# How Large are the Cost Savings from Emissions Trading? An Evaluation of the U.S. Acid Rain Program

# How Large are the Cost Savings from Emissions Trading? An Evaluation of the U.S. Acid Rain Program*

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**Abstract**

Emissions trading programs are designed to keep compliance costs low but studies on actual savings are limited. This paper is the first to conduct a comprehensive analysis of the cost savings from the Acid Rain Program (ARP), the largest emissions trading program implemented in the U.S.. I estimate a discrete choice model of coal procurement and scrubber installation to recover structural parameters of compliance cost functions at the generating unit level. Using the model, I predict compliance choices under a uniform emission standard that yields the same aggregate emissions as the ARP. I estimate cost savings under the ARP to be about 265-380 million (1995 USD) per year. The numbers are much smaller than in previous literature (Carlson et al., 2000; Ellerman et al., 2000). I propose that lower transport costs reduced cost heterogeneity across generating units, and that improvements in scrubbing technology and state policies may have also contributed to a decrease in cost savings.

Keywords: Coal-fired Power Plants, Acid Rain Program, Discrete Choice Model, Cost-effectiveness of Emissions Trading.

JEL Classifications: L94, L98, Q52, Q53, Q58.

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# 1 Introduction

Since the 1970s economists have argued that market-based instruments – in particular, tradable pollution permits – are preferred over command-and-control approaches to environmental regulation (Montgomery, 1972; Tietenberg, 1990). The gains from trade, which occur when firms with higher pollution abatement costs buy permits from lower cost firms, have motivated policy makers to adopt permit trading programs to control air and water pollution. However, there has been little research that measures the cost savings from pollution permits retrospectively, based on actual compliance behavior. If the gains from trade are modest, more politically feasible regulations such as performance standards might be an acceptable alternative.

This paper fills a gap in the literature by estimating the cost savings from the US Acid Rain Program (ARP) based on observed compliance strategies. The Acid Rain Program, enacted under Title IV of the 1990 Clean Air Act Amendments, is regarded as a milestone in the history of cap-and-trade programs in the United States. The program distributed permits to emit sulfur dioxide ($SO_2$) to electric utilities and allowed sources to trade permits in order to achieve an annual cap of 8.95 million tons of $SO_2$, approximately half of 1985 emissions. Before the legislation was passed, the program was predicted to reduce the cost of meeting the $SO_2$ cap by more than $3 billion per year, compared to a uniform performance standard (GAO, 1994). The question is whether these costs savings were realized.

To answer this question I estimate a structural model of compliance behavior for all coal-fired electric generating units (EGUs) covered by the ARP, and use the model to compute the cost savings achieved by the ARP compared to a uniform performance standard that achieved the same aggregate emissions reduction. For each unit I model the joint decision of the type of coal to purchase and whether to install pollution abatement equipment (i.e., a flue-gas desulfurization unit or scrubber). I assume in making these decisions that plants weight various components of costs differently, reflecting various regulatory and institutional factors (e.g., whether the plant is subject to cost-of-service regulation). The main methods of reducing $SO_2$ emissions are to switch to coal with a low sulfur content and/or to install a flue-gas desulfurization unit (scrubber), and geographical distance between plants and coal mines determine the heterogeneity in compliance cost due to transportation cost.

My approach essentially estimates the marginal abatement cost (MAC) 'curves' for every generating unit and uses those to infer the equilibrium in the uniform performance standard case. In the data I observe the equilibrium emission rates and compliance choices in the ARP for each unit. By estimating the discrete choice model, I estimate the slope of the functions which are primarily determined by the transportation cost of coal. This model is used to predict compliance behavior under a performance standard, and to calculate compliance costs and emissions under the ARP and under a performance standard.[1] Estimating a discrete choice model (instead of estimating a continuous function) allows me to take the regulatory and institutional factors into their decision making.

Previous approaches that study the cost savings of ARP are based on either pre-program data or on a subset of units only. (Carlson et al., 2000) project the long-run cost savings achieved by the ARP based on MAC functions estimated using pre-ARP (1985-1995) data. The MAC functions, based on a static cost-minimization model, capture the cost of reducing $SO_2$ emissions only through fuel switching.[2] Carlson et al. (2000)'s estimate of the long-run cost savings from the ARP, compared to a uniform performance standard, is $780 million (1995 USD) per year – a figure much lower than other estimates. No paper since Carlson et al. (2000) has econometrically modeled the abatement decisions of Phase I and Phase II units using actual compliance data. Keohane (2007) estimates a discrete choice model of the scrubber uptake decision but focuses only on the generating units in Phase I of the program. Related research by Arimura (2002) studies the decision to switch low sulfur coal but also focuses only on Phase I units.

There are, however, reasons to believe that Carlson et al. (2000)'s estimate may overstate cost savings: It assumes that the ARP will achieve the least-cost solution to emissions reductions. In fact, state Public Utility Commissions (PUCs), which allowed scrubbers to enter the rate base under cost-of-service regulation and often encouraged the purchase of in-state coal, could well

[1] By doing that I am ignoring the benefit side of the policy. My concurrent work (joint with Andrew Chupp, Maureen Cropper and Nick Muller) addresses this by computing the net benefits of the program.

[2] (Carlson et al., 2000) assume that no additional scrubbers will be built after 1995, the first year of the ARP.

have prevented attainment of the least-cost solution. I explicitly allow for this by estimating a compliance cost function that allows different policies or incentives to enter the cost function. This allows units in my model to deviate from the least cost solution as computed by (Carlson et al., 2000). Second, the costs of coal procurement and scrubber installation have changed since the 1985-95 period. It is difficult to calculate the impact of these cost changes without making simplifying assumptions or using actual data.

I model the long-run compliance behavior coal-fired EGUs in the ARP using a mixed logit model of the choice of whether or not to scrub and what type of coal to buy, described by geographic location. Each EGU chooses a compliance strategy to minimize the weighted cost of compliance subject to a state or local emission standard.[3] The compliance choice for each EGU depends on delivered coal price, the cost of scrubbing, the cost of emissions (i.e., permit cost), on the sulfur and ash content of coal, as well as on the cost of retrofitting the boiler if the unit switches from high to low sulfur coal after the ARP. Coefficients on the various cost components are interacted with state-level regulations including electricity deregulation status and credits for using in-state coal. Given the variation in ash and sulfur content within each coal basin, I use an iterative procedure to estimate the county within each basin from which coal is bought.

After estimating the model, compliance choices, aggregate costs and emissions are predicted under the ARP and under a uniform performance standard that achieves the same aggregate emissions as achieved under the ARP. Both sets of compliance choices are predicted using conditional distributions (i.e., distributions conditional on the observed choice being made) of the random coefficients and the error term in the cost function. Specifically, I treat the conditional mean of the error term in the cost function as a permanent difference in costs. This captures unobserved heterogeneity in costs, which is important to capture, given that the cost savings from emissions trading originate from abatement cost heterogeneity. Unweighted compliance cost – the estimated cost of coal, costs of scrubbing and additional retrofitting cost – are compared across different policy scenarios, conditional on predicted choices.[4]

[3]The state or local emissions standard is imposed by restricting the set of choices available to each EGU.

[4]My approach is similar to (Fowlie, 2010) who estimates a random coefficient logit model to look at compliance

Based on my model, I estimate the cost savings from emissions trading to be between 265 and 380 million (1995 USD) per year. This number is fairly small compared to numbers in Carlson et al. (2000) and Ellerman et al. (2000). This difference may be explained by reductions in the cost of transporting coal following railroad deregulation and lower scrubber operating costs. Both factors lowered compliance costs and reduced heterogeneity in these costs across coal-fired generating units. State and local emissions standards also constrained the alternatives that each generating unit could choose. I also find that, conditional on the above factors, many generating units did not pursue the least-cost options to reducing emissions. Weighted costs differ significantly from unweighted costs, suggesting that many units did not pursue the compliance option that yields the lowest cost.

The rest of the paper is organized as follows. Section 2 provides a concise introduction to the Acid Rain Program. Section 3 presents my model of compliance choice. The data used to estimate the model are described in Section 4, as are the equations used to predict the cost of the options in each unit's choice set. It also provides an overview of compliance strategies chosen. Section 5 discusses estimation methods and Section 6 presents estimation results. These are used in Section 7 to predict compliance choices and calculate the cost savings from emissions trading. Section 8 concludes.

## 2 A Concise Introduction to the Acid Rain Program[5]

The objective of the Acid Rain Program was to reduce sulfur dioxide emissions from fossil-fueled power plants in the U.S. by 50% from the 1985 levels. The program was implemented in two phases: in Phase I (1995-1999) the most polluting 263 generating units were required to participate. In Phase II, beginning in 2000, the program was extended to all generating units

choices with regard to the $NO_x$ trading program. The fundamental difference between our approaches is that she estimates the cost indices associated with engineering cost estimates while I am also estimating the underlying unobserved cost components.

[5]This section presents only the basic facts about the ARP. For more details about the program, see Joskow, Schmalensee and Bailey (1998), Ellerman et al. (2000), Burtraw and Szambelan (2009) and Chan et al. (2012).

with a capacity exceeding 25 megawatts (approximately 1100 coal-fired units).[6] The Environmental Protection Agency (EPA) allocated annual permits to each generating unit equal to the product of the target emission rate (1.2 pounds of $SO_2$ per million Btu) and the unit's heat rate in the 1985-97 reference period. Under the ARP units are free to trade permits within and across states. They are also allowed to 'bank' permits for future use but cannot borrow permits from future years.[7] Figure 1 provides an overview of the market over time.

I focus on all coal-fired generating units that participated in the ARP and study their compliance strategies in Phase II of the program. Units constructed after September 1971 are excluded from my study as those units were subject to New Source Performance Standards (NSPS), i.e. they were subject to $SO_2$ emission regulations at least as stringent as those under the ARP when they were constructed. Plants built between 1971 and September 1977 were required to reduce their $SO_w$ emissions to 1.2 pounds per MMBtu; those built after September of 1977 were, in effect, required to install scrubbers.

Plants have reduced their $SO_2$ emissions under the ARP either by reducing the sulfur content of the coal they burn or by installing scrubbers. The cheapest way to comply with the Acid Rain Program depends primarily on the geographic location of the power plant. For plants located close to the Powder River Basin (PRB) in Wyoming, burning low-sulfur PRB coal may be the cheapest option. PRB coal has the lowest minemouth cost and sulfur content of any coal in the US; however, it has lower heat content than Eastern coal. Boilers deigned to burn high-sulfur coal may have to be retrofitted to burn PRB coal. There is also the cost of transporting coal to the plant. Plants in the Midwest benefit from smaller transportation costs hence low sulfur coal is a common compliance option for these plants. Indeed, differences among plants in the cost of transporting coal from the PRB are the primary source of heterogeneity in compliance costs under the ARP. Another compliance option is to install and operate a flue-gas desulfurization

[6] The Acid Rain Program also regulates gas-fired and oil-fired generating units, which brings the number of regulated generating units to over 1800. I do not study either gas- or oil-fired units emit very small number of sulfur dioxide therefore I am not studying these uni. Gas units emit small quantities of sulfur dioxide. Oil-fired units emit at a higher rate, but do not account for a high portion of $SO_2$ emissions.

[7] Phase I units were allocated allowances based on the emissions level of 2.5 pounds of $SO_2$ per million Btu in the first five years of the program. Some units also received some bonus allowances each year depending on their state incentive schemes or fulfilling early emissions reduction requirements. Many papers have documented that these units use banking as a way to smooth out the compliance cost over time (Schennach, 2000).

device, commonly known as a scrubber. A scrubber uses an alkaline agent to react with $SO_2$ and typically removes 85-90% of emissions. Figures 2 and 3 show the prevalence of these two compliance choices by state.

The flexibility of the cap-and-trade program also allows units to use coal with higher sulfur content and purchase allowances from other plants. Figure 4 shows the difference between actual emissions and allocations at the state level in 2002. It provides evidence of the geographical disparity in cost noted above – generating units in Mid-Atlantic region are buying more permits from the West to cover their emissions, indicating that their average emission rate is above the 1.2 pounds of $SO_2$ per MMBtu threshold. As Figures 2 and 3 show, most of the units did not install scrubbers or utilize low sulfur coal from the West. My model captures compliance choices by allowing units to choose the type of coal and the scrubber installation decision, which ultimately determines the emission rate that each unit wants to achieve. Each strategy is associated with a premium on sulfur that represents the price of allowances.

Allowance trading among compliance units is an important feature of the Acid Rain Program. Table 2 lists (for net buyers of permits) the share of emissions that were covered by trading. This share captures the importance of trading to units that purchased permits to cover emissions. It is calculated as the excess of emissions over current allowances, minus the stock of permits held at the beginning of the period, divided by the total emissions. As we can see from Table 2, permits purchased by net buyers of permits cover about 40% of the emissions in Phase II (2000 onwards). This indicates that trading did, indeed, occur under the program.

Figure 5 presents further evidence of trading activity by showing the transfers of allowances in each year. Even though trades between related entities (under the same utility) sometimes make up more than half of the trades in a given year, they could result in efficiency gains to both entities if their compliance costs differ. Trading activity by itself does not, however, indicate that the program lowered compliance costs – nor does it provide evidence of their magnitude.

To estimate the magnitude of trading gains under the ARP I estimate a model of coal choice and the decision whether or not to install a scrubber using observed compliance choices from the first three years of Phase II (2000 to 2002). I argue in Section 3 that generating units had adjusted to the ARP by this time. It is also the case the regulatory regime changed sharply after this time. EPA revised the regulation on sulfur dioxide by proposing the Clean Air Interstate Rule (CAIR) in late 2003. This rule would have eventually cut $SO_2$ emissions by 73% below 2003 emissions levels. More importantly, complying units were offered an opportunity to trade Title IV permits at some unknown trading ratios to the CAIR (Fraas and Richardson, 2010). This leads to a huge spike in the permit price in 2004, as we can see from Figure 6. The increase in the demand for permits suggests that power plants were strongly reacting to the introduction of CAIR and, therefore, that their compliance choices were not be targeted towards the ARP alone. I therefore do not use compliance choices beyond 2003 in my analysis.[8]

# 3 Model

In this section I describe the structural model of compliance choice. I begin the section by describing the general framework. Then, I will go into details the assumptions, the structure and identification of my random coefficients choice model where each generating unit picks types of coal to burn and whether to install a scrubber (pollution control equipment).

## 3.1 General Framework

The objective of the estimation procedure is to structurally estimate a model that allows me to predict both (1) the aggregate cost of compliance and (2) aggregate emissions under the ARP and the uniform emission standard. In the data, I observe the emission rates and also the compliance choices that the generating units (EGUs) make. To answer the research question on the magnitude of the cost savings, one has to know (1) the cost of compliance associated with the choice they picked, as well as (2) the emission rates and the compliance cost for other compliance choices. I estimate the cost functions associated with difference choices, allowing

[8] I test my robustness by using average compliance from 2000 to 2003. The fit of the model is a bit worse but the main results hold.

for both observed variation in costs (e.g. coal prices and transportation costs), the shadow value that firms place on sulfur emissions and unobserved factors such as cost of retrofitting (modifying boiler to burn a different kind of coal), and operating cost associated with low sulfur coal.

A lot of decisions made by power plants are of discrete nature. When power plants are picking their choices of coal, they decide on which coal region that they want to buy their coal from – located from East to West, different regions offer coal of different quality (sulfur and ash content) associated with different transportation cost. Investing on pollution control equipment, known as scrubbers, is also a discrete choice. Therefore, it is reasonable to estimate a discrete choice model to understand the tradeoffs between these different compliance choices. A discrete choice model, which allows discrete jumps in the compliance cost functions, also helps control for the institutional factors such as electricity market deregulation and credits from using in-state coal (more details in Section 3.2), which are otherwise hard to handle in a continuous or discrete-continuous framework.

My model explains observed choices of what type of coal to burn in an EGU and whether the unit was attached to a scrubber during the period 2000–2002. I assume that these cboices were made to minimize weighted fuel plus abatement costs, plus the cost of allowances to cover emissions. The period 2000–2002 representa a window between thee beginning of the ARP and the change in regulatory regime facing coal-fired power plants. As noted above, plans to increase the stringency of the $SO_2$ cap under CAIR were announced at the end of 2003.[9] This caused a huge spike in allowance prices in 2004 and, beginning in 2005, led many units to install scrubbers in anticipation of the new regulatory regime. My goal is to model compliance behavior under the ARP once power plants had adjusted to it Figure 7, which shows survey data on compliance strategies by Phase I and II units, suggests I argue that this had occured by the period 2000–2002. I do, however, vary this window for sensitivity analysis.

The ARP is seen as a cost-effective way of achieving emissions reduction as it gives power

[9] Although the CAIR was eventually vacated by the courts, it was followed by a series of rules designed to reduce the $SO_2$ cap by more than 50%.

plants the flexible to pick their emissions, taking into account a permit price component that increases with its desired emission rate. With the estimated model, I can then simulate a uniform emission standard, which is an emission constraint imposed on *all* generating units, such that the aggregate emissions reduction is identical to the ARP. The displacement between the ARP equilibrium and the constrained equilibrium (under the standard) indicates the difference in the compliance cost, which can be aggregated as the cost savings achieved from emissions trading. By estimating a discrete-choice model, not only can I predict what the compliance choices are going to be under the constrained standard case, but I can also predict the observed and unobserved compliance *cost*.

I choose to estimate a static not dynamic model for two reasons. Despite the dynamic nature of the permit market, I did not pursue a dynamic model that explicitly models the permit banking decisions (Zhang, 2007). In this paper, I am not interested in studying the permit banking and trading in the equilibrium. Instead, each generating unit chooses a compliance strategy, which is associated with its desired $SO_2$ emission rate, that would implicitly incorporate permit banking motive into account. My model will estimate the shadow price of emissions and compare that to the allowance prices. Permit prices are stable during the period of my analysis (see Figure 6) which suggests that the banking motive should not change much.[10]

Besides the stability of the permit market, price trends for different kinds of coal did not fluctuate much over my study period. If this is violated, the snapshot in 2000–2002 might have just reflected the fact that particular set of coal is cheap during those years, and this does not necessarily reflect the compliance choices that they would otherwise make. Even if the prices do change, it requires some effort by the generating units to change the type of coal they are using given the fixed cost in altering the specification of the boiler as well as changing any contractual arrangement. Figure 11 plots the minemouth prices for three regions – Appalachians, Interior (including Illinois Basin) and the West (sources of low sulfur coal) using data in EIA

[10] Since each compliance strategy would lead to its desired emission rate, the sulfur content of the coal (as well as the presence of scrubber if the unit chooses to install one) should be sufficient in determining the unit's actions in the allowance market. In other words, each unit still has to choose the type of coal that they use besides engaging in permit banking. Both Schennach (2000) and Zhang (2007) suggest that banking serves as a 'pollution smoothing' instrument for Phase I units – most of the allowance bank is owned by Phase I units and the bank of allowances is slowly drawn down for Phase I units but not for Phase II units.

(2013). Though prices are trending down from 1990 to 2000, the trends for these three regions follow each other very closely and there is no evidence of a huge discount from any of the regions. Therefore, current prices should act as a good proxy for the future prices and a static compliance cost function can act as a good proxy for the true compliance cost that they face.[11]

### 3.2 A Model of Compliance Choice

In my model each generating unit $i$ chooses a compliance strategy to minimize weighted compliance cost. There are in total $2N$ compliance strategies that each unit can choose – a binary choice of installing a scrubber as well as choosing one of the $N$ types of coal. Each type of coal is associated with a mean sulfur and ash content. I assume that each generating unit $i$ has no market power in both the electricity and the permit market and produces a constant output – therefore it treats the heat input (in MMBtu, and hence electricity output) as fixed.[12] This is a reasonable assumption as coal-fired power plants are often located at the lower portion of a electricity load curve and they are to generate electricity given they are the least-cost producers. Less than 10 generating units indicate that they decreased utilization to comply with the ARP (as indicated by the EIA survey data in Figure 7). An emissions rate, as a function of the sulfur content used and the scrubber installation status, and compliance cost can then be generated from the estimated model.

Location of the plant is the primary source of the observed heterogeneity of the compliance cost. Plants in Michigan, which are closer to the source of low sulfur coal in Wyoming and Colorado, will have a lower cost compared to the ones in Pennsylvania due to the transportation cost component. The delivered price of coal, which is a sum of the minemouth coal price and the transportation component (which differentiates the plants), will be included in the compliance cost functions. Each generating unit is also subject to a state or local regulation that prohibits

[11] Right now the prices that I am using are the ones that coincide with the 2000–2002 period. In future work, I am going to incorporate other models of price expectations.

[12] I have tested the production / thermal efficiency of different types of coal and they are not statistically different from each other. Heat content is the only factor that matters in electricity production and therefore I will base everything on the heat input in MMBtu.

them from polluting more than a certain emission rate due to the National Ambient Air Quality Standard (NAAQS). This standard is effectively a constraint that affects the choice set for each decision maker. I term this standard the 'state emission standard' as this standard is enforced at the local or state level. The state emission standard is modeled such that generating units could not choose the kinds of coal that will violate this emission constraint. Therefore, each boiler minimizes the per MMBtu compliance cost subject to current emission standard:

$$\min_j C_i(j, \beta) \quad \text{s.t.} \quad (1-\theta(j))SULFUR(j) \leq \overline{SULFUR}_i \tag{1}$$

where $C_i(j, \beta)$ is the weighted compliance cost per MMBtu for generating unit $i$ which chooses compliance strategy $j$. These weights control for different institutional and economic factors (such as utilizing in-state coal, more details to follow) that affect power plants. $\overline{SULFUR}_i$ represents the local or state emission standard (in pounds of $SO_2$ per MMBtu) facing unit $i$ and it is taken as exogenously imposed. To take the emission standard constraint into account, I drop alternatives that violate the constraints based on the 10% quantile of observed sulfur and ash content. The weighted compliance cost per MMBtu takes the following parametric functional form:

$$\begin{aligned} C_i(j, \beta) = \beta^F COALPRICE_i(j) + \beta^A ASH(j) + \beta^S SULFUR(j) + \beta^t SULFUR(j) \times (1-\theta(j)) \\ + \mathbf{1}(j = PRB)(\beta_0^l + \beta_1^l AGE_i) + \beta^z SCRUBCOST_i(j) + \beta^M MODIFY_i(j) + \varepsilon_i(j) \end{aligned} \tag{2}$$

$\beta$ serves two purposes in the above equation. First, it represents the weights that each manager is placing on each category of costs (Fowlie, 2010) and the possible non-cost minimizing motives that they may have respective to each component. Second, it estimates the capital and operating cost that I will discuss it below. Unlike Fowlie (2010), I do not observe the associated capital cost regarding each compliance strategy. I attempt to measure the operating cost by controlling for ash content of coal (per MMBtu) ($\beta^A$).

The compliance cost functions in equation (2) consist of [1] coal prices ($\beta^F COALPRICE_i(j)$), [2] cost of scrubbing ($\beta^z SCRUBCOST_i(j)$), [3] operating cost ($\beta^S SULFUR(j) + \beta^A ASH(j)$), [4] emissions ($(1-\theta(j))SULFUR(j)$, where $\theta(j) = \theta$ if a scrubber is installed, zero otherwise; and

$\theta$ is the exogenous removal rate of the scrubber), [5] operating cost associated with use of low sulfur coal ($\beta_0^l + \beta_1^l AGE_i$), and [6] cost of retrofitting ($\beta^M MODIFY_i(j)$). The last component, $\varepsilon_i(j)$. represents the component of the cost that are specific to each alternative $j$ but not observed by the econometrician. I assume that $\varepsilon_i(j)$ follows type-I generalized extreme value distributes and it is identically and independently distributed across generating unit $i$ and alternative $j$. I will discuss components [4], [5] and [6] below.

Shadow price of permits will be estimated from the model based on coefficient $\beta^t$. $(1 - \theta(j))SULFUR(j)$ represents the emission rate and $\beta^t$ in equation (2) is the permit price (as perceived by firms) and it carries an opportunity cost equal to the permit price. To estimate $\beta^S$ and $\beta^t$, I include sulfur content of coal as well as an interaction term between sulfur and scrub status dummy. Theoretically these coefficients should differ by $\theta$ but I did not restrict that in the estimation due to possible operating cost associated with the sulfur content of coal (represented by $\beta^S$) or different weighting of the two by the decision maker. In the counterfactual both $\beta^S$ and $\beta^t$ will be shut down to indicate that there is no shadow price of permits in the emission standard case.[13]

Components [5] and [6] in the above equations are the two types of unobserved retrofitting costs modeled in my specification. First, using coal from the Powder River Basin often incurs an additional operating cost due to the fact that it has a lower heat content (hence the need to pump coal quickly to achieve the same thermal efficiency). Second, there is a potential cost of modifying the source of the coal. This represents two types of costs – the retrofitting costs that power plants incur when they modify the types of coal they use (as a boiler is often designed to burn a subset of coal types only) and the cost of building the required rail road network to access the mine. I control for these by including the respective dummies in the cost function, interacted with the age of the boiler. I use data on average compliance choice in 1981–1983 and set the retrofitting dummy equal to one if the coal type used in 2000–2002 differs from 1981–1983.

[13] As a robustness check, I have allowed a possible operating cost component from $\beta^S$ in the counterfactual. While the magnitude of the cost savings is similar, the implied abatement cost is significantly lower.

The weights (which are represented by the $\beta$'s) capture some of the differences in economic incentives that may make generating units non-cost minimizing. Units that are regulated under rate-based regulation maybe included towards the scrubber option because the scrubber is viewed as a capital investment included in the rate base (allowed to increase their allowed revenue). Therefore, estimating these parameters rather than assuming their effects can capture non-cost minimizing behavior. This may case cost savings to differ from estimates that assume a least-cost solution.

The coefficients on scrubber cost and coal prices are allowed to be correlated with some observed plant attributes:

$$\beta^z = \beta_0^z + \beta_1^z KBIAS_i + \beta_2^z DEREG_i \tag{3a}$$

$$\beta^F = \beta_0^F + \beta_1^F MINEMOUTH_i(j) + \beta_2^F MATCH_i(j) + \beta_3^F DEREG_i \tag{3b}$$

Several factors may influence the scrubber installation and fuel choice decisions. Minemouth plants, which are plants located next to a mine, will have higher incentives to use coal from neighboring mines as they may not wish to change contractual arrangements with the adjacent mine. Lile and Burtraw (1998) identified plants in three states (Pennsylvania, Ohio and Illinois) as being biased towards capital investments. Plants that have been deregulated in the electricity market may act more like cost minimizers (placing more weight on the cost of scrubber). Chan et al. (2013) and Cicala (2013) show that units in deregulated states (or divested units) purchase coal at a lower price, implying that they certainly put more weight on purchase cost. $MATCH_i(j)$ is a dummy that takes on the value of 1 if the mine and the plant are located in the same state, to control for state-level incentive programs that promote the use of in-state coal.

The observable and unobserved components in equation (2) are identified using different variations in the data. Observable components include the price of coal and scrubbing cost, from the survey forms gathered from the Energy Information Administration (more details in Section 4). Observable cost components can be identified using cross-sectional variation of coal prices and scrubbing costs. Unobserved components, like the cost of retrofitting mentioned above, are identified by using the trade-offs between different compliance options observed in the data and maximizing the likelihood that the observed compliance choice is observed.

The discrete nature of the cost function makes it less trivial to estimate a discrete-continuous model, treating $SO_2$ emissions as being a continuous decision variable (Dubin and McFadden, 1984). In such a framework, I have to estimate a coal price equation as a function of sulfur emissions, which requires a structure that corrects for PRB premium. For instance, one would need to include heat content as one of the explanatory variable in this pricing equation and restrict how the price depends on the heat content – in my model it is handled by including a PRB dummy that represents the cost. It is more flexible and less reliant on the assumption that the additional cost depends on the difference in heat content. Furthermore, it is very difficult to correct for the effects of minemouth and in-state coal as these represent discrete jumps in the pricing equation also.

# 4 Data

This section provides an overview of the data used in this paper. First, I discuss the data sources for coal procurement and prices as well as their shortcomings. Then, I briefly talk about the source for scrubbing cost and regression results for imputing coal prices, as well as other data that I used in this analysis. Before moving to the empirical framework, I conclude this section by discussing summary statistics

## 4.1 Cost and Quality of Coal

Coal procurement data are gathered from EIA-423 and FERC-423 forms, the "Monthly Cost and Quality of Fuels for Electric Plants Report". In the dataset, monthly cost and quality are reported for almost all coal transactions, heat, sulfur and ash content by weight, quantity, contract type, the mine from which the coal was purchased as well as purchase cost (which includes the transportation cost). Since the cost of storing coal is usually very low and I do not observe how much coal is stored, I look at their coal procurement in 2000–2002 as an approximation.

There are three challenges regarding these data. The first challenge is to define the type of coal purchased. Figure 9 summarizes the sulfur content of fuel (per MMBtu) of all the coal transactions observed from 1991 to 2010. There are two spikes below sulfur content of 1 lb/MMBtu – those represent the low and medium sulfur coal respectively. I define six types of coal depending on where the coal originated: North, Central, South Appalachian, Illinois Basin, Uinta Basin (Colorado and Utah) and Powder River Basin (Wyoming and Montana). Figure 8 shows the physical location of these coal basins. The summary statistics of their sulfur content are tabulated in Table 3. North Appalachian and Illinois Basin are the main sources of high sulfur coal – coal plants often buy coal from these regions (often the cheapest coal) and install a scrubber to remove emissions. They could also use coal from these regions and purchase the right to pollute by obtaining extra permits. The Central and South Appalachian regions are sources of medium sulfur coal.

The second challenge is that 20–30% of the plants purchase more than one type of coal, and 5% of them purchase coal not originating from the six regions defined above. To avoid this problem, I assume that plants could buy from at most two regions – they may buy 100% of coal from one region or 50% from each of two coal basins.[14] I drop generating units that do not purchase any coal from these six regions.[15] Since coal transactions are observed at the plant level but not at the boiler (generating unit) level, I use the following algorithm to allocate coal purchases at the unit level: (1) for a plant with minimal difference of emission rates (gathered from the Continuous Emissions Monitoring System (CEMS) database) across its generating units, I assume they are using the same kind of coal; (2) for a plant with boilers of significantly different emission rates, I record the two types of coal used most intensively and assign the one with the higher observed sulfur content to the boiler with the higher emission rate; (3) for a

[14]Less than 3% of my sample units purchase significant amounts of coal from more than 2 regions.

[15]These plants mainly buying lignite coals from Gulf Coast region or importing bituminous coal from Colombia. I attempted to predict the price from Gulf Coast region but the estimated coal price would imply most of the plants should have bought coal from this region. This imprecision is mainly driven by low amount of observed transactions and these transactions are initiated by plants around Gulf Coast region.

plant with scrubbers installed in some of their boilers, I assign and match the coal based on the emission rate and observed removal rate. Often times this is the cheapest coal with the highest sulfur content.

The third challenge is that I observe coal prices only for coal that a plant has purchased. Therefore, I run the following coal price equation for each coal basin using all transactions from 1991 to 2010 to predict the price of coal for each coal plant and coal basin in my sample[16]

$$\begin{aligned}
&\ln(COALPRICE_{ijt} - \tau DISTANCE_{ij}) \\
&= \alpha_1 \ln SULFUR_{ijt} + \alpha_2 \ln ASH_{ijt} + \alpha_3(\ln SULFUR_{ijt})^2 + \alpha_4(\ln ASH_{ijt})^2 \\
&+ \alpha_5(\ln SULFUR_{ijt}) \times (\ln ASH_{ijt}) + \alpha_6 SPOT_{ijt} + \delta_t + \varepsilon_{ijt} \qquad (4)
\end{aligned}$$

$COALPRICE_{ijt}$ is the observed real coal price (in cents per MMBtu) that plant $i$ pays if $i$ purchases from mine $j$ at year $t$.[17] [18] $DISTANCE_{ij}$ is the county to county rail distance between plant $i$ and mine $j$, gathered from CTA Transportation Networks. This is taken as the physical distance between the plant and the mine as most coal is transported by rail. $SULFUR$ and $ASH$ are the observed sulfur and ash content (per millions Btu), $SPOT$ is a dummy that indicates a spot market purchase, and $\delta_t$ is a time dummy. $\tau$ represents per ton per mile transportation cost in cents, and it is estimated using nonlinear least squares, along with other coefficients. By subtracting the transportation cost component, the left hand side of equation (4) represents the predicted minemouth price.

Results for all of the six major coal basins are displayed in Table 4. The coefficients on the year dummies represent the average price for coal transactions in that particular year. Signs for sulfur content are reasonable as coal of higher sulfur content is cheaper. Transportation costs are of similar magnitudes as the ones reported and estimated by EIA. Normally plants do not prefer coal with high ash content as it affects the reliability of a generating units, but

[16] I have also tried a different specification where sulfur and ash content (and their interaction) have a linear relationship with delivered coal prices. My estimation and simulation results do not change significantly.

[17] All costs are expressed in 1995 dollars using the GDP deflator, downloaded from Federal Reserve Bank of St. Louis.

[18] 'Mine' is defined as a specific county where the coal is transported from. Mine-level information is incomplete that would otherwise allow me to define mine-specific quality.

the positive correlation between cost and ash content is also found in earlier literature (Lange and Bellas, 2007). To estimate the average price for each plant and for each coal basin, I use the weighted distance from plant to each of the coal mines (using observed transactions as weights) and the average quality at the *mine level* to predict the average coal price in a region. I also predict the coal prices at the mine level using the same algorithm.

### 4.2 Scrubbing Cost and Other Sources of Data

Operating and installation cost for scrubbers are recorded in "Steam-Electric Plant Operation and Design Report" (EIA-767). As for coal, I observe the scrubber operating cost and installation cost only for the scrubbed units so I restimate models similar to Lange and Bellas (2005) to impute the scrubbing costs. I separately estimated two equations, one for operating cost and another equation for installation cost, using plant characteristics like size, operating hours and physical location, as well as technical attributes of the scrubbers like age of scrubber, removal rate and percentage of gas entering the scrubber. Results are shown in Table 5. For scrubber-specific regressors, their average values are used to impute the scrubbing cost. In the simulation, I assume a scrubber removes 85% of the total emissions.

To estimate equation (2), it is necessary to annualize the scrubber installation cost. Assuming a 11.33% discount rate and a 25 year lifetime (Ellerman et al., 2000), I annualize the predicted installation cost and compute the average cost of scrubbing as the sum of predicted operating cost (based on the size, age and location of the boiler) and annualized installation cost. This is expressed per MMBtu of heat input. Same as the coal prices, all scrubbing cost in the empirical section below are imputed costs from the regression results presented earlier.

I treat the unit's production level as fixed and assume that it does not change in the counterfactual scenario. The corresponding heat input is taken to be the average heat input used in 2000–2002.[19] There is no evidence that using different kinds of coal impacts the thermal effi-

[19]Heat input used is gathered from the CEMS database; in case that is missing, I supplemented it with data in EIA-767 form. Technically speaking the heat input use data in CEMS may include generation using energy sources other than coal, while the data in the EIA-767 isolate that for different fuels. While EIA-767 data may seem more

ciency of the boiler.[20] I also gathered the data on plant location, age of the boiler and NSPS regulation status using data from EIA-767 and EIA-860 forms.[21]

### 4.3 First Look at the Data

Table 10 summarizes the generating units in my sample and the ones that I excluded. The majority of the excluded units are regulated under New Source Performance Standards (NSPS). These units were constructed after 1971 and were required to use low sulfur coal or install scrubbers when they operate. Their compliance decisions were therefore not affected by the Acid Rain Program.[22] For the rest of the units, I either have no data on coal procurement or they buy coal other than the six major basins that I defined. This brings the total number of units in my sample to 777. By excluding the NSPS units from both the estimation and simulation, I am implicitly assuming that NSPS units are not changing their compliance strategies in case of a uniform emission standard. This is a fair assumption given that they face more stringent regulations. The otherwise excluded units account for less than 1% of the total emissions.

Before moving to the empirical section of the paper, it is important to understand how generating units pick their sources of coal. Table 6 summarizes the actual coal prices observed in the data for the three major coal basins – Powder River Basin (low sulfur), Central Appalachian (medium sulfur) and North Appalachian (high sulfur). Table 7 presents similar results based on imputed prices. Powder River Basin is often the cheapest coal facing coal plants. This might suggest that most coal-fired power plants would purchase coal from the Powder River Basin (PRB); whereas in practice, only a portion of them do so. Units often incurs additional costs to burn PRB coal, this includes operating costs to increase the speed of pumping coal into the

superior, it suffers from some data availability and reliability issues. Coal is usually used to generate 95% of the electricity output and therefore the cost associated with ignoring other fuel types should be small.

[20]When I run a fixed-effect regression of heat input on power generated, and I cannot reject the hypothesis that the inverse heat rates (the coefficient on heat input) for low, medium and high sulfur coal are the same from each other.

[21]In case the age of a unit is missing, I use the age of the plant as a proxy.

[22]There are different classes of the NSPS, depending on whether they were constructed after September 1971 (designated as "D" units) or August 1978 (designated as "Da" units). Although "D" units have more flexibility in choosing how to meet the NSPS, the required emission standard is still far below the target set by the Acid Rain Program, therefore I also excluded these units from my analysis.

boiler to keep the same output plus additional retrofitting costs. Therefore it is empirically important to estimate the hidden cost (or premium) in using PRB coal.

The identification of compliance strategies relies on the geographical variation in (imputed) coal prices, the variation in the sulfur and ash content of coal as well as the exogenous variation in the local emission standard. The geographical distances between the coal mines and plants determine the type of coal chosen as we can see from the imputed prices in Table 7. Further evidence can be seen by looking at the biggest buyers for different coal basins. For each coal basin, I check which states the buyers are from and summarize the results in Table 8. The bigger buyers are all very close by – Pennsylvania units are buying from North Appalachian, Midwest (Michigan, Illinois, Missouri) units are getting PRB coal, while South Appalachian coal are bought by the Alabama coal plants only. Table 9 provides similar summary statistics by looking at the coal procurement practice in each state.

Another important dimension of the compliance strategies is the choice of scrubbing. Out of my sample units, 88 (11.34%) scrubbed and 688 other units did not install a scrubber as of 2002. This is summarized in Table 11 together with the coal blending status of the boiler. However, out of these 88 units, 44 were installed before 1988 – indicating that they installed scrubbers for a reason other than the Acid Rain Program. Therefore, I exclude these 44 units in my estimation but not in the simulations, by restricting these units to choose a compliance option with scrubber installed. For the other 44 units, the average unit installed a scrubber in 1995 while half of these units installed a scrubber between 1993 and 1997. Table 12 provides a summary statistics of other variables including the cost of scrubbing for my sample – on average it is of similar magnitudes with the low sulfur premium observed in the data.

## 5 Empirical Framework

In this section I discuss the methods used to estimate the model outlined in Section 3. I begin with the standard conditional logit model. Then, I discuss the estimation using a mixed logit model and its benefits compared to using the conditional logit model. To conclude, I discuss an iterative procedure to more accurately predict coal choice and emissions, developed based on the random coefficient logit model.

### 5.1 Estimating a Discrete Choice Model

The most simple and straightforward way to estimate the model in Section 3 is to use a conditional logit model. Given that $\varepsilon_i(j)$ follows a type-I extreme value distribution, the probability that alternative $j$ is chosen is given by

$$\Pr(j|X_i, \beta) = \frac{\exp(-C(j, \beta; X_i))}{\sum_{j'=1}^{J} \exp(-C(j', \beta; X_i))} \tag{5}$$

where $X_i$ are all the observable characteristics of $i$ used to estimate $C(\cdot)$. Here the key assumption is that $\varepsilon_i(j)$, which represents the unobserved cost component, is i.i.d. across generating units and alternatives. The corresponding likelihood function is given by

$$\mathcal{L}(\beta|Y, X) = \sum_i \sum_j \mathbf{1}(Y_i = j) \ln \Pr(j|X_i, \beta) \tag{6}$$

As mentioned in Section 3, local emission standards are taken into account by eliminating alternatives that lead to a violation of the constraint. In predicting scrubber installation decisions, Keohane (2004) had the state emission standard entered as a of covariate to control for its indirect effects. The state emission standards impact the scrubber installation decision in my model directly by restricting the feasible choice set.

However the conditional logit model restricts the coefficients to be homogeneous across generating units. Even after controlling for observed attributes that influence scrubber installation, allowing the coefficients to vary can capture unobserved heterogeneity that impact generating units, given that some of these coefficients represent unobserved cost components. More importantly, underestimating these unobserved heterogeneity will likely lead to an underestimation of the cost savings in my simulation. Therefore, random coefficient logit model is used instead of the conditional logit model. Its log-likelihood function takes the following form:

$$l(b,\Sigma) = \sum_i \sum_j \mathbf{1}(Y_i = j) \ln \int_{-\infty}^{\infty} \frac{\exp(-C(j;b,X_i))}{\sum_{j'}^{J} \exp(-C_i(j';b,X_i))} f(\beta|b,\Sigma) d\beta \tag{7}$$

where $Y_i$ is the actual choice made by $i$, $f(\beta|b,\Sigma)$ is the probability distribution for the random coefficients and $b,\Sigma$ are the parameters associated with the probability distribution. The integral has no closed-form solution and it will be approximated by simulation using 200 Halton draws and I will use maximum simulated likelihood to estimate the parameters associated with equation (2).

I allow the coefficients on scrubbing cost, operating cost for using Powder River Basin coal and implicit cost of retrofitting to depend on an idiosyncratic unobserved component $\varphi$ where $\varphi$ is assumed to be normally distributed with zero mean and a diagonal variance-covariance matrix $\Sigma$. I use the coefficient of coal price to scale all parameters to a dollar value so it is kept as a fixed coefficient. In the results below, I assume $\varphi$ to be identically and independently distributed for each generating unit, although these coefficients may be correlated within a plant. [23]

## 5.2 Extension to allow within region coal choices

As seen in Table 3, each coal basin is associated with a range of sulfur content that may not capture the actual sulfur choice that they want to achieve – they may be buying coal with a lower sulfur content (while it is still in the same coal basin) to comply with the Acid Rain Program. In this subsection I introduce an algorithm to take the huge variance into account without the need to extend the choice set further. A plant may find coal in the West of region 1 better while another plant may find coal in the East of region 1 attractive.

[23] In future work, I will also check the robustness of my results by allowing a plant or a utility to draw one $\varphi$ for all associated generating units (Fowlie, 2010). The otherwise 'panel' setting assumes a plant as being a decision maker – I will keep the unit as a decision maker by restricting the random coefficients to be identical across units within a plant.

Therefore I extend the random coefficient logit model above to capture a nested decision making using the algorithm below:

1. Start with a guess of $\beta^{(0)}$.

2. For each choice $j$, I assume that each generating unit $i$ picks a coal type $k$ within $j$, associated with attributes $FUELCOST(k;j)$, $SULFUR(k;j)$ and $ASH(k;j)$, that minimize the *same* compliance cost function as in equation (2)

$$\min_k C_i(k;j) \text{ for all } i \text{ and } j \tag{8}$$

3. After determining the optimal $k^*(i,j)$ for each $i$ and $j$, unit $i$ will choose $k^*(i,j)$ if it chooses alternative $j$. Substitute the attributes of coal type $k^*(i,j)$ to the matrix $X_i$ in the logit model

4. Re-run the maximum simulated likelihood procedure on the mixed logit model based on these new attributes from region $j$ to get $\beta^*$.

5. Update $\beta^{(t)} = 0.8\beta^{(t-1)} + 0.2\beta^*$ and repeat Steps 2 to 4 until $\beta^{(t)}$ is sufficiently close to $\beta^{(t-1)}$, i.e. $|\beta^{(t)} - \beta^{(t-1)}| < 1 \times 10^{-6}$.

This algorithm is reliable as long as the units weigh cost and quality for coal within a region the same way when they select different regions. Each coal type $k$ is represented as coal from a mine-producing county (within a coal basin) in my data. I infer the average cost based on the same regression equation (4) using the rail distance between the plant and mine counties and the average sulfur and ash content for produced coal in that mine. Similar to the non-nested model, I allow a unit to buy coal from at most two counties – they can be within the same region or in different regions (which would end up as two different alternatives). I excluded mines with fewer than 300 observed coal transactions in 20 years because the observed average may not coincide with actual quality.

## 6 Cost Function Estimation Results

Table 13 displays the estimated coefficients of the cost functions. These coefficients will be scaled by the coefficient on coal price to give values in dollars. I will discuss the mean effects of the estimated coefficients, and move to their standard deviation and heterogeneity. First, as expected, all the signs are positive as we expect ash content (which lowers reliability) and other retrofitting and operating expenditures to increase compliance costs. Powder River Basin coal shows a large positive coefficient indicating that even though its coal may be the cheapest (as demonstrated in Table 6), it bears additional costs that deter units from using it. More importantly, older generating units incur a higher cost in adopting Powder River Basin coal. Based on the average age of 44, it is equivalent to a premium in the price of coal of around 50 cents. After adding 50 cents premium to the purchase cost of coal, PRB coal is roughly the same price as Uinta Basin coal (which does not have a statistically significant premium). Often times they are the most expensive coal source for Northeast units.

A second point to notice is that deregulated units are more sensitive to coal prices and cost of scrubbing and they tend to buy cheap coal. This result is also found in earlier literature on the effect of electricity market deregulation (Cicala, 2013; Chan et al., 2013) who found that deregulated plants incur a lower cost of coal procurement. This follows the theoretical predictions that competitiveness in electricity markets provides incentives to power plants to minimize their cost. Cicala (2013) in particular found that this is done by selecting more efficient coal mines instead of a pure transfer of rent from mine to plant. Other interaction terms with state policies also show the expected signs: there is an effective 'discount' to using in-state coal, and units in states with capital intensive investment bias also attach a lower weight to the cost of scrubbing. I also found a huge discount for minemouth units to use minemouth coal – this may reflect the value of long-term contracts.

The implied shadow price on the permit, based on the coefficient on the interaction term of sulfur content of coal and scrubber status, is about \$180 (per ton of emissions, constant 1995 dollars).[24] The actual prices were around \$150 - \$200 in nominal US dollars in 2000–2002, so the shadow price is not too far from the actual price. This implies that the permit market is operated efficiently when the estimated shadow price coincides with the observed price.

Third, there is considerable heterogeneity in the impacts of the observables. Table 13 shows a statistically significant variation in the random coefficients. This again shows the importance of estimating my model using the more flexible mixed logit approach. These random coefficients lead to unit-specific parameters as a conditional distribution of parameters, conditional on the observed choices (Train, 2009). Taken into account these unit-specific variation, 77% of my sample units chose the compliance strategies which have the highest predicted probability (and 71% of the scrubbing choices). The aggregate predicted emissions are 8.70 million tons of $SO_2$ which are slightly bigger than actual emissions.

Even though a prediction rate of 77% indicates good model fit, it is important to understand why the other 23% are not choosing the predicted compliance strategies. Traditionally, unobserved cost differences are dealt with using plant fixed effects. Since my model is static, I work on the unobserved cost term $\epsilon_i(j)$ and argue that there must be some unobserved cost components that are orthogonal to the observables that lead to the result: if my model predicted $i$ to use option $j$ but it used $j'$ instead, it must be more costly for $i$ to use $j$ (or less costly for $i$ to use $j'$). These potentially permanent differences in costs may be important because they may be 'carried over' to the uniform emission standard scenario, and that will also lead to more or less heterogeneity across different compliance units.

Therefore, I estimate the conditional mean of these unobserved cost terms ($\varepsilon$'s) and incorporate them in the simulation. I first draw 40,000 shuffled Halton draws (Bhat, 2001) for each unit and each alternative, then select those draws that lead to the highest predicted probability for the choices made, and average them to estimate the conditional mean. After taking the conditional means into account, I can perfectly predict compliance choices. Using the predicted choices, I

[24] I recover the shadow price in a few steps. First, I divide the coefficient by the average removal rate of 85% and by the coefficient on coal prices to scale the parameter to a value in cents. Second, I multiply the coefficient by 2000 to convert it from pounds to tons and divide that by 2 since 1 unit of sulfur content leads to 2 units of $SO_2$. Finally, I divide that number by 100 to convert the price from cents to dollars terms.

compute emissions as the product of emission rates (as a function of sulfur content of coal and scrubber installation status) and heat input. I plot the predicted and actual emission rates in Panel A of Figure 10. Due to the nature of the discrete choice model, the predicted emission rates take on discrete values. They do not perfectly align with the actual ones, though the trends closely match one another. After taking the unobserved cost components into account, aggregate emissions are predicted to be 7.97 million. From Panel B of Figure 10, the prediction errors seems to be centered around zero and the predicted emission rates appear not to be systematically different from the observed emission rates.

### 6.1 Comparison to other models

Table 14 compares my baseline model in Table 13 with two other alternative specifications – a conditional logit modelwith no random coefficients which restricts the effect of observables to be fixed, and a random coefficient logit model which approximates the coal attributes in each coal basin by their mean values (without using the iterative algorithm presented in Section 5.3). The estimates all have the same signs but differ in magnitude. The conditional logit and the standard mixed logit would have predicted a lower shadow price since the coefficient on the interaction term of sulfur and scrubbing status is much smaller. These two models also predict a higher operating and retrofitting for PRB coal.

To further compare the models, I look at how well they predict the compliance choices made by the units. Not surprisingly, the conditional logit model predicts less than 67% of the compliance choices. Although the mixed logit model without the iterative algorithm performs slightly better than the baseline model (79% over 77%), the prediction error in emissions is considerably larger: baseline model (without accounting for the conditional distribution of $\epsilon$'s) predicts emissions to be 8.7 million tons while mixed logit model predicts 10.6 million tons; actual emissions are 7.16 million tons, as documented in Table 10. Therefore, this alternative mixed logit model may not be able to predict well the cost savings for an emission standard that achieves the same emissions reduction, even though it can predict the compliance choices more accurately.

# 7 Estimating Cost Savings from Emissions Trading

In this section, I used the estimated parameters in Section 6 to estimate the cost savings from the Acid Rain Program. To begin this section, I present the methodology. I use the estimates to predict the choices under the ARP and compute aggregate emissions and compliance cost. Then, by removing the allowance price component from the compliance cost function and limiting the choice set for each unit $i$, I predict what their compliance choice would be under a uniform performance standard. After presenting the methodology, I present the simulation results and discuss the difference between my results and those in the literature.

## 7.1 Methodology

Before running the counterfactual, I estimate the conditional distributions of the unobserved terms in my model (conditional on the observed choices made by generating units), namely the coefficients on scrubber, PRB and retrofitting costs, as well as the unobserved cost terms. I control for unobserved cost terms using their conditional means, estimated using shuffled Halton draws. The motivation behind using the conditional distribution is that these can be permanent unobserved effects. In a dynamic setting one can use fixed effects for each decision maker to control for the unobserved time-invariant differences, while in my static model I have to rely on the distributional assumption to compute the conditional distribution. The unobserved cost terms can lead to a smaller or bigger estimate of the cost savings. Cost savings are smaller if they suggest that units are 'stuck' at an alternative that look attractive to them but not to the econometrician based on the mean values, or the savings can be larger as more cross-sectional heterogeneity leads to higher cost savings from theoretical predictions.

Based on the conditional distribution of random coefficients and unobserved costs, I predict the compliance choice with the highest probability and compute the implied aggregate emissions and *unweighted* compliance cost – I omitted the coefficients and computed the inferred costs from the coal price equation, scrubbing cost equations, estimated operating costs, retrofitting costs, as well as the premium to PRB coal, scaled by the coefficient on coal price to give dollar values. Weights in my model are used to predict actions by generating units while these weights should be set to one when I predict compliance costs. I scale all parameters that represent cost using the coefficient on coal price. Two of the three random coefficients – PRB and retrofitting costs – enter the compliance cost function as conditional mean. The compliance cost function that will used in the counterfactual scenario takes the following form:

$$
\begin{aligned}
COMPC_i(j) = SCRUBCOST_i(j) + COALPRICE_i(j) + \underbrace{\mathbf{1}(j = PRB)(\mathbf{E}_i\beta^l_0 + \beta^l_1 AGE_i)/\beta^F}_{\text{Premium for PRB Coal}} \\
+ \underbrace{\beta^A ASH(j)/\beta^F}_{\text{Operating Cost}} + \underbrace{\mathbf{E}_i\beta^M(j)/\beta^F}_{\text{Retrofitting Cost}} + \underbrace{\varepsilon_i(j)/\beta^F}_{\text{Unobs. Cost}}
\end{aligned} \tag{9}
$$

In the counterfactual scenario where the uniform emission standard is in place, the objective function (2) is the same except that the emissions components (both $\beta^S$ and $\beta^t$) are removed. This implies under a uniform emission standard, generating units should have picked the type of coal which has the lowest cost, taking into account all the other operating cost components. This is a different methodology compared to the one used in Keohane (2007) – while Keohane (2007) assumes they select the otherwise cheapest coal under a uniform emission standard, he did not estimate the unobserved cost components.

I begin by setting a starting value for an uniform emission standard, and the target is to find a standard such that the new aggregate emissions match the predicted aggregate emissions in the ARP. I assume that only the ARP is changed in the counterfactual and the current local emission standards are still in place. In other words, the uniform emission standards are relevant for $i$ only if it is tighter than the state emission standard imposed on $i$. This holds the benefit of the policy almost constant (ignoring that the social damage may be different across regions (Muller and Mendelsohn, 2009)) and the difference in the compliance costs for the two scenarios can be regarded as the cost savings from the Acid Rain Program.

Using the algorithm developed in Section 5.2, I allow more discrete jumps in the aggregate emissions that help get the aggregate emissions matched up. Instead of using the observed choice $k$ within $j$, I run the algorithm above to predict $k$ within each $j$ since I observe the coal procurement data with noise – it is more confident for me to say that $i$ uses coal from region $j$ rather than $i$ uses coal from mine $k$ in region $j$ given that they can blend coal from multiple mines. By allowing for additional variation within each coal basin, I can also more accurately predict the sulfur content of coal and hence their respective emissions.

The following list summarizes the above steps in details:

1. Estimate unit-specific scrubbing cost conditional distribution (Revelt and Train, 2000)

$$\mu_i(\beta|D_i = Y, X_i, b, \Sigma) = \frac{P(D_i = Y|X_i, \beta) f(\beta|b, \Sigma)}{P(D_i = Y|X_i, b, \Sigma)} \tag{10}$$

   where $Y$ is the observed choice made by $i$. This will be used to predict the choice made by each generating unit $i$

2. Estimate the conditional mean of the logit error term which represents the unobserved cost using shuffled Halton Draws. Treat them as separate unit-specific and alternative-specific constant terms.

3. Compute the total compliance cost as well as predicted emission based on the predicted choice $\hat{j}_i$ for each unit

$$AGGCOMPC = \sum_{i=1}^{I} COMPC_i(\hat{j}_i) q_i \tag{11}$$

   where $q_i$ is the observed heat input in MMBtu.

4. Set $\beta^s = \beta^t = 0$ and start with a uniform emission standard $\bar{s}_{(0)}$. Repeat the iterative procedure described in Section 5.2 with coal types that violate with a uniform emission standard $\bar{s}_{(0)}$ are ruled out. Predict the optimal compliance strategy $j$ that minimizes the

new weighted compliance cost function, or maximizes the following probability

$$\widehat{\Pr}_i(j|X_i, b, \Sigma) = \int_{-\infty}^{\infty} \frac{\exp(-\tilde{C}(j; b, X_i))}{\sum_{j'}^{J} \exp(-\tilde{C}(j'; b, X_i))} \mu_i(\beta|X_i, b, \Sigma) d\beta \tag{12}$$

5. Compute the aggregate compliance cost and emissions as in Step 3, using the same observed heat input in MMBtu. If aggregate emissions exceed the predicted emissions in the emissions trading case, repeat Step 4 again with $\bar{s}_{(t)} = \bar{s}_{(t-1)} - 0.01$ until the emissions are close to or lower than the one in the last iteration.

## 7.2 Simulation Results

Table 1 reports the simulation results. The implied abatement costs are all expressed in 1995 Million US$ for better comparison across studies. The compliance costs for the uniform standard are weighted averages of two compliance costs under two standards (by assuming that the abatement cost curve is locally linear) to achieve the same emissions. The implied abatement costs can be viewed as the average aggregate costs per year.

Table 1: Simulation Results

| Cost | ARP | Standard | Cost Savings | |
|---|---|---|---|---|
| Mean Zero | 843.43 | 1108.51 | **265.07** | **(23.91%)** |
| Conditional | 688.39 | 1067.10 | **378.71** | **(35.49%)** |
| *Prior Literature* | | | | |
| Carlson et al. (2000) | 1040 | 1820 | 780 | (42.87%) |
| Ellerman et al. (2000) | 1923 | 4037 | 2115 | (52.39%) |

*Note: The numerical figures are all Annual Cost in constant 1995 Million USD.*

Table 1 presents two sets of results – numbers in the first row assume that the unobserved cost components are random (or white noise) and can be treated as mean zero (implying that the unobserved effects are not permanent) while numbers in the second row assume that the unobserved costs are permanent and it is equivalent to the conditional means estimated in Step 2. After controlling for the unobserved costs, the cost savings increase from 265.07 million to

378.71 million. The unobserved cost components are estimated to rationalize the choices made by generating units – if the unobserved factors that affect the choices are carried over to the uniform emission standard case, my model may have predicted a smaller cost savings as it implies less flexibility for them and less cost heterogeneity. On the other hand, from what we have seen in Table 1, after taking into account the unobserved cost differences, we achieve a larger estimate of cost savings due to a larger degree of heterogeneity.

Through this simulation exercise I can also predict each unit's compliance choice under the uniform emission standard. Table 15 provides an overview of the number of units in each compliance strategy categories in the ARP and simulated uniform emission standard cases. Generating units, under the uniform emission standard, cannot use coal from Illinois Basin to comply without installing a scrubber. Therefore, there is a huge shift in compliance choices from burning high sulfur coal (and obtain more permits) to either blending high and medium sulfur coal or install a scrubber. Out of the 171 units that switched their compliance choices, 125 of them were burning high sulfur coal under the cap-and-trade. Since these units are still using high sulfur coal as their main or secondary source of coal, any general equilibrium effects that lead to adjustments in coal prices should be of second order.

### 7.3 Why Are the Cost Savings Low?

The estimated cost savings are much smaller compared to the existing literature. Carlson et al. (2000) predicted a cost savings of around \$780 million (while they estimated a \$250 million actual savings in the first two years); Ellerman et al. (2000) predicted a \$2 billion cost savings in Phase II of the program, while Keohane (2007) estimated a \$150 million cost savings among Phase I Table A (mandatorily complied) units.[25] It is worth noting some features of the methodology used in these studies. Carlson et al. (2000) estimate a long-run cost function, and assume that plants are cost minimizers and the Acid Rain Program would have achieved the

[25]Normally we expect a much higher number for cost savings for Phase II as it involves more units and hence potentially more cost heterogeneity, so results in Keohane (2007) are not directly comparable to the numbers presented in this paper.

least cost solution. There are several reasons why that may not be the case: first, plants under cost-of-service regulation may not have a lot of incentives to minimize their cost, and second, state-level policies might also magnify the value for certain options. State emission standard, although it is not as stringent as the ARP target, limits the compliance strategies that different generating units can use – it is not viable for units to buy permits even if it may be cheapest for them to do so. In my model I capture some of these differences by allowing the weights to be correlated with state level policies.

Using estimated operating costs, I study whether a least-cost solution is achieved and I find that most generating units are not using the cheapest way to comply with the program. I compute the (unweighted) compliance costs for two most common compliance strategies: (1) fuel switch to low sulfur coal (PRB) or (2) install a scrubber (with high sulfur coal). For more than half of the 44 scrubbers installed after 1988, I find that it is 10 to 100 cents cheaper for them to fuel switch.[26] I also compute a per ton cost of $SO_2$ removal for units that use PRB coal and I find that more than 60% of these units are spending more than the price of a permit to reduce their $SO_2$ by buying PRB coal – the median unit spends more than \$350 to remove one ton while the shadow price of permit is only \$180.

Here I also propose two other reasons why we may see a decrease in cost savings – a decrease in the transportation cost for Powder River Basin coal and a decrease in the operating cost of scrubbers. I re-estimated the transportation cost indices using equation (4) by dividing my sample into 1991-93 and 2001-03. The estimated coal transportation rates (in constant 1995 dollars) are shown in Table 16. The most striking observation is that the transportation cost for Powder River Basin coal has been cut for almost half in 10 years time, while the minemouth prices follow almost the same trends for these coal basins (as shown in Figure 11). Since rail road deregulation, known as the Staggers Rail Act in 1980, the transportation cost for coal has been drastically decreased (Christensen Associates, 2008; Schmalensee and Stavins, 2013) – it implies that the coal plants in Ohio do not have to pay that much if they intend to switch to Powder River Basin coal.[27] This also implies that the heterogeneity in compliance cost is smaller

[26] I get similar numbers by looking at only scrubbers installed beyond 1995.

[27] Transportation to and from Powder River Basin is traditionally operated by two major rail lines (Busse and Keo-

compared to earlier literature which is based on the pre-1990 or early 90s levels.

Cost heterogeneity is also reduced through the improvement in scrubber technology. Using the estimates in the scrubber operating cost equation, I plotted the estimated coefficients on the time dummies which represent the average operating cost over time in Figure 12. Year 1991 is the excluded category therefore all the coefficients are relative to the 1991 level. Clearly the operating cost for scrubbers are at a decreasing trend and the operating cost in 2000 is around 40% lower than the 1991 level. This implies that originally units might need to pay a lot to operate a scrubber, and now the difference is smaller. Bellas (1998) also found similar evidence in the technological advancement in scrubber technology using the same data source. It also suggests that the marginal abatement cost is lower than earlier estimates – and this will lead to a decrease in both the compliance cost and predicted cost savings.

## 8 Conclusions

In this paper, I quantify the cost savings from a market-based instrument compared to a command-and-control instrument by using ex-post data in the first three years in Phase II of the Acid Rain Program (ARP) to help identity their optimal choice of coal as well as a scrubber installation decision. Cost heterogeneity arises primarily because of geographic variation - some generating units are closer to the sources of low sulfur coal yet some other states may enact incentive programs that favor scrubbing. Compared to the existing literature, the approach allows me to (1) estimate the unobserved components in the compliance cost function, (2) use ex-post data that covers almost all participants and (3) consider a wider range of strategies that they can do.

I proceed by first estimating a static random coefficient logit model to identify optimal compliance strategy for regulated generating units and recover parameters associated with the compliance cost function. I found economically and statistically significant unobserved com-

hane, 2007) and therefore the effect of increasing competition may have significantly decreased transportation rate for PRB coal compared to other kinds of coal (Pittman, 2010).

ponents for retrofitting cost as well as additional cost for using Powder River Basin coal, which rationalizes the puzzling fact that they are often the cheapest source of coal. By estimating a mixed logit model I can control for statistically significant variation on the impacts of the covariates on the compliance cost functions. Observed components include electricity market restructuring status, whether the generating unit is located next to a mine, and other state policies that might favor scrubbing. As found in the literature on electricity market restructuring, I found that deregulated units attach a great weight on the coal price and scrubbing cost, that lead them to act more like cost minimizers.

I include only non-NSPS units in my analysis and my model can predict 77% of their compliance strategies. I estimate a conditional mean for the unobserved cost components and treat them as a possible permanent effect. Based on my estimated model, I simulate what would happen to the aggregate compliance cost when we have a uniform emission standard that achieves the same emissions reduction compared to the ARP. I found that the cost savings is around 265–380 million dollars (in 1995 US dollars) per year, depending on how the unobserved cost components are treated. This number is considerably smaller than estimates from earlier literature. I postulate that three effects may lead to the difference in our estimates: (1) lower transportation cost induces less cost heterogeneity across generating units, (2) technological improvement in scrubbing technology also lowers the marginal abatement cost curves, (3) state policies, in particular state emission standard, might have limited their choice sets and prevented the coal-fired units to achieve the least cost solution.

This analysis helps us to take a step back when we are designing environmental policies – emissions trading program may not be always superior than other less flexible regimes. Often times political economy in designing these programs, although sometimes these efforts are trying to make it more efficient, impedes the program from operating efficiently. One great example is the failure of the Clean Air Interstate Rule (CAIR) in 2005. After the EPA learned that the inter-state transport of pollutant is affecting upwind and downwind states differently (Fraas and Richardson, 2010), EPA proposes the CAIR to phase out ARP. The Court ruled that the EPA has to re-design a new policy when it was striked down by the court in 2008 as the rule is allowing unconstitutional trade between states. Afterwards, the EPA proposes Transport Rule which is also deemed unconstitutional later in 2012 because of it is granting inter-state trading rights too. Not only it generates huge regulatory uncertainty on the permit market in ARP, but it also affects the efficiency of the environmental regulation as it got delayed. Tightening up state emission standards, which is less flexible than adopting a cap-and-trade program, may not be a terrible alternative if it turns out that cost savings are not that large.

While the results apply to the largest trading program in the U.S., the claim here that emissions trading may not yield such a large cost savings may not hold in other trading programs. My estimation is based on coal-fired electricity generators, and it is on this particular trading program. Other markets might have less influenced by the state or federal government; also, there may be a large cost heterogeneity across compliers – in those cases, other firms may be able to achieve the least-cost solutions and capture the large cost savings. Further research is required on ex post evaluations of policies – in general ex ante studies might have inflated the numbers of interest and things might have changed. Studying the effects of state-level policies on the efficiency on federal-level policies remain an important direction for future research.

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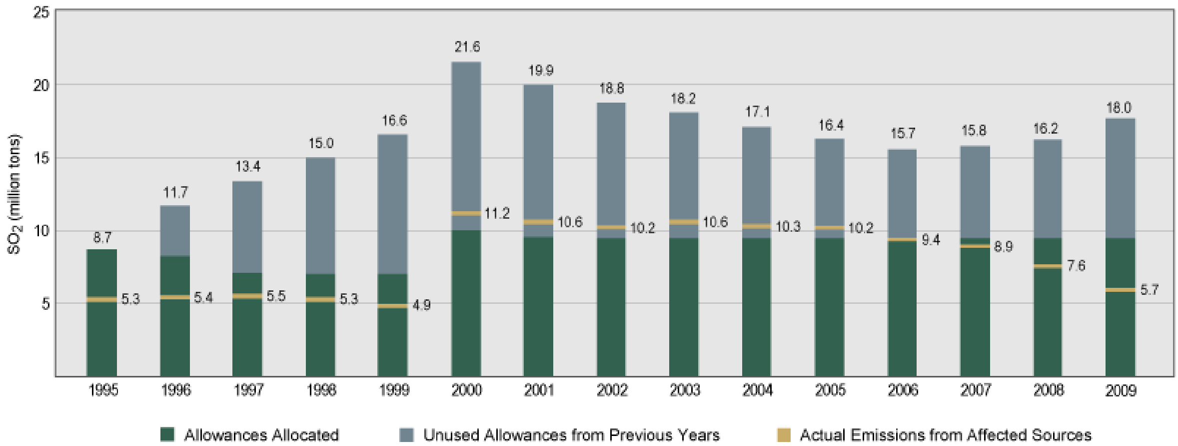
Figure 1: Allowance Bank




Source: EPA (2009)

Figure 2: Percentage of Scrubbed Units in 2002

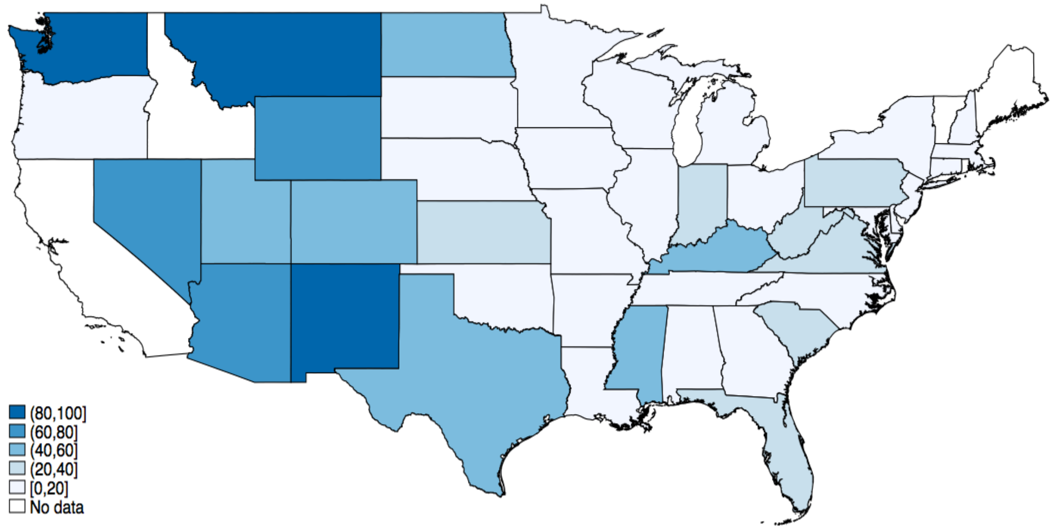
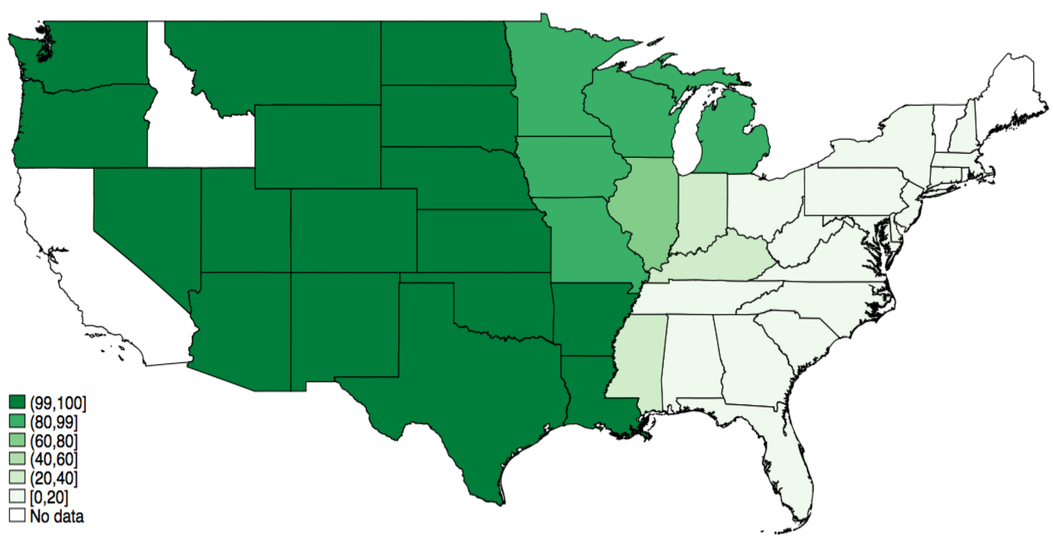



Figure 3: Percentage of Units Utilizing Low Sulfur Coal in 2002




N.B. Based on units where coal procurement data are available.

Figure 4: Emissions Net of Allocations in 2002

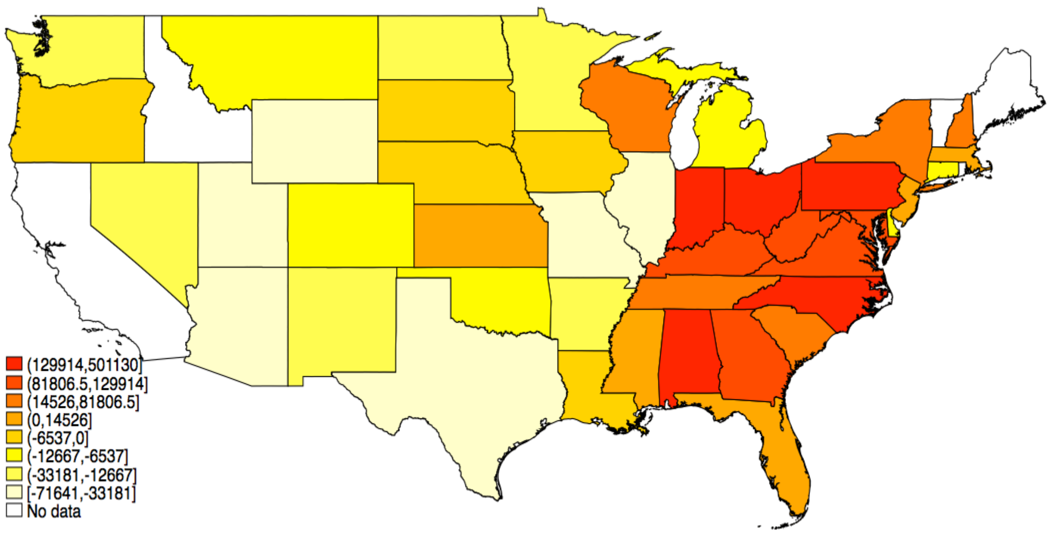
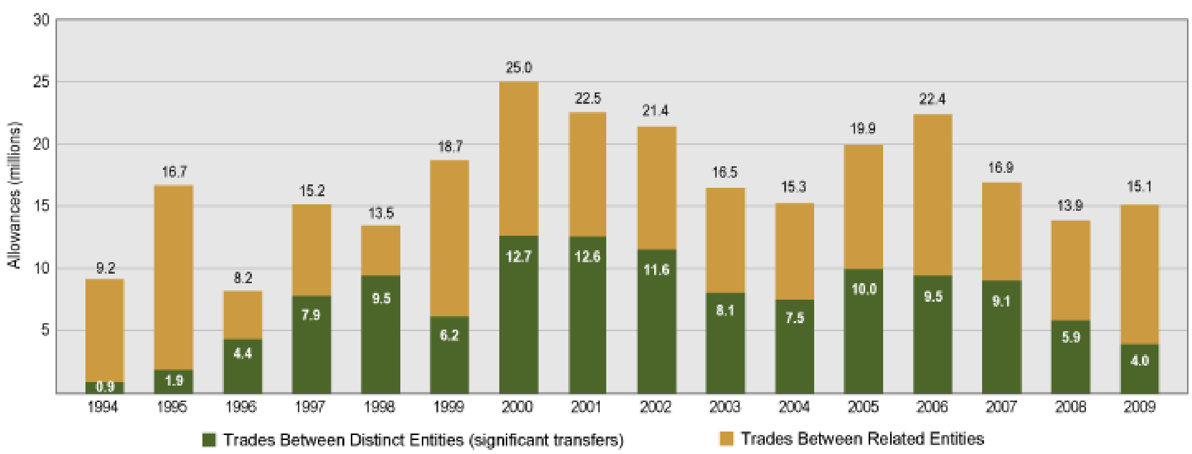



Figure 5: Allowance Transferred




Source: EPA (2009)

Figure 6: Permit Price

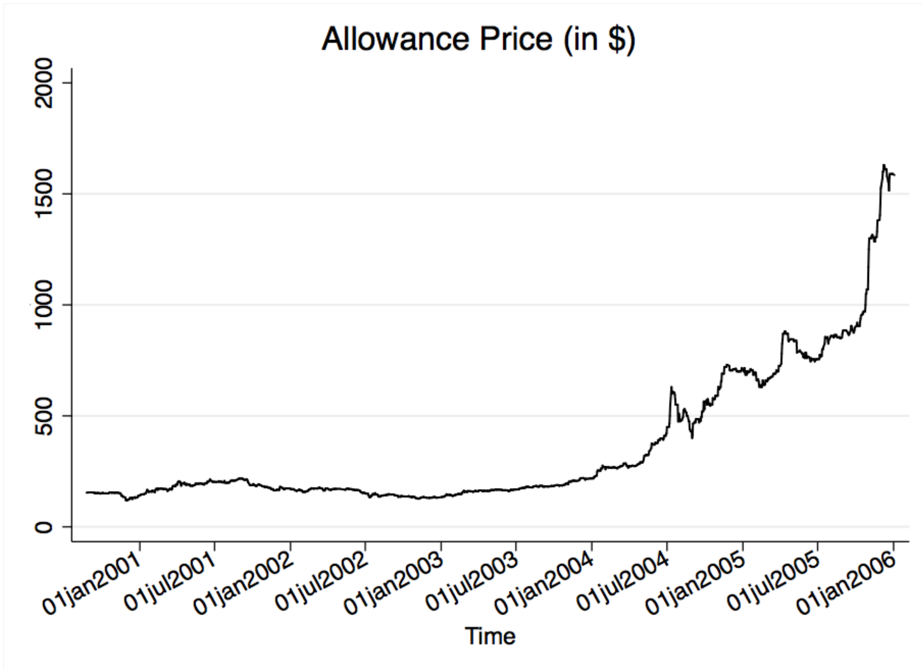



Figure 7: Stable Compliance Strategy

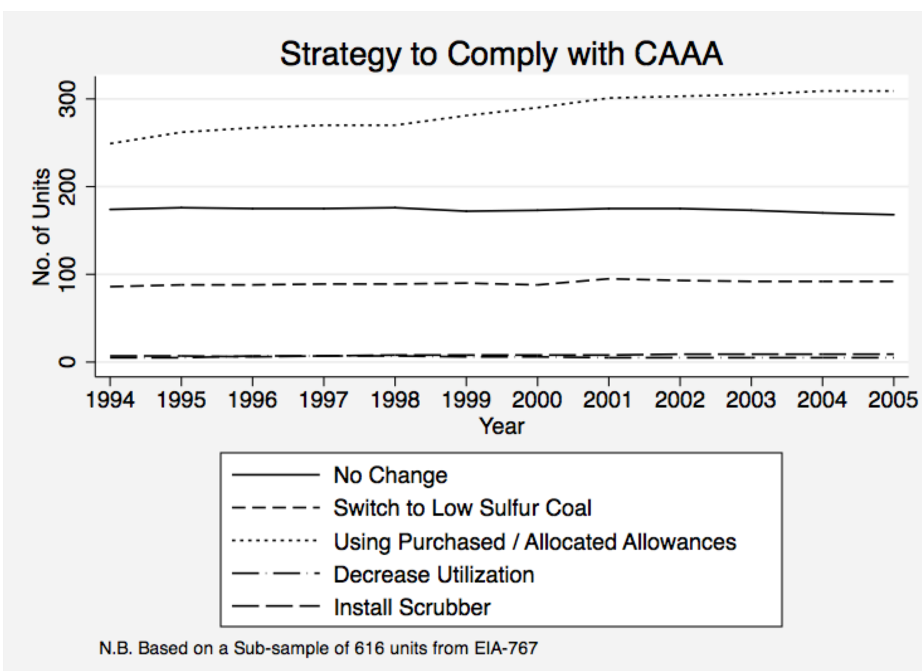
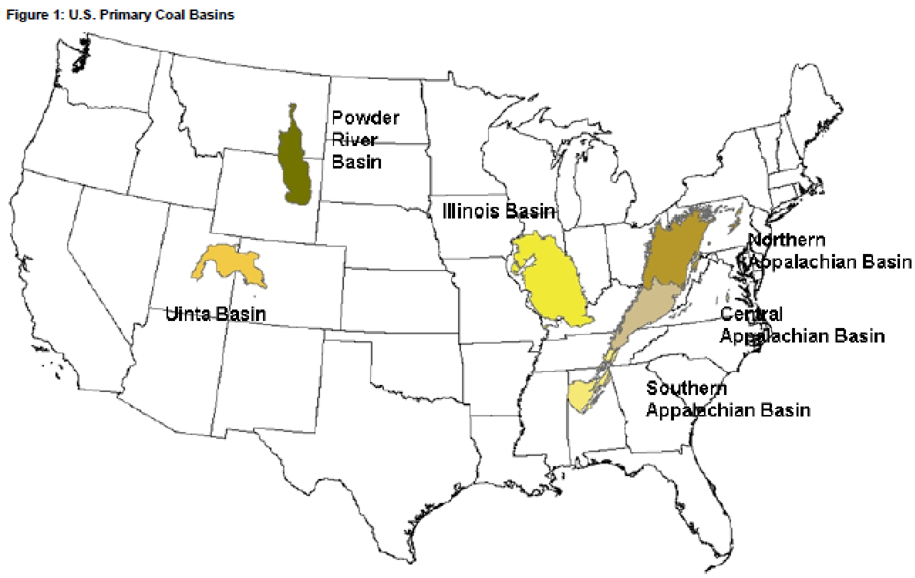


Figure 8: Coal Basins




Source: Enviroknow

Figure 9: Distribution of Sulfur Content

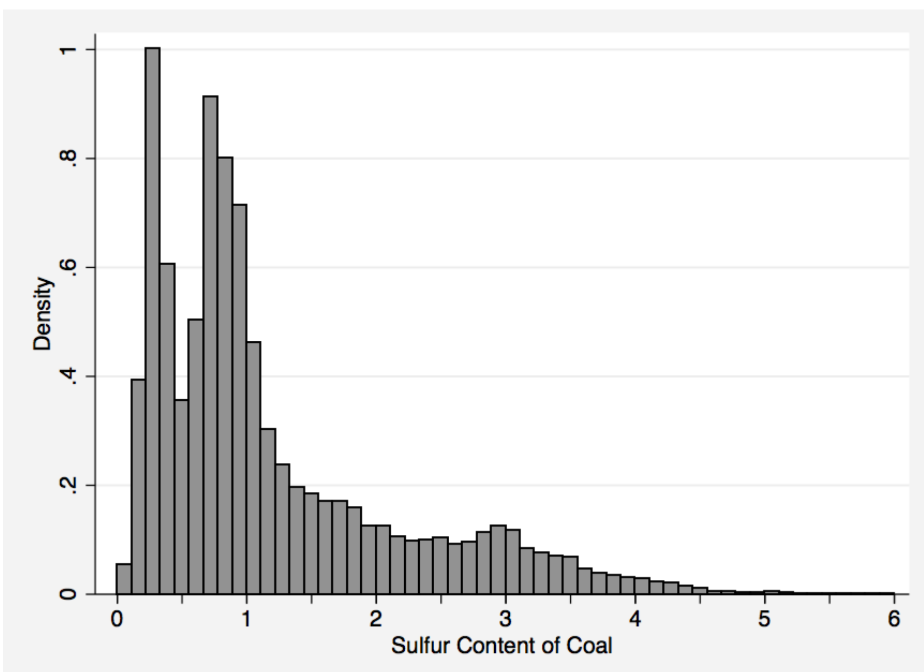
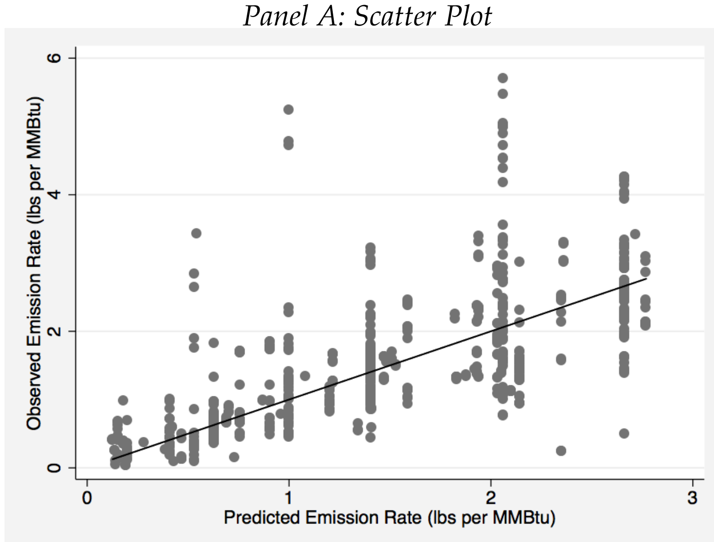


Figure 10: Predicted Emission Rate

*Panel A: Scatter Plot*




*Panel B: Difference between Actual and Predicted Emission Rate*

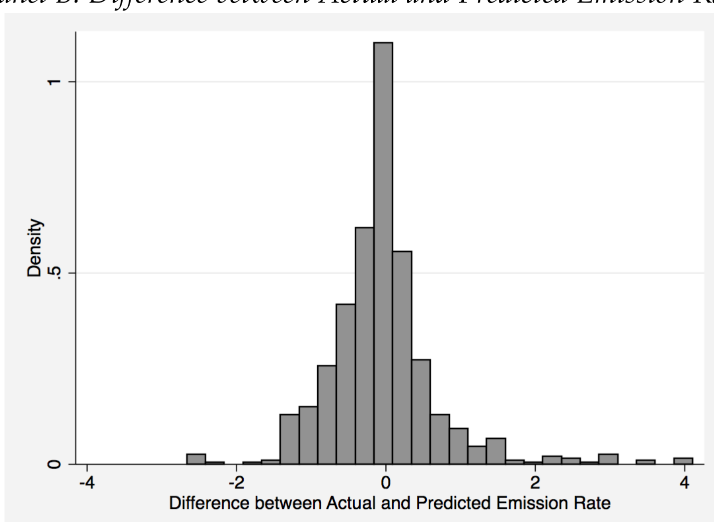
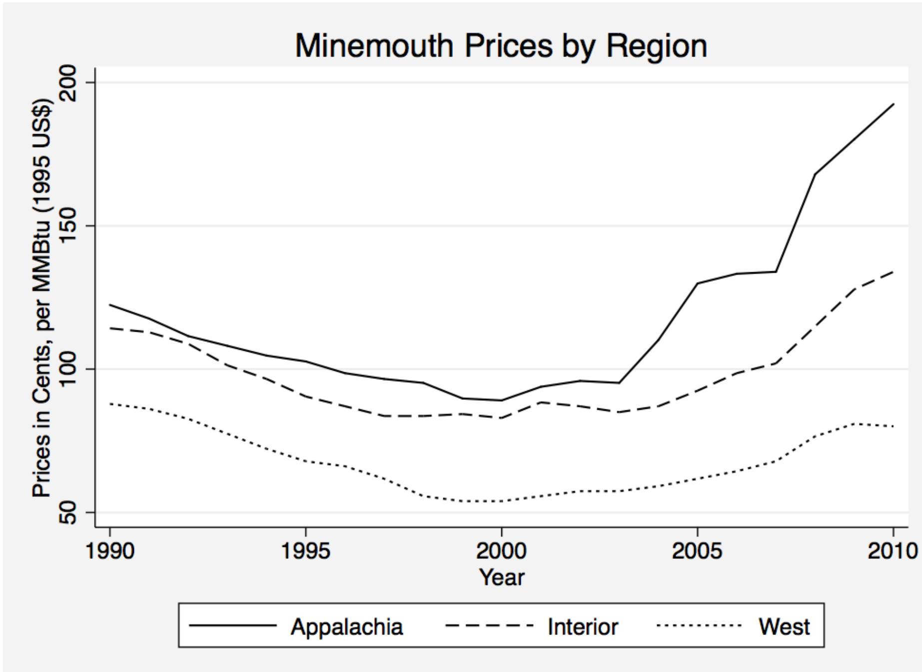


Figure 11: Minemouth Price for Coal




Source: EIA (2013)

Figure 12: Predicted Operating Cost for Scrubbers

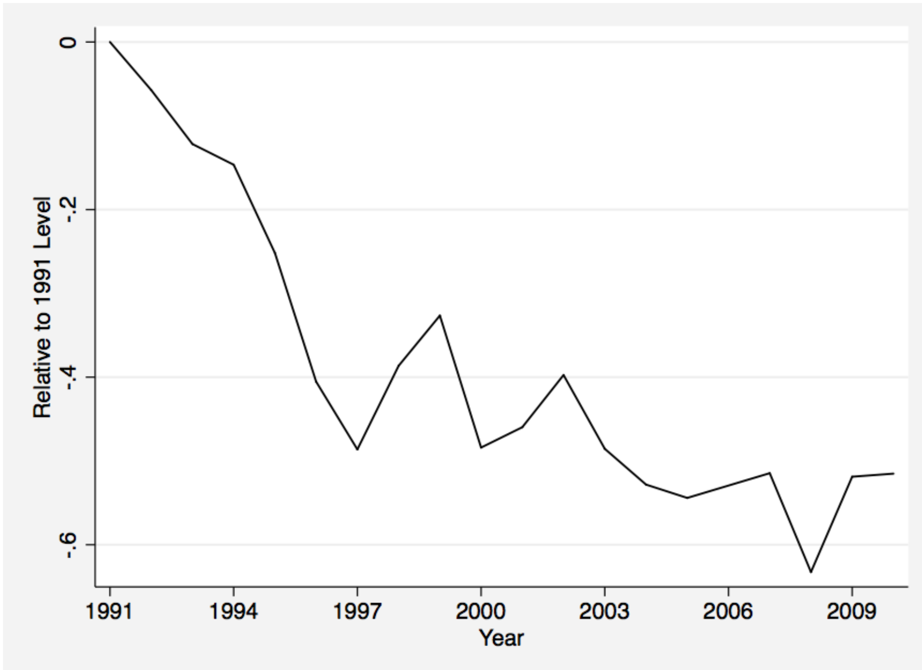



Table 2: Share of Emissions Covered by Trading

| | Share (in %) | | Emissions (in 1000's tons) | |
|---|---|---|---|---|
| Year | All | Excl. NSPS | All | Excl. NSPS |
| 1995 | 19.88 | 19.88 | 5246.7 | 4957.6 |
| 1996 | 35.54 | 33.85 | 5370.3 | 5231.5 |
| 1997 | 31.15 | 30.62 | 5429.9 | 5302.5 |
| 1998 | 26.56 | 24.95 | 5217.5 | 5115.1 |
| 1999 | 23.71 | 23.71 | 4903.2 | 4816.2 |
| 2000 | 39.74 | 43.36 | 10587.3 | 8159.4 |
| 2001 | 35.46 | 37.67 | 9951.8 | 7597.1 |
| 2002 | 39.59 | 42.14 | 9749.1 | 7431.1 |
| 2003 | 42.18 | 44.27 | 10004.0 | 7667.0 |
| 2004 | 39.09 | 40.88 | 9729.8 | 7462.7 |
| 2005 | 39.98 | 40.73 | 9727.1 | 7448.1 |

"Share of Emissions Covered by Trading" is defined as the ratio of the net purchase (positive only) of allowances over the emissions, deducting the permits carried over the next period (in the case where total permit holding exceeds emissions).

Table 3: List of Coal Basins

| Basin | Mean Sulfur | Range |
|---|---|---|
| North App. | 3.700 | (1.895,6.207) |
| Central App. | 1.575 | (1.066,2.228) |
| South App. | 2.118 | (1.078,3.225) |
| Illinois Basin | 4.499 | (2.063,6.462) |
| Uinta Basin | 0.990 | (0.659,1.663) |
| Powder River Basin | 0.758 | (0.462,1.059) |

Unit is in pounds of $SO_2$ per MMBtu. Range is based on the observed 10th to 90th percentile. Summary statistics are based on observed transaction data from 1991 to 2010.

Table 4: Cost Equation for Coal

| | NA | CA | SA | IL | UB | PRB |
|---|---|---|---|---|---|---|
| Year = 1999 | 3.758*** | 4.564*** | 4.483*** | 3.815*** | 5.046*** | 1.211*** |
| | (0.027) | (0.023) | (0.135) | (0.045) | (0.146) | (0.353) |
| Year = 2000 | 3.668*** | 4.501*** | 4.405*** | 3.772*** | 4.969*** | 1.069*** |
| | (0.028) | (0.023) | (0.135) | (0.045) | (0.146) | (0.353) |
| Year = 2001 | 3.700*** | 4.665*** | 4.417*** | 3.833*** | 5.028*** | 1.002*** |
| | (0.028) | (0.023) | (0.135) | (0.045) | (0.146) | (0.353) |
| Year = 2002 | 3.772*** | 4.662*** | 4.390*** | 3.855*** | 5.000*** | 1.076*** |
| | (0.027) | (0.023) | (0.136) | (0.045) | (0.145) | (0.353) |
| Year = 2003 | 3.773*** | 4.653*** | 4.344*** | 3.828*** | 4.969*** | 1.064*** |
| | (0.027) | (0.023) | (0.136) | (0.045) | (0.146) | (0.353) |
| $\ln SULFUR$ | -0.370*** | -0.420*** | -0.192** | -0.285*** | 0.242*** | -0.464*** |
| | (0.015) | (0.017) | (0.089) | (0.023) | (0.070) | (0.163) |
| $(\ln SULFUR)^2$ | -0.053*** | -0.076*** | -0.064*** | 0.002 | 0.063*** | 0.149*** |
| | (0.004) | (0.005) | (0.015) | (0.004) | (0.016) | (0.020) |
| $\ln ASH$ | 0.997*** | 0.243*** | 0.541*** | 0.892*** | -0.404*** | 1.938*** |
| | (0.023) | (0.020) | (0.121) | (0.042) | (0.121) | (0.298) |
| $(\ln ASH)^2$ | -0.243*** | -0.094*** | -0.135*** | -0.235*** | 0.070*** | -0.362*** |
| | (0.005) | (0.005) | (0.028) | (0.010) | (0.025) | (0.063) |
| $\ln SULFUR \times \ln ASH$ | 0.081*** | 0.144*** | -0.032 | 0.056*** | -0.084*** | 0.323*** |
| | (0.007) | (0.008) | (0.038) | (0.011) | (0.031) | (0.072) |
| Spot Market | -0.022*** | -0.009*** | -0.153*** | -0.034*** | -0.123*** | -0.155*** |
| | (0.002) | (0.001) | (0.008) | (0.003) | (0.008) | (0.007) |
| Transport (Per Mile-Ton) | 1.312*** | 1.483*** | 0.549*** | 1.781*** | 1.008*** | 0.971*** |
| | (0.018) | (0.011) | (0.120) | (0.016) | (0.012) | (0.006) |
| Observations | 81987 | 165073 | 6166 | 47799 | 16082 | 70155 |
| Adjusted $R^2$ | 0.938 | 0.953 | 0.953 | 0.948 | 0.925 | 0.929 |

Note: For all regressions, the dependent variable is Log(Cost) where cost is defined as cents per million Btu. 'NA', 'CA', 'SA', 'IL', 'UB' and 'PRB' are abbreviations for North, Central, South Appalachians, Illinois Basin, Uinta Basin and Powder River Basin respectively. The above regressions also include other year dummies which are omitted here for exposition purposes. All standard errors are robust standard errors. *, **, and *** indicate significance at the 10, 5, and 1 percent levels.

Table 5: Cost Equation for Scrubbers

| | (1) | (2) | (3) |
|---|---|---|---|
| | Log(OM Cost) | | Log(Install Cost) |
| Log(UnitAge) | | | 0.374** |
| | | | (0.164) |
| Log(ScrubAge) | 0.131*** | 0.098* | |
| | (0.048) | (0.056) | |
| Log(CoalUse) | 0.124 | 0.453*** | 0.929*** |
| | (0.081) | (0.048) | (0.102) |
| PRB = 1 | -0.451*** | -0.418*** | |
| | (0.118) | (0.126) | |
| Log(Removal) | 0.359*** | 0.371*** | 0.866*** |
| | (0.090) | (0.099) | (0.245) |
| Log(Hour) | 0.589*** | 0.423*** | -0.527** |
| | (0.095) | (0.104) | (0.239) |
| Federal Reg. | 0.160 | 0.219** | -0.460** |
| | (0.106) | (0.107) | (0.230) |
| Log(Exit Rate) | 0.491*** | | |
| | (0.109) | | |
| Log(% Entering) | 0.531** | 0.845*** | 0.020 |
| | (0.243) | (0.228) | (0.629) |
| Northeast | 0.680*** | 0.796*** | 0.467 |
| | (0.205) | (0.268) | (0.361) |
| South | -0.008 | -0.004 | 0.157 |
| | (0.170) | (0.175) | (0.245) |
| Midwest | 0.175 | 0.141 | 0.275 |
| | (0.174) | (0.178) | (0.241) |
| Observations | 4213 | 4218 | 364 |
| Adjusted $R^2$ | 0.468 | 0.412 | 0.495 |

Note: All standard errors are robust standard errors clustered at the plant level. *, **, and *** indicate significance at the 10, 5, and 1 percent levels. The regressions for operating cost also include year dummies, and are based on observed scrubbing costs for all generating units from 1991 to 2010. The regression for capital cost includes dummies for the installation decade.

Table 6: Observed Delivered Coal Prices, in 1995 cents

| | Northeast | | | Midwest | | | South | | |
|---|---|---|---|---|---|---|---|---|---|
| Period | PRB | CA | NA | PRB | CA | NA | PRB | CA | NA |
| 1998-2001 | | 157.0 | **122.8** | **92.1** | 122.7 | 112.9 | **108.5** | 133.4 | 111.3 |
| 2002-2005 | 168.7 | 189.5 | **138.6** | **86.6** | 145.1 | 116.3 | **103.7** | 157.2 | 126.1 |
| 2006-2010 | 202.8 | 256.9 | **191.3** | **116.1** | 204.8 | 177.6 | **136.1** | 237.1 | 177.8 |

Table 7: Imputed Delivered Coal Prices, in 1995 cents

| Coal Basin | West | Northeast | Midwest | South |
|---|---|---|---|---|
| North Appalachian | 215.6 | 126.0 | 145.4 | 148.6 |
| Central Appalachian | 242.1 | 160.0 | 163.4 | 155.6 |
| South Appalachian | 177.5 | 159.0 | 154.3 | 148.3 |
| Illinois Basin | 226.0 | 164.9 | 136.1 | 151.2 |
| Uinta Basin | 122.2 | 180.3 | 149.3 | 170.3 |
| Powder River Basin | 82.6 | 135.6 | 95.2 | 128.4 |

Table 8: Major Buyers from the Coal Basins

| Coal Basin | Three Major States | Other Buyers |
|---|---|---|
| North Appalachian | PA (29.41%)<br>OH (17.65%)<br>NY (13.53%) | DE, IA, IN, MD, MI, NC,<br>NH, NJ, WI, WV |
| Central Appalachian | NC (16.19%)<br>OH (15.11%)<br>GA (9.71%) | AL, CT, DE, FL, IN, KY,<br>MA, MD, MI, MO, NJ, NY,<br>PA, SC, TN, VA, WI, WV |
| South Appalachian | AL (100%) | – |
| Illinois Basin | IN (34.43%)<br>IL (17.21%)<br>TN (12.30%) | AL, FL, IA, KY, MN, MO,<br>MS, WI |
| Uinta Basin | CO (17.54%)<br>IA (12.28%)<br>KY (12.28%) | AZ, IL, KS, MA, MI, MO,<br>NM, NV, UT, WI |
| Powder River Basin | MI (17.94%)<br>IL (15.25%)<br>MO (12.56%) | AZ, CO, IA, IN, KS, KY,<br>MN, MT, ND, NE, OH, SD,<br>WA, WI, WY |

Table 9: Coal Procurement by Non-NSPS Units

| | | (All in %) | | | | | | |
|---|---|---|---|---|---|---|---|---|
| State | Total | NA | CA | SA | IL | UB | PRB | Others |
| AL | 33 | 0 | 36.36 | 60.60 | 33.33 | 0 | 0 | 0 |
| AZ | 5 | 0 | 0 | 0 | 0 | 80.00 | 20.00 | 0 |
| CO | 15 | 0 | 0 | 0 | 0 | 66.67 | 33.33 | 0 |
| CT | 1 | 0 | 100.00 | 0 | 0 | 0 | 0 | 0 |
| DE | 5 | 60.00 | 40.00 | 0 | 0 | 0 | 0 | 0 |
| FL | 17 | 0 | 58.82 | 0 | 35.29 | 0 | 0 | 5.88 |
| GA | 29 | 0 | 93.10 | 0 | 0 | 0 | 0 | 6.90 |
| IA | 30 | 3.33 | 0 | 0 | 16.67 | 23.33 | 60.00 | 10.00 |
| IL | 55 | 0 | 0 | 0 | 38.18 | 3.64 | 61.82 | 0 |
| IN | 56 | 10.71 | 19.64 | 0 | 75.00 | 0 | 16.07 | 0 |
| KS | 11 | 0 | 0 | 0 | 0 | 45.45 | 90.91 | 9.09 |
| KY | 39 | 0 | 35.90 | 0 | 35.90 | 17.95 | 5.13 | 5.13 |
| MA | 5 | 0 | 80.00 | 0 | 0 | 20.00 | 0 | 0 |
| MD | 13 | 100.00 | 30.77 | 0 | 0 | 0 | 0 | 0 |
| MI | 46 | 15.22 | 41.30 | 0 | 0 | 2.17 | 86.96 | 0 |
| MN | 20 | 0 | 0 | 0 | 5.00 | 0 | 85.00 | 10.00 |
| MO | 30 | 0 | 6.67 | 0 | 10.00 | 10.00 | 93.33 | 0 |
| MS | 2 | 0 | 0 | 0 | 100.00 | 0 | 0 | 0 |
| MT | 2 | 0 | 0 | 0 | 0 | 0 | 100.00 | 0 |
| NC | 49 | 4.08 | 91.84 | 0 | 0 | 0 | 0 | 8.16 |
| ND | 3 | 0 | 0 | 0 | 0 | 0 | 100.00 | 0 |
| NE | 8 | 0 | 0 | 0 | 0 | 0 | 100.00 | 0 |
| NH | 5 | 100.00 | 0 | 0 | 0 | 0 | 0 | 0 |
| NJ | 6 | 66.67 | 66.67 | 0 | 0 | 0 | 0 | 0 |
| NM | 6 | 0 | 0 | 0 | 0 | 100.00 | 0 | 0 |
| NV | 4 | 0 | 0 | 0 | 0 | 100.00 | 0 | 0 |
| NY | 37 | 62.16 | 27.03 | 0 | 0 | 0 | 0 | 21.62 |
| OH | 68 | 44.12 | 61.76 | 0 | 0 | 0 | 17.65 | 0 |
| PA | 53 | 94.34 | 1.89 | 0 | 0 | 0 | 0 | 5.66 |
| SC | 21 | 0 | 80.95 | 0 | 0 | 0 | 0 | 19.05 |
| SD | 1 | 0 | 0 | 0 | 0 | 0 | 100.00 | 0 |
| TN | 29 | 0 | 48.28 | 0 | 51.72 | 0 | 0 | 0 |
| TX | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 100.00 |
| UT | 3 | 0 | 0 | 0 | 0 | 100.00 | 0 | 0 |
| VA | 31 | 0 | 80.65 | 0 | 0 | 0 | 0 | 19.35 |
| WA | 2 | 0 | 0 | 0 | 0 | 0 | 100.00 | 0 |
| WI | 33 | 18.18 | 6.06 | 0 | 6.06 | 12.12 | 60.61 | 6.06 |
| WV | 30 | 66.67 | 40.00 | 0 | 0 | 0 | 0 | 0 |
| WY | 11 | 0 | 0 | 0 | 0 | 0 | 100.00 | 0 |

Note: This table is compiled using all non-NSPS coal-fired generating units available. Proportions are calculated as the percentage of units in the respective state that procure coal from the region specified during my sample period. 'NA', 'CA', 'SA', 'IL', 'UB' and 'PRB' are abbreviations for North, Central, South Appalachians, Illinois Basin, Uinta Basin and Powder River Basin respectively. 'Others' represent the proportion of units that did NOT make any significant purchase to the six major coal basins. Proportions may not sum up to 100 due to the fact that they may blend coal from more than one region.

Table 10: Sample in Estimation and Simulation

| Class | Count | Emissions | Heat Input |
|---|---|---|---|
| Sample | 777 | 7160.6 | 11174.7 |
| NSPS D / Da | 246 | 2341.6 | 8443.4 |
| Excluded | 69 | 357.3 | 593.3 |

Note: Emissions are in 1000's tons and heat input are in million of MMBtu.

Table 11: Coal Blending and Scrubbing Status for Sample Units

| | Scrub? | | |
|---|---|---|---|
| Blend? | No | Yes | Total |
| No | 600 | 83 | 683 |
| Yes | 89 | 5 | 94 |
| Total | 689 | 88 | **777** |

Table 12: Other Summary Statistics

| Variable | Mean | Std.Dev. |
|---|---|---|
| Scrub Cost (in cents per MMBtu) | 38.64 | 23.96 |
| Boiler Age | 43.43 | 10.08 |
| Deregulated | 0.3376 | 0.473 |
| Phase 1 | 0.3840 | 0.487 |
| Heat Input (in 1000s MMBtu) | 14392.1 | 14365.5 |

Table 13: Estimates for the Cost Function

| | | | |
|---|---|---|---|
| Sulfur | 6.3711*** | Scrub Cost | 0.2752** |
| | (0.9223) | | (0.1313) |
| Sulfur × Scrub | -2.4772** | Scrub Cost × Bias | -0.0456 |
| | (1.1053) | | (0.0844) |
| Ash | 0.9870*** | Scrub Cost × Restr. | 0.1198 |
| | (0.3533) | | (0.1000) |
| Coal Price | 0.1607*** | PRB | 4.7562*** |
| | (0.0139) | | (1.1498) |
| Coal Price × In-state | -0.0107** | PRB × Age | 0.0599*** |
| | (0.0041) | | (0.0166) |
| Coal Price × Restr. | 0.0149 | Part. PRB | 3.7166*** |
| | (0.0115) | | (0.7330) |
| Coal Price × Minemouth | -0.0652*** | Part. PRB × Age | 0.0263* |
| | (0.0161) | | (0.0138) |
| Modification | 2.6756*** | Part. Modif. | 1.7527*** |
| | (0.3175) | | (0.1472) |
| Standard Deviation | | | |
| $\sigma^Z$ | 0.1256* | $\sigma^M$ | 1.8300*** |
| | (0.0758) | | (0.4627) |
| $\sigma^{PRB}$ | 1.0323* | | |
| | (0.5977) | | |

Note: All standard errors are resulted from a bootstrap process that estimates coal price equation, scrubbing cost equations and the mixed logit model. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels. In all specifications NSPS units are dropped. All columns are estimated based on observed choices for generating units that have not installed a scrubber or they have installed a scrubber after 1988. The 51st to 200th Halton draws are used to simulate the integral. “Part." indicates separate dummies for choices that blend PRB with other kinds of coal (Part. PRB) or modify 50% of their compliance choices from the choices in 1983.

Table 14: Comparison Across Models

| | Baseline | Cond. Logit | Mixed Logit |
|---|---|---|---|
| *Estimates* | | | |
| Sulfur | 6.3711*** | 2.9876*** | 3.9460*** |
| | (0.9223) | (0.2265) | (0.3158) |
| Sulfur $\times$ Scrub | -2.4772** | -0.6765*** | -1.3212*** |
| | (1.1053) | (0.2503) | (0.3616) |
| Coal Price | 0.1607*** | 0.1479*** | 0.1951*** |
| | (0.0139) | (0.0116) | (0.0162) |
| Modification | 2.6756*** | 2.3069*** | 3.3048*** |
| | (0.3175) | (0.2052) | (0.3884) |
| Scrub Cost | 0.2752** | 0.0969*** | 0.1808*** |
| | (0.1313) | (0.0121) | (0.0336) |
| PRB | 4.7562*** | 8.9360*** | 12.7364*** |
| | (1.1498) | (0.9350) | (1.3909) |
| Log Likelihood | -867.94 | -880.71 | -850.15 |
| Prediction (%) | 77.48 | 66.75 | 79.25 |
| Pred. Emissions | 8.7008 | 11.1745 | 10.6296 |

Note: All models are based on the same covariates presented in Table 13, except for omitting the standard deviations for the random coefficients for conditional logit. 'Baseline' model uses the same specification as in Table 13 while 'Mixed Logit' is otherwise the same except that it is not run on an iterative algorithm correcting for variation within each coal basin, i.e. only mean values in each coal basin are used. All models are based on the same set of sample units (777). All standard errors are robust standard errors except for the 'Baseline' model which is bootstrapped standard errors. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels.

Table 15: Compliance Choice in ARP and Emission Standard

| | Number of Units | |
|---|---|---|
| Choice | ARP | Standard |
| *No Scrubber* | *689* | *665* |
| High | 201 | 76 |
| Med | 215 | 214 |
| Low | 196 | 177 |
| High+Med | 41 | 155 |
| High+Low | 11 | 33 |
| Med+Low | 22 | 10 |
| *Scrubber* | *88* | *112* |
| High | 48 | 74 |
| Med | 3 | 1 |
| Low | 35 | 35 |

Note: Total number of units = 777. 'High' includes (a mix of) Illinois Basin and North Appalachian, 'Med' includes (a mix of) South and Central Appalachian, and 'Low' includes (a mix of) Uinta Basin and Powder River Basin. Categories for coal blending for scrubbers are omitted for exposition purposes.

Table 16: Est. Coal Transportation Rate (in cents)

| | 1991-93 | 2001-03 |
|---|---|---|
| Powder River Basin | 1.11 | **0.66** |
| Central Appalachian | 1.15 | 1.78 |
| North Appalachian | 1.38 | 1.30 |
| Illinois Basin | 1.80 | 1.39 |