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

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Abstract

Many coal-fired power plants are retiring since around 2012. The existing empirical studies have diverse conclusions regarding the relative impact of market conditions and environmental regulations on coal-fired power plants' retirement decisions. My study aims to better understand these two factors, with uncertainty in the environmental regulation, on coal-fired power plants' investment and exit decisions. A model incorporating these important factors can help guide the government in designing environmental regulations to reduce emissions efficiently. This study introduces a modified investment and exit model under policy uncertainty and discusses the counterfactuals of different scenarios.

JEL code: Q52, Q58
Key words: environmental regulation uncertainty, natural gas prices, coal power plants

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1 Introduction

The coal-fired power plant industry, once representing more than half of the U.S. electricity generation, 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. Since around 2010, more than one-third of the capacity has retired (Figure 1). The underlying reasons may include both market conditions and government regulations. However, the relative strengths of these factors are empirically unclear. Several market factors evolved very differently from projections, including natural gas prices, renewable energy generation portfolios, and electricity demand. The natural gas prices in 2016 dropped to around one third of the level in 2008 and the whole trajectory deviated to a much lower level than previously projected. Further, regulations that aim to reduce air pollution from electricity generation have also expanded during this time period.

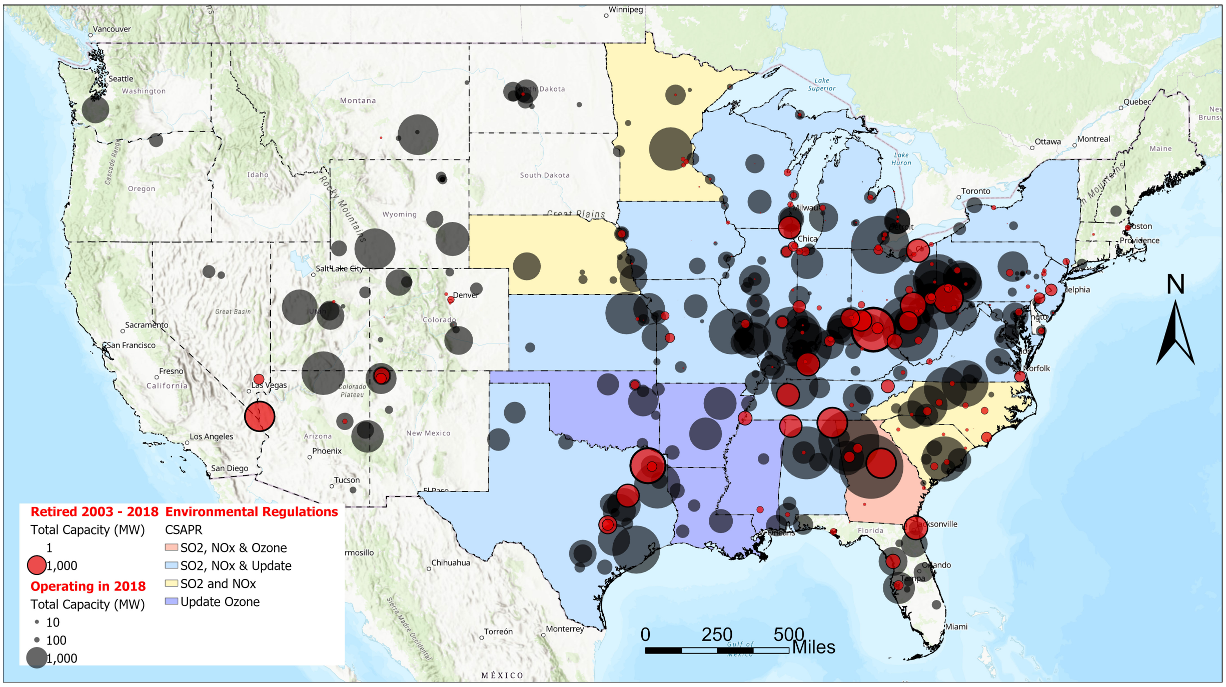

Figure 1: Coal-fired Power Plant Retirement

My study aims to better understand the relative impact of market conditions and government regulations, possibly with uncertainty, on coal-fired power plants' retirement decisions. This can help guide the government in designing environmental regulations to reduce emissions efficiently. I consider the natural gas price changes and several environmental regulations over time. One important environmental regulation included in my study is the Mercury and Air Toxics Standards (MATS). The U.S. Environmental Protection Agency (EPA) announced MATS on December 21, 2011. This is the first national standards to reduce mercury emissions and other toxic air pollutants from coal- and oil-fired electric generating units (EGU) with capacity more than 25MW. The first compliance date was April 2015, though power plants could apply for a one-year extension. However, this regulation had undergone many legal challenges before its compliance date, which might create regulatory uncertainty. There are ample theoretical models that suggest that uncertainty in environmental regulations delays firms' capital investments for compliance. The same logic may be applied to show that coal-fired power plants may delay their abatement technology investment or exit decision when they are uncertain about the execution of an environmental regulation, such as MATS. This paper explores the relative impact of two factors that have been suggested as the main driving force for the coal-fired EGUs to exit the market, the natural gas prices fall and the environmental regulation MATS. In addition, this study also considers the possibility that people may have a subjective probability of a controversial environmental regulation being retreated.

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 in one of their policy scenario. 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 2). 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. Allowing variation in market conditions and plants' expectations of environmental regulations may help identify their impact as information revealed.

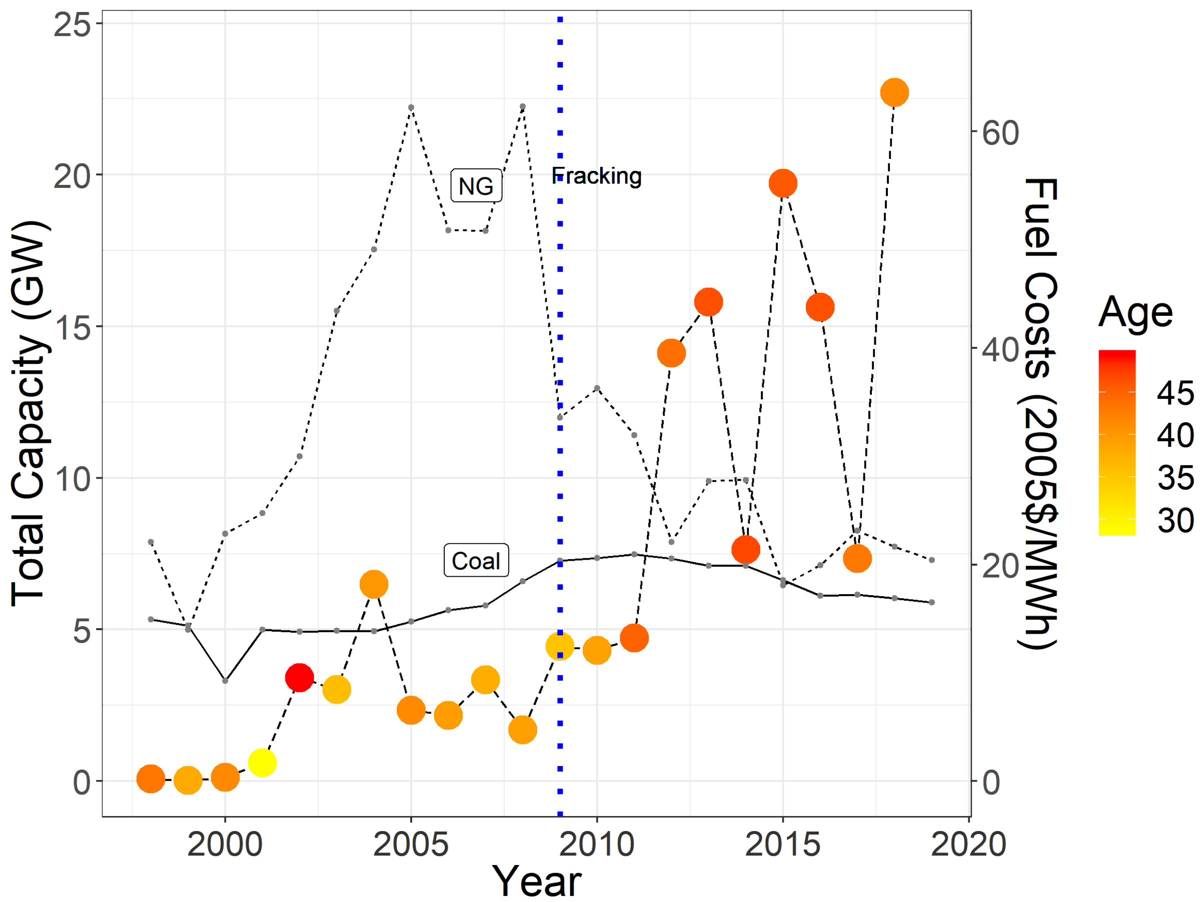

Figure 2: Coal-fired Generating Units Retirement Trend

My approach adds to the previous studies in that I use a dynamic structural model which permits market information and expectations to update annually. This approach also allows for estimating the subjective probability of MATS being in place and thus for considering the policy uncertainty. Having a framework that can compare the impact of various important factors can help guide environmental regulation design and reduce emission costs effectively.

To the author's knowledge, there is only a little empirical evidence regarding the impact of policy uncertainty on investment and exit decisions. This is primarily due to the challenge of measuring the perceived uncertainty and that all regulated individuals are often subject to the same regulatory uncertainty (Dorsey, 2019). There is almost no time or spatial variation in the execution of MATS. Therefore, it is hard to separate the 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 prior to 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.

This study also contributes to the literature that applies structural models to the electricity sector (Borenstein et al., 2002; Cullen and Reynolds, 2017; Gowrisankaran et al., 2016; Linn and McCormack, 2019) and the literature using entry and exit models (Curtis, 2018; Mansur, 2007; Ryan, 2012; Shapiro and Walker, 2018) by providing a modified dynamic investment and exit model to analyze the usual market conditions along with the unusual environmental regulation shocks. The structural model has the potential for certain counterfactual analyses.

I study the aforementioned two factors affecting the coal-fired power plants' retirement decisions under a modified investment and exit decision model. Specifically, my empirical approach consists of a static dispatch model to estimate the annual variable profit for each coal-fired generating unit and a single agent dynamic model to estimate the exit costs. The main modifications to the investment and exit model include: 1) decision makers do not have perfect foresight regarding the policy shocks; and 2) there are periods of time with various length when decision makers can make decisions knowing the deadline of compliance. Like such policies, MATS was announced in the end of the year 2011 with a specified compliance year.[1] With this model, I conduct the following counterfactual analyses to compare the relative impact of each factor on coal-fired power plant retirement decisions: 1) absent the environmental policy MATS or without uncertainty; 2) sustained high natural gas prices; 3) the interaction of the two factors. In addition, the model can predict decisions for each coal-fired power plant, with which we can examine if the responses are spatially heterogeneous.

The study focuses on the coal-fired EGUs in the eastern United States (U.S.), which contains most of the coal-fired EGUs in the U.S.

Findings: not ready.

The remainder of the paper is organized as follows. Section 2 describes the regulation, 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.

[1] There is a first deadline in April 2015, and an extension generally available to all in April 2016. I use 2016 as the compliance year for simplicity.

2 Policy Background

The discussion of regulating air toxics from the electricity sector has started since early 2000. However, the MATS 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. This policy has been through several debates and legal challenges but has survived until its compliance date.

2.1 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 (See Figure 1). The time range is from 1998 to 2018. I restrict the data to the eastern interconnection. There are three major interconnections in 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 operate 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.

Information for the state level policy is from a website.[2] The state level policy is combined with the self-reported mercury policy stringency collected from the EIA 860 form (See Figure 3). This creates the two group "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 will be used as the comparison group.

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 the year 2018 and 2019, then 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 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.[3]

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.

[2] Online source last visited 1/31/2020.

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

The values are shown in Figure 2. 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.

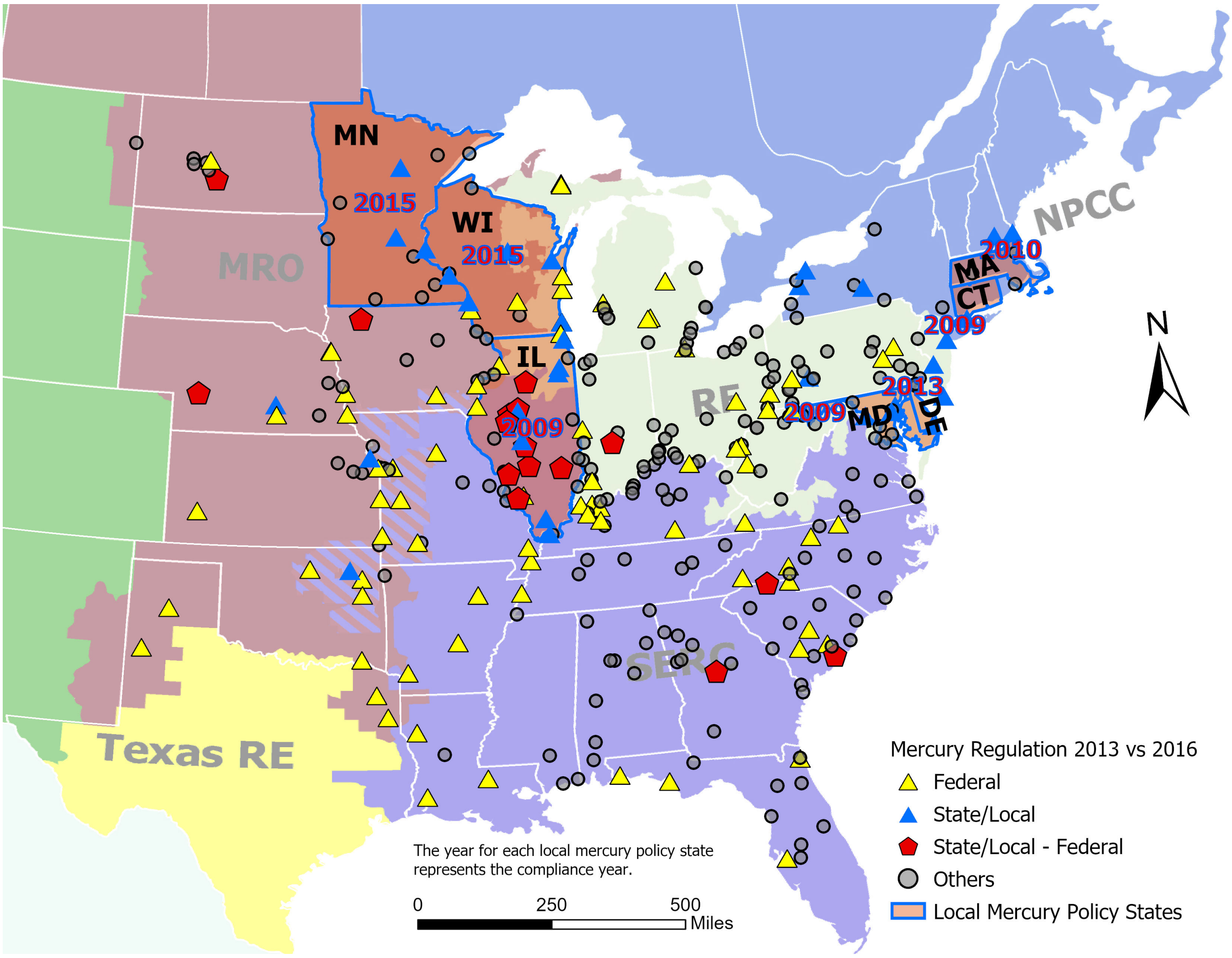

Figure 3: Self-Reported Mercury Policy Stringency

Figure 3 shows the geographical distribution of the coal-fired units by self-reported mercury policy stringency. The states with red boundary are known to have announced and effected local mercury policies before 2015. The announced and effective years are in Table 10 in the appendix.

Table 1: 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 2: 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 1 summarizes the coal-fired units in the eastern interconnection while Table 2 summarizes for the natural gas-fired units. [4] The data used for the dispatch model include 904 coal-fired 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 cost.[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 are no large gap between the two regions in terms of the observed year and the units' commercialize 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.

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

[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 2, which uses the national level cost and heat rate reported by EIA.

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 8.[6] 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.

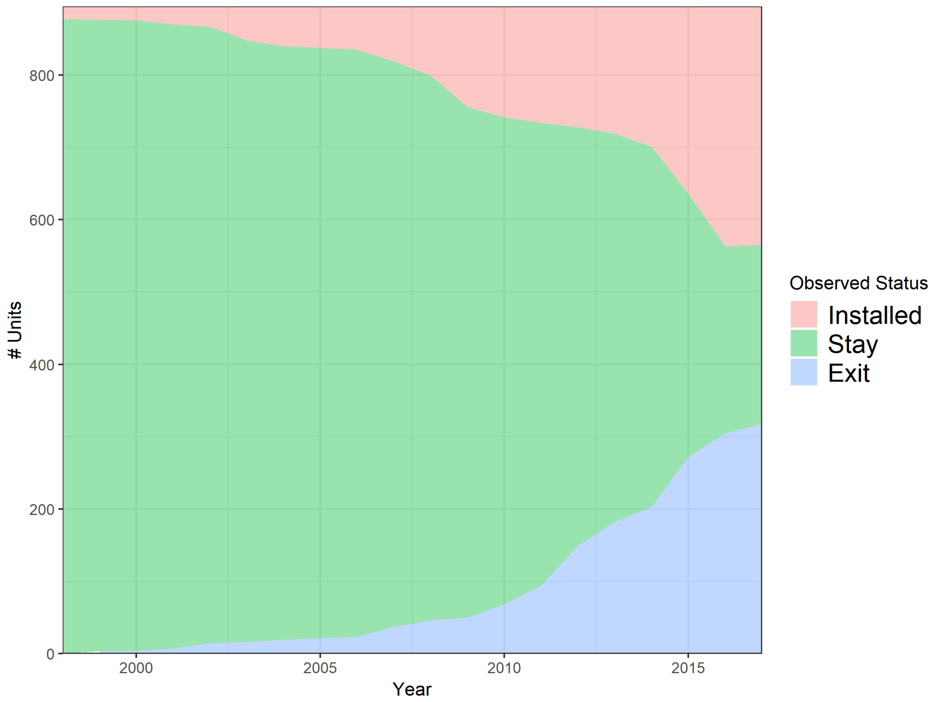

Figure 4: EGUs Status Over Time

Theoretically most of the units should be in compliance by the year 2017, excluding those filed for an extension. However, according to CEMS, this was not the case. There may be delay in the information update, 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 exited in that year.

3 Model

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

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

[6]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 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.

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 5).[7] 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 next step.

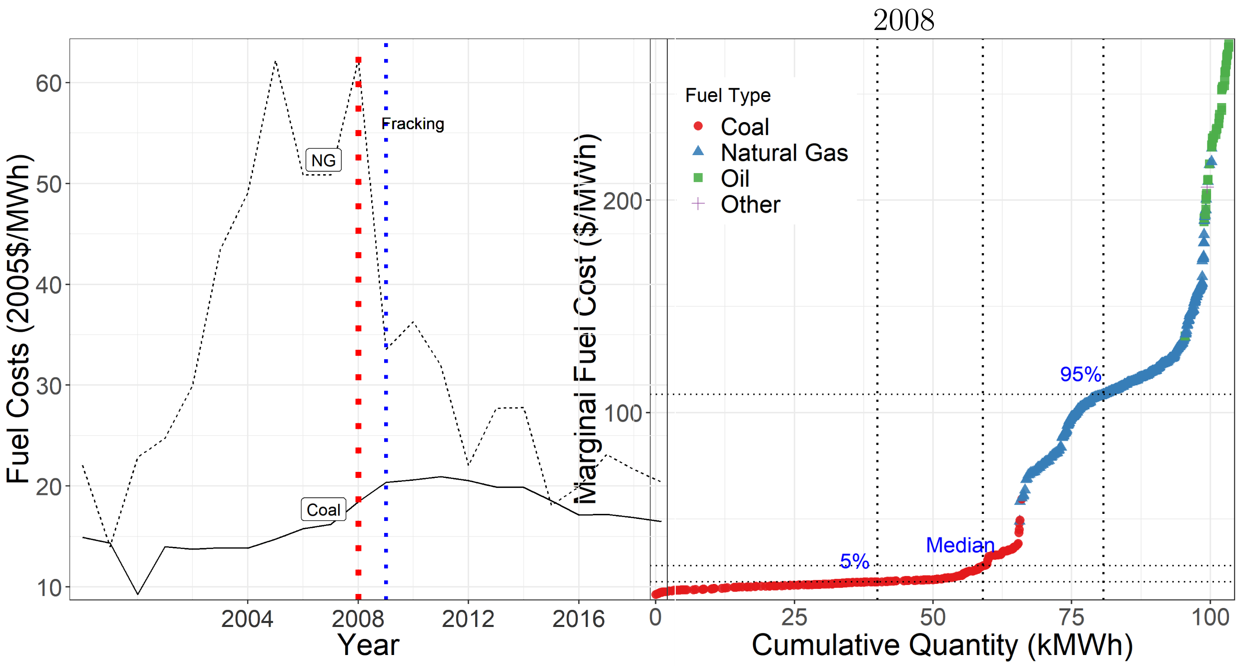

Figure 5: Fuel Costs and the Marginal Fuel Cost

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 level, 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.[8]

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.

It is necessary to consider the costs of purchasing permit for NOx and SO_2 during the earlier part of the study period, before the 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 is 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

[7]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.

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

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.[9] 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. [10] Then the fitted non-fuel costs are fixed in predicting all other years. [11]

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. [12] These provide the 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:

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

where the f contains the combination of each variable by 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 from 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 extend of turning on and off hourly (Zhang, 2020). Linn and McCormack (2019) show that a conventional economic dispatch model may over predict the impact of natural gas prices on coal-fired power plants' hourly operation and thus exit decision.

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

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

[11] 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.

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

3.2 Single Agent Model

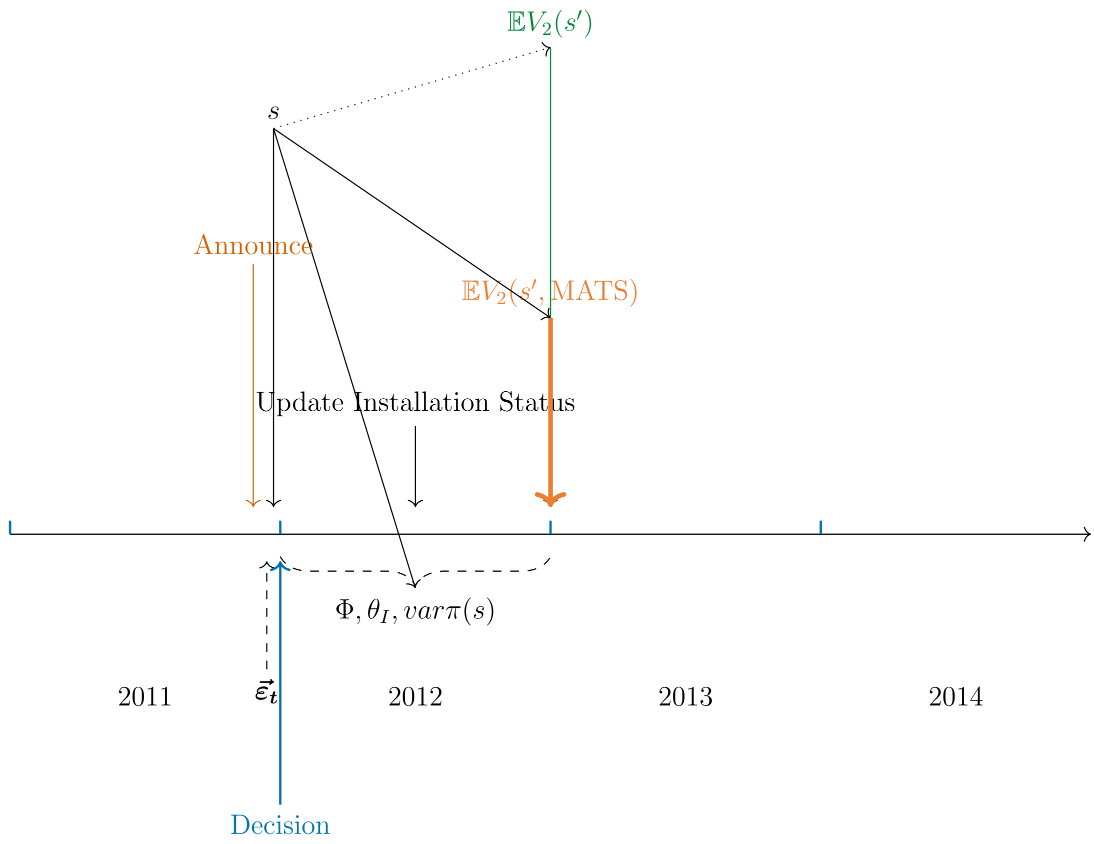

Figure 6: Timing of Decision Making

Figure 6 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 Φ 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 these information and the future continuation value $\mathbb{E}V(s'|s)$ can be calculated, based on the transition assumed. Knowing these 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. The continuation value can be written recursively as follows:

$$V(s,\varepsilon;\theta) = \begin{cases} \max\limits_a \left\{ \begin{array}{rl} \Phi + \varepsilon_0 & a = 0 \\ var\pi(D, cap, hr, r) + \beta\mathbb{E}[V(s')|s,a] + \varepsilon_2 & a = 2 \end{array} \right\} & t = Ddl \\ \\ \max\limits_a \left\{ \begin{array}{rl} \Phi + \varepsilon_0 & a = 0 \\ var\pi(D, cap, hr, r(t)) + \beta\mathbb{E}[V(s')|s,a] + \varepsilon_1 & a = 1 \\ \theta_I + var\pi(D, cap, hr, r(t)) + \beta\mathbb{E}[V(s')|s,a] + \varepsilon_2 & a = 2 \end{array} \right\} & o.w. \end{cases}$$

where Φ is the scrap value for exit and θ_I represents the installation cost, both are the same for all units. $var\pi(D, cap, hr, r,)$ is the variable profit from annual operation, estimated in the dispatch model, and predicted using the regression, as a function of electricity demand D, unit capacity cap, unit heat rate hr, and the coal over natural gas price ratio r in year t. The expectation $\mathbb{E}$ for the continuation values $V(s')$ is taken over the possible transited values of r' in the next stage, conditional on the current r. 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.[13] The discount factor $\beta = 0.9$ is as generally assumed.

The choice set for each unit i in year t, A, changes due to the policies shock. If year t is not the compliance year for the unit, the unit can choose a_t 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. Note that the model allows the decision makers to install an abatement technology even when the they have installed the necessary technology, but do not keep track of the number of such decision. There are very few re-installation observed in the data. Estimating the parameters using such information is neither useful nor helpful for the main 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.[14] If the year t is the compliance year for the unit n, the choice set A only contains two choices, $A = \{a_0, a_2\}$.

The state s summarises the sufficient information for decision makers to form expectation about the future. Let Ω denote the set of possible states $\{s\}$.

$$s = (\underbrace{D, cap, hr}_{\Omega_1}, \underbrace{i}_{\Omega_2}, \underbrace{r, Ddl}_{\Omega_3}), \quad s \in \Omega$$

There are three sets of variables in the state S. Ω_1 contains all the constant variables, which remain constant for each unit over time; Ω_2 contains the deterministic variables, n, for installation status, its transition is completely determined by the action. Once action 0 (exit) is chosen, the status will remain in 0 and no more action will be made; when action 2 is chosen, the status will transit to 2 and only action 0 can change this status. In 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 following transition matrix in Table 3.

Table 3: 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	0.75	0.25

The transition probability is estimated from the actual price ratio observed from 1990 to 2016. The ideal case is to have more intervals that better approximate different scenarios. However, due to the

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

[14] 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.

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 represents the actual profit. [15]

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 subjecting 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 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 $\theta = (\Phi, \theta_I, p, \theta_b)$.

Because there is a large time dimension in this model, instead of using a nested fixed point algorithm (Rust, 1987), this paper uses the backward induction from 150 years after 2017 and accumulate back to the starting year. The final year is assumed to have 0 value. The number of years is large enough that before 2017, the value function converges to a stable value, so this will be a good approximation of the fixed point solution.

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[16]

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

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, calculate the probability of each choice and maximize the above likelihood . [17]

Each unit has its own Bellman equation, due to the differences in their capacity and heat rate. This is important to get a better estimate for the variable profit. However, there is no heterogeneity in the parameters for the units. All units are assumed to share the same set of parameters $\theta = (\Phi, \theta_I, p, \theta_b)$.

The transition for installation is completely determined by the decision. The policy transition is a sudden change from none to announcement and from the compliance year to none existence.

Implicitly assumed here is that the mercury policy at the state or local level requires installing an abatement technology that has the same costs as MATS, and there is no policy uncertainty in these local policies. Likely the local policies are with certain uncertainty. Assume the costs are the same across different policies, then ignoring such uncertainty will bias the costs upwards, thus the estimated uncertainty for MATS is biased downwards.[18]

[15] Other number of intervals can be easily implemented if time permits.

[16] When $n = 1, m = 1$ in the compliance year, A_s contains only $\{0, 2\}$, otherwise, $A_s = \{0, 1, 2\}$

[17] Using nloptr with Neldermead algorithm in R (Nelder and Mead, 1965).

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

4 Estimation

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 17. Figure 7 shows the prediction of the annual variable operational profit for the year 2015. [19] 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.

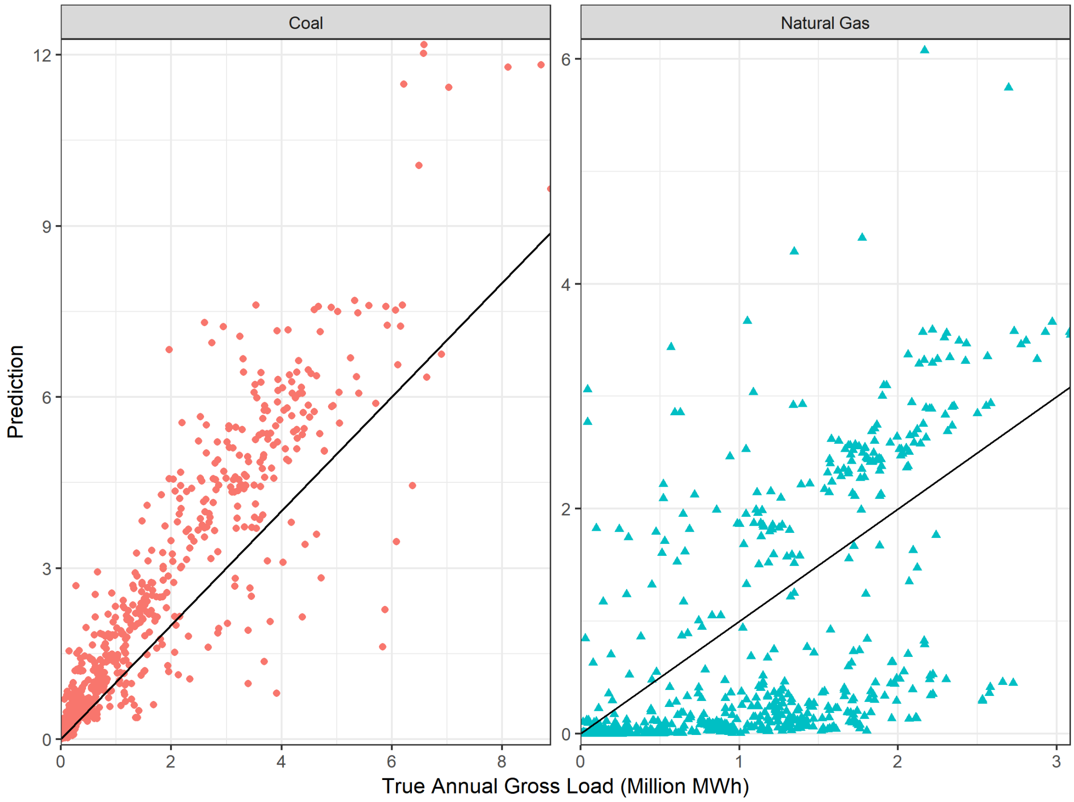

Figure 7: Fitting the Predicted Profit in another Year 2015

4.1 First Stage Estimates

Table 4 shows the regression results for fitting the variable profit using different specifications. 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.

[19] The prediction for the year 2010 is in the appendix in Figure 18.

Table 4: Variable Profit Prediction

Coal Cost			-0.464***			-0.468***	
			(0.008)			(0.008)	
NG Cost			0.009*			0.010*	
			(0.004)			(0.004)	
Coal/NG ratio				-129.981***			-130.564***
				(2.656)			(2.687)
Demand	Y	Y	Y	Y	Y	Y	Y
Capacity		Y	Y	Y	Y	Y	Y
Heat Rate					Y	Y	Y
Observations	15,007	15,007	15,007	15,007	15,007	15,007	15,007
adj.R-squared	0.0148	0.568	0.6592	0.6312	0.5699	0.661	0.633

Note: Standard errors in parentheses

Cost in cents/MMBtu. Profit in 2005$ Million. Capacity in MW. Demand in GWh.

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

4.2 Bellman Equation Estimation Results

Table 5 shows parameters the estimated in the dynamic model. The scale is in 100 million (2005$) for the first two variables. The estimated cost of investment is far too high. This may be resulted from the not accurate estimation of profit. The exit value Φ represents not only the scrap value, but also the best outside option. Given the fast developing technologies in renewable energy, it is possible that this value is positive. 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. As mentioned above, this is a relative value to the local policy and thus the actual absolute probability could be smaller. The last 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 5: Dynamic Parameters Estimation

Φ	θ_I	Prob(MATS)	θ_b
40.866	-116.081	0.817	28.001

Note: Standard errors will be added later.

4.3 Goodness-of-Fit

In Table 6, 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.[20] According to Table 6, the model over predicts exit and installation in all cases other than under MATS but not installed. The mechanism that decision makers anticipate MATS and make exit and installation earlier due to the time requirement of installation than the deadline may not be fully captured in the current model. Besides, the range of price ratio on the simulation grid is wide and may not fully capture the various situations that may lead to a higher or lower profit.

Table 6: Observed versus Simulated Choices (%) by Policy X Installation Status

	Observed				Simulated			
	# Obs	Exit	Stay	Install	# Obs	Exit	Stay	Install
No Policy								
Not Installed	10554	1.042	97.878	1.080	9853	1.451	96.813	1.736
Installed	1103	0.544	98.277	1.179	1883	1.540	97.132	1.328
Local								
Not Installed	697	4.304	88.379	7.317	480	11.250	80.417	8.333
Installed	87	0.000	96.552	3.448	248	1.613	97.177	1.210
MATS								
Not Installed	1873	8.970	82.648	8.382	1712	6.075	87.675	6.250
Installed	693	0.577	99.278	0.144	830	1.687	97.349	0.964

Note: Observed Obs = 15,007, Simulated Obs = 15,006.

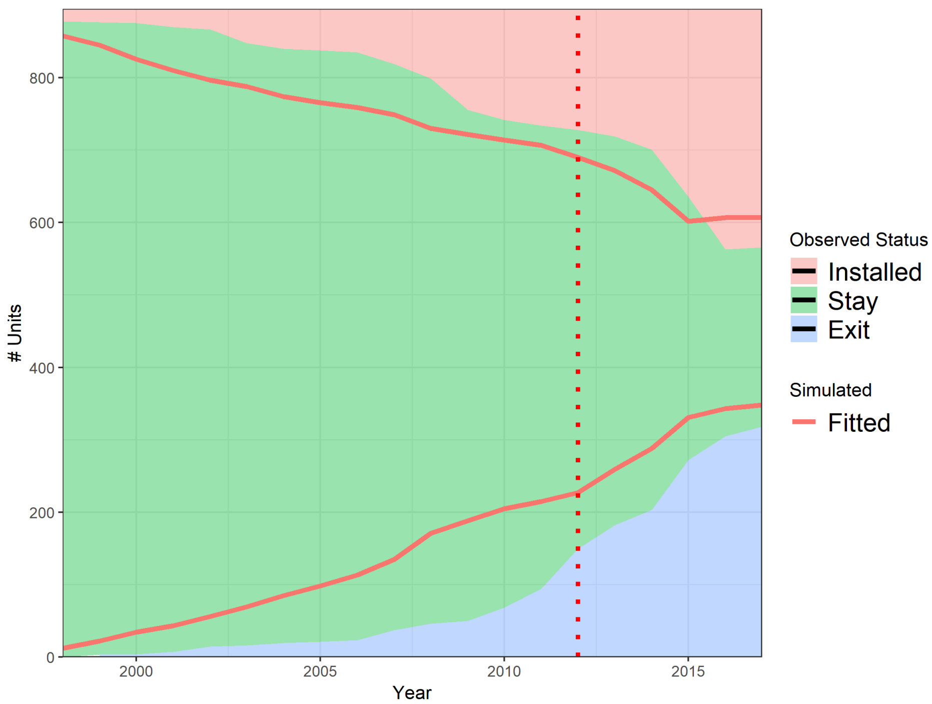

Figure 8: Simulated EGUs Status Over Time

[20]Test of the goodness-of-fit will be added later.

Figure 8 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. [21] The simulated choices predicts installation and exit decision earlier than observed. This may be due to starting all units from the year 1998 instead of conditioning on the first year observing the units. The last year of the simulated path is close to horizontal, suggesting mild investment or exit after the MATS policy.

Table 6 does not correspond to Figure 8 as the observed choices are not a full panel. There are missing observations both in the beginning and in the end of the study period due to late entry and early exit.

For the geospatial distribution of the prediction, I collapse the decision into one for each unit and compare whether they have ever decided to install the abatement technology or exit. The results are shown in 9 and 10. "FN" represents false negative, "TP" represents true positive, and so on. The values are in percentage. The prediction does not work well when comparing each individual unit.

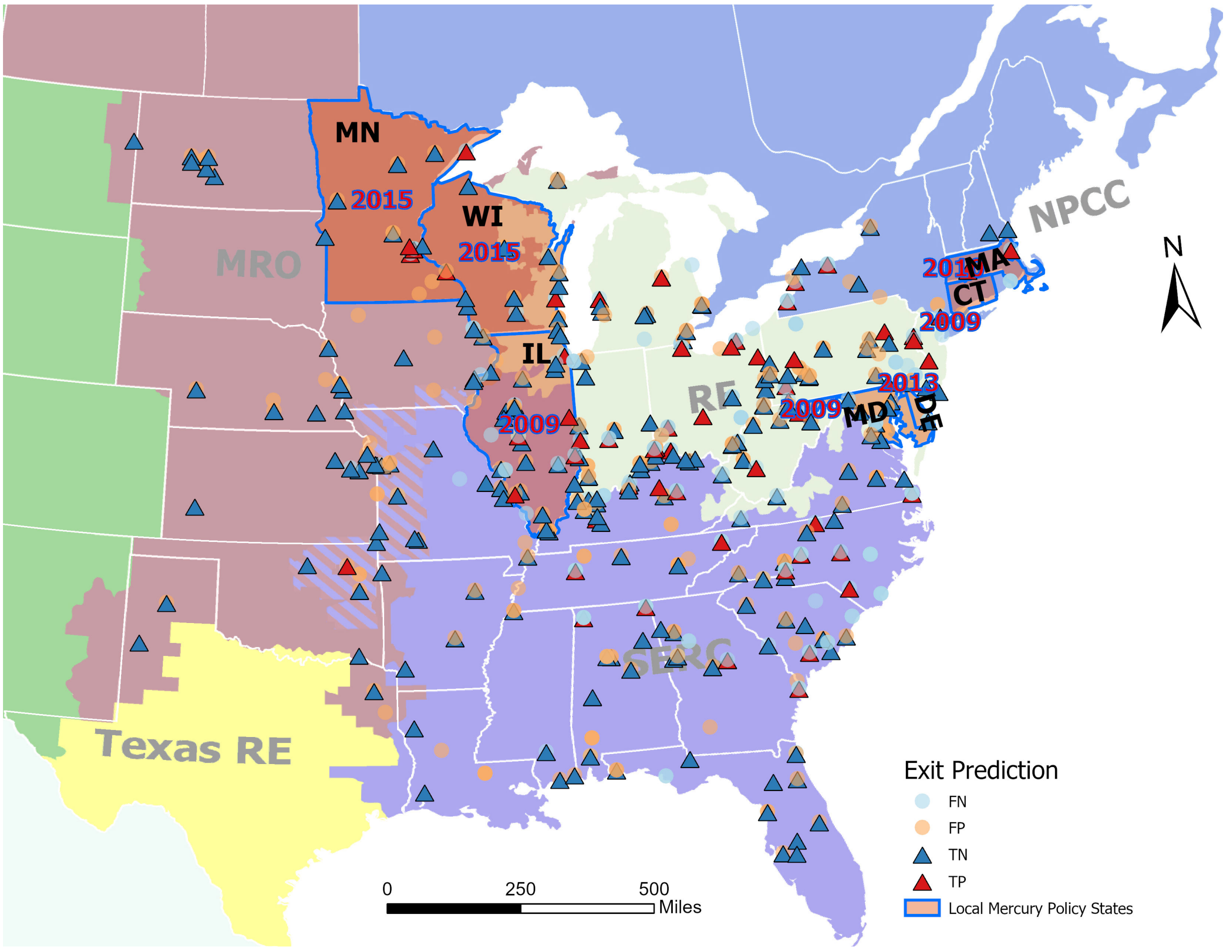

Figure 9: Geopatial Exit Decision Prediction

[21]The confidence interval will be added later.

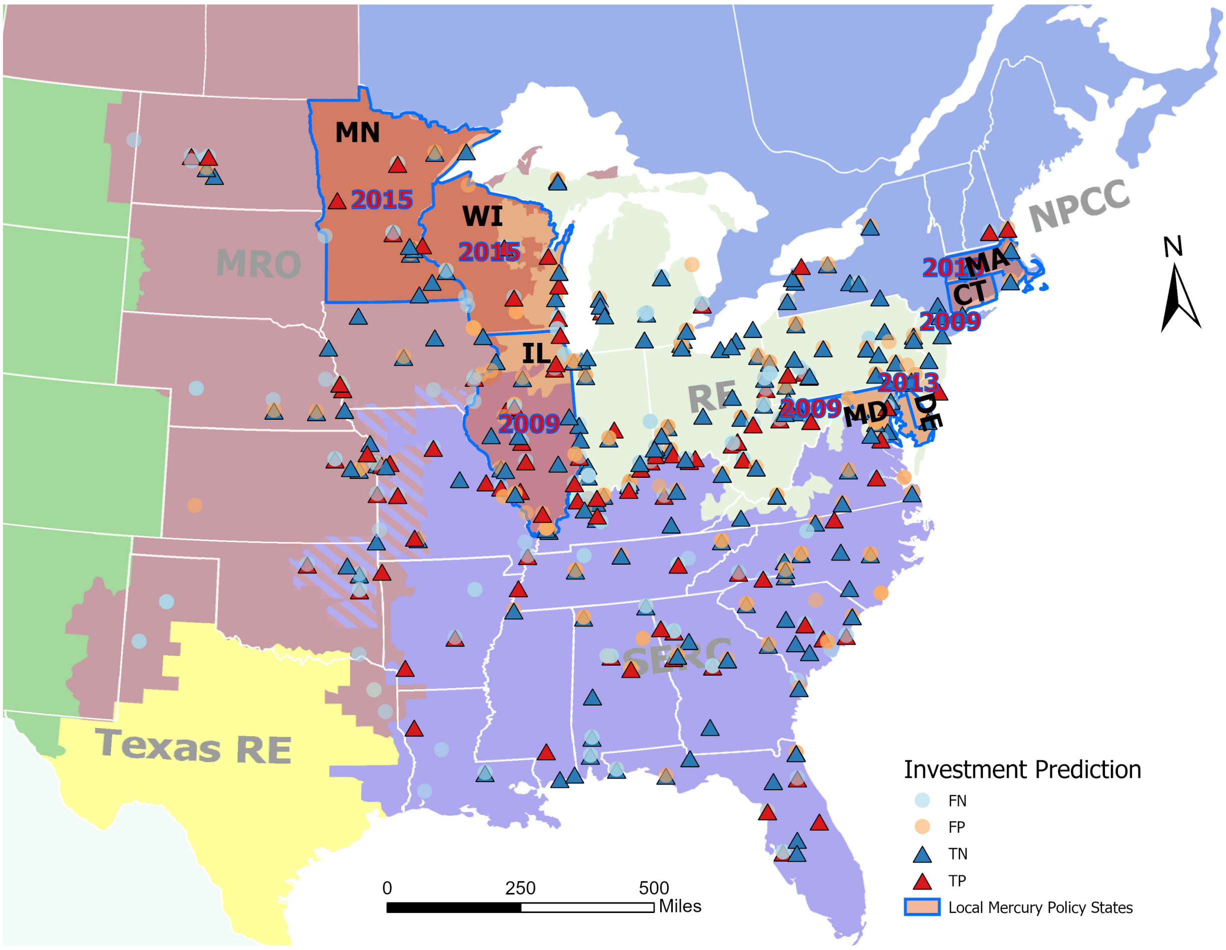

Figure 10: Geopatial Investment Decision Prediction

Table 7: Geospatial Prediction of Investment and Exit Decisions

	FN	FP	TN	TP
Installation	22.123	21.676	40.447	15.754
Exit	23.128	26.480	37.989	12.402

Note: Values in (%). N = 895

5 Counterfactuals

Figure 11 shows the counterfactuals under different subjective probabilities of MATS being in place the next year. If the subjective probability is lower, the number of investment in the abatement technologies would be smaller, while the number of exit would be lower too.

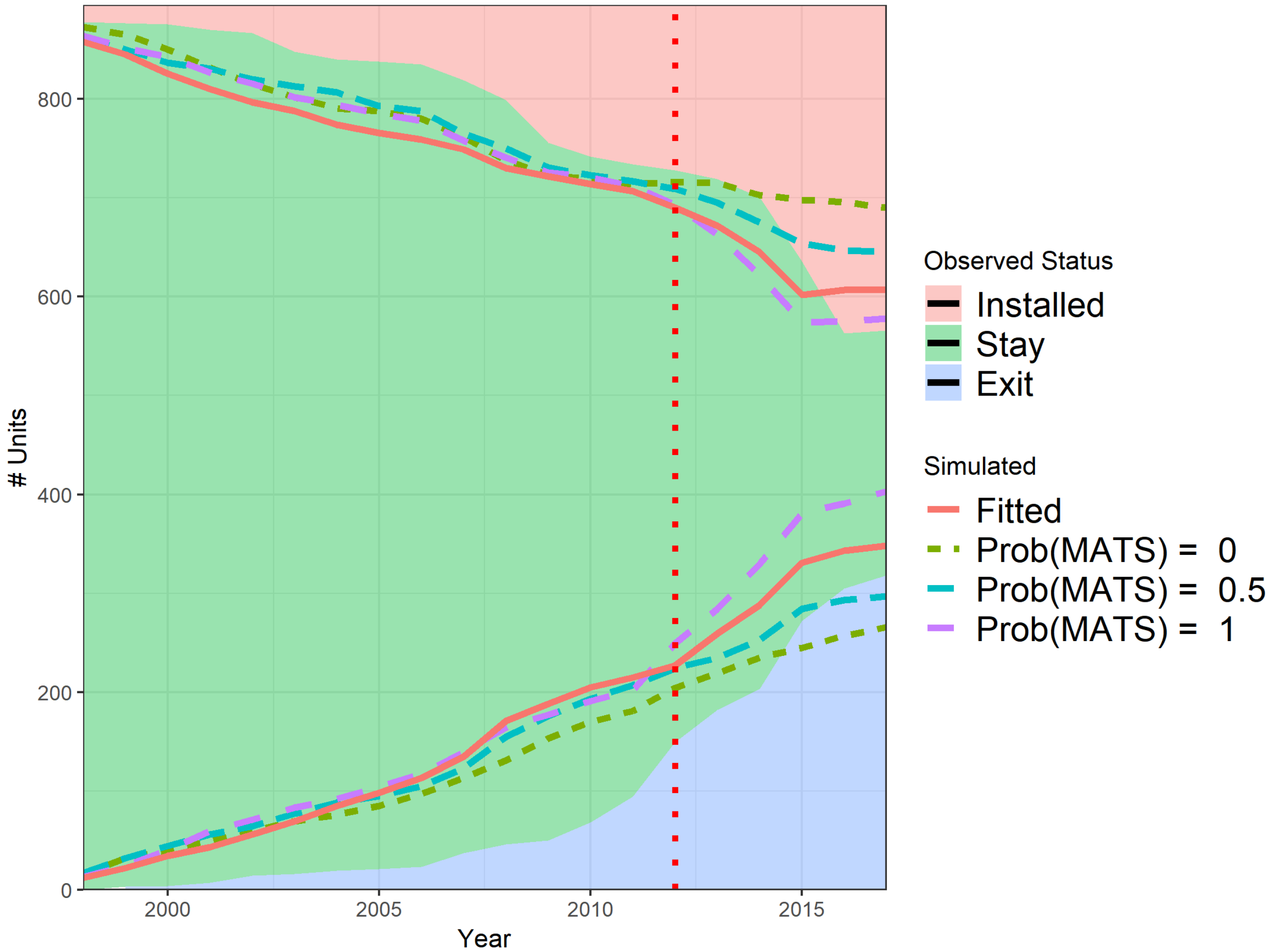

Figure 11: EGUs Status Over Time With Different MATS Probabilities

One counterfactual for different coal over natural gas prices is done by assuming the same transition matrix, but with different realized national price ratio, starting from the fixed year. For example, the simulation for the price ratio fixed 2009 is assuming that the price ratio will remain the same as in the year 2009 and from then on. This is only a small disturbance and does not fully resemble the fact that current low price changes the subjective belief regarding the future price level. The simulation only represents the pessimistic belief regarding the future price ratios through the future continuation value, indirectly from the transition matrix and the current price ratio. Figure 12 shows the result of one simulation. The small changes in the path may suggest large noise in the random shock and small differences in the continuation values under the three price ratio states. The confidence interval for the simulated path may be very wide.

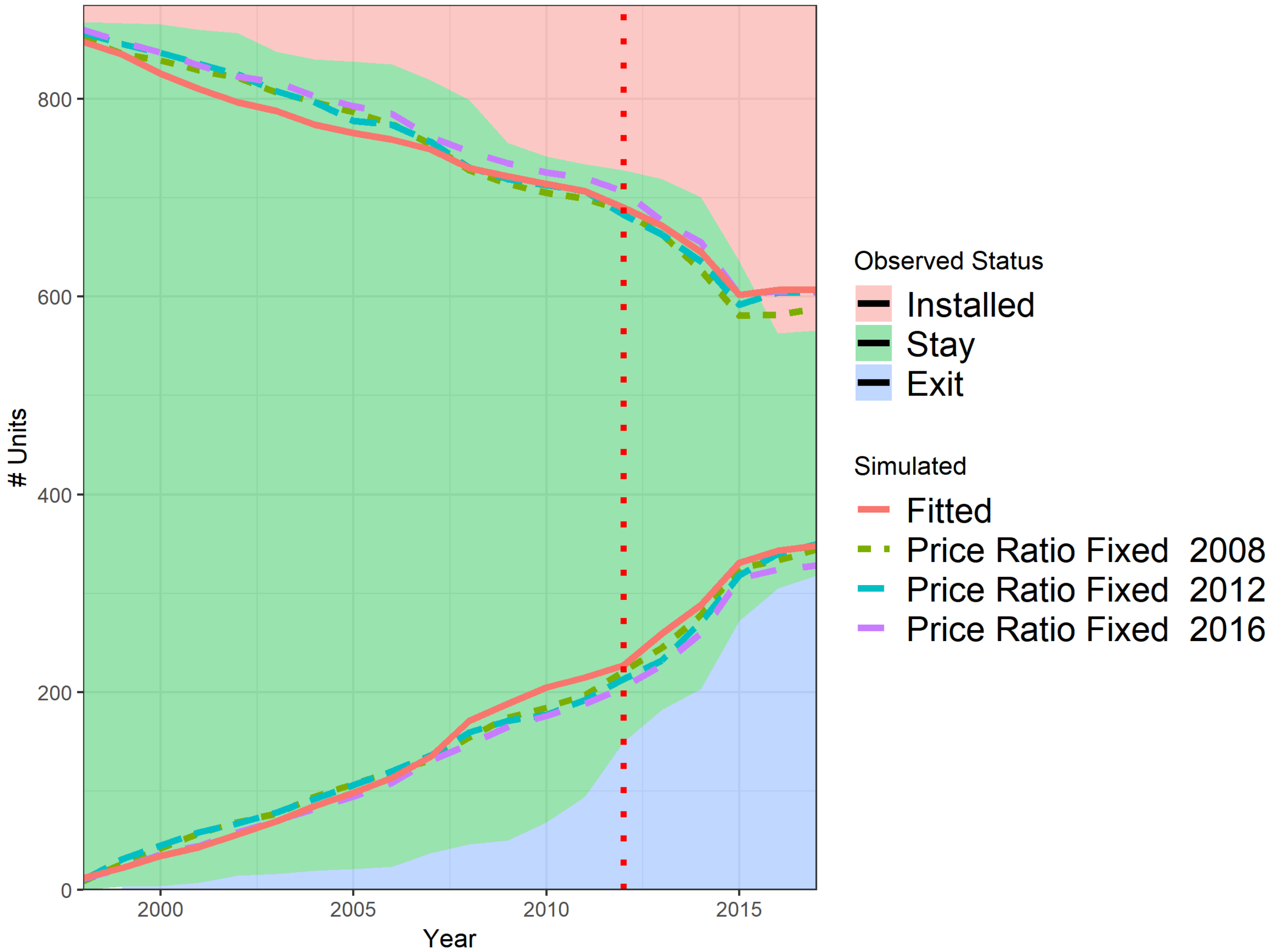

Figure 12: EGUs Status Over Time With Different Coal Over Natural Gas Prices

6 Conclusions and Discussions

This paper examines the relative impact of natural gas prices fall and the environmental regulation MATS under regulatory uncertainty on the coal-fired EGUs' exit and investment decision. The study uses a modified investment and exit model under an environmental regulation with uncertainty, to approach the problem.

The findings: not ready.

There are many limitations in this study. My model only consider the natural gas prices as the market condition and the MATS policy with uncertainty as the major environmental regulation. The model does not consider 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.

The estimation may be subject to large standard errors, according to the numerical simulation. This is also due to the limiting number of observations, the estimation may not be accurate enough. This caveat reduces the reliability of the counterfactual analyses.

There are many limitations in the current model. For example, the coal-fired generating units are modeled as single agent and multiple units within the same power plant is assumed to operate independently. One extension can be using a dynamic game 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.

My analysis does not speak to the impact on emission and thus the environmental benefit affected by the two factors. Future research can look into extending the study to analyze the cost in terms of increased electricity prices versus the benefit in terms of health improvement.

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Appendices

A Demand over Time

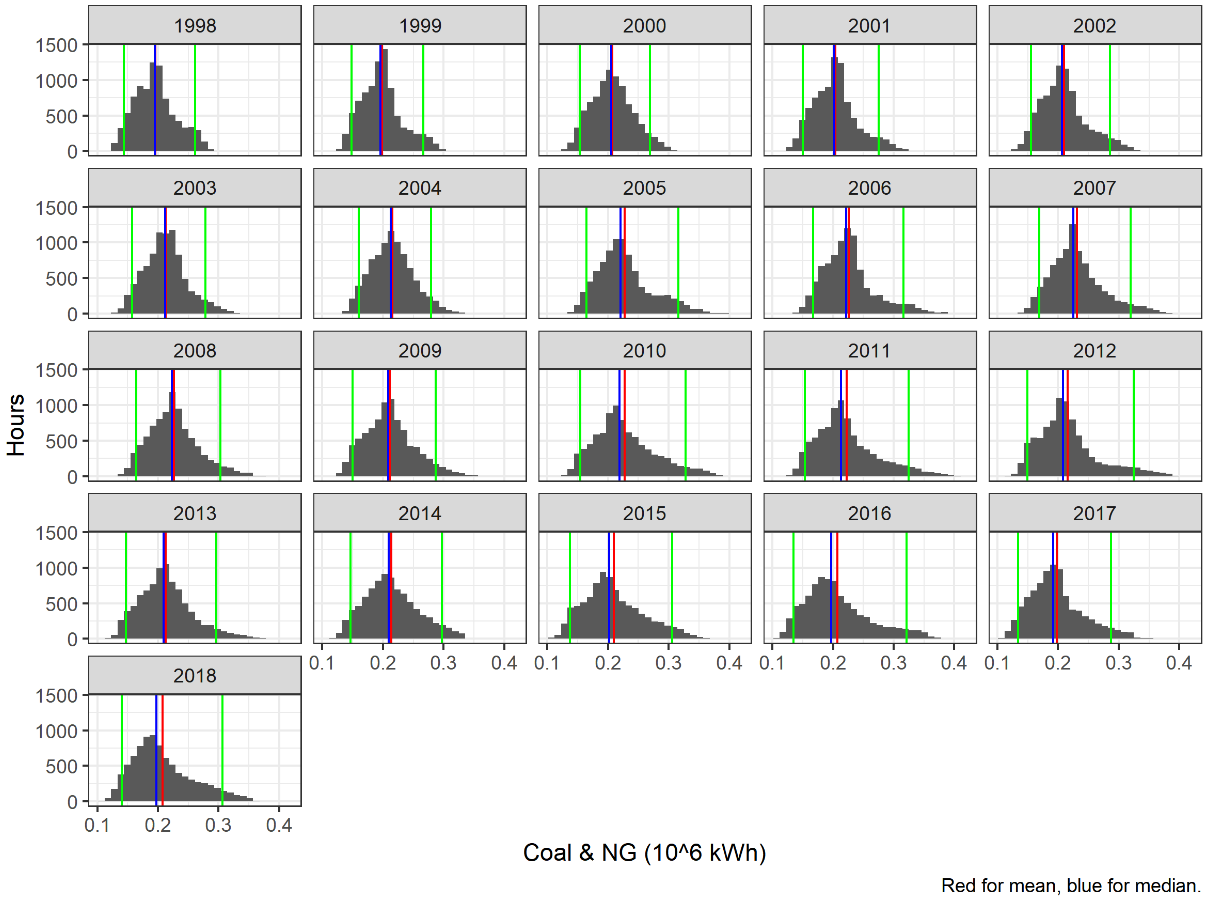

Figure 13: Annual Hourly Demand Histogram in the Eastern Interconnection

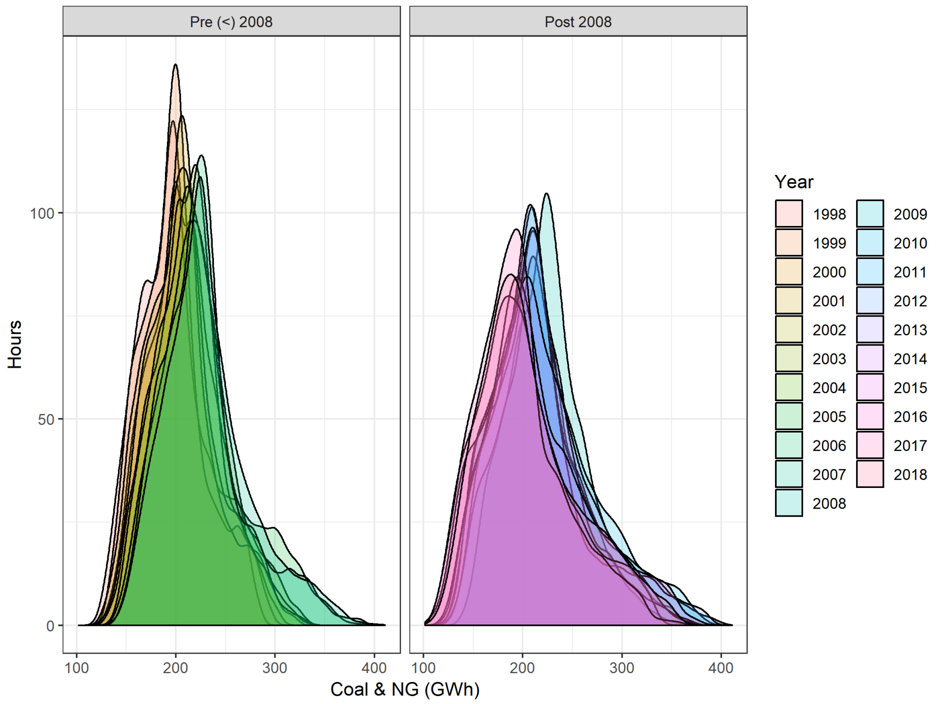

Figure 14: Annual Demand over Time in the Eastern Interconnection

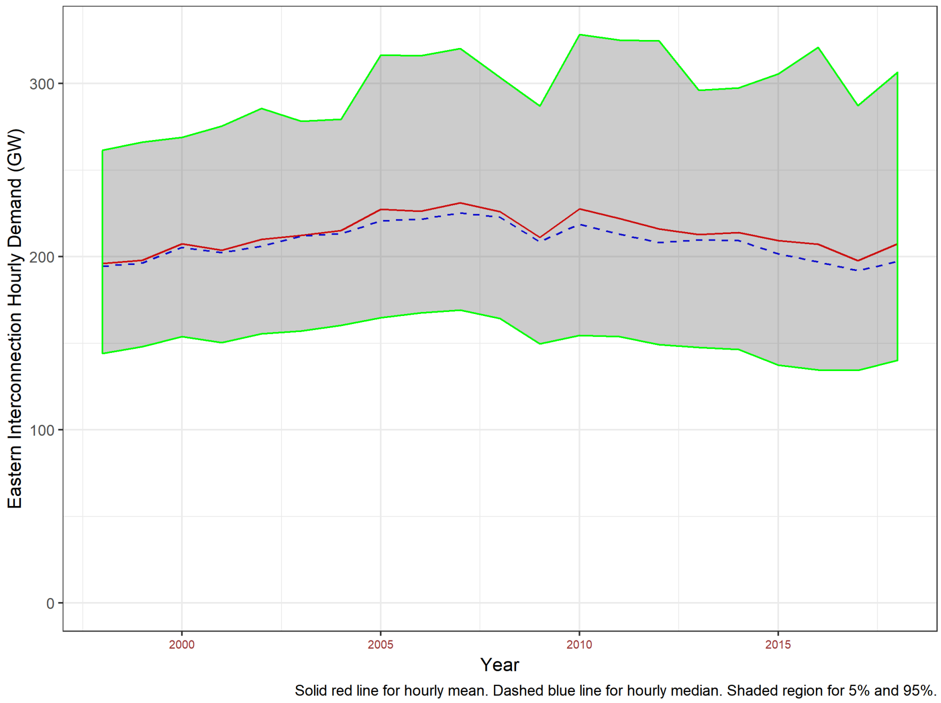

Figure 15: Aggregated Demand in the Eastern Interconnection

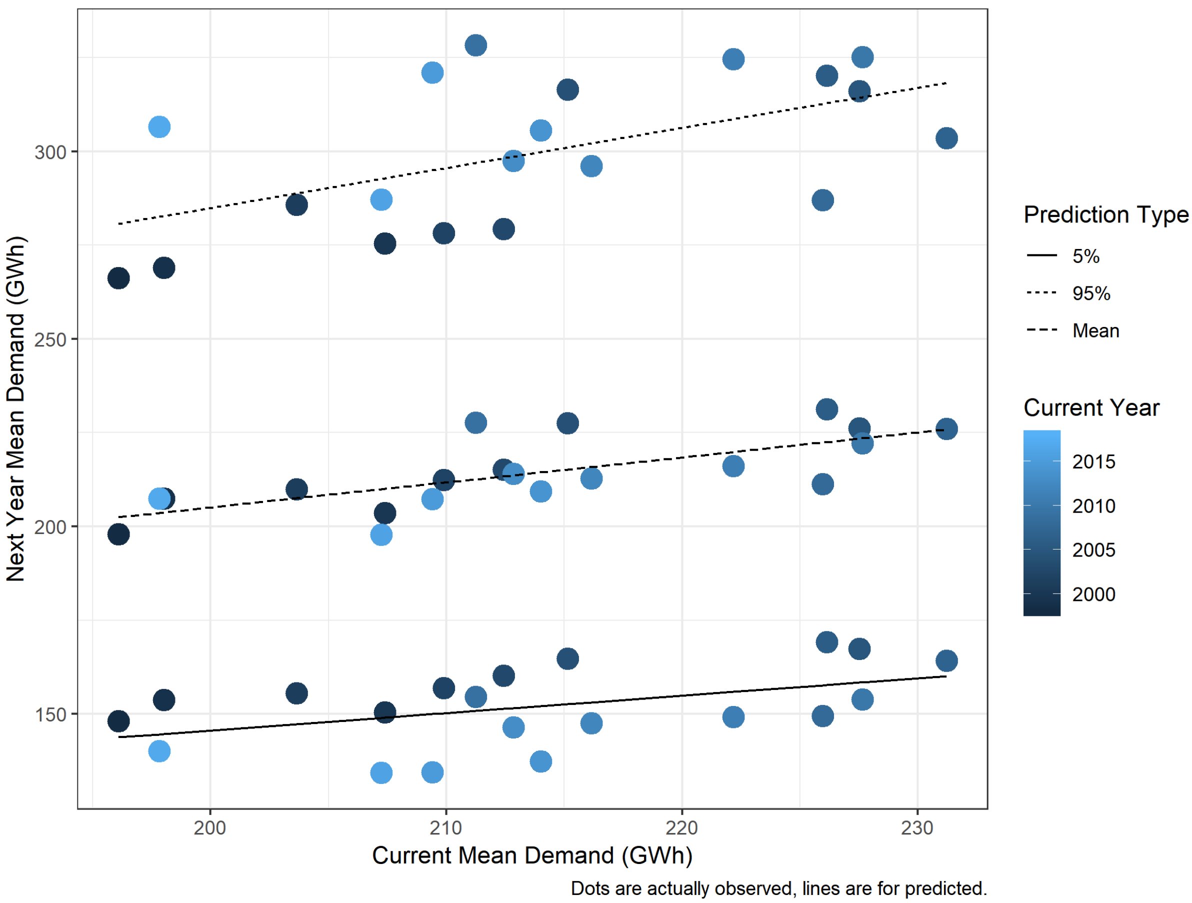

Figure 16: Demand Prediction

B 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

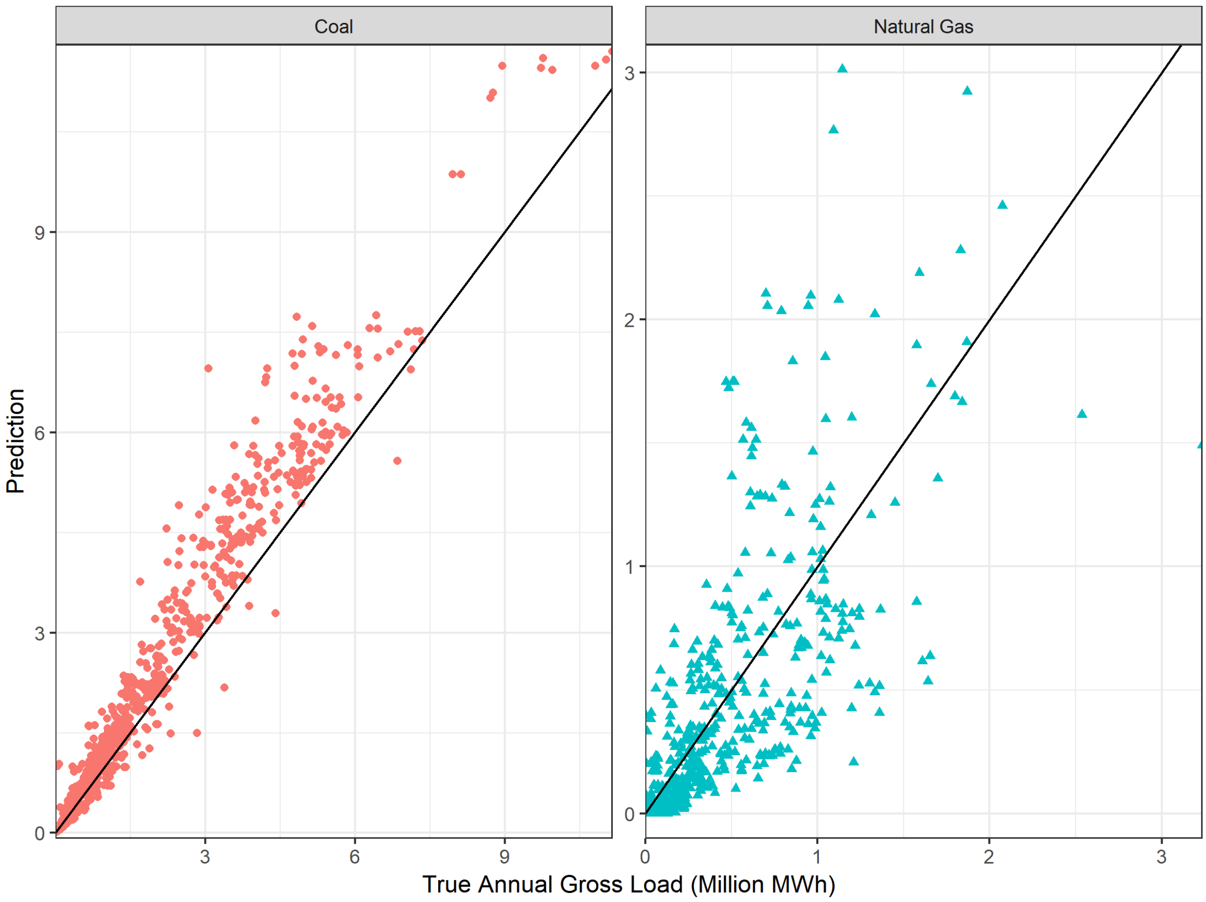

Figure 17: Fitting the Profit in the Base Year 2005

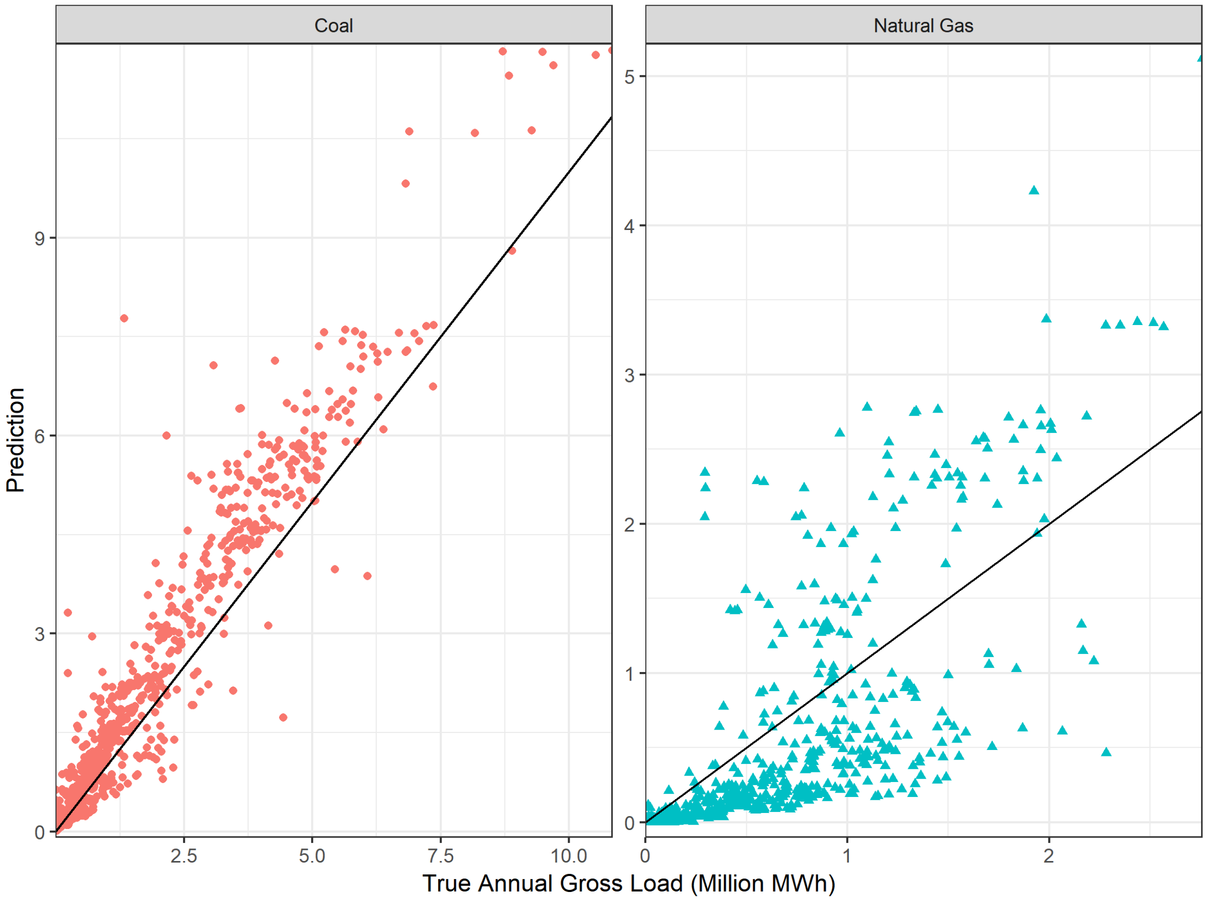

Figure 18: Fitting the Predicted Profit in another Year 2010

C Dynamic Model

Table 10: Local Policy Enacted and Effected Years

StateAbbr	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