_t is a vector for natural gas prices and coal prices, which also approximates the electricity prices. D_{st} stands for the electricity demand in each state, R_{st} represents the renewable portfolio, together $D_{st} - R_{st}$ represents the residual demand for fossil fuel power generators. A_t is for abatement cost, which reflects the stringency of the pollution regulations. The current period profit π_{it} is determined by electricity prices, quantity of electricity supplied by each unit, cost of burning coal, cost of emitting pollutants, maintenance cost and investment in capital-intensive abatement techniques (I_{it}). The first two factors are determined in the equilibrium given the factors listed in the profit function. ε_{it} is the privately observed shock associated with each per-period profit.

To simplify the analysis, assume the manager is only facing a two-period operation problem, either retire in the current period or the next, with perceived probability p that the machine can continue operating in the last period. Let p^H denote a high probability of continued operation, p^L denote a lower one, $p^H \geq p^L$. Simplify the second period efficiency $E_{i,1}$ to be either high (E^H) or low (E^L), $E^H \geq E^L$. Maintenance is executed or not, $M_{i1} \in \{0, M\}$, operation frequency is whether to operate normally (O_n) or more frequently than usual (O_f). Investment is also invest or not, $I_{it} \in \{0, I\}$.

$$V_{i0}(E_{i0}) = \max_{O_{i0},I_{i0},M_{i0}} \pi(P_0, D_0 - R_0, A_{i0}, O_{i0}, E_{i0}) - I_{i0} - M_{i0} + \varepsilon_{i0}$$
$$+ \delta p\{\max_{O_{i1}} \pi(P_1, D_1 - R_1, A_{i1}, O_{i1}, E_{i1}) + \varepsilon_{i1}|E_{i0}, O_{i0}, I_{i0}, M_{i0}\}$$

In each period, the following relationships hold: higher natural gas price, higher residual demand, smaller abatement cost, higher operation frequency and higher efficiency lead to higher profit for the coal-fired power plants.

$$\frac{\partial \pi}{\partial p_{NG}} > 0 \ , \ \frac{\partial \pi}{\partial (D-R)} > 0 \ , \ \frac{\partial \pi}{\partial A} < 0 \ , \ \frac{\partial \pi}{\partial O} > 0 \text{ and } \frac{\partial \pi}{\partial E} > 0$$

All else the same, assume scheduling a maintenance can improve efficiency in the next period, $E^L \Rightarrow E^H$, while increasing operation frequency will lower the efficiency in the next period, $E^H \Rightarrow E^L$.

First of all, the manager decides whether to invest in capital-intensive abatement techniques. Doing so is beneficial if $I_{i0} < \delta p\{\pi(\cdot, A^L) - \pi(\cdot, A^H)\}$. Installing a technique to remove extra pollutants can incur a high fixed cost as well as subsequent maintenance costs, but machines with such techniques have a smaller marginal abatement cost (Jung et al., 1996). It is predicted (Averch and Johnson, 1962) and empirically shown (Fowlie, 2010) that power plants regulated under rate-of-return tend to invest more in capital-intensive abatement techniques. The different life tracks provide different decision environments for regulated and not regulated power plants.

Second, the manager decides whether to schedule a maintenance for the machine and the technology. Doing so is beneficial if $M_{i0} < \delta\{p^H\pi(\cdot, E^H) - p^L\pi(\cdot, E^L)\}$. This implies that if the gain from improving efficiency is low in the next period, the manager will be less likely to schedule a maintenance. As a result, efficiency will be lower and emission rate will be higher. However, in the case when the manager does maintenance for the machine but not for the pollution reduction technology, only the emission rate will be higher.

Third, the manager also decides how often to operate in each period. Coal power generating units used to be the base electricity supplier and did not start-up and shutdown so often. As shown in Table 1, on average each unit shuts down 3.8 times in each month. Due to the physical constraint of the machine, $\frac{\partial E}{\partial O} < 0$ and $\frac{\partial p}{\partial O} < 0$. This means turning the machine on and off too often will hurt the machine and result in a lower efficiency in future. However, the coal-fired power plant manager has an incentive to increase the start-up and shutdown frequency if $\pi(\cdot, O_f) - \pi(\cdot, O_n) > \delta\{p^H\pi(\cdot, E^H) - p^L\pi(\cdot, E^L)\}$, the profit from increasing operation frequency is higher than the loss from the second period operation. Similar to the reasoning of maintenance, when the gain from the second period is not high enough, the manager will choose to start-up and shutdown the machine more frequently than normal operation.

Finally, in the case when the manager decides to terminate the operation in the second period, $p^H = p^L = 0$, they will skip maintenance and turn the machine on and off more frequently to gain more profit in the operation period. As a result, the efficiency decreases as each machine approaches the end of operation, and emissions per unit of electricity generated increases. In general, when p decreases, the manager is less likely to invest, schedule maintenance and more likely to ramp the machine.

According to the Bellman equation (1), the tendency to increase the start-up and shutdown frequency, as well as maintaining the efficiency, will be different for managers with different projections about the future as well as coal-fired power plants that are subject to rate-of-return.

3 Data

The main data set for the analysis contains coal-fired EGUs' monthly operation records, from 1998 to 2018. The data downloaded from the Continuous Emission Monitoring System (CEMS) include monthly records for all generating units under certain policy regulations (as shown in Figure 8) to limit emissions. The data set is nationally representative thanks to the acid rain program (ARP), which covered the conterminous United States. Variables to measure emission rates are created from the original variables including CO_2, NO_x and SO_2 emission mass, Gross load (MWh) as total electrical generation and Heat Input (MMBtu).[1] I use the first date of commercial operation to calculate the age of each generating unit. To create variables that measure the start-up and shutdown frequency, I use hourly operation records, I define the variable "Shutdown" by calculating how many times each generating unit shutdown from operating in each month. The variable "Ramping" is defined by dividing Shut Down by number of hours operating in each month.

To supplement the analysis, I link this data set with EIA860 report to get regulatory status for power plants, summer capacity for generators, reported retirement date and announced planned retirement date. More information about the composition of coal is obtained from Form 923. It lists all the coal purchase records for each coal-fired power plant, which contains the coal mine, quantity and cost if the coal-fired power plant is under regulation. I calculate the percentage quantity of bituminous coal (BIT) in purchased coal for each month. However, adding such information does not improve the model by much and is not discussed below. To control for the macro economic environment, I obtained monthly NG gas prices from Henry Hub, Coal prices and average electricity prices from EIA electricity monthly report. These are all at the national level.[2] Although retirement year and month are reported in EIA 860 for each generator and boiler, I use the last date of operation observed in CEMS as the "retirement" date.[3] There are at least three reasons. First of all, there are data discrepancies in the EIA 860 reports across different years. Second, the generating units in CEMS is not exactly the same as generators in EIA 860, only 790 out of 1168 generating units can be matched to EIA 860, around 68%. Lastly, generating units may stop operating long before the reported retirement date.

[1] Heat Input is the total heat provided by fuel.

[2] Coal prices can vary significantly by region, I use the national averaged price as a proxy to compare with the shocks from natural gas.

[3] I have data until 2018 and define those operated in 2017 but never operated in 2018 as retired in 2017. Similar for other years.

The emission rate is measured in two ways. The first one is pollution mass per MWh electrical generation (lbs/MWh), the other one is pollution mass per heat input (lbs/MMBtu). The first one concerns how much emission is being generated in order to supply one more MWh of electricity. The second one concerns how much pollution is finally emitted when each MMBtu heat is used.

I exclude generating units that are only observed during some months of the year.[4] I define this resulting data set as the "full data set". After this, I further restrict the sample to those with non-missing gross load, no missing emission mass for all three types of emissions.[5] Some generating units provide steam rather than electricity, to make sure the regression results are comparable across different specifications, I take only units that supply electricity, i.e. Gross Load is not missing. In addition to this restriction, I also require each observation to have no missing value for emission and can be linked to hourly operation data in each month, which is necessary for using shutdown per operation hour.

[4]This does not reduce the sample size by much.

[5]This reduce the sample size by around 10%.

Table 1: Operating and Retiring Coal-fired EGU Characteristics

	Operating	Retired	Difference
Max Heat Input[a] (10^3 MMBtu/Hr)	3.741	2.006	-1.735
	[0.094]	[0.090]	[0.130]
Monthly Heat Input[b] (10^6 MMBtu)	1.613	0.461	-1.151
	[0.045]	[0.031]	[0.055]
Age	38.911	53.550	14.638
	[0.394]	[0.465]	[0.610]
Operation (%)	77.869	27.208	-50.661
	[0.444]	[1.300]	[1.374]
Shutdown[c]	3.817	5.430	1.613
	[0.096]	[0.337]	[0.351]
Ramping[d]	0.015	0.055	.039
	[0.001]	[0.004]	[0.004]
Efficiency (MW/MMBtu)	0.105	0.088	-.016
	[0.002]	[0.001]	[0.002]
CO_2 (lbs/MMBtu)	205.483	202.081	-3.402
	[0.209]	[0.945]	[0.968]
SO_2 (lbs/MMBtu)	1.050	1.319	.269
	[0.027]	[0.059]	[0.065]
Nox (lbs/MMBtu)	0.367	0.377	.01
	[0.005]	[0.010]	[0.012]
Regulated	0.742	0.710	-.031
	[0.013]	[0.023]	[0.027]
# Units	1,057	393	1,057

Standard error in brackets. Data source: CEMS, 1998-2017.

a. The design heat input capacity (in MMBtu/hr) for the unit or the highest hour. Unit is 1000 MMBtu/hr.

b. The measure of utilization that is calculated by multiplying the quantity of fuel by the fuels heat content. Unit is 10^6 MMBtu.

c. The number of shutdown in each month, from none zero operation to not operating.

d. Shutdown over total operation hours in each month.

e. The number in Difference represents the total number in both groups.

Table 1 compares the characteristics of the generating units between those operating and those retired.[6] Those retired have smaller capacity, operate and produce less, older, shut down more frequently, have lower efficiency. Without controlling for other factors, the summary statistics does not suggest a higher CO_2 emission rate in the retiring units, but does show a significantly higher SO_2 emission rate.

[6] Retired groups contain only information in the last year of operation. Operating groups are those still operating or observations at least 5 years before last year of operation.

4 Empirical Design

I approach the problem through three steps. First, I use a semi-log specification to examine the trajectories for efficiency and emission rates when coal-fired EGUs approach their retirement year. Second, I compare the trajectories across different pollutants and power plants under different regulatory status to infer the underlying mechanism. Third, I estimate the marginal treatment effect of exit probability using the annual operational profit as an IV.

4.1 Trajectories for Efficiency and Emission Rates

The first step is to analyze the trajectories for efficiency and emission rates, and determine whether there is an abnormal pattern. To study the efficiency and emission conditions in years leading to retirement, I build up the model step by step. I start with a basic regression with only number of years to the last year of operation fixed effect, then add different sets of control variables. The change in adjusted R-square help decide whether to include that set of control variables. The resulting preferred specification is in (2). $ln(Y_{iym})$ can be log of efficiency or log of emission rate, for each generating unit i in each operation year y and month m. Using a semi-log specification reflects the change in terms of percentage of the average, and may better fit the data when the original variable has very large range. However, NO_x and SO_2 emissions have decreased by a lot since 2000.[7] Multiplying the percentage increase to the average emissions in different years will give very different results. To get a better sense of how much more emissions have been released during the end of operations in absolute term rather than percentage, a linear regression is applied to all emission rates as well.

$$\begin{aligned} ln(Y_{iym}) = &\sum_{\tau=0}^{T} \beta_\tau 1\{\tau \text{ Years to Retirement}\} \ + \text{cubic}(\text{Age}_{iym})\phi \\ &+ \text{cubic}(\text{NG/Coal Price}_{ym})\kappa + \psi ln(\text{demand})_{sym} \\ &+ \alpha_i + \gamma_y + \theta_m + \epsilon_{iym} \end{aligned} \tag{2}$$

The coefficients of interest are the year to last operation fixed effects (β_τ). These coefficients show how much the efficiency or emissions are different from when they operate as business as usual. β_τ represents the τ^{th} year to last operation year, 0 is the year of last operation, -1 is the year before the year of last operation and so on. I choose to use back to 5 years before last operation year. There are two reasons for this choice. First, although EIA 860 report require each generating unit to report if they plan to retire in the next 10 years, most reports are at most 5 years ahead.[8] Thus, I consider 5 years as an appropriate length for manager to make plans for the generating units. Second, the data range from 1998 to 2017 and most retirement happened after 2010. Controlling for too many years before retirement will weaken the effect of individual fixed effects for those early retirements.

[7] SO_2 emissions were 11.2 million tons in 2000 and 1.3 million tons in 2017, NO_x emissions were 5.1 million tons in 2000 and 1.07 million tons in 2017. Source: https://www.epa.gov/airmarkets, accessed 7/28/2018.

[8] See Figure 10 in the appendix.

The first type of control variable is the EGU characteristics. Let Age_{iym} denote the age of each generating unit, measured in months. Age captures the cumulative usage of the EGU as well as the life expectancy, both have an impact on the exit decision.

The second set of control variables represents the macro economic environment.[9] NG/Coal Price is the natural gas price divided by the coal price in each month. $ln(\text{demand})_{sym}$ is the log of aggregated gross load from all monitored generating units, which approximates the residual demand from fossil fuel, in each state each month.

The third set of control variables is fixed effects. α_i represents individual fixed effect, which takes away the average Y level of each generating unit. The individual fixed effect can alleviate the selection bias in retirement. EGUs with generally higher emission rate may be older, less efficient and thus less profitable and more likely to retire. Let γ_y denote the year fixed effect for year y. The time trend for SO_2 and NO_x emissions is decreasing and is correlated with year to retirement. Without controlling for the year fixed effect, the emissions will decrease closer to the end of operation. Furthermore, the retirement may cluster in some years while less in others. Controlling for year fixed effect will control for such clustering. Let θ_m denote the month fixed effect for month m. This is to control seasonal differences and the selection of which month to operate more. For example, there are seasonal policies to regulate ozone pollutants, which will affect NO_x emissions. Electricity usage is at the highest in July and August while at the lowest in April.

To decompose the causes of changes in the efficiency and emission rates, a variable indicating whether any abatement technology was installed, denoted as $1\{\text{Tech}\}_{iym}$ and a variable capturing start-up and shutdown frequency, denoted as "Ramping", are added sequentially to the specification. The "lag Ramping" variable, which is the Ramping in the previously observed month, replaces "Ramping" in the last specification to examine the lag effect of start-up and shutdown frequency.

4.2 Underlying Mechanism

To understand the underlying mechanism, I first compare across the three major pollutants, CO_2, NO_x and SO_2. These three emission sources may exhibit different patterns for several reasons. First of all, one important difference among CO_2 and NO_x or SO_2 is the various techniques required to reduce each pollutant. There is no special technique installed to reduce CO_2[10] but there are different techniques to remove NO_x and SO_2. Second, coal purchased from different coal mines have various sulfur content as well as heat content, which will lead to different emission rates for different pollutants. Third, regulations for CO_2, NO_x and SO_2 vary across different states and local government. Last but not least, switching from using coal to natural gas as the primary fuel source is a common practice in recent years, SO_2 emissions from pipeline natural gas-fired generating units are low.[11] Comparing

[9] Source: EIA (2012)

[10] The EIA 860 form asks if carbon capture techniques are installed, answers are either N (No) or left blank.

[11] Switching to use natural gas emits less pollutants. Excluding those that switched will increase the emission rates estimates.

the emission rate pattern across these three different emission types may provide insight in the mechanism of how emissions are being reduced.

To further explore the incentives under different institution, I compare the emission trajectories separately for different regulatory status. Before the 1990s, the production and sale of electricity was regulated by the government or in the form of vertically-integrated Investor-Owned Utilities (IOUs). In the 1990s, some state tried to make the electricity industry a competitive market through divestiture (Jarrell, 1979; Stigler and Friedland, 1962). During the restructuring process, IOUs have to sell their generating assets to private investors. When regulated, power plant owners can get reimbursements from the Public Utility Commission to cover their costs, if their investment was deemed prudent. The restructure process was forced to stop in around 2000 due to the California energy crisis (Fabrizio et al., 2007). The regulated and not regulated power plants have different cost structure and make investment decisions accordingly. The regulated coal-fired power plants spend more on purchasing coal and tend to invest more in capital-intensive sulfur abatement techniques. On the contrary, not regulated coal-fired power plants shift their coal purchases to more productive coal mines (Cicala, 2015). Comparing these two groups may provide information regarding how different operation strategies may lead to different emission trajectories by retirement.

4.3 Marginal Treatment Effect of Exit Probability

The exit decision may contain certain unobserved information that may be correlated with the lower efficiency and higher emission rates. For example, lower efficiency can be one factor that drives coal-fired EGU to retire. To deal with this reverse causality problem and other potentially unobserved factors, I follow Fell and Kaffine (2018) to use a dispatch model to estimate the annual operational profit for each EGU. This approach uses the annual operational profit as an IV to extract the effect of active decision when EGUs expect themselves to retirement. More details can be found in Zhang (2020). There are entries and exits of coal-fired power plants in each Independent Systems Operator (ISO) during the long time period under examination. Therefore, instead of using the ISO as in Fell and Kaffine (2018), I model each Interconnection as a market. To estimate the marginal treatment effect, I apply the two-step method. In the first step I estimate the exit probability with a logit regression as follows:

$$1\{\text{Exit}\}_{iy} \quad = \quad \alpha + \beta\pi_{iy} + X_{isy}\xi + \nu_{isy} \tag{3}$$

where X_{isy} contains a second-order polynomial of age, square(Age_{iy}); the national natural gas over coal prices in each year, NG/Coal Price_y; log demand in each state in each year, $ln(\text{demand})_{sy}$; annual shutdown frequency, Ramping_{iy}; a constant heat rate (inverse of efficiency), Heat Rate_i; a constant capacity, Max Capacity_i and an indicator for installing abatement techniques $1\{\text{Tech}\}_{iy}$. ν_{isy} represents a random shock unobserved to the researcher. The indexing is the same as above.

In the second step, I use the following semi-log specification.

$$ln(Y_{iy}) = \zeta + \text{cubic}(\widehat{Pr(Exit)})\theta + X_{isy}\gamma + \mu_{isy}$$

where $\widehat{Pr(Exit)}$ is predicted from regression (3), X_{isy} the same as above and μ_{isy} is an unobserved random shock. The marginal treatment effect is the partial derivative with respect to the exit probability.

5 Results

5.1 Efficiency and Emission Trends

Table 2 shows the efficiency trend and Figure 1 compares the efficiency trend with and without controlling for ramping. The efficiency falls as EGUs approach their last year of operation in all specification. In the basic specification, efficiency drops by around 4% in the last year of operation. The average efficiency of EGUs operating at least 5 years before their last year of operation is 0.105 MW/MMBtu, with a standard deviation of 0.002. So the efficiency lost is about two standard deviation of the business as usual efficiency. Installing abatement technology may affect efficiency and the exit decision is correlated with the technology installation decision. The second specification controls for whether the EGU has any abatement technology installed. The coefficient does not change by much. I use this specification as the preferred specification. The third specification adds ramping to the preferred specification. As a result, the efficiency drop is only around 2.4% in the last year of operation. A simple comparison of the efficiency before and after controlling for ramping shows that ramping in the same month can explain 43% of the efficiency decrease.

The last specification replace ramping with the previous observed ramping. All the coefficients of interest become the same as those in the preferred specification. This suggests that the monthly ramping does not have a lag effect in the efficiency. However, further analysis is necessary to conclude that ramping does not have a permanent impact on efficiency.

Table 2: Efficiency Trend

	Basic	Tech	Ramping	Lag Ramping
0	-0.042**	-0.043**	-0.024*	-0.043**
	(0.013)	(0.013)	(0.011)	(0.013)
1	-0.024	-0.024	-0.010	-0.024
	(0.012)	(0.012)	(0.011)	(0.012)
2	-0.020	-0.020	-0.012	-0.020
	(0.010)	(0.010)	(0.010)	(0.010)
3	-0.009	-0.009	-0.003	-0.009
	(0.010)	(0.010)	(0.010)	(0.010)
4	-0.010	-0.010	-0.007	-0.010
	(0.010)	(0.010)	(0.009)	(0.010)
5	0.001	0.001	0.001	0.001
	(0.008)	(0.008)	(0.007)	(0.008)
log(demand)	0.036*	0.036*	0.013	0.036*
	(0.014)	(0.014)	(0.013)	(0.014)
Tech=1		-0.014	-0.016	-0.014
		(0.008)	(0.008)	(0.008)
Ramping			-1.749***	
			(0.118)	
Lagged Ramping				-0.008
				(0.005)
Cons	-3.089***	-3.087***	-2.594***	-3.084***
	(0.268)	(0.266)	(0.280)	(0.265)
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	200358	200358	200358	200358
R-squared	0.284	0.284	0.321	0.284
adj.R-squared	0.280	0.280	0.317	0.280

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Clustered standard errors in parentheses. Twoway clustered by year and plant.

All regressions include EGU, year and month of year fixed effects.

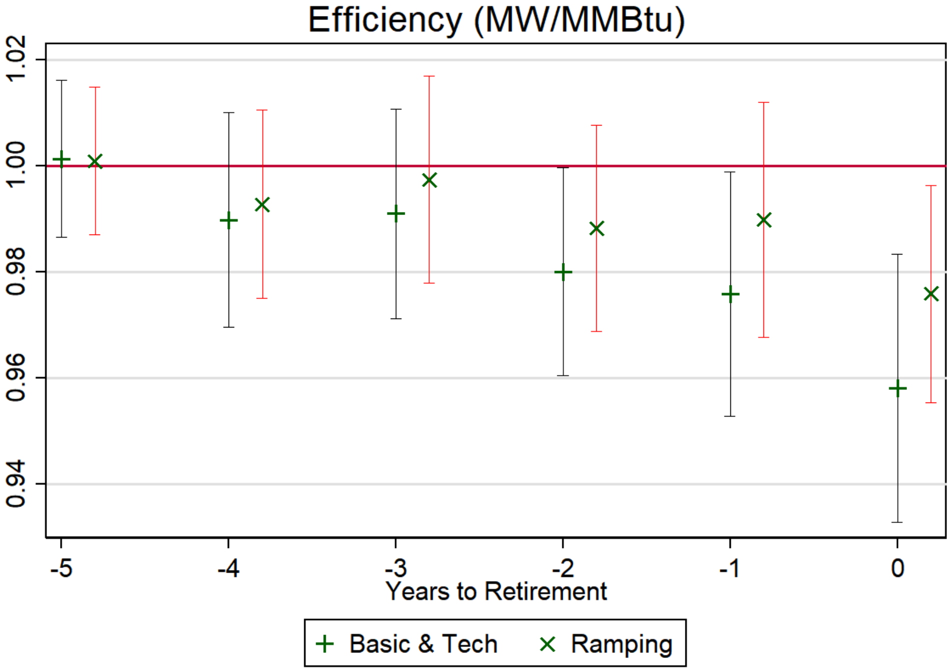

Figure 1: Efficiency Trend with and without Controlling Ramping (95% CI)

The CO_2 emission rate can be measured in two ways. One is the the CO_2 emission per unit of electricity generated, which captures the total the CO_2 emission in supplying electricity. However, the efficiency decrease has a direct impact on the increase in CO_2 emission per electricity generated. Thus the increase in CO_2 emission per unit of electricity generated may be due to the efficiency drop. The other measure is CO_2 emission per heat input, which exclude the direct effect of the efficiency drop. Figure 2 presents the comparison across different specifications for CO_2 emission rates. The first specification, labeled "per MW", uses CO_2 emission per unit of electricity generated as the dependent variable. There is significant extra emission rate in the last three years of operation.[12] The rest of the specifications use CO_2 emission per heat input as the dependent variable. Once the efficiency factor is excluded from the specification, the CO_2 emission rate increase is no longer significant and controlling for ramping cannot further reduce the emission rate. In this case, efficiency explains all the extra CO_2 emission during the last several years of operation.

[12]The regressions are in Table 4 in the appendix.

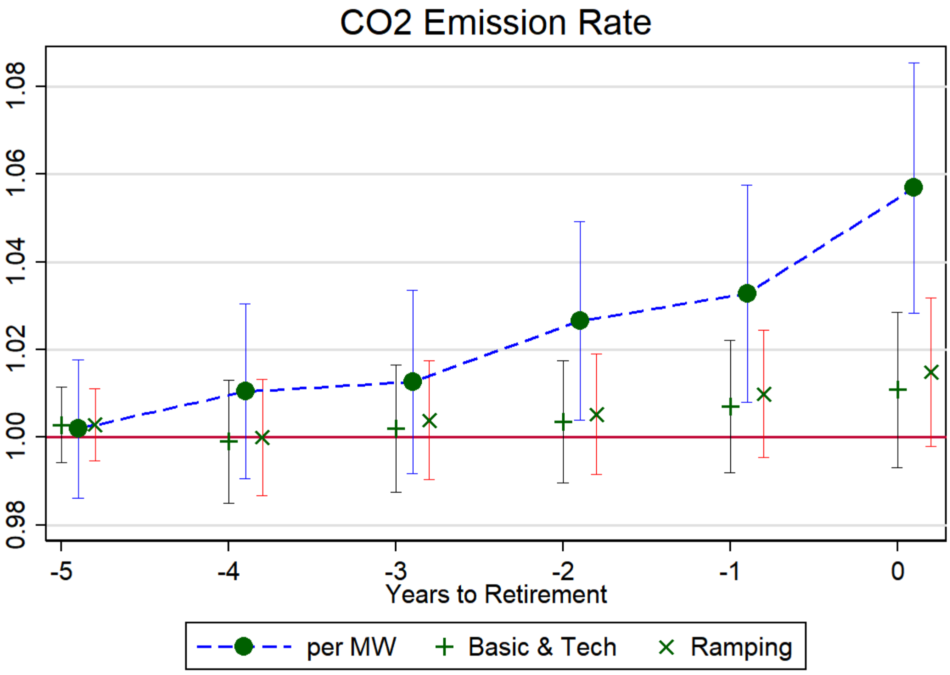

Figure 2: Comparison across CO_2 emission rates (95% CI)

Figure 3 presents the results for NO_x and SO_2 in a similar format as Figure 2. The emission rates for NO_x and SO_2 show different patterns than the CO_2 emission trend. Even after excluding the efficiency channel, the two emission rates are increasing significantly and at a much higher magnitude than each EGU during business as usual operation. Efficiency only explains around 20% of the emission rates increase for NO_x and SO_2 during their last year of operation. Controlling ramping does not further eliminate the extra emission rates conditional on excluding the efficiency channel. The R-squares of the regressions are larger for NO_x and SO_2 than CO_2.[13] This means the NO_x and SO_2 emission rates are less noisy than CO_2 and better approximated by the regression specification. There are other mechanisms that lead to the increase in these two types of emission rates.

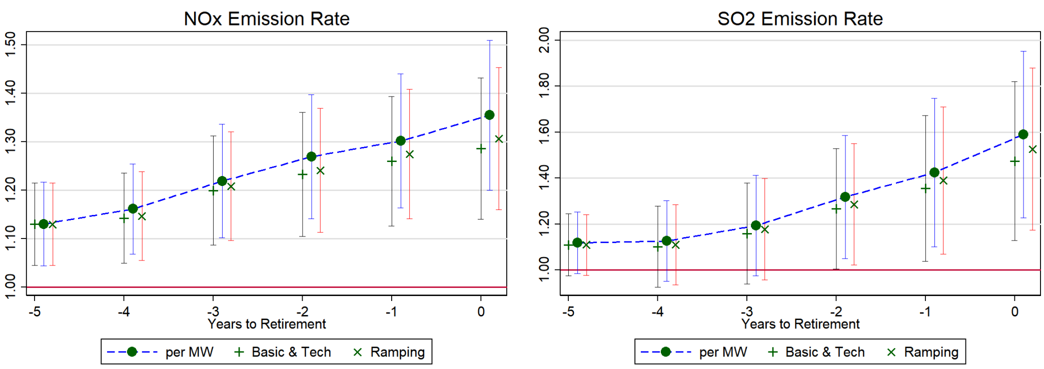

Figure 3: Comparison across NOx and SO_2 Emission Rates (95% CI)

[13] Around 0.7 for NO_x and SO_2 and 0.3 for CO_2. See Table 5 and 6 in the appendix.

5.2 Regulatory Status

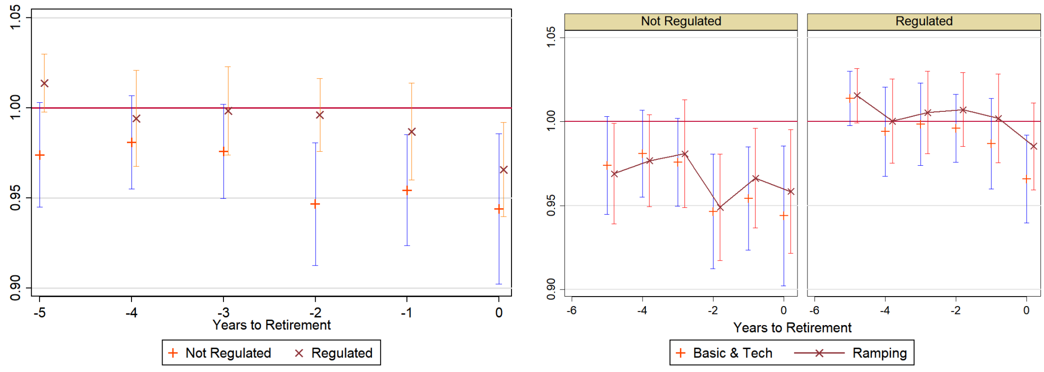

Figure 4: Efficiency Trend under Two Regulatory Status (95% CI)

Figure 4 shows the coefficients of interest interacted with the regulatory status. The group regulated under fee-for-service maintains their efficiency until a sudden drop in their last year of operation. On the contrary, the not regulated group has a lower efficiency during their last three years of operation. This may suggest that the not regulated power plants delayed exit. Controlling for ramping explains around 55% of the efficiency lost in the regulated group, but only 26% for the not regulated group.

Figure 5 shows the comparison for CO_2 emission rate under different regulatory status. The left figure shows the different patterns in the CO_2 emission per unit of electricity generated. The tends correspond to the efficiency drop. The right figure presents the comparison across different specifications, from the CO_2 emission per unit of electricity generated (labeled "per MW"), to the CO_2 emission per heat input under the preferred specification (labeled "Basic & Tech"), and adding ramping (labeled "Ramping"). Both groups show similar pattern as when analyzed jointly.

The two groups do not show significantly different trends for NO_x and SO_2 emission rates.[14] However, the confidence intervals are larger, suggesting further heterogeneity in the operation strategy within each subgroup.

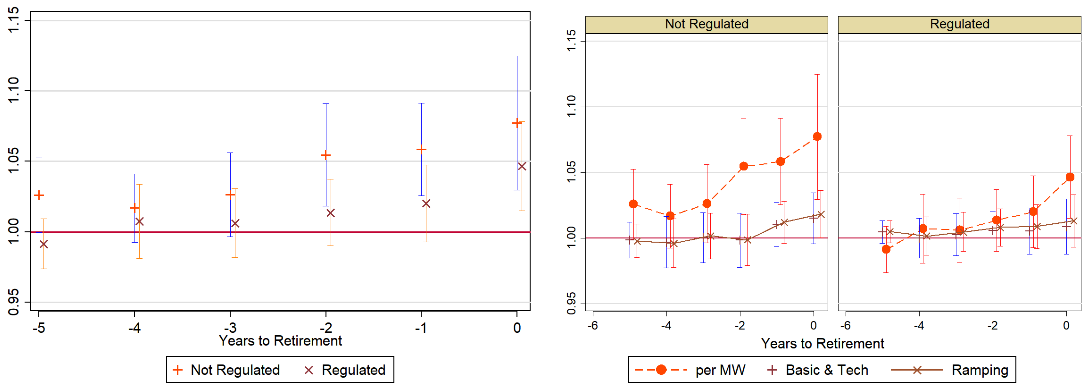

Figure 5: CO_2 Emission Rate under Two Regulatory Status

[14] See Figure 11 and 12 in the appendix.

5.3 Marginal Treatment Effect

For illustration, I only show the result for the eastern interconnection. Figure 6 exhibits the marginal treatment effect of efficiency at different levels of exit probability separately by regulatory status. Consistent with the semi-log estimation, the regulated group significantly reduce their efficiency when the exit probability is high while the not regulated group does not drastically change their efficiency in response to the exit probability. Nevertheless, the estimation is noisy and further analysis is necessary to argue how much of the efficiency drop is due to anticipating retirement.

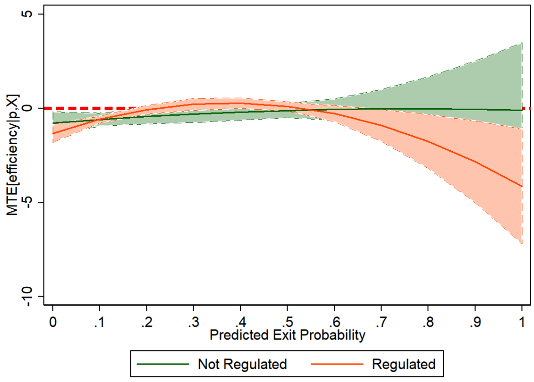

Figure 6: Marginal Treatment Effect of Efficiency by Regulatory Status

5.4 A Back-Of-The-Envelope Calculation

Table 3 shows a back-of-the-envelope calculation of the extra emissions when evaluated at the mean of each continuous variable, in 2012 and each month. Over time the SO_2 and NO_x emissions have decreased by a lot. The total emission in 2017 is only one fifth of the total amount emitted in 2000 for NO_x and is one tenth for SO_2. I use the year 2012 as an approximation for the mean of the total emission across the 20 years. The average age taken over all observations is 38.57, average ramping 0.0128, average natural gas over coal price ratio 2.81, average log demand 15.54 and percentage abatement technologies installed is 84%, all weighted more towards earlier years due to exits. Each retiring EGU on average emits extra 78.88 million lbs CO_2 (1.6%), 0.88 million lbs NOx (10.1%) and 5.01 million lbs SO_2(16.9%), comparing to their baseline level in 2012. Around half of the extra CO_2 emission and 10% of the extra NOx and SO_2can be attributed to ramping.

Table 3: Extra Emission Estimation

	Gross Load			Heat Input		
	CO_2	NOx	SO_2	CO_2	NOx	SO_2
Gross Load or Heat Input	2339.10			23084.52		
Final Year Gross Load/Heat Input	55.64			581.62		
Base Emission Rate	2076.67	3.73	12.71	208.04	0.37	1.28
Base Total Emission	4857.55	8.71	29.73	4802.47	8.62	29.64
Final Year Extra Emission Rate	118.13	1.32	7.50	2.25	0.11	0.61
Final Year Total Extra Emission	78.88	0.88	5.01	15.70	0.74	4.25
Extra emission over Regular (%)	1.6	10.1	16.9	0.3	8.6	14.3

***Note*: Gross Load measured in 1000 MWh, Heat Input measured in 1000 MMBtu/hr. Emission rate measured in lbs/MWh, total emission measured in Million lbs.**

6 Conclusions and Discussions

I found that coal power generating units have a decreasing efficiency as well as increasing emission rates for CO_2, NO_x and SO_2, as they approach their last year of operation. Efficiency in the last year of operation is around 4% lower than business as usual, which is around two standard deviation of the normal efficiency. Ramping explains 43% of the efficiency lost. CO_2 emissions per unit of electricity generated on average increase by 5.7% in the last year of operation, 36% for NO_x and 59% for SO_2. The CO_2 emissions rate no longer has an increasing trend once the efficiency channel is excluded. Efficiency lost only explains around 20% of the increase in NO_x and SO_2 emission rates. The marginal effect analysis suggests that regulated EGUs are more sensitive to profit for their long-run decision and efficiency drops dramatically. However, not regulated units do not show similar responsiveness. This group shows the tendency of delayed exit.

A back-of-the-envelope calculation shows that each EGU in their last year of operation on average emits an extra 78.88 million lbs CO_2 (1.6%), 0.88 million lbs NOx (10.1%) and 5.01 million lbs SO_2(16.9%), comparing to their baseline level in 2012.

A large part of the mechanism that leads to NO_x and SO_2 emission rates increase remains unclear. One possible direction is to explore the emission reduction techniques. There are differentiated marginal costs associated with using various NO_x and SO_2 abatement techniques. Another possible channel that affects emission rates is maintenance, either for the generator itself or for the emission reduction techniques. However, I do not have the information to directly control for maintenance.

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A Background Information

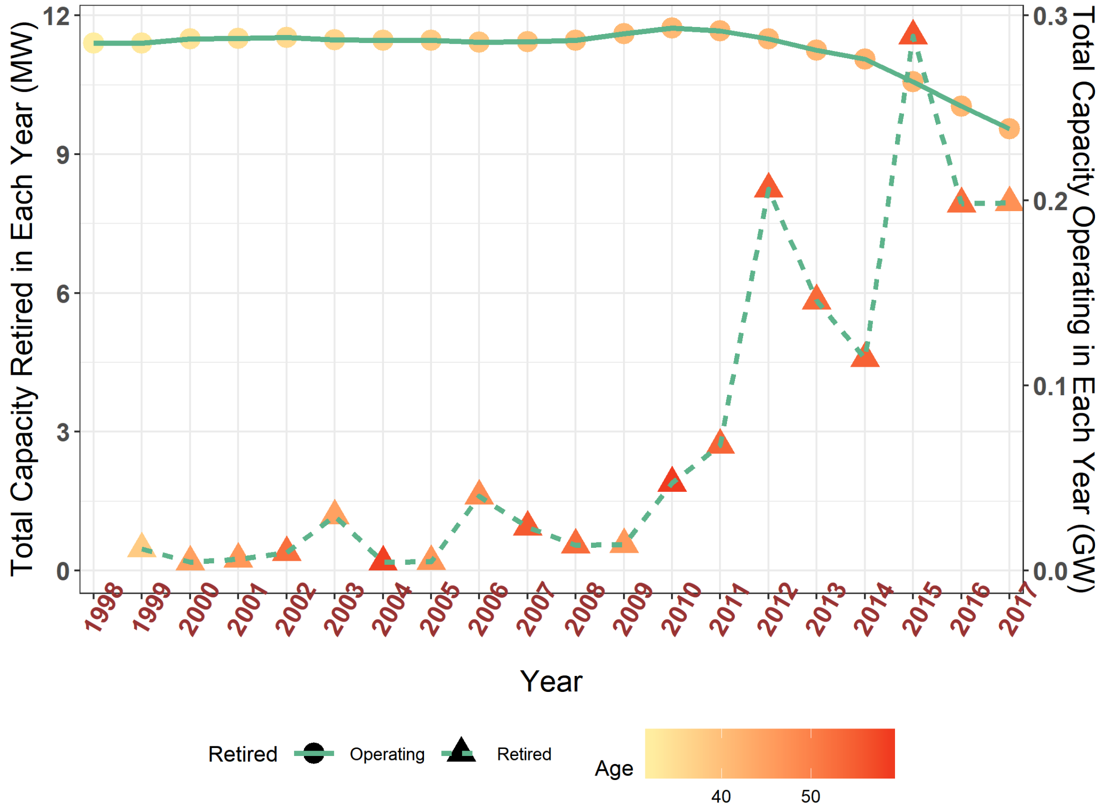

Figure 7: Operating and Retiring Coal-fired EGUs Characteristics

Note: Data from Continuous Emissions Monitoring System (CEMS).

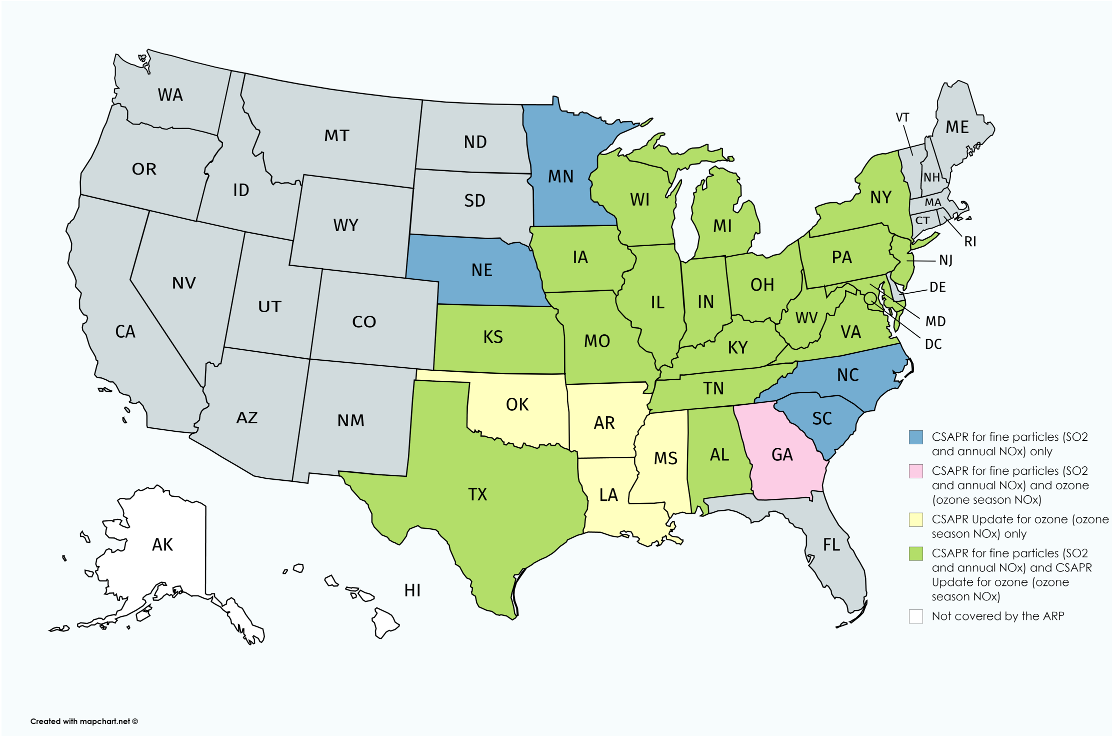

Figure 8: Important Regulations for Air Pollutants

Note: Information from EPA, map created with mapchart.net.

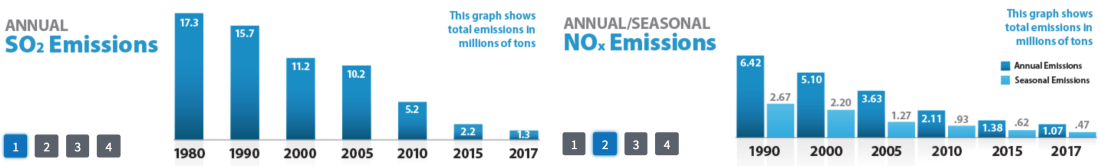

Figure 9: Reduction of SO_2 and NO_x (Source: EIA)

A.1 Planned and Actual Retirement

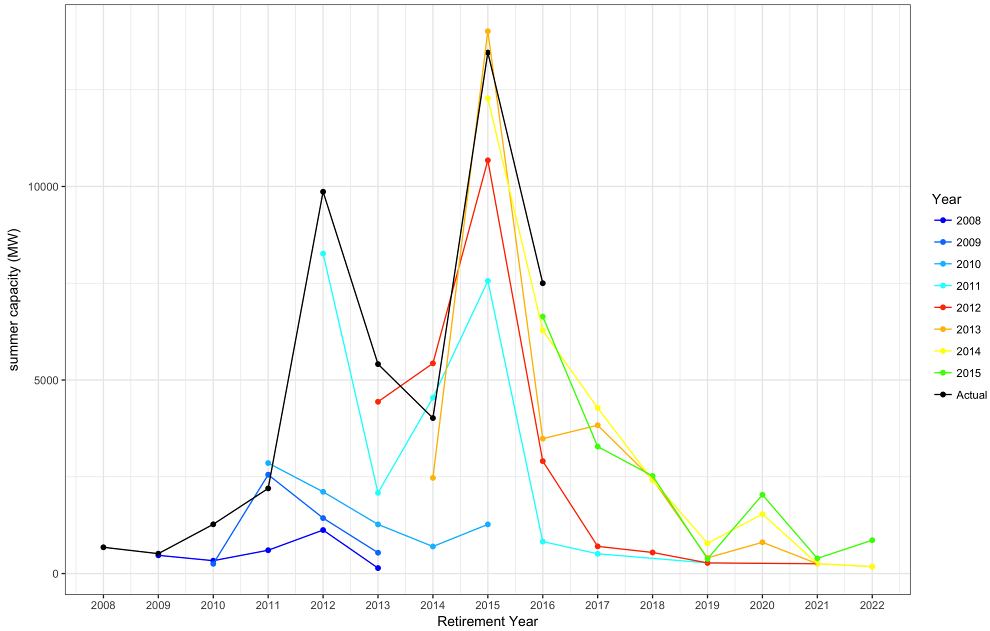

Figure 10: Planned and Actual Retirement 2008 - 2015 (Source: EIA 860 - Generator)

B Regressions

Table 4: CO_2 Emission Rate Trend

	per MW	Tech	Ramping	Lag Ramping
0	0.055***	0.011	0.015	0.011
	(0.014)	(0.009)	(0.008)	(0.009)
1	0.032*	0.007	0.010	0.007
	(0.012)	(0.008)	(0.007)	(0.008)
2	0.026*	0.004	0.005	0.004
	(0.011)	(0.007)	(0.007)	(0.007)
3	0.013	0.002	0.004	0.002
	(0.011)	(0.007)	(0.007)	(0.007)
4	0.010	-0.001	-0.000	-0.001
	(0.010)	(0.007)	(0.007)	(0.007)
5	0.002	0.003	0.003	0.003
	(0.008)	(0.004)	(0.004)	(0.004)
log(demand)	-0.050***	-0.013	-0.018*	-0.013
	(0.013)	(0.007)	(0.007)	(0.007)
Tech=1	0.021*	0.008	0.007	0.008
	(0.009)	(0.004)	(0.004)	(0.004)
Ramping			-0.292***	
			(0.053)	
Lagged Ramping				-0.005
				(0.003)
Cons	8.299***	5.195***	5.306***	5.197***
	(0.314)	(0.209)	(0.204)	(0.208)
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	200358	201158	201158	201158
R-squared	0.285	0.293	0.318	0.293
adj.R-squared	0.281	0.289	0.314	0.289

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Clustered standard errors in parentheses. Twoway clustered by year and plant.

All regressions include EGU, year and month of year fixed effects.

Table 5: NO_x Emission Rate Trend

	per MW	Tech	Ramping	Lag Ramping
0	0.304***	0.251***	0.267***	0.251***
	(0.058)	(0.058)	(0.057)	(0.058)
1	0.263***	0.231***	0.242***	0.231***
	(0.054)	(0.054)	(0.053)	(0.054)
2	0.238***	0.209***	0.216***	0.209***
	(0.052)	(0.053)	(0.053)	(0.053)
3	0.198***	0.182**	0.189***	0.182**
	(0.049)	(0.048)	(0.047)	(0.048)
4	0.149**	0.133**	0.137**	0.133**
	(0.041)	(0.041)	(0.041)	(0.041)
5	0.122**	0.122**	0.122**	0.122**
	(0.039)	(0.038)	(0.038)	(0.038)
log(demand)	0.191**	0.231***	0.210**	0.231***
	(0.060)	(0.057)	(0.058)	(0.057)
NOx Tech=1	-0.383***	-0.391***	-0.394***	-0.391***
	(0.040)	(0.039)	(0.039)	(0.039)
Ramping			-1.182***	
			(0.167)	
Lagged Ramping				0.011
				(0.009)
Cons	-15.002*	-18.279**	-17.830**	-18.283**
	(5.892)	(5.944)	(5.902)	(5.944)
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	200358	201158	201158	201158
R-squared	0.663	0.678	0.681	0.678
adj.R-squared	0.661	0.676	0.680	0.676

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Clustered standard errors in parentheses. Twoway clustered by year and plant.

All regressions include EGU, year and month of year fixed effects.

Table 6: SO_2 Emission Rate Trend

	per MW	Tech	Ramping	Lag Ramping
0	0.464***	0.388**	0.423**	0.388**
	(0.116)	(0.120)	(0.118)	(0.120)
1	0.354**	0.304*	0.330*	0.305*
	(0.115)	(0.119)	(0.117)	(0.119)
2	0.276*	0.236*	0.252*	0.236*
	(0.103)	(0.106)	(0.105)	(0.106)
3	0.177	0.148	0.164	0.148
	(0.094)	(0.097)	(0.095)	(0.097)
4	0.119	0.097	0.105	0.097
	(0.079)	(0.081)	(0.080)	(0.081)
5	0.112	0.104	0.104	0.104
	(0.061)	(0.062)	(0.061)	(0.062)
log(demand)	-0.116	-0.053	-0.100	-0.054
	(0.081)	(0.085)	(0.085)	(0.085)
SO2 Tech=1	-2.053***	-2.096***	-2.098***	-2.096***
	(0.169)	(0.169)	(0.167)	(0.169)
Ramping			-2.622***	
			(0.429)	
Lagged Ramping				-0.016
				(0.021)
Cons	2.326	-1.505	-0.511	-1.500
	(2.391)	(2.487)	(2.443)	(2.487)
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	200358	201158	201158	201158
R-squared	0.722	0.724	0.729	0.724
adj.R-squared	0.720	0.723	0.728	0.723

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Clustered standard errors in parentheses. Twoway clustered by year and plant.

All regressions include EGU, year and month of year fixed effects.

Table 7: Efficiency Trend under Two Regulatory Status

	Basic	Tech	Ramping	Lag Ramping
NR 0	-0.057*	-0.058*	-0.042*	-0.058*
	(0.022)	(0.023)	(0.020)	(0.023)
NR 1	-0.046*	-0.047*	-0.034*	-0.047*
	(0.016)	(0.016)	(0.016)	(0.016)
NR 2	-0.054**	-0.055**	-0.052**	-0.055**
	(0.018)	(0.018)	(0.017)	(0.018)
NR 3	-0.024	-0.024	-0.019	-0.024
	(0.014)	(0.014)	(0.017)	(0.014)
NR 4	-0.019	-0.019	-0.024	-0.019
	(0.014)	(0.013)	(0.014)	(0.013)
RE 0	-0.034*	-0.035*	-0.015	-0.035*
	(0.014)	(0.014)	(0.013)	(0.014)
RE 1	-0.013	-0.013	0.002	-0.013
	(0.014)	(0.014)	(0.013)	(0.014)
RE 2	-0.004	-0.004	0.007	-0.004
	(0.010)	(0.010)	(0.011)	(0.010)
RE 3	-0.002	-0.002	0.005	-0.002
	(0.013)	(0.013)	(0.012)	(0.013)
RE 4	-0.006	-0.006	0.000	-0.006
	(0.014)	(0.014)	(0.013)	(0.014)
log(demand)	0.036*	0.036*	0.013	0.036*
	(0.014)	(0.014)	(0.013)	(0.014)
Tech=1		-0.015	-0.017	-0.015
		(0.008)	(0.008)	(0.008)
Ramping			-1.752***	
			(0.117)	
Lagged Ramping				-0.008
				(0.005)
Cons	-3.086***	-3.084***	-2.589***	-3.081***
	(0.267)	(0.265)	(0.279)	(0.264)
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	200358	200358	200358	200358
R-squared	0.284	0.285	0.321	0.285
adj.R-squared	0.280	0.281	0.318	0.281

* p<0.05, ** p<0.01, *** p<0.001

Clustered standard errors in parentheses. Cluster by year and plant.

All regressions include EGU, year and month of year fixed effects.

Table 8: CO_2 Emission Rate under Two Regulatory Status

	per MW	Tech	Ramping	Lag Ramping
Tech=1	0.022*	0.008	0.007	0.008
	(0.009)	(0.004)	(0.004)	(0.004)
NR 0	0.074**	0.015	0.018	0.015
	(0.023)	(0.010)	(0.009)	(0.010)
NR 1	0.057**	0.010	0.012	0.010
	(0.016)	(0.009)	(0.008)	(0.009)
NR 2	0.053**	-0.001	-0.001	-0.001
	(0.018)	(0.011)	(0.010)	(0.011)
NR 3	0.026	0.000	0.002	0.000
	(0.015)	(0.010)	(0.009)	(0.010)
NR 4	0.017	-0.003	-0.004	-0.003
	(0.012)	(0.010)	(0.009)	(0.010)
RE 0	0.046**	0.009	0.013	0.009
	(0.015)	(0.011)	(0.010)	(0.011)
RE 1	0.020	0.006	0.009	0.006
	(0.014)	(0.009)	(0.008)	(0.009)
RE 2	0.014	0.006	0.008	0.006
	(0.012)	(0.007)	(0.007)	(0.007)
RE 3	0.006	0.003	0.005	0.003
	(0.012)	(0.008)	(0.008)	(0.008)
RE 4	0.007	-0.000	0.002	-0.000
	(0.013)	(0.008)	(0.007)	(0.008)
log(demand)	-0.050**	-0.013	-0.018*	-0.013
	(0.013)	(0.007)	(0.007)	(0.007)
Ramping			-0.293***	
			(0.053)	
Lagged Ramping				-0.004
				(0.003)
Cons	8.295***	5.195***	5.306***	5.197***
	(0.314)	(0.208)	(0.204)	(0.208)
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	200358	201158	201158	201158
R-squared	0.285	0.293	0.318	0.293
adj.R-squared	0.281	0.289	0.314	0.289

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Clustered standard errors in parentheses. Cluster by year and plant.

All regressions include EGU, year and month of year fixed effects.

Table 9: NO_x Emission Rate under Two Regulatory Status

	per MW	Tech	Ramping	Lag Ramping
NOx Tech=1	-0.383***	-0.392***	-0.394***	-0.392***
	(0.040)	(0.039)	(0.039)	(0.039)
NR 0	0.308***	0.238**	0.251**	0.238**
	(0.074)	(0.075)	(0.076)	(0.075)
NR 1	0.280***	0.233**	0.240**	0.233**
	(0.066)	(0.067)	(0.067)	(0.067)
NR 2	0.232**	0.176*	0.177*	0.176*
	(0.066)	(0.072)	(0.071)	(0.072)
NR 3	0.192**	0.163*	0.169*	0.163*
	(0.062)	(0.063)	(0.063)	(0.063)
NR 4	0.133*	0.114	0.111	0.114
	(0.051)	(0.055)	(0.055)	(0.055)
RE 0	0.302***	0.258***	0.276***	0.258***
	(0.062)	(0.064)	(0.063)	(0.064)
RE 1	0.256***	0.230**	0.244***	0.230**
	(0.059)	(0.060)	(0.059)	(0.060)
RE 2	0.241***	0.224***	0.234***	0.224***
	(0.056)	(0.057)	(0.057)	(0.057)
RE 3	0.200**	0.190**	0.199***	0.190**
	(0.053)	(0.052)	(0.051)	(0.052)
RE 4	0.157**	0.142**	0.149**	0.142**
	(0.047)	(0.049)	(0.048)	(0.049)
log(demand)	0.191**	0.231***	0.210**	0.231***
	(0.060)	(0.057)	(0.058)	(0.057)
Ramping			-1.185***	
			(0.167)	
Lagged Ramping				0.011
				(0.010)
Cons	-15.003*	-18.277**	-17.827**	-18.281**
	(5.893)	(5.944)	(5.904)	(5.945)
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	200358	201158	201158	201158
R-squared	0.663	0.678	0.681	0.678
adj.R-squared	0.661	0.676	0.680	0.676

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Clustered standard errors in parentheses. Cluster by year and plant.

All regressions include EGU, year and month of year fixed effects.

Table 10: SO_2 Emission Rate under Two Regulatory Status

	per MW	Tech	Ramping	Lag Ramping
SO2 Tech=1	-2.046***	-2.088***	-2.090***	-2.088***
	(0.169)	(0.170)	(0.167)	(0.170)
NR 0	0.430*	0.363*	0.392*	0.363*
	(0.158)	(0.155)	(0.160)	(0.155)
NR 1	0.265	0.213	0.229	0.213
	(0.132)	(0.134)	(0.138)	(0.134)
NR 2	0.137	0.080	0.083	0.080
	(0.144)	(0.148)	(0.149)	(0.148)
NR 3	0.040	0.005	0.018	0.006
	(0.140)	(0.147)	(0.149)	(0.147)
NR 4	-0.013	-0.028	-0.035	-0.028
	(0.123)	(0.124)	(0.129)	(0.124)
RE 0	0.488***	0.409**	0.447**	0.409**
	(0.121)	(0.128)	(0.125)	(0.128)
RE 1	0.402**	0.353*	0.384**	0.354*
	(0.127)	(0.132)	(0.129)	(0.132)
RE 2	0.343**	0.311*	0.333**	0.311*
	(0.110)	(0.111)	(0.111)	(0.111)
RE 3	0.242*	0.215	0.233*	0.215
	(0.106)	(0.108)	(0.107)	(0.108)
RE 4	0.180	0.155	0.170	0.155
	(0.094)	(0.096)	(0.096)	(0.096)
log(demand)	-0.117	-0.054	-0.101	-0.055
	(0.081)	(0.085)	(0.086)	(0.085)
Ramping			-2.633***	
			(0.425)	
Lagged Ramping				-0.016
				(0.021)
Cons	2.330	-1.497	-0.496	-1.491
	(2.392)	(2.488)	(2.443)	(2.487)
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	200358	201158	201158	201158
R-squared	0.722	0.725	0.729	0.725
adj.R-squared	0.721	0.723	0.728	0.723

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Clustered standard errors in parentheses. Cluster by year and plant.

All regressions include EGU, year and month of year fixed effects.

C Figures

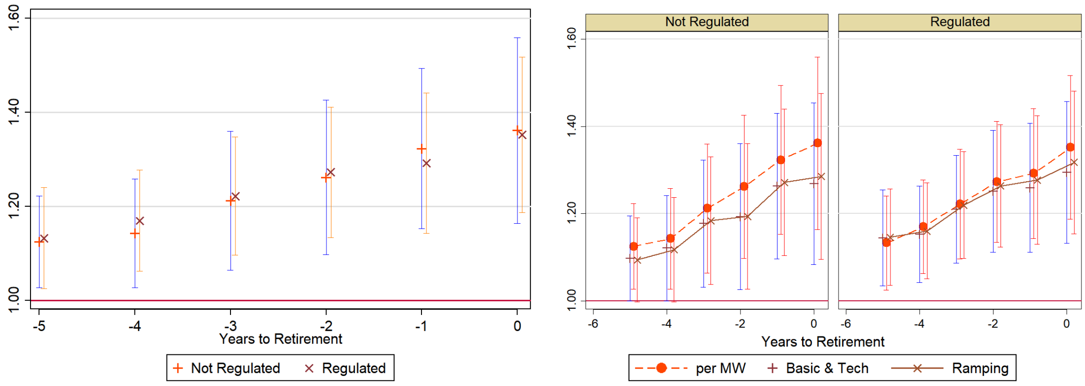

Figure 11: NO_x Emission Rate under Two Regulatory Status

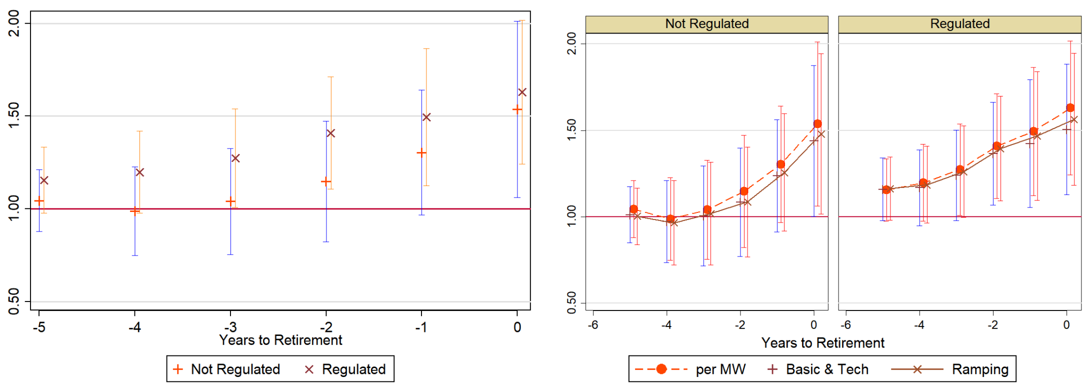

Figure 12: SO_2 Emission Rate under Two Regulatory Status

D Marginal Treatment Effect

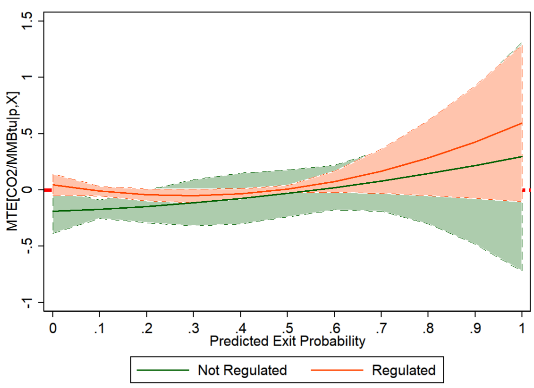

Figure 13: Marginal Treatment Effect of CO_2 by Regulatory Status

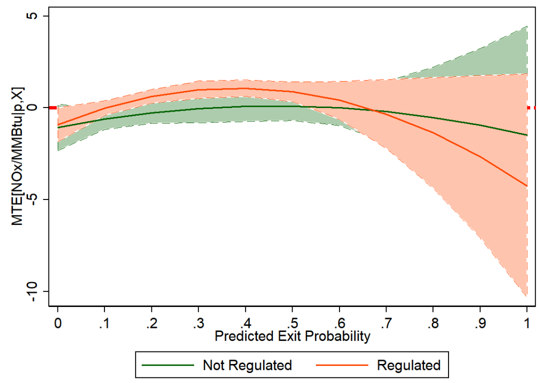

Figure 14: Marginal Treatment Effect of NO_x by Regulatory Status

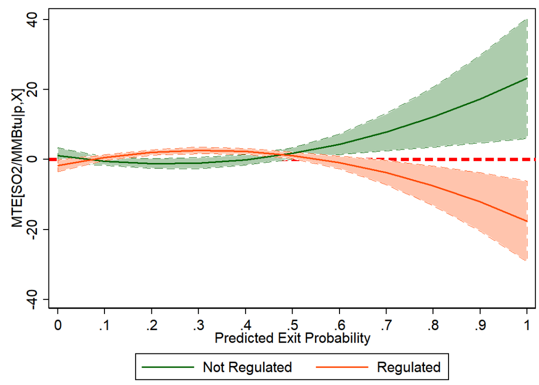

Figure 15: Marginal Treatment Effect of SO_2 by Regulatory Status