Measuring Policy Uncertainty Using Coal Power Plants' Investment and Exit Decisions

Wendan Zhang*

Current Version
November 14, 2020

Abstract

Uncertainty in regulatory policies may reduce durable good investment, thereby leading to poor regulatory outcomes. Mercury and Air Toxics Standards (MATS) is an environmental policy regulating mercury and other air toxics from coal-fired power plants. The policy went through several legal challenges and was subject to high uncertainty before its compliance date. I measure the subjective belief regarding the MATS remaining in place using a modified investment and exit model. The dynamic structural model incorporates a difference-in-differences design to use the coal-fired power plants' investment and exit decisions to reveal the subjective probability of the MATS policy relative to local mercury rules. I estimate that plants believed that the MATS would not be implemented in 2016 as announced with around 17% probability before the compliance year. The result suggests that policy design should take uncertainty into account.

JEL code: D81, L51, L94, Q58
Keywords: environmental regulation uncertainty, coal power plants, decision making under uncertainty

*Department of Economics, University of Arizona (e-mail: wzhang357@email.arizona.edu). I thank my advisor Ashley Langer for thoughtful comments. I also thank Gautam Gowrisankaran and Derek Lemoine for helpful suggestions. I am grateful to participants at the 2020 AERE Summer Virtual Conference and 2020 AAEA Virtual Meeting. All mistakes are mine.

1 Introduction

The coal-fired power plant industry, once representing more than half of the electricity generation in the United States, is a major polluting source of various emissions, including greenhouse gas (CO_2), sulfur dioxide (SO_2), nitrogen oxides (NOx), and other toxics such as mercury. These pollutants are harmful to people's health, while electricity prices affect people's wealth. Together, regulating the emission in this industry has an enormous welfare impact nationwide.

Environmental concerns and technological advancement have pushed the U.S. energy sector to transit from coal power to cleaner power, primarily natural gas and renewable resources. Meanwhile, the U.S. Environmental Protection Agency (EPA) strives to design environmental policies to regulate emissions. Environmental regulation design is vital for reducing pollution efficiently, but regulatory uncertainty may affect a policy's efficiency, causing large deadweight losses. Regulatory uncertainty surrounding environmental policies may arise from legal challenges and political debates. Uncertainty is an essential factor in many investment and dynamic models. Under certain assumptions, economic theory may predict that firms delay irreversible decision-making (Dixit et al., 1994). However, theoretical predictions may vary under different contexts and for different outcomes. On the empirical venue, studies are limited. Two main difficulties lie in measuring policy uncertainty and identifying its causal impact on firms' reactions (Dorsey, 2019).

The Mercury and Air Toxics Standards (MATS) is an important environmental regulation that was subject to high policy uncertainty. The U.S. Environmental Protection Agency (EPA) announced MATS on December 21, 2011. MATS is the first national standards to reduce mercury emissions and other toxic air pollutants from coal- and oil-fired electric generating units (EGU) with a capacity of more than 25MW. Coal-fired EGUs can install abatement technologies to comply with MATS, convert to natural gas units, or retire. The first compliance date was April 2015, though power plants could apply for a one-year extension. Several states challenged the rule in the U.S. Supreme Court, which resulted in the EPA to reconduct the cost-benefit analysis and introduced high regulatory uncertainty. From 2012 to 2016, EPA made several technical corrections and clarifying changes to MATS, proposed supplemental finding to support the appropriateness of MATS, reviewed the requests to reconsider certain aspects of the MATS rule but denied all petitions for reconsideration. Such environmental regulation uncertainty can cause substantial inefficiency in implementing the policy because the decisions to comply with the policy are usually with a large stake and irreversible. As theory suggests, uncertainty in regulations may delay firms' investment in installing abatement technologies and exit. The more firms postpone compliance with the environmental regulation, the total benefit that the regulation could bring will be lower.

This paper aims to estimate the coal-fired EGUs' perceived probability regarding MATS being enforced by 2016. Understanding the expectation of MATS can help evaluate the potential inefficiency caused by regulatory uncertainty. To reveal the subjective probability, I use a revealed preference approach with a two-stage model. The model consists of a static dispatch model and a dynamic single-agent investment and exit model. In the first stage, I use the dispatch model to estimate the annual operating profit for each coal-fired EGU. The calculated profits are fitted to a regression model to be used in the dynamic model. In the second stage, the dynamic model incorporates a difference-in-difference (DID) framework to recover the mean exit value per unit of capacity, the mean investment costs per unit of capacity, the standard deviation of the unobserved shocks associated with the choices, and reveal the perceived probability of MATS in 2012-2015. I use the states that enacted a stricter mercury emission limit for the coal-fired EGUs before the compliance year of MATS as the comparison group, assume there is no policy uncertainty in these local policies, and infer the mean exit value and investment costs per unit of capacity from the decisions observed in this group. Then by assuming that the EGUs that are regulated under MATS face the same exit value and investment costs, the subjective probability of MATS can be identified from the investment and exit decisions made by the MATS treatment group. The model incorporates the important factors affecting coal-fired power plants' operation, investment, and exit decisions to identify the effect of the policy uncertainty.

The primary contribution of this paper is the approach to unravel firms' subjective beliefs from their decisions. Other approaches to reveal the probabilities may include using option prices. For example, Langer and Lemoine, 2020 derive two models which use the option prices to infer the probability of certain event. Carvalho and Guimaraes (2018) propose a method to estimate the vulnerability of state-controlled companies to a series of political risks. This paper provides an estimation of multi-year perceived probabilities of MATS using firms' investment and exit decisions. Besides, this article adds an empirical study to the literature of policy uncertainty affecting investment decisions(Dorsey, 2019; Kellogg, 2014).

My study builds on the literature investigating the factors that drive coal-fired power plants' retirement. The existing empirical studies have diverse conclusions regarding the relative impact. Linn and McCormack (2019) find the decrease of natural gas prices to be the main driving force rather than environmental regulations, even after comparing with the MATS rule in one of their policy scenarios. On the contrary, Schiavo and Mendelsohn (2019) argue that stricter air pollutant regulations, especially MATS, are the main cause. Besides, Fell and Kaffine (2018) show that different factors interacting with each other may have a compound effect. These studies differ in many dimensions, and MATS is a critical factor included in the first two papers but with very different approaches and results. Linn and McCormack (2019) fix the available market information and projection for the whole study period and only use the updated market conditions in the counterfactual analyses to study the long-run equilibrium. However, the effect of MATS may be embedded in the natural gas shocks due to the close timing of the collapse of natural gas prices and the announcement of MATS (See Figure 3). Schiavo and Mendelsohn (2019) apply a reduced form approach with a set of instrumental variables (IV), which may bias the effect of environmental regulations upwards. I include both elements in the model and allow the information to unravel over time. Allowing variation in market conditions and plants' expectations of environmental regulations may help identify their impact as information revealed.

My study also builds on and contributes to the extensive literature using computational or structural models in the electricity sector (Cullen and Reynolds, 2017; Gowrisankaran et al., 2016). Specifically, I adopt a dispatch model (Borenstein et al., 2002; Linn and McCormack, 2019), reproduce the calculated profits with a regression model, and then incorporate the results into a modified DID style single-agent investment and exit model to unravel the perceived environmental policy uncertainty. The major modifications to the investment and exit model include: 1) decision-makers do not have perfect foresight regarding the policy shocks, 2) there are periods with various lengths when decision-makers can make decisions knowing the deadline of compliance, and 3) decision-makers can hold a subjective belief regarding the enforcement probability of the policy and the probability may vary across years.

The remainder of the paper is organized as follows. Section 2 describes the background, the data sources and summarizes the characteristics of the U.S. coal power generating units used in this study. Section 3 introduces a model to study the investment and exit decisions of the coal-fired power generating units. Section 4 discusses the estimation of the model. Section 5 presents the estimated results and Section 6 concludes.

2 Policy Background and Data

2.1 MATS with Coal-fired Power Plants

The coal-fired power plant industry once supplied more than half of the electricity in the United States. However, the lower natural gas prices, the higher costs to comply with environmental regulations, and the advancement in renewable technologies have been driving down the profitability of the coal-fired EGUs. By the end of 2018, more than one-third of the coal-fired EGUs has retired (Figure 1). Among the environmental regulations, MATS is considered the most costly regulation to comply with.

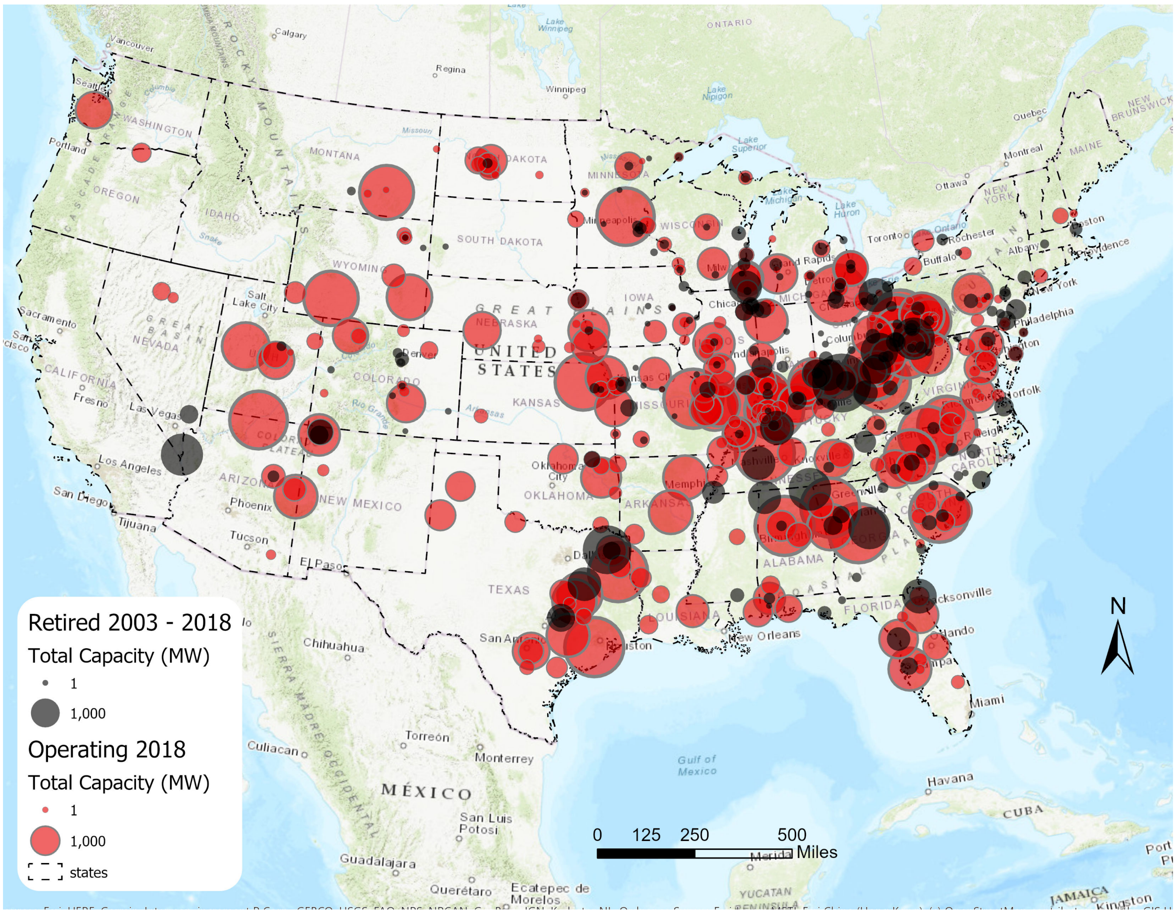

Figure 1: Coal-fired Power Plant Retirement

The discussion of regulating air toxics from the electricity sector has started since early 2000. However, the MATS rule proposed by the EPA in 2011 and finalized in 2012 was the first national regulation to set limits for mercury emissions, along with other air toxics, from coal- and oil-fired power plants that are larger than 25 MW. The first compliance year is 2015, with an extension generally available in April 2016. Such ambiguity adds to the uncertainty of the policy and is absorbed in the perceived probability in the dynamic model. I assume the compliance year is 2016. To comply with MATS, decision-makers can choose to install abatement technologies, retire the unit, or switch to natural gas. Not all EGUs can be retrofitted into natural gas-fired units, and the number of such cases is small. I classify such a case as an exit. For abatement technologies, available choices include Activated Carbon Injection (ACI), Selective Catalytic Reduction (SCR), sorbent systems, and scrubbers. ACI is the primary technology that is designed specifically for removing mercury, while the other technologies are mainly for removing other pollutants but have the co-benefit of removing mercury. The costs and installation times may vary substantially for different abatement technologies and for different units. According to the EIA 860 form and the Brattle group analysis, ACI has the lowest costs and shortest time among these abatement technologies, with around $10 per kilowatt of capacity and 20 months for installation while the flue gas desulfurization has the highest costs, around $230 per kilowatt of capacity, and longest construction duration, around 50 months.[1] According to EIA, most of the pollution control equipment installed in 2015 and 2016 were ACI, and similar proportion among the other technologies. Several EGUs needed to install multiple technologies to comply with different environmental regulations. I consider installing any such abatement technologies as an investment, with similar costs, and can satisfy the MATS requirements.

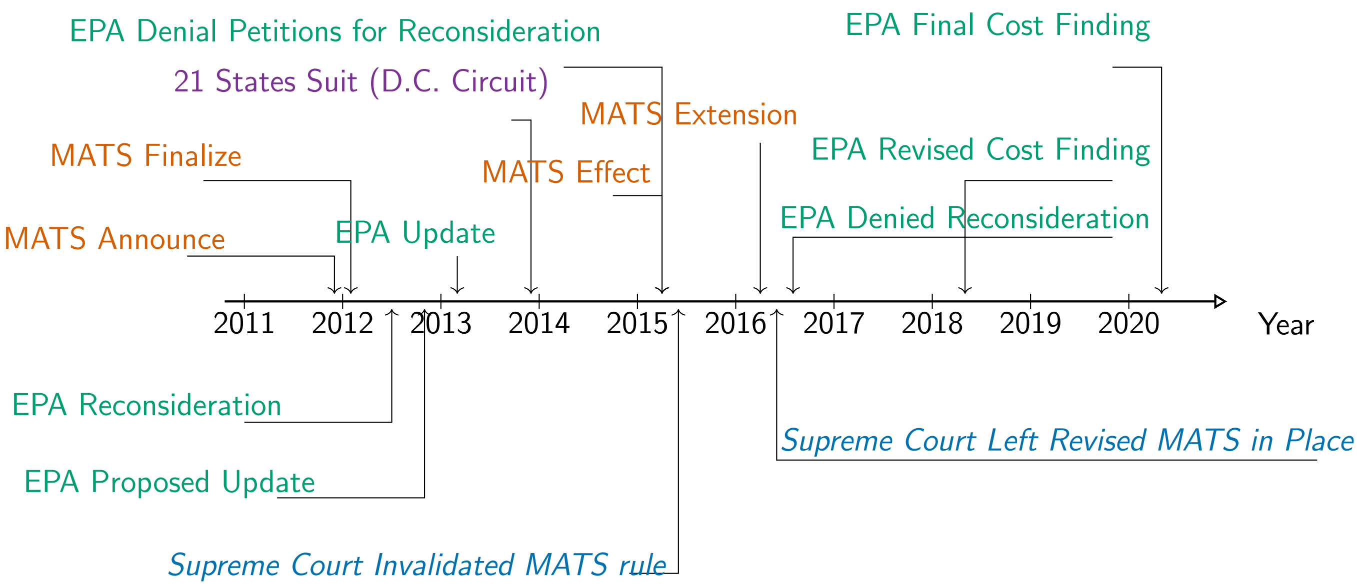

Figure 2: Time Line for MATS

MATS went through several legal challenges and made modifications in response to some petitions, which created policy uncertainty, but the policy survived until its compliance date. Figure 2 shows the history of MATS. Twenty one states sued the policy (Figure 11 in Appendix) in the U.S. Court of Appeals for the Disctrict of Columbia Circuit in December 2013, challenging the cost consideration of the MATS rule. The circuit court allowed the EPA to postpone cost analysis until it set specific pollution standards. EPA reconsidered and proposed to update emission limits under the MATS rule for new power plants but made no changes to the rule for the existing plants. In November 2014, the Supreme Court granted certiorari and consolidated three separate petitions into one case, Michigan v. EPA. EPA modified some technical details regarding MATS. In June 2015, the Supreme Court reversed the D.C. Circuit decision and ruled against the EPA. EPA issued rules to clarify the reporting procedure for MATS, denied all remaining petitions for reconsideration, and proposed supplemental finding of the costs of the rule according to the U.S. Supreme Court's decision. In February 2016, twenty states asked the U.S. Supreme Court to stay the implementation of MATS based on the June 2015 ruling. However, the request was denied by the Chief Justice John Roberts. Until April 2016, the extended compliance date, EPA had been making technical corrections and clarifications to the MATS rule while issuing findings to support that it was appropriate and necessary to regulate coal- and oil-fired power plants under MATS. Therefore, power plants still had to comply with MATS.

[1]The construction time does not represents the duration that an EGU has to stop operating. I did not observe more than one year of non-operation before installing any of the abatement technologies.

However, in late 2018, EPA revised the cost finding for MATS and determined that it was not "appropriate and necessary" to regulate hazardous air pollutant emissions from power plants under Section 112 of the Clean Air Act. Nevertheless, since EPA did not propose to remove the MATS rule, the emission standards and other requirements first announced in 2012 would remain in place. Even in 2020, EPA keeps modifying MATS and publishing new findings for the benefit and cost of MATS. For example, in April 2020, EPA established a new subcategory for EGUs that burn eastern bituminous coal refuse in MATS, which affected six small existing EGUs in Pennsylvania or West Virginia. And in May 2020, EPA again proposed the appropriate and necessary finding for MATS, stating the inappropriateness of the rule after correcting the flaws in the 2016 supplemental cost finding (**us˙epa˙regulatory˙2015**).

There is almost no time or spatial variation in the execution of MATS. Therefore, it is hard to separate the possibly time-varying impact of MATS from other time-correlated factors. To capture the major impact of MATS, I focus on one of the main objectives of MATS, which is to reduce mercury emissions. Several states announced and executed certain regulations to control mercury in coal-fired power plants before the MATS compliance date. I assume there is no regulation uncertainty in these states and use these states as a comparison group, analog to a fixed-effect model, to help infer the cost of investment and the installation timing before the compliance year. These will help the identification of the perceived probability of MATS being in place.

2.2 Data Sources

The data used in this study are from the Continuous Emission Monitoring System (CEMS), which includes all the coal-fired power plants regulated by the Acid Rain Program (ARP) in the U.S. The time range is from 1998 to 2018. I restrict the data to the eastern interconnection. There are three major interconnections in the U.S., and there is little transmission across the interconnections. This region is a suitable area for the study because it contains most of the coal-fired EGUs in the U.S. Electricity generation, and consumption can be shared within this region. Understanding how decisions are made in the eastern interconnection will be informative for how coal-fired power plants make decisions nationally. This data set contains the unit characteristics, including vintage year, heat input, gross load, abatement technology installed, total operating hours, and location. These variables are then used to compute the heat rate, capacity, aggregated demand, and define the mercury policy they subject to, local or federal (MATS), by their state.

Although the EIA 860 form provides the retirement year and month of each generator and boilers, there are discrepancies in the value reported across different years. Besides, the generating units observed on CEMS cannot be matched one-to-one to the generator or boilers. Lastly, generating units may stop operating long before the reported retirement date. Therefore, I use the last date of operation observed in CEMS as the retirement date. For the last year 2017, if the units did not operate at all in 2018 and 2019, it is considered retired. This definition matches the reported retirement well. The installation of an abatement technology is defined when a new technology is added to the generating unit and is qualified for removing mercury. The installation of an abatement technology is defined as when a new technology specifically for mercury is installed. Because other technologies can also remove mercury to a certain extent, I define the compliance of mercury policies as when they install a qualified technology for removing mercury or a combination of Selective Catalytic Reduction (SCR) and Wet Lime Flue-gas desulfurization (FGD). The installation year and thus the in compliance year is the latter of the two.[2]

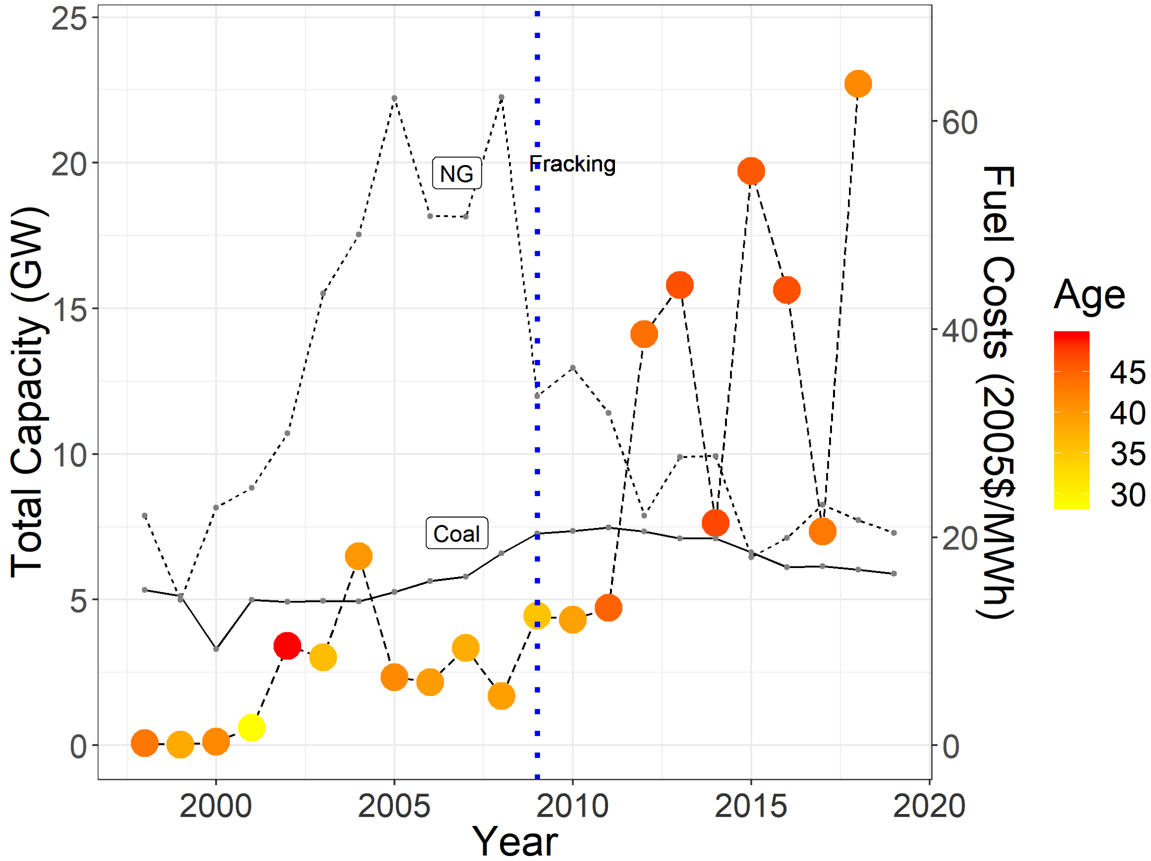

Figure 3: Coal-fired Generating Units Retirement Trend and Fuel Prices

I obtained annual Natural Gas prices and Coal prices from the Energy Information Administration (EIA) State Energy Data System. The data were only available up to the year 2017 by that time. The values are shown in Figure 3. Since the coal prices remained stable during the study period, considering the natural gas prices along is similar to considering the natural gas over coal prices ratio. However, I choose to include both variables for completeness.

Information for the state-level policy is collected by the Every Congressional Research Service (CRS) Report.[3] Due to the complexity of these policy specifications and the diverse conditions of the EGUs in these states, I cannot simply determine whether a state-level policy is stricter than MATS by reading the regulations. I supplement the state-level policy with the self-reported

[2]EPA also determines the compliance based on the technology installed rather than the emission level (Linn and McCormack, 2019).

[3]EveryCRS last visited 1/31/2020.

mercury policy stringency, collected from the EIA 860 form, to choose a set of states with stricter policy requirements as a comparison group. This creates the two groups “Local” and “MATS” and is used to determine the states to be used as the comparison group. However, due to the self-reporting noise, only the form in the year 2016 was used. If more than three units in one state report that the state level is stricter than MATS, that state is defined as a state with a more binding mercury policy and is used as the comparison group.

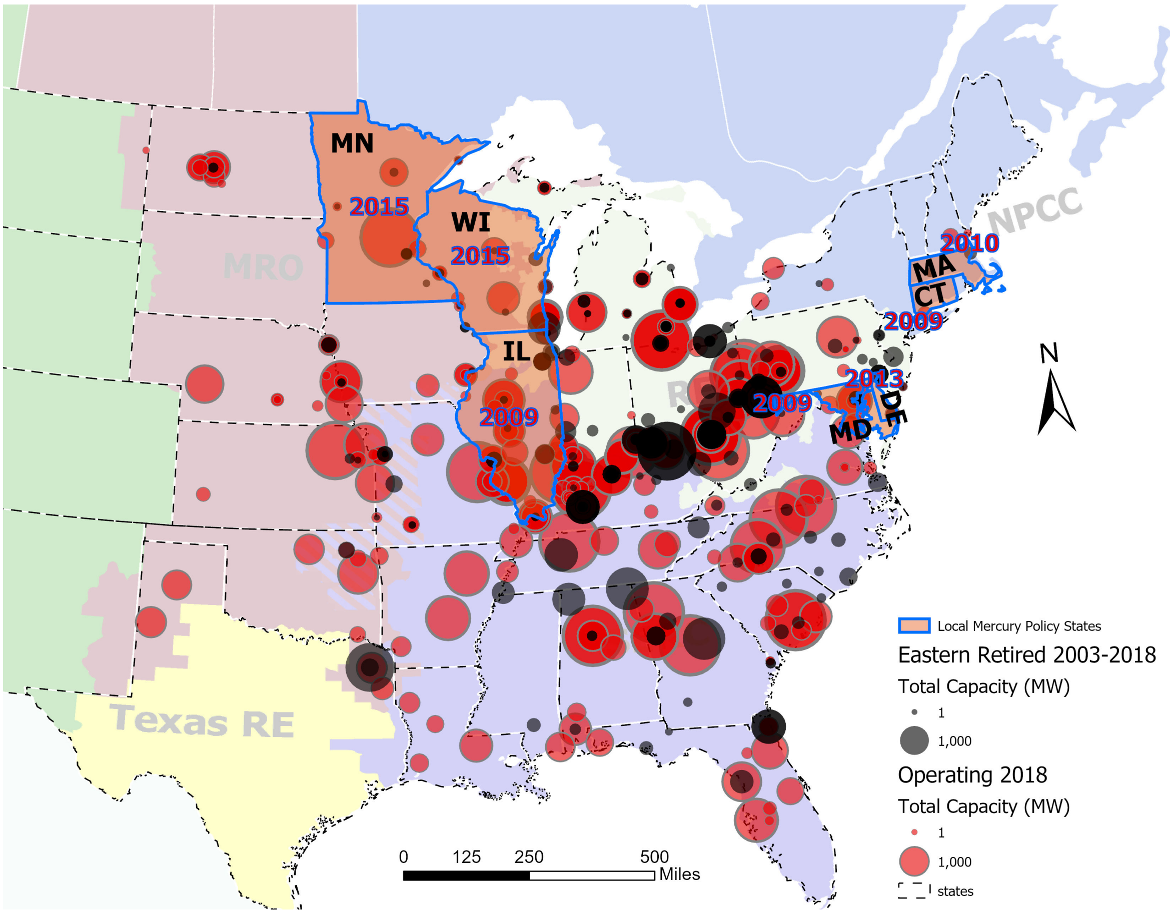

Figure 4: Local Mercury Policies

Table 1: Local Policy Enacted and Effected Years

State Abbreviation	State	Enacted	Effect
CT	Connecticut	2003	2009
MD	Maryland	2006	2009
IL	Illinois	2006	2009
MA	Massachusetts	2007	2010
DE	Delaware	2006	2013
MN	Minnesota	2006	2015
WI	Wisconsin	2008	2015

Figure 4 shows the geographical distribution of the coal-fired units by self-reported mercury policy stringency. The states with red boundaries are known to have announced and effected local mercury policies before 2015. The announced and effective years are in Table 1. These states promulgated their mercury policies separately and before the first announcement of MATS. The proposal of mercury policies are likely due to the environmental and health concerns of the state government rather than the coal-fired power plants' characteristics or the fuel or rate structure of the local power plants. Table 2 and table 3 compare the EGUs' characteristics in the two groups to support this argument.

Table 2: Summary Statistics for Coal-fired Units in the Two Regions

	Local (Obs = 3,283, N = 205)		MATS (Obs = 11,981, N = 699)		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Unit
Year	2006.547	5.505	2006.87	5.561	
Commercial Year	1964.069	12.896	1967.122	12.226	Years
Heat Rate	10.602	1.338	10.28	1.327	MMBtu/MWh
Annual Hours	6310.34	2106.512	6689.937	1936.112	Hours
Capacity	276.506	235.391	339.918	279.795	MW
Fuel Marginal Cost	19.033	6.296	18.028	5.913	2005$/MWh

Table 3: Summary Statistics for Natural Gas-fired Units in the Two Regions

	Local (Obs = 5,983, N = 439)		MATS (Obs = 22,995, N = 1,704)		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Unit
Year	2009.361	5.073	2009.15	5.156	
Commercial Year	1996.92	11.571	1991.209	16.074	Years
Heat Rate	11.998	4.062	11.909	3.692	MMBtu/MWh
Annual Hours	1096.912	1836.833	1971.869	2488.844	Hours
Capacity	195.58	3553.88	125.02	109.041	MW
Fuel Marginal Cost	60.48	34.812	58.228	31.324	2005$/MWh

Table 2 summarizes the coal-fired units in the eastern interconnection while Table 3 summarizes the natural gas-fired units. [4] The data used for the dispatch model include 904 coal-fired

[4] The other fossil fuel-fired units are in the appendix, Table 8 and Table 9.

generating units and 2,143 natural gas-fired units. The coal-fired units are similar in their characteristics except for their capacity. Units without a binding local mercury policy (the MATS group) on average are bigger, operate more hours annually, and have lower fuel costs.[5] Similar pattern for the natural gas-fired units in terms of operation hours and fuel cost, but the reverse relationship is observed for the capacity. On the contrary, in the MATS-only regions, these units tend to be smaller and supply a smaller amount of electricity annually. There is no large gap between the two regions in terms of the observed year and the units' commercialized year. Comparing across different fuel type, the natural gas-fired units are generally around thirty years younger and observed on average 3 years later than the coal-fired units, with higher heat rate (lower efficiency), operate around one-sixth or one-third of the time of the coal units and only supply around half as much as the coal-fired units in each hour.

Figure 5 compares the abatement technology installation for the two groups using an event study style graph. The y-axis shows the cumulative installation percentage of the units eventually installing the abatement technologies. The x-axis is the year to the compliance year of each mercury policy. The red line aligns the different compliance years in each state to 0. The green line is plotted by assuming that the targeted the deadline is 2015.[6] The slopes for the MATS group are generally smaller than those for the local group, which suggests a delay in installation.

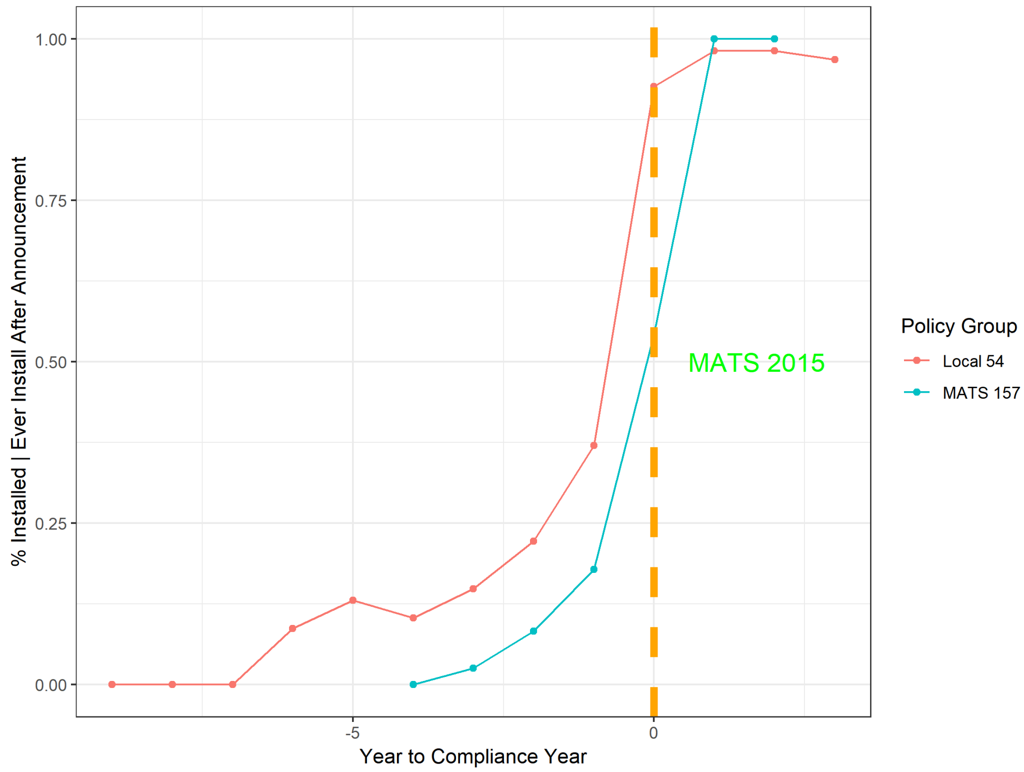

Figure 5: Installation Percentage Over Time

[5]The difference in the fuel cost comes from both their heat rate and the state-level annual coal prices. The values are different from those in Figure 3, which uses the national level cost and heat rate reported by EIA.

[6]This assumes that the policy was designed with 2015 as the compliance year to estimate the costs and benefits of the policy but allowed for an extension to 2016.

The final data set used for the dynamic model contains 895 coal-fired units. The status of these EGUs over time is depicted in Figure 10.[7] We see an increase in installing Mercury specific abatement technology in around 2014 and continue until 2016. There is also an increase in exit starting in around 2011 and continue until around 2015.

Theoretically, most of the units should comply by the year 2017, excluding those filed for an extension. However, according to CEMS, this was not the case. There may be a delay in the information updates, but the data were downloaded in 2019. Alternatively, there may be other combinations of technologies that qualify the units for MATS. The year 2018 is not included in the analysis due to the lack of price data. However, many units retired in that year.

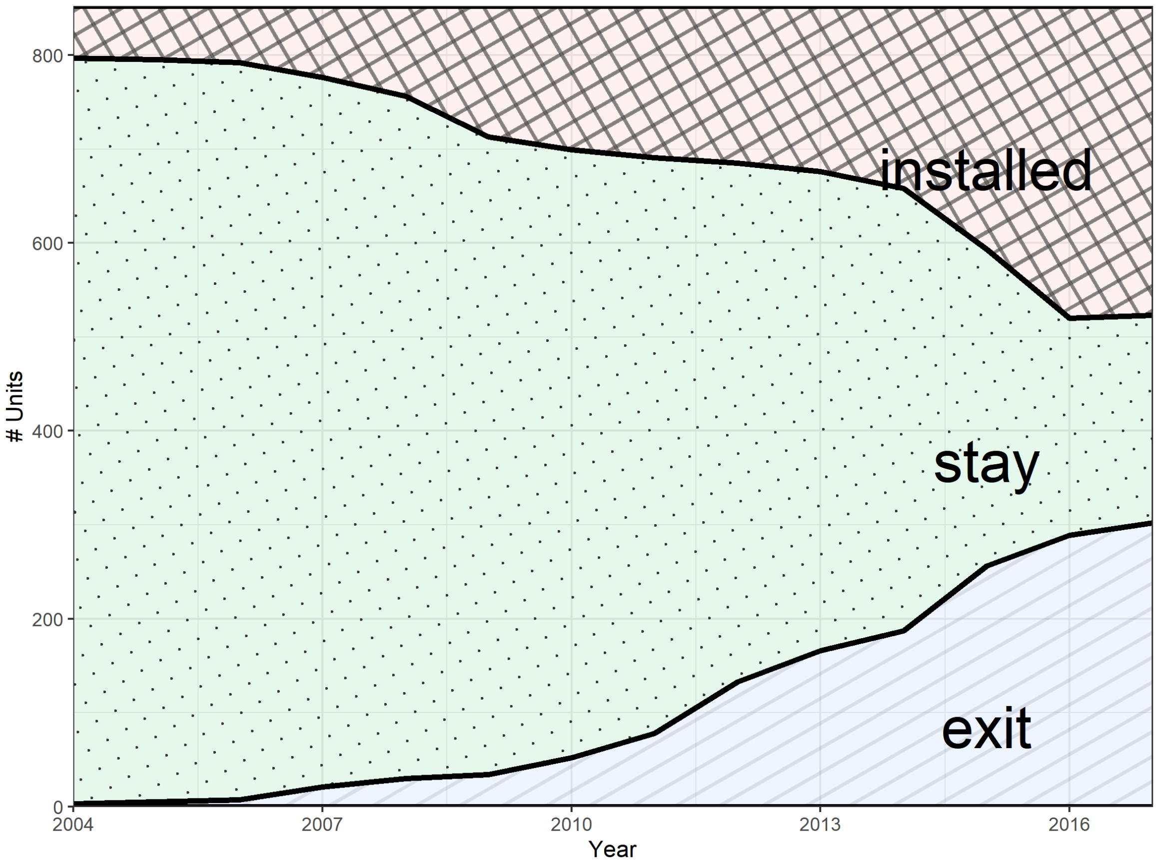

Figure 6: EGUs Status Over Time

3 Model

The model includes two main parts: the static dispatch model to estimate the variable annual operating profit and the dynamic investment and exit model to study the decision making under an evolving environment.

[7]Some units are not observed during the whole study period. This can either be due to not being regulated under any environmental policy that requires CEMS monitoring or late entry to the market. In making a graph, I assign the same status as their first observed status, while in doing the optimization, the choices were not observed and thus were ignored.

3.1 Dispatch Model

The dispatch model closely follows the approach of Borenstein et al. (2002), with some modifications in such as dealing with unit unavailability. The main idea is to calculate the marginal costs for each EGU to produce one hour of electricity, then order these units to create a supply curve. The demand curve is generally assumed to be perfectly inelastic, which determines the quantity and thus the equilibrium price given the supply curve (Figure 7).[8] I am aware that this approach may over-predict the effects of changing natural gas prices on coal-fired plants as shown in Linn and McCormack (2019). I plan to adopt their approach in the future work.

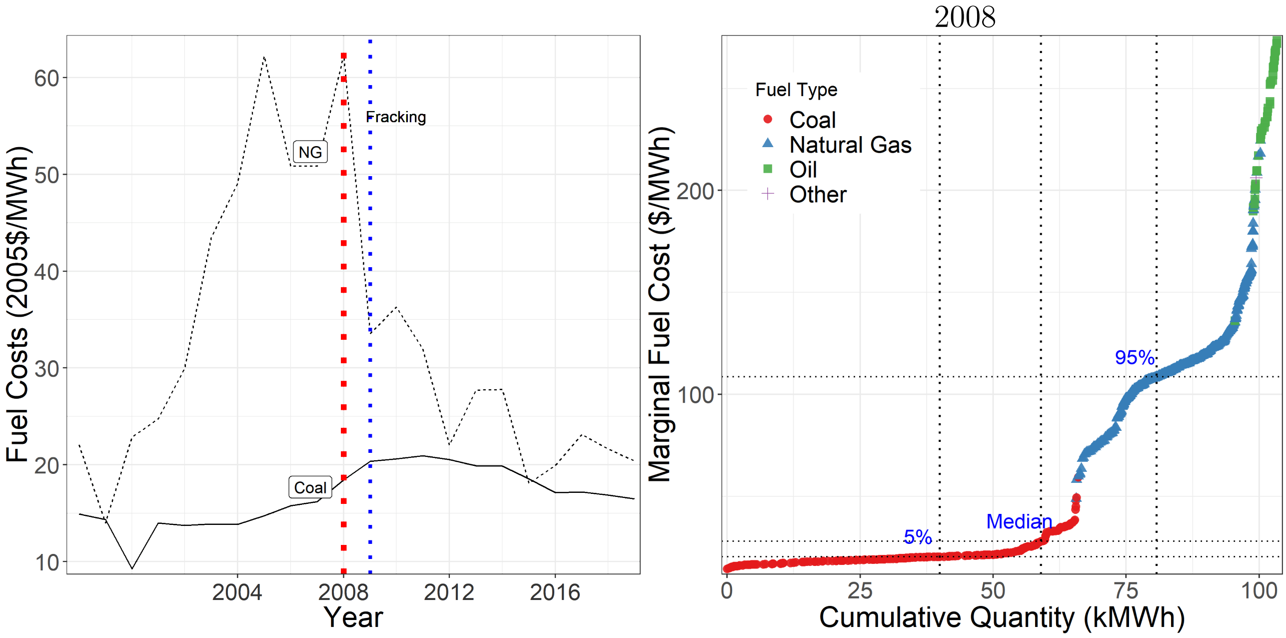

Figure 7: Fuel Costs and the Marginal Fuel Cost

To get the marginal costs, I consider only the fuel costs and non-fuel costs. The fuel cost is generally calculated as the fuel price times the heat rate, but the fuel price can vary at different levels, including at each unit level (Knittel et al., 2015), by state-year-fuel type (Johnsen et al., 2019) or by NERC-month-fuel type Linn and McCormack (2019). Due to restriction in the model computation complexity, I use the fuel prices at the state level and vary by year-fuel type.[9]

Similarly, there are many different approaches to estimate the non-fuel costs. I parameterize the non-fuel costs according to the fuel type and unit capacity and use optimization to get the parameters.

[8]The marginal fuel cost does not include the non-fuel cost and the units only include those in the PJM region. This is just an illustration of the supply curve but not the one actually used in the dispatch model.

[9]It may not be necessary to extend to month level as data are not available and profit will be aggregated to the annual level.

It is necessary to consider the costs of purchasing permits for NOx and SO_2 during the earlier part of the study period, before a large amount of exit was observed. However, soon the permit price dropped and the allocation was no longer binding (Cullen and Reynolds, 2017; Johnsen et al., 2019). Most of such costs lied in installing abatement technologies and most EGUs install abatement technologies that are intended for NOx.

The major steps for the dispatch model are as follows: first estimate the non-fuel costs parameters, calculate the non-fuel costs and then the marginal costs for each unit, schedule the dispatch curve according to the marginal costs to get the supply curve and calculate the variable annual profit.

To estimate the non-fuel costs parameters, I first run a simple regression using the actual operation hour only controlling for the marginal fuel costs from 1998-2017 during hours that the total gross load is within 30% - 70% of the distribution. The residuals from this regression are taken as the non-fuel costs.

$$y_{ift} = \alpha \text{fuel cost}_{ift} + \zeta_{ift}$$

where y_{ift} is the annual operating hours for unit i using fuel type f in year t. Using the gross load within this range is because when demand is in this range, there is unlikely to have transmission congestion across the smaller regional transmission organizations (RTOs) (Linn and McCormack, 2019).

I then adjust the non-fuel costs using the following parametrization:

$$\text{non-fuel cost}_{ift} = \alpha_{0f} + \alpha_{1f} * \hat{\zeta}_{ift}$$

where α_{0f} is a constant for each fuel type and α_{1f} represents the scaling of each fuel type, applied to the estimated residual.[10] Using the adjusted non-fuel costs, I run the dispatch model and search for a set of parameters that better fit the observed operation decision using only the base year 2005. [11] Then the fitted non-fuel costs are fixed in predicting all other years. [12]

After getting the non-fuel cost, the marginal cost of producing electricity in each hour is calculated and used to schedule the supply curve. The demand is stable over time and is assumed to be known at the beginning of the study period. [13] These provide sufficient information for running the dispatch model. After estimating the profit in each year using the dispatch model, the variable annual operational profit $var\pi$ for coal-fired EGUs are estimated and will be predicted using a regression of the following specification:

$$var\pi_{it} = f(D_t, cap_i, hr_i, r_t) + \eta_{it}$$

[10] There are four fuel types, coal, natural gas, oil and other. The constant for oil is normalized to 0.

[11] The base year is pseudo-randomly picked (mainly because this is the base year used in Linn and McCormack (2019)).

[12] In the previous version, when I did this only in the PJM region, I allow each unit to have its own non-fuel cost by doing the optimization one for each unit.

[13] The actual demand is lower than the trajectory projected by EIA, I plan to incorporate such expectation in the future model.

where the f contains the combination of each variable on their own and the two-by-two interaction of the three variables.

There are several features in the conventional dispatch model. The first one is that it does not consider the dynamic startup and shutdown as discussed in Cullen and Reynolds (2017). Instead, it assumes that each hour is independent of other hours. The startup and shutdown frequency for coal-fired generating units is low. The frequency may increase when coal-fired EGUs approach their retirement but certainly not to the extent of turning on and off hourly (Zhang, 2020). Linn and McCormack (2019) show that a conventional economic dispatch model may overpredict the impact of natural gas prices on coal-fired power plants' hourly operation and thus exit decision.

3.2 Single Agent Model

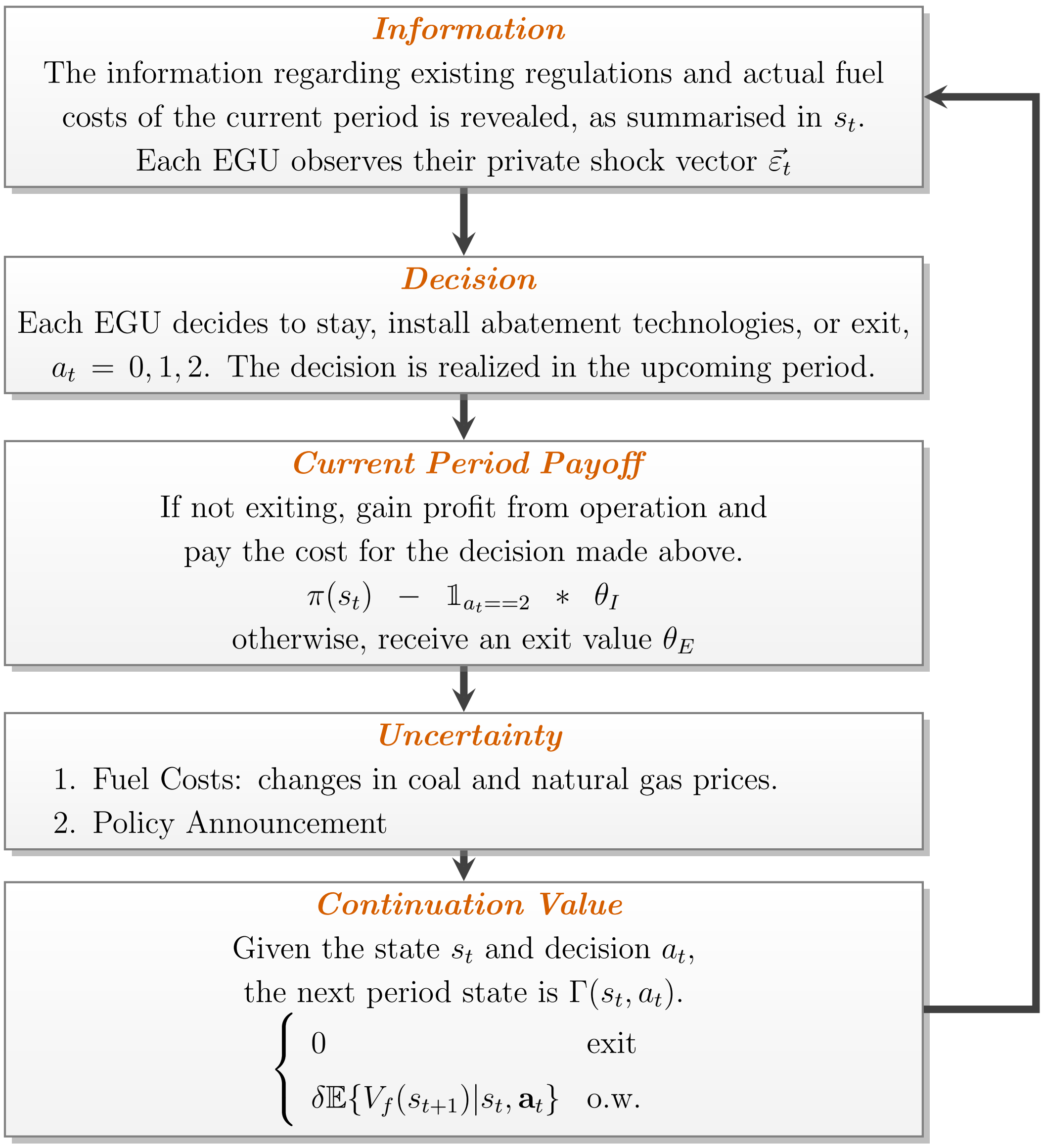

Figure 8: Dynamic Model Timeline

Figure 8 shows the timing of the dynamic model. By the end of each year, the decision-maker privately observes the set of shocks $\vec{\varepsilon_t}$ associated with each decision they make. The exit value θ_E and installation value θ_I is known and remains constant all the time. The state of the coming year s is realized. Next, the variable profit $var\pi$ can be calculated based on this information, and the future continuation value $\mathbb{E}V(s'|s)$ can be calculated, based on the transition assumed. Knowing this information, the decision-maker can choose an action among exit, stay in the market and install an abatement technology while staying in the market. If the decision-maker chooses to install an abatement technology, the installation is assumed to be completed in the next year. Therefore, observing any technology in the coming year will infer an installation decision at the end of the previous year.

For a unit i without any environmental regulations for mercury, the continuation value can be written as the Bellman equation:

$$V(s,\varepsilon;\theta) = \max_a \begin{cases} \theta_E\kappa + \varepsilon_0 & a=0 \\ \pi(s_1,r) + \beta\mathbb{E}[V(s')|s,a] + \varepsilon_1 & a=1 \\ \theta_I\kappa + \pi(s_1,r) + \beta\mathbb{E}[V(s')|s,a] + \varepsilon_2 & a=2 \end{cases}$$

where κ is the capacity of each EGU, θ_E is the exit value per unit of capacity, and θ_I is the value for installing the abatement technology per unit of capacity. Both parameters are the same for all EGUs.

The current state variable $s = (s_1, s_2, s_3) \in \Omega$ summarises the sufficient information for decision makers to form expectation about the future. Let Ω denote the set of possible states,

$$s = (\underbrace{D,\kappa,hr}_{s_1\in\Omega_1}, \underbrace{i,t}_{s_2\in\Omega_2}, \underbrace{r,Ddl}_{s_3\in\Omega_3}), \quad s\in\Omega$$

$s' = (s'_1, s'_2, s'_3) \in \Omega$ is the transited state variable given s, action a, and transition function Γ, $s' = \Gamma(s,a)$. $s_k, s'_k \in \Omega_k$, $k = 1,2,3$. There are three sets of variables in the state. Ω_1 contains all the constant variables, which remain constant for each unit over time; Ω_2 contains the deterministic variables, t for the calendar year and i, for installation status, its transition is completely determined by the action. Once a unit chooses to exit, the status will remain "exit" and no more actions can be made; when a unit chooses to install, the status will transit to "installed" and only choosing "exit" can change this status. In all other cases, the status remains the same as the previous period. Finally, Ω_3 contains the stochastic variables r and policy compliance year Ddl. The second one is determined by the actual observed policy, though not known to the decision-makers until the announcement year. The first one is stochastic and transit according to the transition matrix in Table 4.

$\pi(s_1, r)$ is the variable profit from annual operation, estimated in the dispatch model, and predicted using the regression $\pi(s_1,r) = \hat{f}(D,\kappa,hr,r)$, a function of electricity demand D, unit capacity κ, unit heat rate hr, and the coal over natural gas price ratio r in each year t and is predicted by the regression. The expectation $\mathbb{E}$ for the continuation values $V(s')$ is taken over the possible transited values of r', conditional on the current r, and the unobserved shocks in the next period. I assume there are random shocks associated with each action that are privately observed by the decision-makers, ε_a, which are i.i.d. following the Extreme Value Type I Distribution with mean $\mu = 0$ and a scale parameter θ_b. One example of such shocks can be the maintenance schedule of the units. [14] The discount factor $\beta = 0.9$ is as generally assumed. [15]

The choice set A changes depending on the policies' compliance year, Ddl, the current year t, and the units' installation status. After the year 2016, there are no environmental policies for mercury. Each decision-maker can choose among three options, 0 for exit, 1 for staying in the market without installing any abatement technologies, and 2 for installing a technology to comply with the policy, $A = \{0, 1, 2\}$. Note that the model allows the decision-makers to install an abatement technology even when they have installed the necessary technology but do not keep track of the number of such decisions. There are very few re-installation observed in the data. Estimating the parameters using such information is neither useful nor helpful for the primary goal of the model. However, it is natural to keep this option available for the installed EGUs to be comparable to those have not installed, although the option of installing the technology again is too bad to be chosen again.[16] At the beginning of the compliance year, for units that have not installed the necessary abatement technologies, they can only choose between two actions, exit or install, $A' = \{0, 2\}$. Take units subjecting only to MATS, have not installed the necessary abatement technologies, and in the compliance year, they are choosing between two options, and the continuation value is

$$V^M(s, \varepsilon; \theta) = \max_a \begin{cases} \theta_E \kappa + \varepsilon_0 & a = 0 \\ \theta_I \kappa + \pi(s_1, r) + \beta \mathbb{E}[V(s')|s, a] + \varepsilon_2 & a = 2 \end{cases}$$

where the modified continuation value has a superscript M to indicate that the units are in the compliance year of a mercury policy and are not yet in compliance. This information is included in s but writing this out distinguishes such continuation values from others, which are denoted as $V(s)$.

Roll back one year to 2015, let $\mathbb{1}_M$ be an indicator for whether the unit needs to take action to be in compliance. $\mathbb{1}_M = 1$ for units not yet in compliance and $\mathbb{1}_M = 0$ otherwise. Assume all

[14] This is coded as scaling the profit, exit value, and the investment cost by $\frac{1}{\theta_b}$, they are mathematically equivalent.

[15] The identification of the subjective probabilities relies on the discount factor. If the discount factor were heterogeneous across EGUs, this would bias the estimation downwards, since firms with a smaller discount factor will delay making decisions.

[16] Simulating the model while restricting the choice set of those installed to only exit and stay will lead to very little investment because removing the option makes the two paths no longer comparable.

units believe that MATS will be enforced in 2016 with probability p_{15}:

$$V_{15}(s,\varepsilon;\theta_{15}) = \max_a \begin{cases} \theta_E\kappa + \varepsilon_0 & a=0 \\ \pi(s_1,r) + \beta\mathbb{E}[\mathbb{1}_M p_{15} V^M(s') + (1-\mathbb{1}_M p_{15})V(s')|s,a] + \varepsilon_1 & a=1 \\ \theta_I\kappa + \pi(s_1,r) + \beta\mathbb{E}[V(s')|s,a] + \varepsilon_2 & a=2 \end{cases}$$

where θ_{15} means using p_{15} as the probability. With the type I extreme errors, the expected value for the continuation value over the possible shocks is

$$\begin{aligned} \mathbb{E}_\varepsilon[V_{15}(s,\varepsilon;\theta_{15})] &= \iiint_{\boldsymbol{\varepsilon}} \max_a \begin{cases} \theta_E\kappa + \varepsilon_0 \\ \pi(s_1,r) + \beta\mathbb{E}[\mathbb{1}_M p_{15} V^M(s') + (1-\mathbb{1}_M p_{15})V(s')|s,a] + \varepsilon_1 \\ \theta_I\kappa + \pi(s_1,r) + \beta\mathbb{E}[V(s')|s,a] + \varepsilon_2 \end{cases} d\boldsymbol{F}(\boldsymbol{\varepsilon}) \\ &= \theta_b\left\{\gamma + \ln\left[\exp\left(\frac{\theta_E}{\theta_b}\right) + \exp\left(\frac{\delta_{1,15}(s)}{\theta_b}\right) + \exp\left(\frac{\delta_2(s)}{\theta_b}\right)\right]\right\} \end{aligned}$$

where $\delta_{1,15}(s) = \pi(s_1,r) + \beta\mathbb{E}[\mathbb{1}_M p_{15} V^M(s') + (1-\mathbb{1}_M p_{15})V(s')|s,a]$ and $\delta_2(s) = \theta_I\kappa + \pi(s_1,r) + \beta\mathbb{E}[V(s')|s,a]$.

Iterate the above procedure for 2014, 2013, and 2012 with probability p_{14}, p_{13} and p_{12} respectively, for $t = 14, 13, 12$:

$$V_t(s,\varepsilon;\theta_t) = \max_a \begin{cases} \theta_E\kappa + \varepsilon_0 & a=0 \\ \pi(s_1,r) + \beta\mathbb{E}[V_{t+1}(s',\varepsilon;\theta_t)|s,a] + \varepsilon_1 & a=1 \\ \theta_I\kappa + \pi(s_1,r) + \beta\mathbb{E}[V(s')|s,a] + \varepsilon_2 & a=2 \end{cases}$$

And for the years before, all units that are not subject to their local regulations are making decisions using the fixed-point solution. The backward induction for units subjecting to their local regulations is the same as MATS except for that all probabilities are 1. Altogether, there are seven parameters to be estimated: $\theta = (\theta_E, \theta_I, \theta_b, p_{12}, p_{13}, p_{14}, p_{15})$

Table 4: Transition Matrix For Natural Gas Over Coal Price Ratio

		next period price ratio		
		0.45	0.6	0.75
current price ratio	0.45	0.882	0	0.118
	0.6	0.333	0.5	0.167
	0.75	0	0.5	0.5

Table 4 shows the transition probabilities. They are estimated from the actual national price ratios observed from 1990 to 2016. The ideal case is to have more intervals that better approximate different scenarios. However, due to the lack of observations, the transition probability will not be accurate when using more intervals. One drawback of this is that the variation in the annual variable profit will be limited by the number of intervals and may not well represent the actual profit.

The expectation of the next period continuation value $V(S')$ is taken over all the possible next period price ratios and if during 2012 to 2015 without a binding local mercury policy, the expectation also includes two possibilities: MATS will remain in place the next period or MATS will be removed, and no other policy is binding. Note that units subjected to a more binding local policy are completely not affected by MATS. The situation is more complicated when there is a local policy weaker than MATS. Since the number of observations in such a case is small, this is ignored. The subjective probability that decision-makers believe that MATS will remain in place the next period is denoted as p.

The set of parameters to be estimated in the dynamic model is $\theta = (\theta_E, \theta_I, \theta_b, \vec{p})$.

4 Estimation

4.1 Dispatch Model

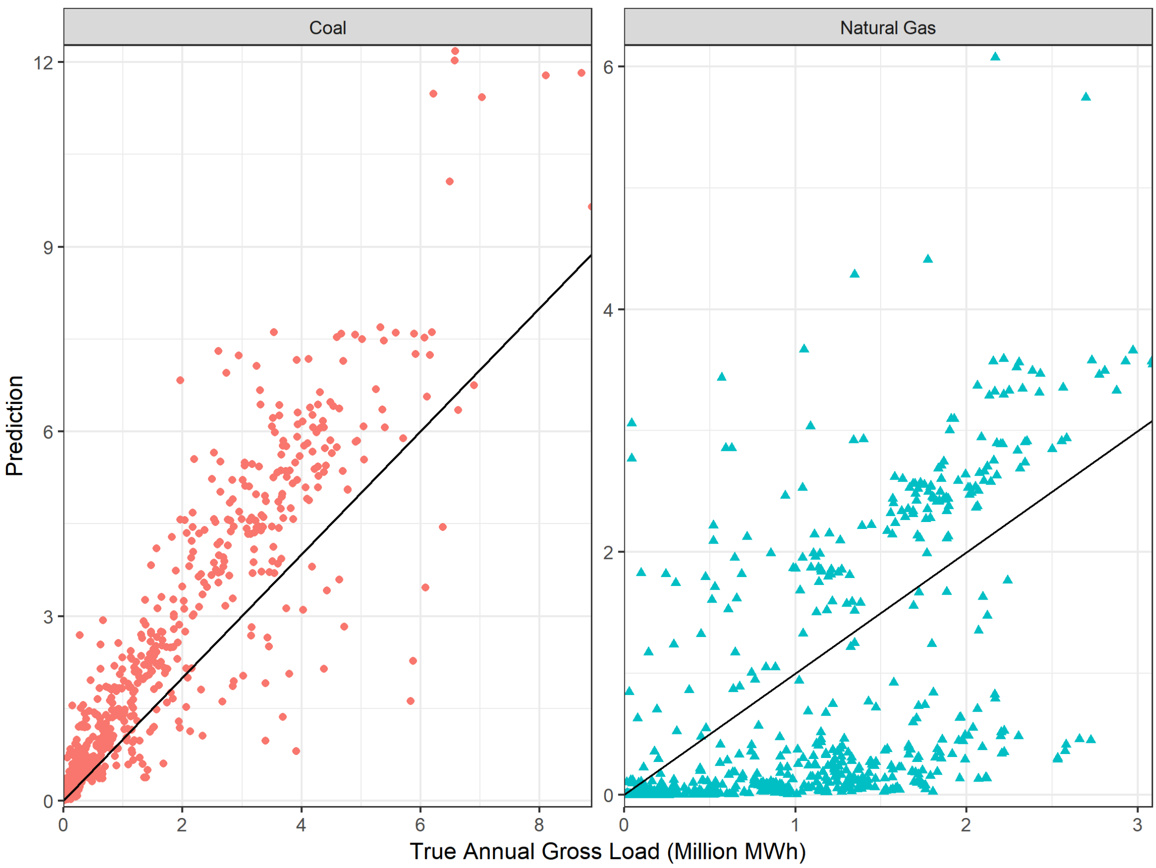

Figure 9: Fitting the Predicted Profit in another Year 2015

The dispatch model is used in all years to calculate the annual variable profit. Then the profit is used in a regression to for estimating the variable profit under other market conditions. The goodness-of-fit for the regression is included in the appendix in Figure 16. Figure 9 shows the prediction of the annual variable operational profit for the year 2015. [17] The prediction for coal units fit the results well, though not so much for some natural gas-fired units. This could be due to that most of the natural gas-fired units are built in the latter years and were not included in the optimization search in the base year, so the estimation for the constant and scale for the natural gas-fired units do not represent the features for the newer units.

4.2 Dynamic Model

Assume after the year 2017, market conditions do not change and there will not be any new policy. Then the model in this part is the standard Bellman equation and can be solved using a nested fixed-point algorithm (Rust, 1987). Given the fixed-point solution, the earlier years' value function can be calculated using the backward induction as described in the model part.

By assuming that the error terms are i.i.d following the type I extreme value distribution with mean 0 and a scale parameter of θ_b, $\varepsilon \sim G(0, \theta_b)$, the probability of each choice is as follows[18]

$$P(a^*|s,\theta) = \frac{\exp(\delta_{a^*}/\theta_b)}{\sum_{a \in A_s} \exp(\delta_a/\theta_b)}$$

And use maximum likelihood estimation to estimate the parameters of interest (John, 1988).

$$\max_{\theta \in \Theta} \log(\mathscr{L}) = \sum_{t,n} \log(\sum_{c} \mathbb{1}\{c_{t,n} = a^*\} P(c_{t,n}|s_{t,n}, \theta))$$

Given the continuation value, the probability of each choice can be calculated, and finally, maximizing the above likelihood to estimate the parameters of interest. [19]

Each unit has its own Bellman equation due to the differences in their capacity and heat rate. Having a separate Bellman equation for each unit is important to estimate the variable profit better. However, there is no heterogeneity in the parameters for the units, except for scaling by their capacity. All units are assumed to share the same set of parameters $\theta = (\theta_E, \theta_I, \theta_b, \vec{p})$. Due to the limited number of observations and the investment decisions in year 2012, the estimation for p_{12} is constrained to be the same as p_{13}.

Implicitly assumed here is that the mercury policy at the state or local level requires installing an abatement technology with the same costs as MATS, and there is no policy uncertainty in

[17] The prediction for the year 2010 is in the appendix in Figure 17.
[18] When $n = 1, m = 1$ in the compliance year, A_s contains only $\{0, 2\}$, otherwise, $A_s = \{0, 1, 2\}$
[19] Using nloptr with Neldermead algorithm in R (Nelder and Mead, 1965).

these local policies. Likely the local policies are with a certain uncertainty. Assume the costs are the same across different policies, then ignoring such uncertainty will bias the costs upwards. Thus the estimated subjective probability for MATS is biased downwards.[20]

5 Results

5.1 First Stage Estimates

$$\pi(s_1, r)_{it} = f(D, \kappa, hr, \text{Fuel Cost}) + \zeta_{it}$$

Table 5 shows the regression results for fitting the variable profit using different specifications. The number 1 and 2 indicate the highest degree of the variable in the regression function. The preferred specification is in the last column in which all the interaction of demand, capacity, and heat rate are included and only includes one stochastic variable, coal over natural gas prices ratio, as the control variable. The model fit for this specification is not much worse than the best model fit, and it uses only one stochastic variable, which reduces the complexity of the dynamic model.

Table 5: Variable Profit Prediction

Coal Cost			1			1	
NG Cost			1			1	
Coal/NG ratio				2			2
Demand	2	2	2	2	2	2	2
Capacity		2	2	2	2	2	2
Heat Rate					1	1	1
Observations				10,048			
adj.R-squared	0.0274	0.5992	0.7471	0.7122	0.6040	0.7517	0.7159

5.2 Bellman Equation Estimation Results

Table 6 shows parameters estimated in the dynamic model. The scale is in 100 (2005$) per kW for the first two variables. The estimated cost of investment is far too high, around $700 per kW. This may result from the not accurate prediction and the lack of variation in the annual profit. The exit value θ_E may represent not only the scrap value but also the best outside

[20] Alternatively, can think of the estimated probability is conditional on the likelihood that local policy happens, therefore the unconditional probability should be smaller.

option. Given the fast-developing technologies in renewable energy and the decreasing natural gas prices, a positive exit value suggest that retiring the current coal-fired unit and switching to other fuel sources may be profitable. However, this could also be due to the estimation of the profit. The subjective probability of MATS being in place is estimated to be less than 1, though the confidence interval is yet to be estimated.[21] The probabilities for the first two years are restricted to be the same, the estimated probabilities are around 61%, 67%, and 83%, respectively. According to the estimation, in 2015, the decision-makers perceive a 17% probability that MATS will be removed before its compliance year 2016. As mentioned before, this is a relative value to the local policy and thus the actual absolute probability could be smaller. The third parameter represents the scale of the extreme type I value random shocks. A larger value may suggest more heterogeneous conditions that different units in different years are facing.

Table 6: Dynamic Parameters Estimation

θ_E	θ_I	θ_b	$p_{12} = p_{13}$	p_{14}	p_{15}
20.406	-6.988	0.463	0.613	0.669	0.834

Note: Exit value and installation cost in hundred 2005$ per kW.

[21] I will bootstrap a subset of the observations by EGUs, estimate the parameters based on the subset to calculate the standard errors. This will be done with High-Performance Computing (HPC) at the University of Arizona.

5.3 Goodness-of-Fit

Table 7: Observed versus Simulated Choices (%) by Policy X Installation Status

	Observed				Simulated			
	# Obs	Exit	Stay	Install	# Obs	Exit	Stay	Install
No Policy								
Not Installed	5615	1.674	96.972	1.354	4644	1.141	92.808	6.051
Installed	1083	0.554	94.737	4.709	2357	1.103	80.653	18.244
Local								
Not Installed	697	4.304	88.379	7.317	436	8.716	80.505	10.780
Installed	87	0.000	96.552	3.448	376	0.532	82.447	17.021
MATS								
Not Installed	1873	8.970	82.648	8.382	1347	9.800	84.707	5.494
Installed	693	0.577	99.278	0.144	1450	0.759	81.655	17.586

Note: Observed Obs = 10,048, Simulated Obs = 10,610.

In Table 7, I show the percentage of choices under one simulated path using the fitted dynamic model $p(a|s, \hat{\theta})$ versus the observed (nonparametric) estimates of the conditional choice probability $\hat{p}(a|s)$ the observed estimates are just the mean.[22] According to Table 7, the model over predicts exit and installation in all cases other than no policy and not installed.

Figure 10 shows one simulated decision-making over time given the set of estimated parameters. Each unit's path is simulated using a series of pseudo-random draws from the type I extreme value distribution with the estimated scale parameter. [23] The simulated path for exit is close to the observed data but not so for the installation. The simulated choices for installation decisions happen much earlier than the observed. Suggesting that the estimated installation cost may be too small compared to the variation in the unobserved shocks. The last year of the simulated path is close to horizontal for the installation, suggesting mild investment after the MATS policy. On the contrary, the number of exit remains high, which should be driven by the change in fuel prices.

[22]Test of the goodness-of-fit will be added later.
[23]The confidence interval will be added later.

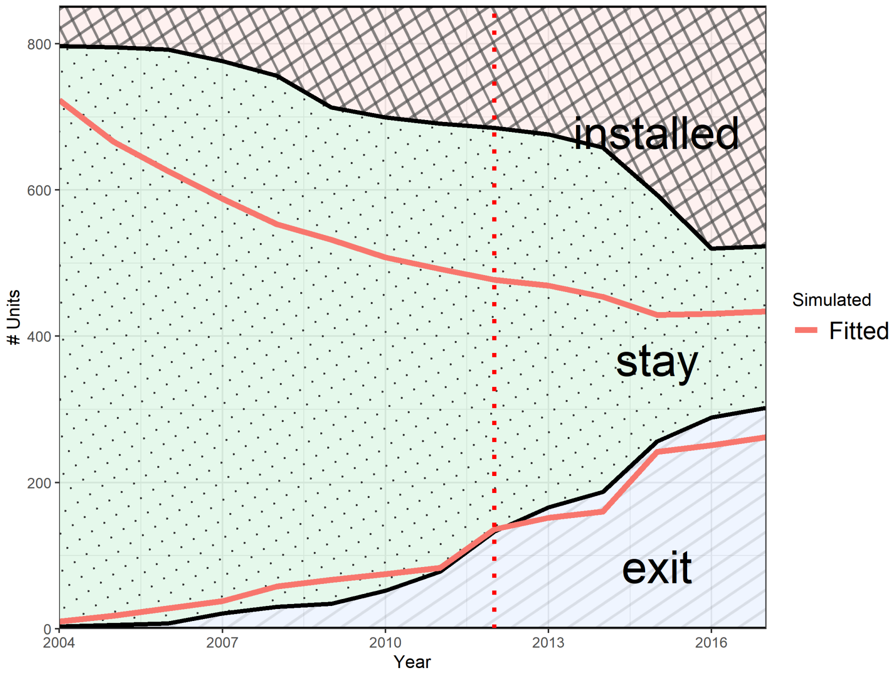

Figure 10: Simulated EGUs Status Over Time

Table 7 does not correspond to Figure 10 as the observed choices are not a full panel. There are missing observations both in the beginning and at the end of the study period due to late entries and early exits.

Since this is a single-agent model, the counterfactual cannot fully reveal the general equilibrium effect like an oligopoly model. Counterfactual analysis is not appropriate in this study.

6 Conclusions and Discussions

Empirical studies about uncertainty are rare due to the difficulties in measuring uncertainty and separating the effects of uncertainty from other factors. I incorporate a DID framework into a single-agent investment and exit model to estimate the policy uncertainty of MATS. Decision-makers perceive a probability of 83% for the last year before the compliance year, which means with a 17% probability, they believe that MATS will not be implemented. The probability of MATS being in place is smaller for the earlier years.

There are many limitations in this study. My model only considers the natural gas prices as the market condition and the MATS policy with uncertainty as the major environmental regulation. The model does not consider other costs, for example, the costs of purchasing permits to emit NOx and SO_2, which are estimated to increase around 10% of the marginal cost mainly in the coal-fired EGUs Linn (2010) during 2000 to 2005.

There are many limitations in the current model. For example, the coal-fired generating units are modeled as a single agent, and multiple units within the same power plant are assumed to operate independently. One extension can be using a dynamic oligopoly model to capture the interaction among the existing generating units. This will incorporate the dispatch model into the dynamic model and improve the calculation of profit. The challenge here is the computational complexity, but the gain is the ability to do counterfactual analysis and quantify the impact of such uncertainty.

My analysis does not speak to the impact on emission and thus the environmental benefit affected by the uncertainty. It only presents the existence of uncertainty. This suggests that environmental policy should take uncertainty into account when at the design stage. Future research can extend the study to analyze the cost in terms of increased electricity prices versus the benefit in terms of health improvement.

References

Borenstein, S., Bushnell, J. B., & Wolak, F. A. (2002). Measuring market inefficiencies in california's restructured wholesale electricity market. *American Economic Review*, *92*(5), 1376–1405.

Carvalho, A., & Guimaraes, B. (2018). State-controlled companies and political risk: Evidence from the 2014 Brazilian election. *Journal of Public Economics*, *159*, 66–78. https://doi.org/10.1016/j.jpubeco.2018.02.002

Cullen, J. A., & Reynolds, S. S. (2017). *Market dynamics and investment in the electricity sector* (tech. rep.). Working paper.

Dixit, A. K., Dixit, R. K., & Pindyck, R. S. (1994). *Investment Under Uncertainty* [Google-Books-ID: VahsELa_qC8C]. Princeton University Press.

Dorsey, J. (2019). Waiting for the Courts: Effects of Policy Uncertainty on Pollution and Investment [00000]. *Environmental and Resource Economics*, *74*(4), 1453–1496.

Fell, H., & Kaffine, D. T. (2018). The fall of coal: Joint impacts of fuel prices and renewables on generation and emissions. *American Economic Journal: Economic Policy*, *10*(2), 90–116.

Gowrisankaran, G., Reynolds, S. S., & Samano, M. (2016). Intermittency and the value of renewable energy. *Journal of Political Economy*, *124*(4), 1187–1234.

John, R. (1988). Maximum likelihood estimation of discrete control processes. *SIAM journal on control and optimization*, *26*(5), 1006–1024.

Johnsen, R., LaRiviere, J., & Wolff, H. (2019). Fracking, coal, and air quality. *Journal of the Association of Environmental and Resource Economists*, *6*(5), https://doi.org/10.1086/704888, 1001–1037. https://doi.org/10.1086/704888

Kellogg, R. (2014). The Effect of Uncertainty on Investment: Evidence from Texas Oil Drilling. *American Economic Review*, *104*(6), 1698–1734. https://doi.org/10.1257/aer.104.6.1698

Knittel, C. R., Metaxoglou, K., & Trindade, A. (2015). *Natural gas prices and coal displacement: Evidence from electricity markets* (tech. rep.). National Bureau of Economic Research.

Langer, A., & Lemoine, D. (2020). What Were the Odds? Estimating the Market's Probability of Uncertain Events, 50.

Linn, J. (2010). The effect of cap-and-trade programs on firms' profits: Evidence from the nitrogen oxides budget trading program. *Journal of Environmental Economics and management*, *59*(1), 1–14.

Linn, J., & McCormack, K. (2019). The roles of energy markets and environmental regulation in reducing coal-fired plant profits and electricity sector emissions. *The RAND Journal of Economics*, *50*(4), 733–767.

Nelder, J. A., & Mead, R. (1965). A simplex method for function minimization. *The computer journal*, *7*(4), 308–313.

Rust, J. (1987). Optimal replacement of gmc bus engines: An empirical model of harold zurcher. *Econometrica: Journal of the Econometric Society*, 999–1033.

Schiavo, J. G., & Mendelsohn, R. (2019). The Effect Of Domestic Air Pollution Mitigation And Fracking On Retirements Of Coal Power Plants. *Climate Change Economics (CCE)*, *10*(02), 1–21. https://doi.org/10.1142/S2010007819500088

Zhang, W. (2020). *Emissions from Coal-Fired Power Plant Retirements* (Working paper). University of Arizona.

Appendices

A MATS

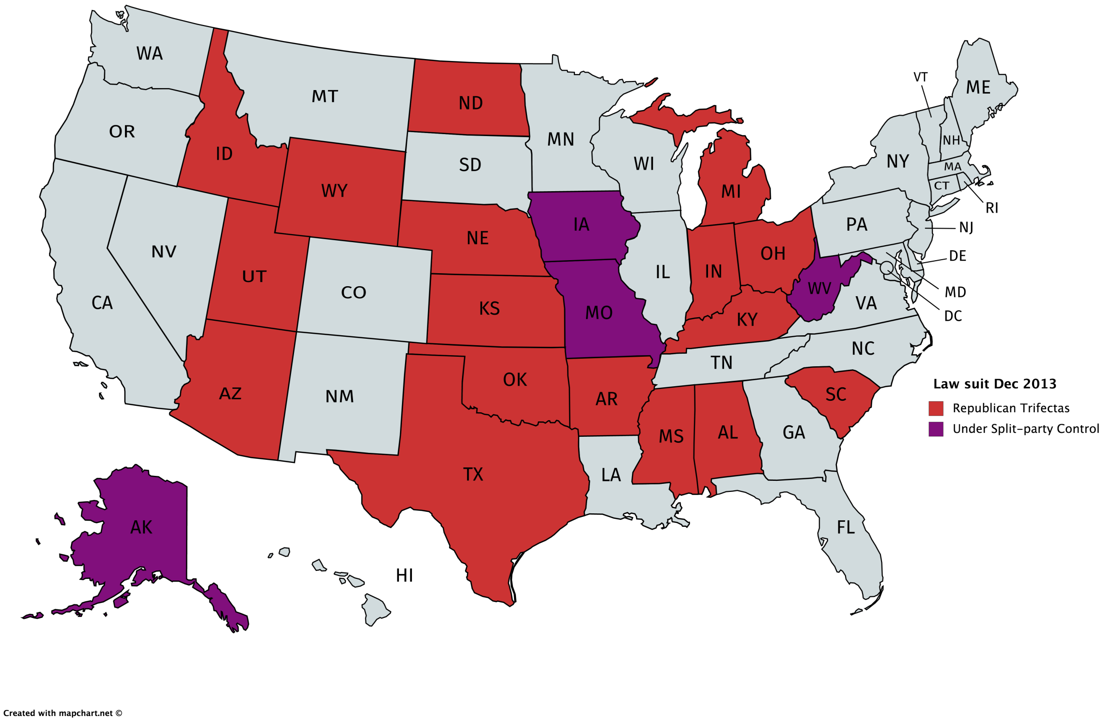

Figure 11: States that Challenged MATS (Source: BallotBALLOTPEDIA)

B Demand over Time

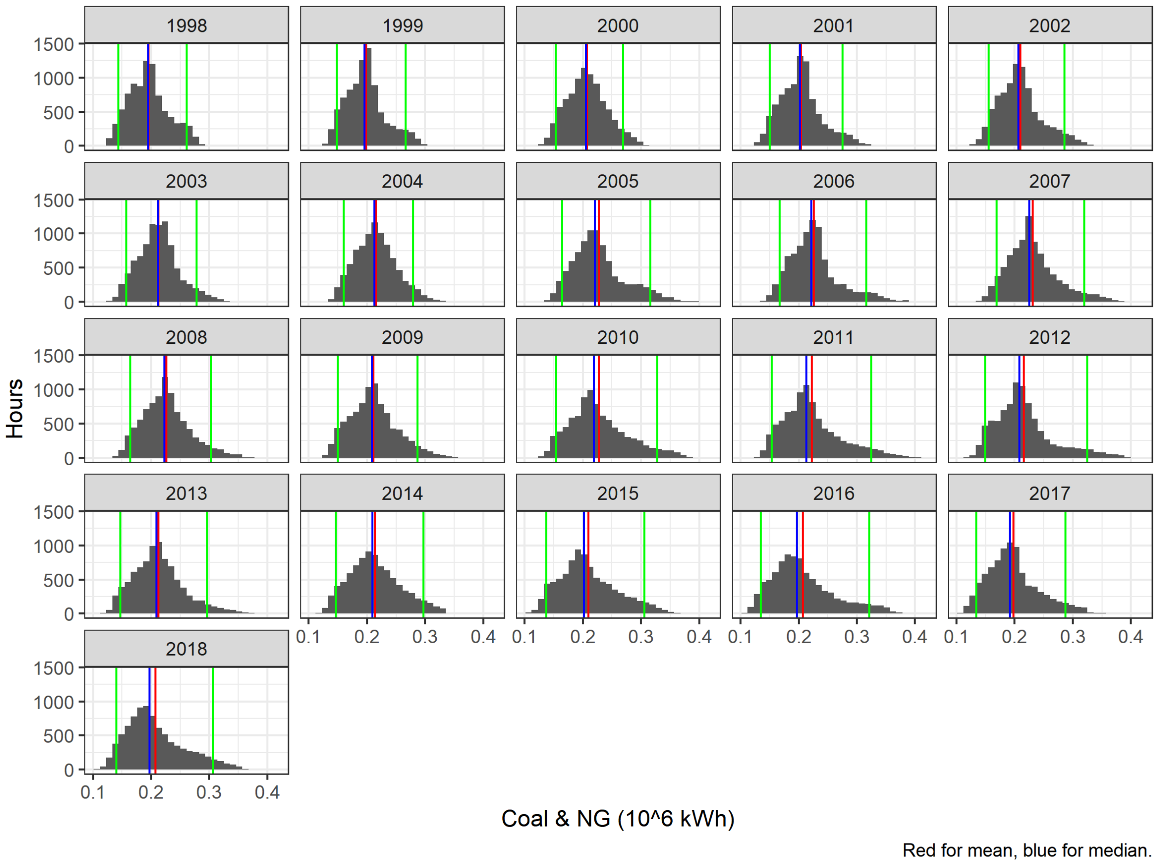

Figure 12: Annual Hourly Demand Histogram in the Eastern Interconnection

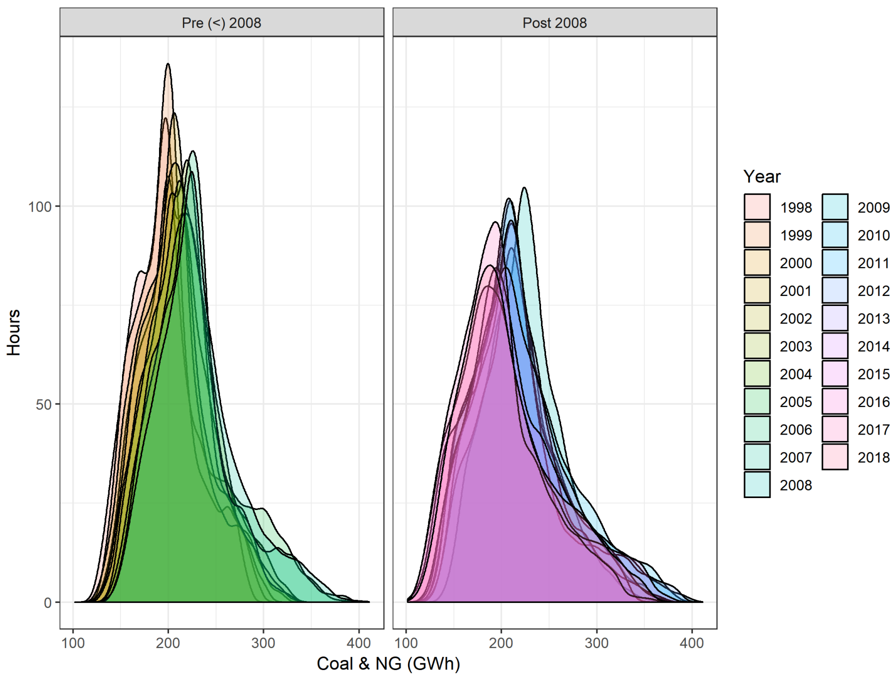

Figure 13: Annual Demand over Time in the Eastern Interconnection

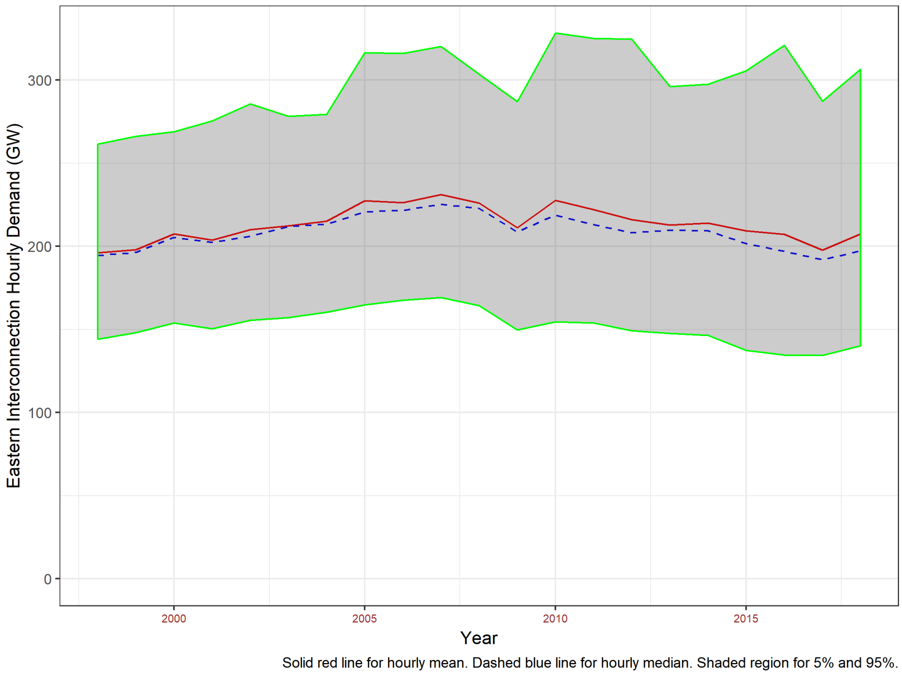

Figure 14: Aggregated Demand in the Eastern Interconnection

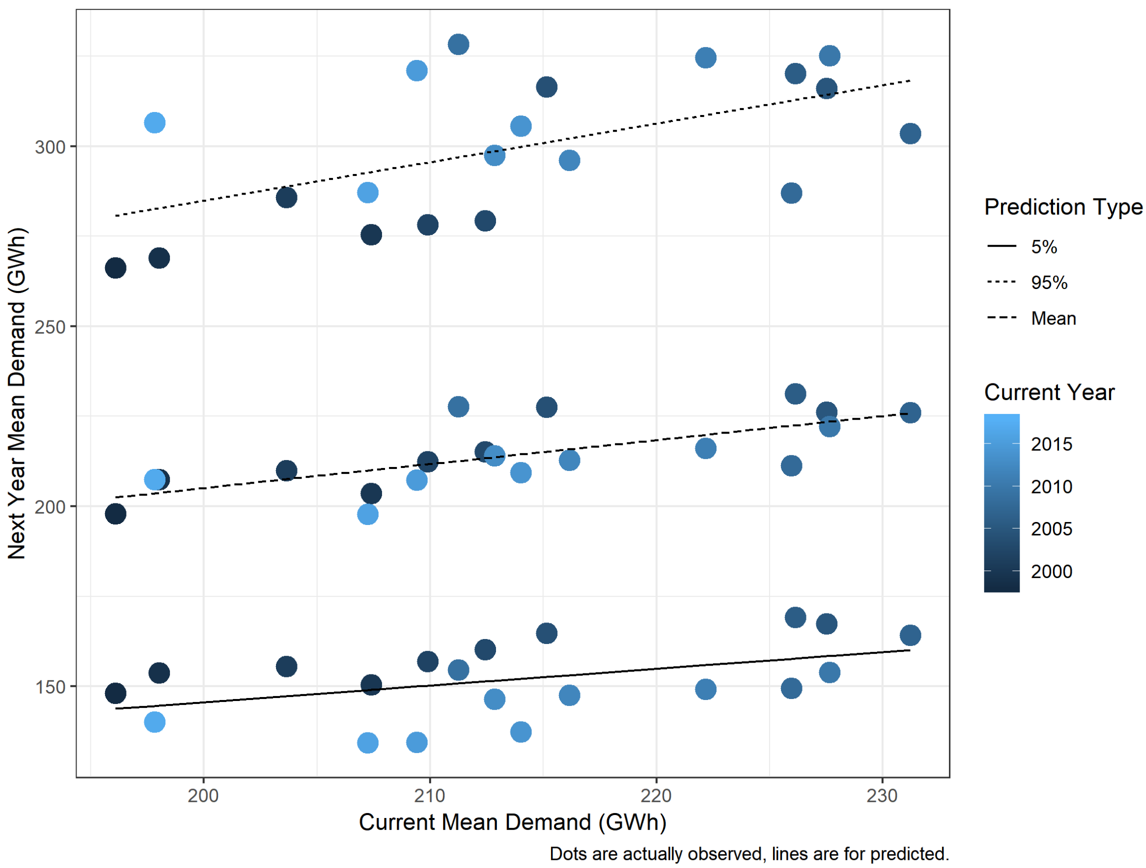

Figure 15: Demand Prediction

C Dispatch Model

Table 8: Summary Statistics for Oil-fired Units in the Two Regions

	Local (Obs = 119, N = 11)		MATS (Obs = 658, N = 76)		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Unit
Year	2004.849	4.573	2006.029	5.295	
Commercial Year	1969.655	9.24	1970.722	14.307	Years
Heat Rate	12.006	1.082	12.949	2.971	MMBtu/MWh
Annual Hours	2100.487	1904.506	2466.65	2692.15	Hours
Capacity	312.147	240.908	209.237	222.303	MW
Fuel Marginal Cost	128.542	62.56	151.609	85.356	2005$/MWh

Table 9: Summary Statistics for Other Fueled Units in the Two Regions

	Local (Obs = 10, N = 2)		MATS (Obs = 35, N = 5)		
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Unit
Year	2013	1.491	2012.057	3.556	
Commercial Year	1950	1.054	1984.057	20.885	Years
Heat Rate	13.337	0.298	11.671	2.121	MMBtu/MWh
Annual Hours	6846.5	1286.059	6509.743	1892.469	Hours
Capacity	22.3	1.059	131.771	101.953	MW
Fuel Marginal Cost	231.81	39.809	176.545	66.26	2005$/MWh

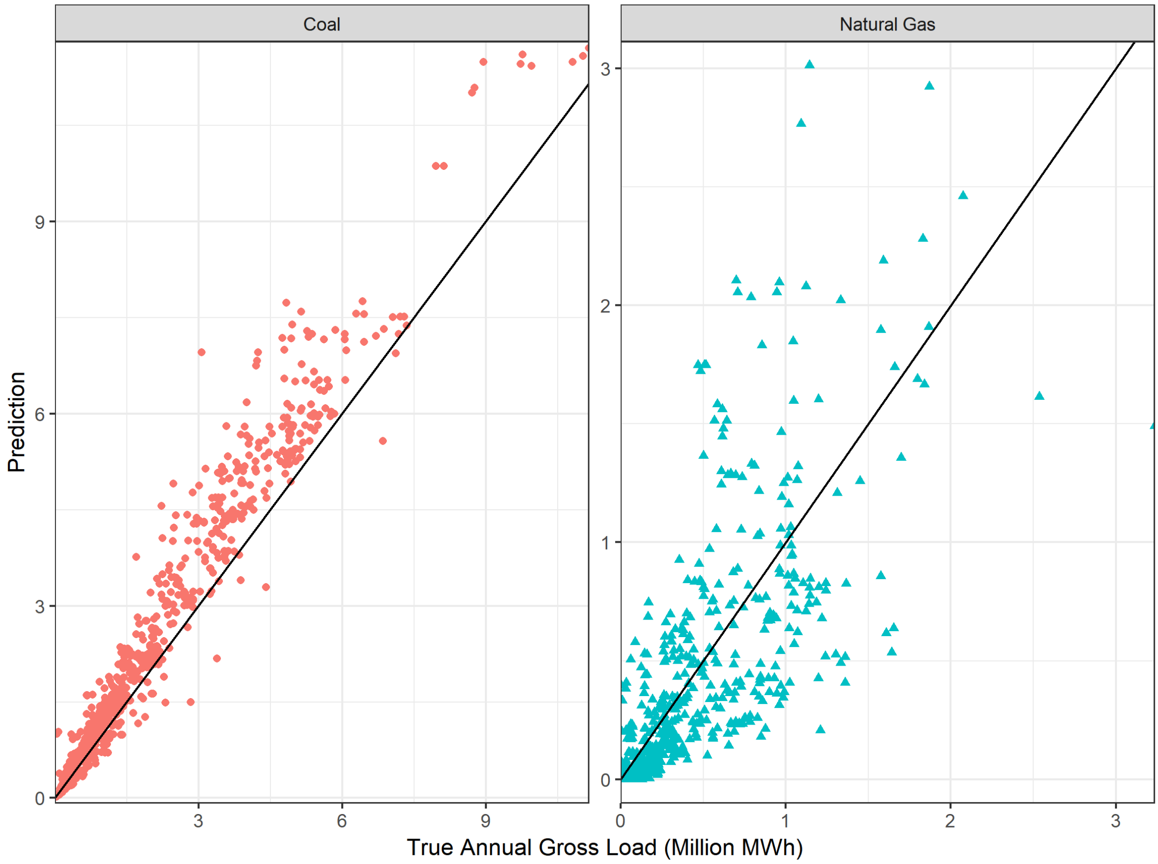

Figure 16: Fitting the Profit in the Base Year 2005

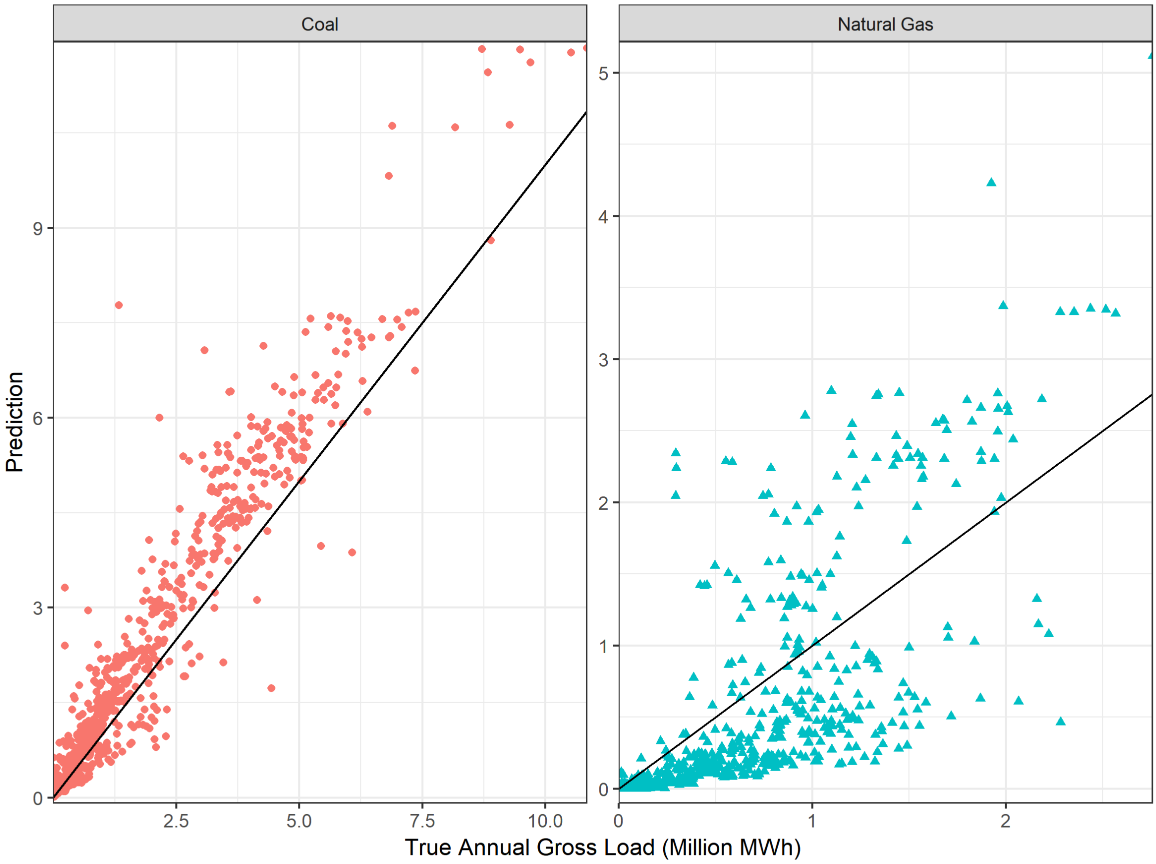

Figure 17: Fitting the Predicted Profit in another Year 2010