ABSTRACT

Title of dissertation: AN EX POST EVALUATION
OF THE U.S. ACID RAIN PROGRAM

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Emissions trading programs have been recommended by economists and implemented by policy makers because they are expected to keep compliance costs low; but, studies on actual savings are limited. This paper is the first to conduct a comprehensive ex post analysis of the cost savings from the Acid Rain Program (ARP), the largest emissions trading program to be implemented in the U.S.

In Chapter 2, I provide a brief overview of the Acid Rain Program. I then discuss other policies that are relevant to evaluating the ARP including the New Source Performance Standard and local emission standards. I conclude the chapter by analyzing the determinants of local emission standards and arguing that it is safe to treat these standards as exogenous.

In Chapter 3 I illustrate the cost savings from a cap-and-trade system such as the ARP, and discuss factors affecting the potential gains from trade and the determinants. I then 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.

In Chapter 4, 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.

AN EX POST EVALUATION OF THE U.S. ACID RAIN PROGRAM

by

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Dedication

To my family and my beloved.

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List of Abbreviations

ARP	Acid Rain Program
CAA	Clean Air Act
CAAA	Clean Air Act Amendments
CAIR	Clean Air Interstate Rule
CSAPR	Cross-State Air Pollution Rule
EIA	(U.S.) Energy Information Agency
EPA	(U.S.) Environmental Protection Agency
IV	Instrumental Variable
MAC	Marginal Abatement Curves
NO_x	Nitrogen Oxides
NSPS	New Source Performance Standards
NSR	New Source Reviews
OLS	Ordinary Least Square
PM	Particulate Matters
SO_2	Sulfur Dioxide
TVA	Tennessee Valley Authority

Chapter 1: Overview

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 thesis 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 (U.S. General Accounting Office (GAO)). 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). 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 compliance choices 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 the 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),

[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.

which allowed scrubbers to enter the rate base under cost-of-service regulation and often encouraged the purchase of in-state coal, could well 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.

In Chapter 2 I provide a concise introduction to the institution, performance and status of the Acid Rain Program. I also discuss other environmental regulations, namely New Source Performance Standards, New Source Review and Local Emission Standards since they also affect the flexibility of how these coal-fired power plants comply with the Acid Rain Program. I focus on the local emission standards, the least studied policy, and evaluate the determinants of these standards. I show that these standards depend on county level characteristic and it is not correlated with sulfur dioxide emissions, Acid Rain Program status and non-attainment status. This variation in local emission standard is treated as exogenous variation for identifying the empirical model.

In Chapter 3, 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.

In Chapter 4, 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 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.

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.

Chapter 2: A First Look at the Acid Rain Program

This chapter provides an overview of the Acid Rain Program (ARP). Section 2.1 talks about the institutional details of the program, description of the emissions and trading patterns as well as the current status of the policy. Section 2.2 introduces other policies that potentially interact with the policy and the importance of controlling them in evaluating the ARP. Of all the policies local emission standards are the least well studied and I provide more description and analysis in Section 2.3.

This chapter 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).

2.1 Background of the Acid Rain Program

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 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 with a capacity exceeding 25 megawatts (approximately 1100 coal-fired units). 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, which emit very small amounts of sulfur dioxide. Gas units emit very small quantities of sulfur dioxide. Oil-fired units emit at a higher rate, but do not account for a high proportion of SO_2 emissions. 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. 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 bonus allowances each year depending on their state incentive schemes or by fulfilling early emissions reduction requirements. Figure 2.1 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_2 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 than plants in the Eastern US, 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 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 2.2 and 2.3 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 2.4 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 the Mid-Atlantic region are buying 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 2.2 and 2.3 show, most of these 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. Figure 2.5 shows how disperse the emission rates in 2002 are. Since they are all allocated roughly similar numbers of permit per MMBtu, that would mean that boilers to the right of the red line (which indicates the intended allocation of 1.2 pounds of SO_2 per MMBtu) would have to purchase extra permits from the boilers to the left of the red line. The first thing to notice from the figure is that units are complying with the program by three major paths: utilizing low sulfur coal or scrubbing, which does not require purchase of permits; purchasing medium sulfur coal and using banked or purchased permits; and buying high sulfur coal. Figure 2.6 breaks down the distribution in Figure 2.5 by the Phase designation of the units.

The second thing to note, which has implications for my estimation strategy, is that there exists a continuum of chosen emission rates; therefore, it will be misleading to model compliance choices by the use of low or high sulfur coal or use of scrubber. Instead of modeling a binary choice of scrubber (over low sulfur coal, as in Keohane (2004)) or a limited number of coal choices, it is important to build a model that allows for a range of emission rates. In the Appendix, I provide an overview of the coal procurement data that are available and define choices using the geographical location from which the coal originated.

Table 2.1 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 total emissions. As we can see from Table 2.1, 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 2.7 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.

Banking of permits is often viewed as an instrument for 'consumption smoothing' for Phase I units, as Phase I units were allocated more permits (per MMBtu) in the first five years (Schennach (2000)). This conjecture is confirmed in the data, as shown in Figure 2.8. The figure shows the stock of banked permits from the end of 1995 to the end of 2005 for Phase I and Phase II units. The average Phase I unit banked permits for the first 5 years. When Phase II had started, Phase I units started to draw down their allowance bank. The bank was gradually drawn down to about 1 million permits by the end of 2005. The number of banked permits for Phase II units is roughly constant from 2002 onward.

2.1.1 Current Status of the Policy: The Clean Air Interstate Rule, Transport Rule and Beyond

In 2003, the Bush administration proposed a bill known the Clear Skies Initiative that would modify the existing Clean Air Act to reduce air pollution by expanding existing cap-and-trade programs. The initial proposal aimed at reducing SO_2 and NO_x emissions by 73% and 67%, respectively from their 2003 levels. More importantly, it recognized the the importance of pollutant transport as they proposed 'nationwide Cap and Trade Programs (that) take into account the impact of upwind sources on downwind areas.' However, a consensus could not be reached between the Senate and the House versions of the bill. A decision was made to implement the trading provisions of the bill administratively through EPA.

As a result, the EPA proposed the Clean Air Interstate Rule (CAIR) to achieve the proposed reduction in emissions. EPA calculated the required emissions reduction for each state accounting for the interstate transport of pollutant where upwind states (a majority of eastern states) had to account for damages in downwind states (New York and New England). States were allowed to either submit a state implementation plan or require their power plants to participate in the new cap-and-trade program administered by the EPA.

More importantly, complying units were offered an opportunity to trade Title IV permits at some unknown trading ratios under CAIR (Fraas and Richardson (2010)). This led to a huge spike in the permit price in 2004, as we can see from Figure 2.9. Given the timely installation of pollution control equipment as well as negotiation of new coal contracts, this served as a buffer to transit into the new regulation where the cap is much lower than the ARP. Unfortunately later in 2008, the Court vacated CAIR, primarily due to the inability of states to control the pollution within their own state. Even though CAIR accounted for the inter-state transport of emissions, if power plants in upwind states purchase permits that grant them right to increase their pollution that is eventually transported to downwind states. Therefore, the D.C. Circuit deemed the law "fundamental flawed" and ruled unconstitutional (531 F.3d). The Court kept CAIR in place temporarily before EPA would eventually replace the rule.

After the Court's decision, EPA announced the Cross-State Air Pollution Rule (CSAPR) in 2011. To address the concern, instead of asking states to submit their proposals, CSAPR adopts federal implementation plans (FIPs) where all states will be covered by this rule (states can still develop a SIP to meet the required emission reductions). Phase I of CSAPR would begin in 2012 while Phase II of reductions begins in 2014. Still, the Court vacated CSAPR on August 21, 2012 due to the same problem of inter-state transport of pollutant. The Court's argument this time was, the Clean Air Act only authorizes EPA to remove a state's 'significant contribution' of emissions to a downwind state, and methodology employed by EPA cannot effectively address the concern raised by the Court. As of now, EPA has been holding stakeholding outreach meetings as well as opening the emissions modeling platform trying to address the methodology issues. However, the Supreme Court reinstated CSAPR in May 2014.

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 the next Chapter that generating units had adjusted to the ARP by this time. As explained above it is also the case the regulatory regime changed sharply after this time as CAIR was announced in 2003. The increase in the demand for permits, as evident in Figure 2.9, 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.[1]

2.2 Interaction with Other Policies

2.2.1 New Source Performance Standard

Before the Clean Air Act Amendments 1990 and the corresponding Acid Rain Program, the federal government regulated sulfur dioxide emissions under the Clean Air Act Amendments of 1970 (CAAA 1970). One of these efforts is the regulation of new stationary sources of emissions, known as the New Source Performance Standards (NSPS). Section 111 of the Clean Air Act requires the U.S. Environmental Protection Agency (EPA) to establish nationwide uniform standards for power plants as well as other industrial generators. Currently NSPS regulations apply to on particulate matter (PM), nitrogen oxides (NOx) and carbon monoxide (CO), as well as SO2.

[1] 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.

The NSPS regulate all fossil fuel fired steam generators that began construction after August 17, 1971 (known as the subpart D). The NSPS require the best available control technology (BACT) ('technology standard) be in place as well as set an emission cap for these units. The emission cap is set based on air benefits, costs and other secondary benefits. Normally EPA would conduct a technology review and power plants are still free to choose the option that they believe is the most feasible. The NSPS also mandates the installation of flue-gas desulfurization devices (scrubbers, or FGDs) for all new coal-fired power plants that are constructed after September 18, 1978 (known as the subpart Da). It is very important to consider NSPS when analyzing the Acid Rain Program, given that NSPS is imposing an emission cap or a technology mandate on the plants constructed after 1971. Because these plants are restricted in their pollution abatement options by the NSPS, I am going to exclude these units in my estimation and simulations.

Studies of the effect of NSPS were among the first analyses of how environmental regulation affects firm performance and productivity. Gollop and Roberts (1983) study the productivity growth of electric utilities following NSPS caps by estimating a firm-specific measure of regulatory intensity. They found that the NSPS on average reduced the productivity growth by 0.59 percentage points per year. Berman and Bui (2001) carry out a similar analysis on oil refineries that are also subject to the NSPS regulation. Surprisingly they found the opposite result of Gollop and Roberts (1983) as they showed that abatement has increased productivity. Other researchers have looked at the impact of the NSPS on investment choices. Nelson, Tietenberg and Donihue (1993) found that the age of the capital increased following the regulation. Bellas (1998) studies the cost of adopting scrubber and he finds that NSPS-D units spent significantly more on FGDs than non-NSPS units.

2.2.2 New Source Review

One drawback of the NSPS is that they regulate new sources without imposing any standards on existing sources. For coal-fired power plants, the majority of electric power is generated from very old power plants which the NSPS do not affect. As a result, the Clean Air Act was once again amended in 1977. As notes above, it requires the installation of scrubbers as part of the NSPS (subpart Da). New Source Review (NSR) was formally established.

The motivation for establishing the NSR is to make sure existing power plants do not undergo investments that prolong the life of the boilers to avoid being regulated under NSPS. NSR requires all existing generating units who underwent major modifications to be reviewed by the EPA. If it is determined that the investment violates the NSR, then either the boiler must be regulated under NSPS or it has to be shut down. Utilities have expressed concerns that it may be difficult to distinguish "major modifications" from "routine maintenance. Thus NSR discourages the energy efficiency investments that might have increased the reliability of the system (U.S. Environmental Protection Agency (EPA)). There was very limited enforcement of NSR for the first 20 years until a case arose in November 1999 that involved a number of large utilities such as the American Electric Power, Dynegy and the federal Tennessee Valley Authority (TVA).

Keohane, Mansur and Voynov (2009) have documented the first lawsuit and settlement cases under the NSR between utility companies and the EPA. They predicted that plants which had large emissions and investments would be more likely to be subject to New Source Review. Bushnell and Wolfram (2012) found that the NSR had reduced capital investments for plants that had not installed FGDs while they found no impact on fuel efficiency and emissions. Heutel (2011) estimated a structural model and concluded that NSR decreased investment in new boilers. Lange and Linn (2008) used the changes in stock prices after the 2000 presidential election to look at the value of coal-fired boilers. They found that the value of coal-fired power plants rose under Bush administration, when NSR was less strictly enforced.

2.2.3 Local Emissions Standards

The Clean Air Act Amendments of 1970 also granted EPA authority to establish the National Ambient Air Quality Standards (NAAQS) for six criteria pollutants that are considered harmful to public health and the environment (EPA). These include CO, lead, SO2, NOx, Ozone and PM10, The CAAA allowed two kinds of standards to be established by the EPA. Primary standards are designed to protect the health of human beings, and they are also designed to protect vulnerable populations such as the elderly, children and patients with asthma; while secondary standards are used to account for economic losses and protect public welfare.

The EPA requires states to submit proposals called "State implementation plans" (SIPs) to outline how the state authorities are going to meet the NAAQS. In Section 107a, it says "(e)ach state shall have the primary responsibility for assuring air quality within the entire geographic area comprising such State by submitting an implementation plan." Following the 1970 CAAA, states submitted their SIPs and subsequently approved or requested revision by the EPA (37 FR 10842). Typically SIPs include a regulatory portion as well as a non-regulatory portion. Depending on the state, the regulatory portion may include the imposition of standards, construction requirements for the smokestacks, and technology mandates. Non-regulatory portions of the SIP include the means of monitoring or progress targets.

The SIP that the State of New York submitted declares"no person shall sell, offer for sale, purchase or use any fuel which contains sulfur in a quantity exceeding the following limitations ... specified in Table 1". The SIP of New York, like other states, set standards at the local level: it has different standards in New York City (0.2 percent, by weight), Suffolk County (0.6 percent) and parts of Niagara Counties (1.7 percent). For the State of Ohio, the SIP has county level rules while it is also assigned specifically to an emitting source: "Ohio Edison Company, Toronto Plant ... shall not ... exceed a maximum of 2.0 pounds of sulfur dioxide per MM Btu actual heat input from each boiler provided that an emission limit of 2.0 pounds of sulfur dioxide per MM Btu actual heat input is approved by U.S. EPA." (61 FR 52883)

When the NAAQS are violated, EPA assigns nonattainment status to areas, and states are required to submit proposals to lower the emissions. Nonattainment statuses are assigned for areas that potentially cover part of a county or more than one county, and for each criteria pollutant. As an example, Ingham County in Michigan was classified as nonattainment in 1978 due to "utiliz(ation) a supplementary control system (SCS) to demonstrate attainment of the (SO_2 NAAQS)" (40 CFR Part 52). The State of Michigan required "complete good engineering practice designed stacks ... to eliminate the downwash problem in addition to meeting the emission limitations in the SIP." This was approved by EPA and the SIP did not have to be revised. The county has been in attainment (for SO_2) since 1984.

To the best of my knowledge, there are no comprehensive analyses of these local emission standards (though they are widely recognized in the literature, e.g. Keohane (2007)). In the following section, I will provide descriptive statistics and some reduced form estimates to explain variation in the standards.

2.3 Analysis of the Local Emission Standards

2.3.1 Descriptive Statistics

The local emission standards normally take several forms. The most common is to limit emissions to pounds of sulfur dioxide per MMBtu of coal (referred as DP). Table 2.2 lists the five major forms that these standards. More than 80% of the standards follow one of the five forms, while an additional 7.5% (sulfur content of fuel and pounds of sulfur per MMBtu) are related to the most preferred standards. Other formats for emission standards are more difficult to link to compliance choice: hourly emission rate depends on the efficiency and utilization of the boiler and ambient air quality may depend on the surrounding plants and the transport of pollutants. For the remaining analyses in this section, I focus only on the DP standard.

Most emission standards are enforced at the state level (77.5 percent, as presented in Table 2.3) while a small number of standards are enforced at the federal level. Most of the latter are stringent standards that are imposed on new sources. Figure 2.11 shows the distribution of the standards for year 2002. There is a spike at about 1.2 pounds of SO_2 which suggests those are being regulated under NSPS. Otherwise, there is quite a bit of variation of the emission standards: the existence of such variation in standard leads to different emission rates observed in Figure 2.5. With the help of such variation in emission rates (and in purchases of coal), this helps identify the structural parameters in the cost functions.

Before explaining determinants of the standards, It is important to notice that local emission standards are very stable over time. Figure 2.12 depicts the average of the local emission standards from 1995 to 2005 for the units that are present in the sample in for all years. There is only a slight downward trend from 2.65 to 2.5 lbs per MMBtu. In fact, a closer look at the data shows that most of these units have *not* changed their emission standards over the 11-year periods. Table 2.4 shows that 88.4% of the units have the same emission standards throughout; only about 35 units (about 3.5%) experience a permanent shift. In the next section, I focus on the cross-section in 2002 and attempt to understand the determinants of local emission standards in that year.

2.3.2 Determinants of the Local Emission Standards

Before proceeding to the empirical analysis, I discuss some of the potential determinants of the standards to guide the empirical analysis. One of the objectives in the NAAQS is to limit the emissions and protect the well-being of people surrounded by emission sources. We should then expect the standard to be more stringent in more densely populated areas and in counties where there are more persons who are susceptible to pollution (infants, elderly and patients with chronic respiratory illness). Areas with high incomes or highly educated groups may also see stringent regulations.

Since the linkage between sulfur dioxide emission and health effects occurs through local ambient concentrations (Pope III et al. (2002)), the concentration of power plants in the area could be an important factor in setting the standard. Places that are very polluted already, especially those that are under non-attainment, may be targeted by state or local authorities to improve their air quality. The standards may be less stringent for units located near borders whose emissions may be transported to other jurisdictions.

Political economy motives should also be taken into account. One of these can be measured by the number of power plants in the area or whether the power plants belong to a large utility company that may have more power in lobbying the government for relaxing the standard. In setting the individual standards, state governments may have overlooked at some of the design parameters at the unit level (when it was built, whether it is operated often). More details of the data sources are in Appendix B. County level data are downloaded from the County and City Data Book.

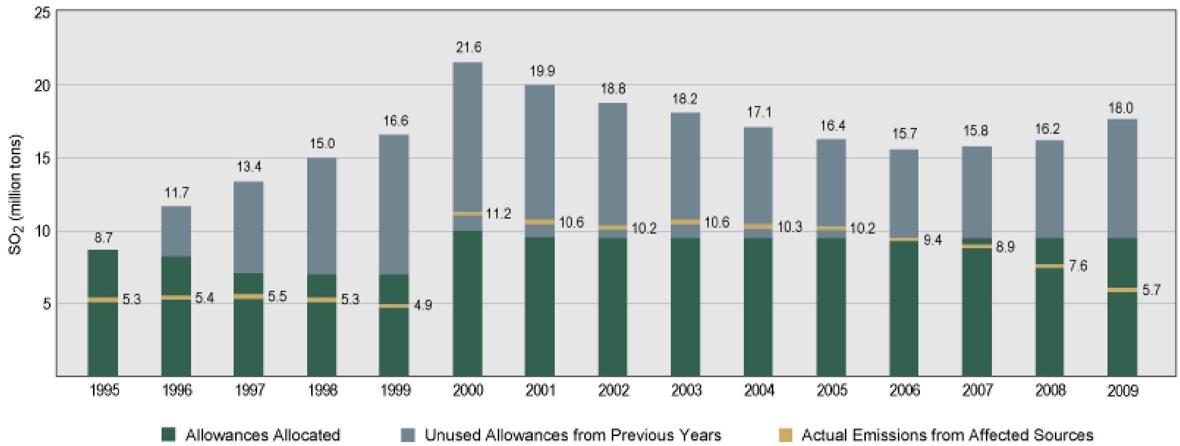
To test the effect of pollution concentration on correction on state emission standards requires estimating a model with the emission standard as the dependent variable and pollution as one of the explanatory variable. This, however, raises concerns of endogeneity, as stricter standard lead to lower emissions, which will bias the coefficient upwards. I address the endogeneity using standard instrument variable methods. I employ variables that affect pollution but are unlikely to be correlated with the sulfur standard. I use anomalies in weather pattern and carbon monoxide emissions as instruments. Weather anomalies measure the deviation of monthly mean temperature in summer months (April to August) in 2002 against climate normals 1981-2010. The idea is that on hotter days, there will be more electricity generation and more pollution. I use carbon monoxide emissions as an instrument as most of these emissions come from mobile sources and therefore should be less correlated with the electricity generation.

Table 2.5 presents the regression results. The first two columns show the OLS results with the emission standard as the dependent variable. It shows a positive and statistically significant correlation between emissions and the standard. As argued earlier, this could be due to simultaneity bias. Coal capacity percentage, and whether the county is located in the nonattainment area (for sulfur dioxide) or next to a state border seem to have no explanatory power. The standard is negatively correlated with income and it shows that richer counties will enact tighter standards. The emission standard also shows a perplexing positive correlation with population which seems to suggest that the standard is lax in crowded areas. Compared to Phase II units, Phase I units are more loosely regulated. This can be partly due to the fact that they are older. When the Phase I dummy is dropped, the in service year variable shows a statistically negative coefficient.

Since most regulation occurs at the state level, there are likely to be many factors that affect the state's decision in setting standards that are unobserved by the econometrician. Therefore, in column (2), I added state dummies to control for state characteristics that may explain some of the variations observed in the data. Unsurprisingly, the adjusted R^2 is higher for (2) but the difference is not large. Other variables show similar signs as (1) and emissions remain positively correlated with emission standard. Columns (3) and (4) employ the IV strategy described above to (1) and (2). In the IV specifications, SO_2 and the standard are negatively, but statistically insignificantly, correlated in (4). The IV strategy removes some of the positive bias in OLS. Other coefficients remain of similar signs compared to the previous specifications. NSPS units have much stricter standards and I therefore exclude them in the last two specifications. The results are very similar.

The results here show that emission standards (i) depend on county characteristics such as income and (ii) are not correlated with endogenous plant and unit characteristics. In the next Chapter, I will treat local emission standards as exogenous to the Acid Rain Program. They provide exogenous variation in the choice set that helps identify the parameters of the cost functions.

Figure 2.1: Allowance Bank



Source: U.S. Environmental Protection Agency (EPA)

Figure 2.2: Percentage of Scrubbed Units in 2002

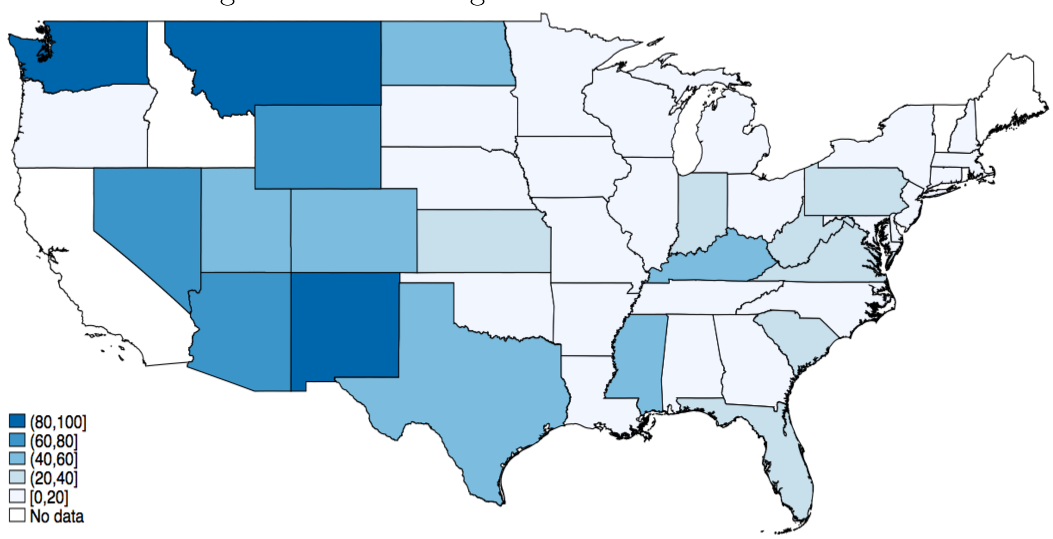
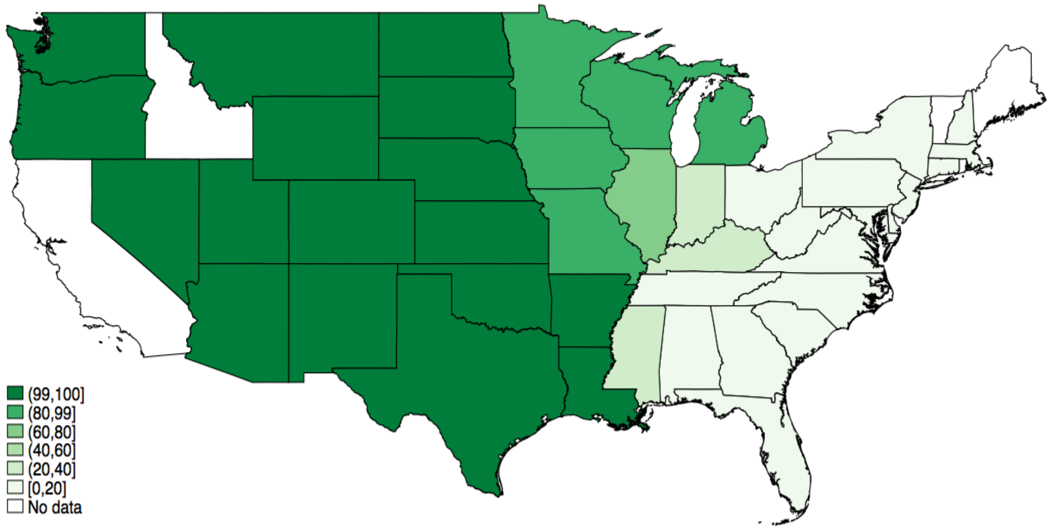


Figure 2.3: Percentage of Units Utilizing Low Sulfur Coal in 2002



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

Figure 2.4: Emissions Net of Allocations in 2002

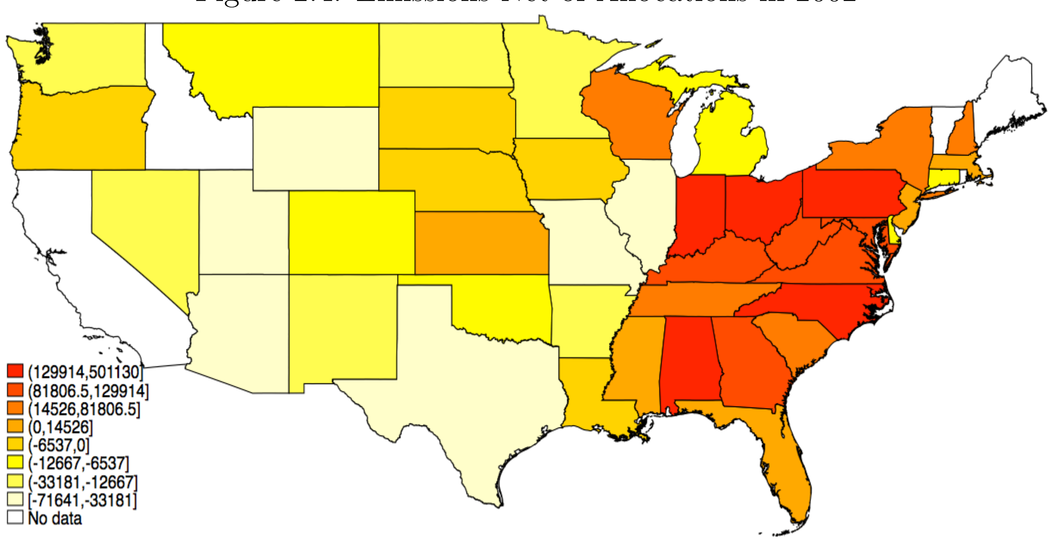


Figure 2.5: Emission Rates

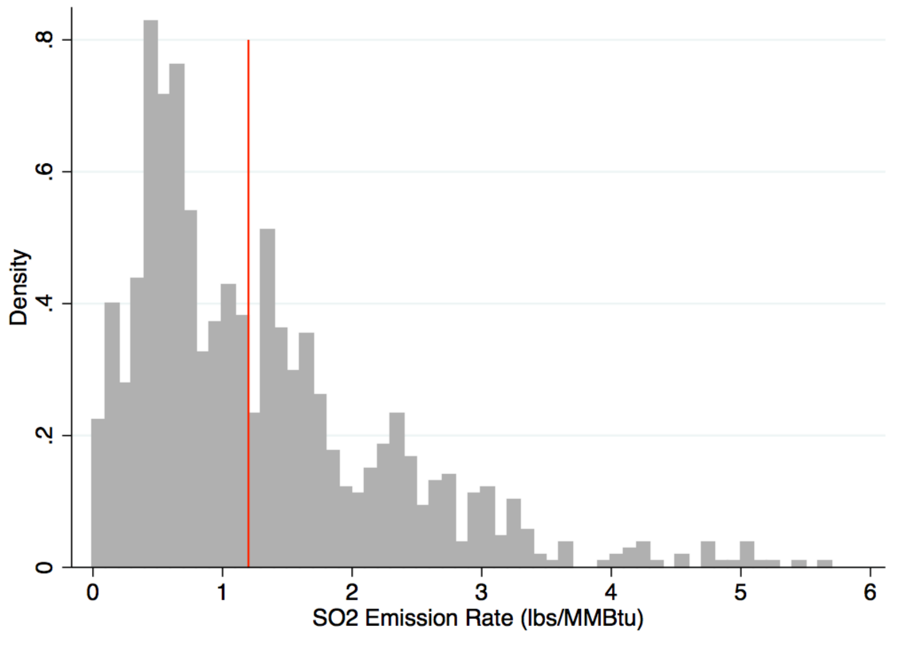


Figure 2.6: Emission Rates, by Phase I/II Designation

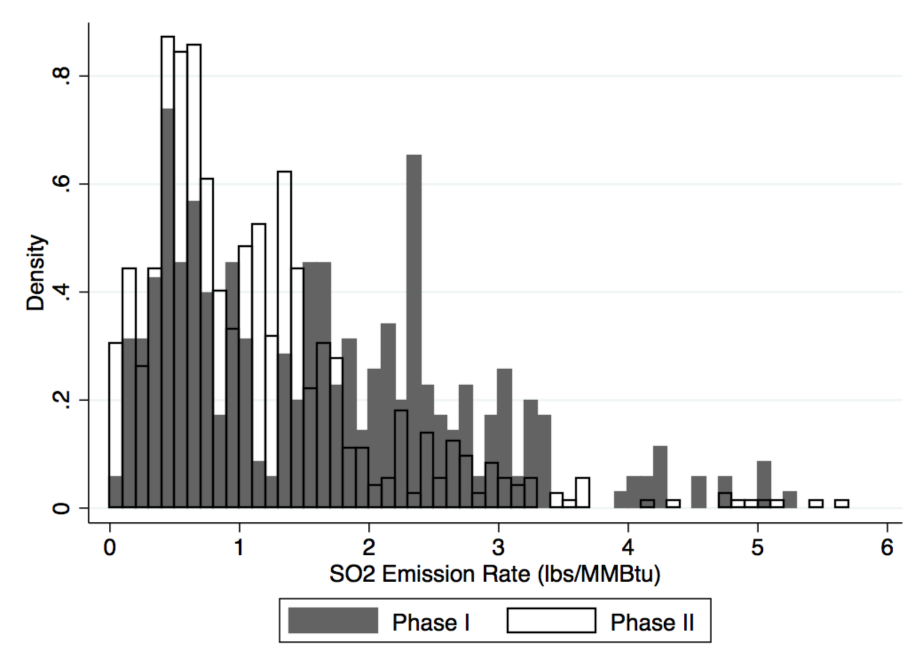
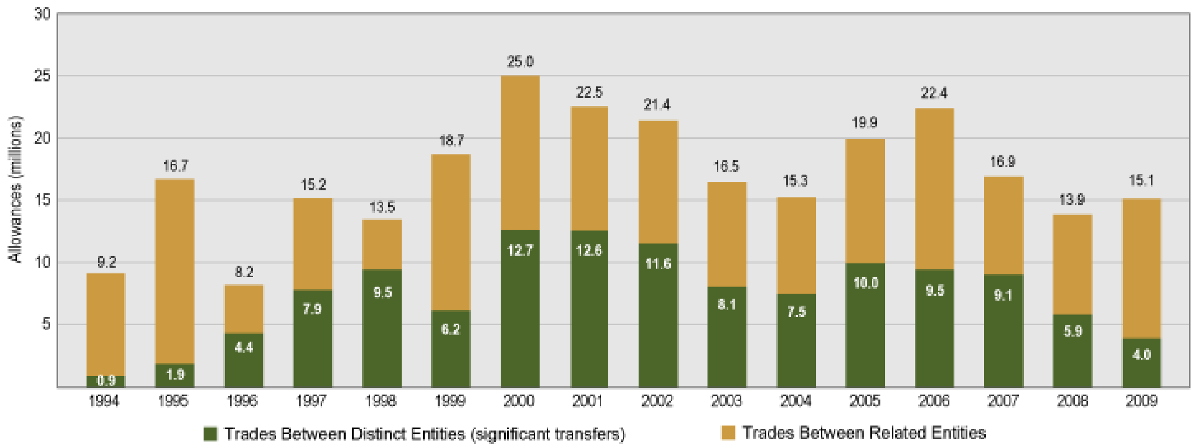


Figure 2.7: Allowance Transferred



Source: U.S. Environmental Protection Agency (EPA)

Figure 2.8: Banked Permits, by Phase I/II Designation

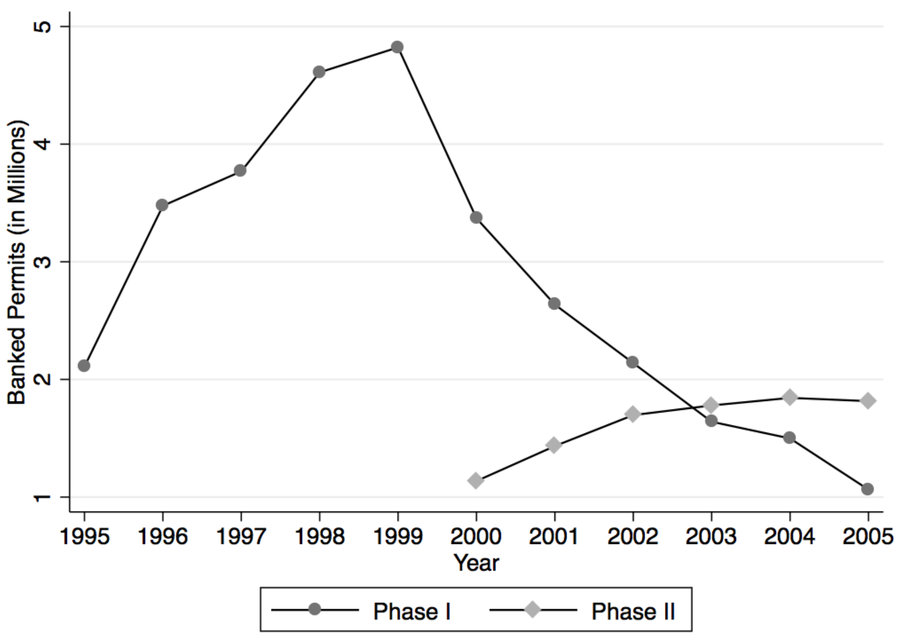


Figure 2.9: Permit Price

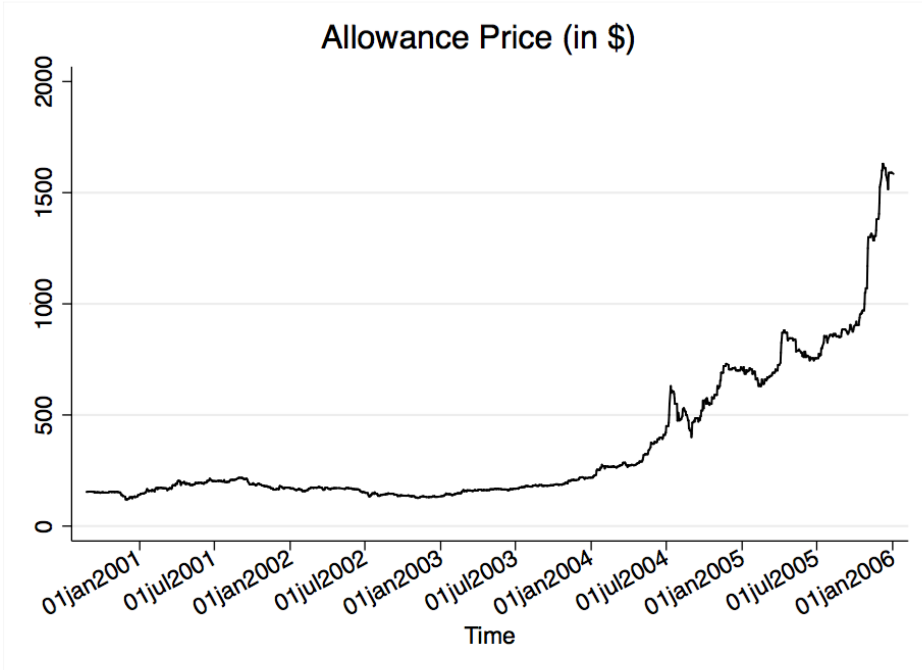


Figure 2.10: Stable Compliance Strategy

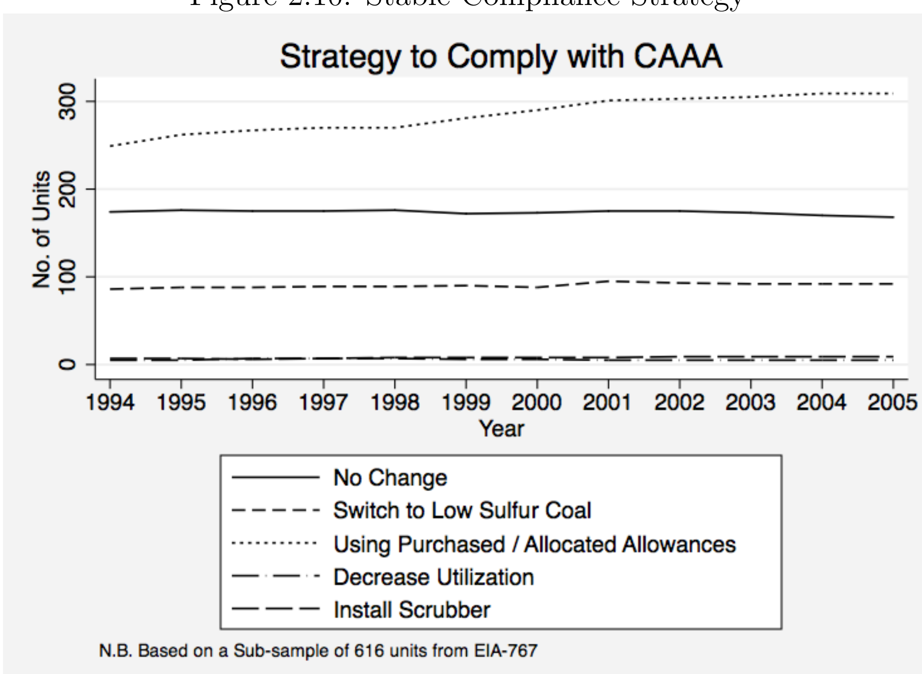


Figure 2.11: Distribution of the Emission Standard (DP)

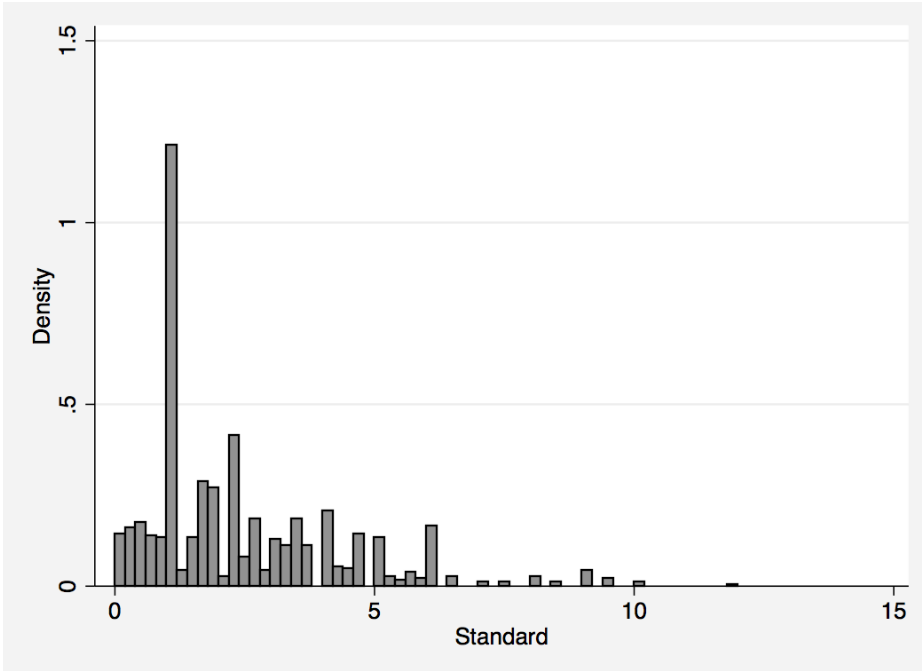


Figure 2.12: Trend of the Emission Standard (DP)

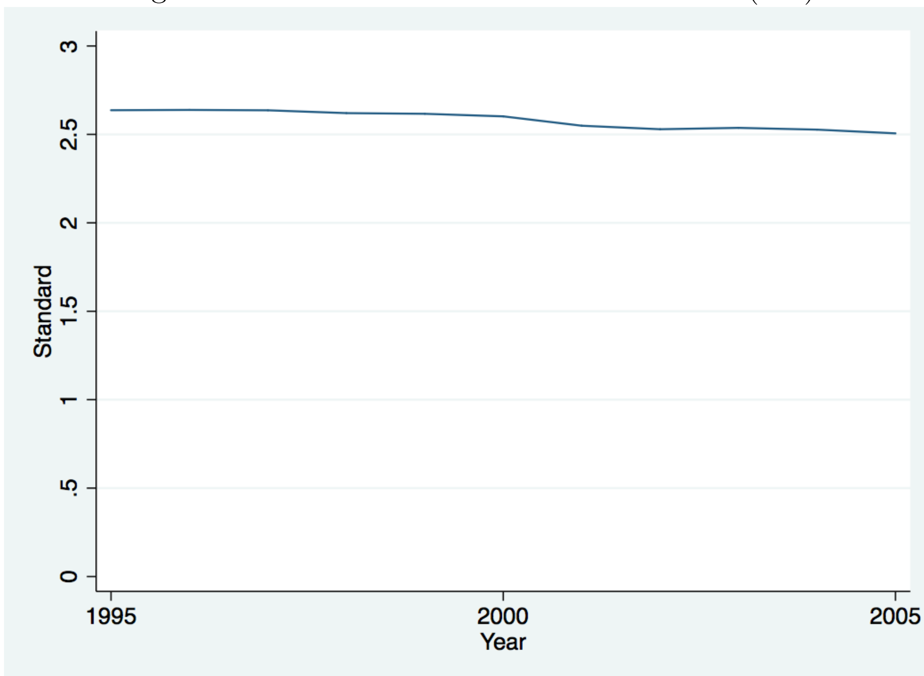


Table 2.1: Share of Emissions Covered by Trading

	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 2.2: Major Types of Emission Standards

Unit of Measurement	Count
Pounds of SO_2 per MMBtu in fuel (DP)	943 (80.05%)
Pounds of SO_2 emitted per hour	93 (7.89%)
Percent sulfur content of fuel (by weight)	45 (3.82%)
Pounds of sulfur per MMBtu in fuel	43 (3.65%)
Parts per million of SO_2 in stack gas	20 (1.70%)

Note: All standards are at the boiler/EGU level. Unlisted categories include ambient air quality concentration, percent sulfur removal efficiency and other uncategorized ones.

Table 2.3: Statute of Emission Standards

Type	Count	Average (DP)
Federal	230 (19.52%)	1.42
State	913 (77.50%)	2.50
Local	35 (2.97%)	2.65

Table 2.4: Stability of Emission Standards, 1995–2005

Stable Number of Years	Count
11	794 (88.42%)
10	26 (2.90%)
9	10 (1.11%)
8	32 (3.56%)

Note: The sample is 898 units that have continuous presence in my data from 1995 to 2005 and have used only DP as the unit of the standard. 'Stable number of years' calculated the number of years where the standard is unchanged, compared to the baseline which is the standard that is observed most often.

Table 2.5: Analysis of Emission Standards

	(1) OLS	(2) OLS	(3) IV	(4) IV	(5) IV	(6) IV
$\text{Log}(SO_2)$	0.250***	0.159*	-0.029	-0.054	-0.090	-0.120
	(0.092)	(0.092)	(0.180)	(0.212)	(0.269)	(0.337)
Coal Capacity	0.221*		0.327*		0.519*	
	(0.127)		(0.169)		(0.294)	
Nonattainment	-0.343	0.209	-0.281	0.281	-0.053	0.468
	(0.440)	(0.567)	(0.493)	(0.586)	(0.654)	(0.701)
Border	0.101	0.059	0.091	0.049	0.101	0.019
	(0.181)	(0.201)	(0.183)	(0.198)	(0.243)	(0.263)
Log(Heat Input)	-0.156*	-0.097	-0.051	-0.014	-0.032	-0.010
	(0.091)	(0.087)	(0.103)	(0.108)	(0.123)	(0.141)
Log(Income)	-1.574**	-2.148***	-1.313*	-1.907**	-2.148**	-2.495***
	(0.697)	(0.800)	(0.695)	(0.769)	(0.975)	(0.952)
Log(Population)	1.400*	1.884**	1.193*	1.659**	1.917*	2.092**
	(0.716)	(0.824)	(0.718)	(0.790)	(1.009)	(0.997)
Phase I	1.150***	0.838***	1.234***	0.859***	1.331***	0.826***
	(0.252)	(0.250)	(0.241)	(0.238)	(0.286)	(0.287)
ARP	-0.381	-0.207	-0.333	-0.186	-0.541	-0.279
	(0.381)	(0.362)	(0.407)	(0.371)	(0.509)	(0.472)
In Service Year	-0.019	-0.017	-0.018	-0.016	-0.021	-0.014
	(0.012)	(0.011)	(0.012)	(0.011)	(0.014)	(0.012)
NSPS	-1.165***	-1.247***	-1.193***	-1.318***		
	(0.255)	(0.234)	(0.257)	(0.222)		
Number of Obs.	803	803	803	803	570	570
State FE	No	Yes	No	Yes	No	Yes
Sample	All	All	All	All	No NSPS	No NSPS
Over-id p-value			0.063	0.647	0.011	0.870
Adj. R^2	0.401	0.458	0.377	0.447	0.319	0.294

Note: Standard errors are in parentheses, clustered at the plant level. *, **, and *** indicate statistical significance at the 10, 5, and 1 percent levels. In all specifications, the dependent variable is the standard, measured in lbs of SO_2 per MMBtu in fuel. All samples are coal-fired generating units that are regulated under the most preferred method (DP). The sample is a cross-section of observed emission rates in 2002. Other controls, not shown here for exposition purposes, include county area, percentage of individuals with high school or higher, percentage of individuals with age below 5 and above 65. In IV specifications $\text{Log}(SO_2)$ is instrumented with weather anomalies in the summer and Log(CO).

Chapter 3: Modeling Compliance Choice: Illustration and Empirical Model

After discussing the institutional background in the Chapter 3, this chapter introduces the empirical model to be used in simulating the counterfactual exercise in Chapter 4. The chapter starts with a simple illustration in which two power plants optimally choose their emission levels that makes clear how the gains from trade arise. Then, I introduce the empirical model that I will estimate. After presenting summary data statistics, I review methods used to estimate the model and discuss the estimation results.

3.1 Estimating the Gains from Trade: An Illustration

Consider a simple model where there are two profit-maximizing polluting firms (power plants) competing in a static, perfectly-competitive electricity market. They choose an emission rate z and heat input x. The emission rate is also the pollution intensity that can be chosen and the total pollution will be equal to z times x. The objective function can be written as

$$\max_{z,x}(p - c(z,x))q(z,x) - p^z(zx - A) \tag{3.1}$$

where p is the selling price of the power generated, which is assumed to be fixed. $q(z, x)$ denotes the production function. Often times a production function is written in terms of the heat input necessary to generate electricity, hence the heat rate $HR(z, x) = x/q(z, x)$. Joskow and Schmalensee (1987) estimates the determinants of the gross heat rate using data before the Acid Rain Program. The sulfur content of the coal is not a statistically significant determinant of the heat rate. Linn, Mastrangelo and Burtraw (2014) argues that low sulfur coal and scrubbers can potentially affect the operating heat rate. However, they also show that the distribution of heat rate across different categories of plants overlap, hence there is no clear-cut evidence that bigger plants or cleaner units have a smaller heat rate.

$c(z, x)$ denotes the marginal cost of producing a unit of electricity. It is clear that dirtier coal is cheaper therefore $c(z, x)$ should depend on z. Whether or not $c(z, x)$ depends on x is not a very clear. On one hand, there might be some quantity discount in purchasing coal (Chan et al. (2013)) but it will be difficult to predict the coal purchase price for every *generating unit* since all coal purchases occur at the plant or utility level. Therefore, at the unit level, the correlation should not be too strong. I therefore assume that $c(z, x)$ is a function only of the quality of coal and the distance between the mine and the plant, but not of the other characteristics.

The polluting firms participate in the permit market. They are allocated a fixed number of permits A that are determined before they compete in the market. $(zx - A)$ denotes the excess demand for permits. This can be negative if the plant chooses emission rates that are less than 1.2 pounds of SO_2 per MMBtu. As long as the units are small and they cannot change the market price of permits, the actual allocation would be independent of the permit demand decision. Early work by Joskow, Schmalensee and Bailey (1998) showed that strategic bidding behavior has limited effect on the market price of permits. What matter remaining in determining emission rates are how marginal cost depends on emissions and on the market price of permits, denoted by p^z, which is also assumed fixed.

Therefore, I impose the following assumptions throughout the paper. In future work, I will test and relax them.

Assumption 1 *In the illustration and the empirical model, the following assumptions hold:*

- *Utilization rate is fixed throughout.*
- $HR(z,x)$ *is independent of* z, x.
- $c(z,x)$ *is independent of* x.
- *Each generating unit has no market power in the permit market and takes* p^z *as given.*

Using Assumption 1, the objective function in 3.1 can be collapsed and rewritten as the following, in which an emission rate is chosen to minimize the cost of pollution:

$$\min_z C(z) + p^z z \tag{3.2}$$

where $C(z)$ is the average cost per MMBtu. The slope of the $C(z)$ function denotes the sulfur premium that the unit has to pay. When a unit is closer to the source of low sulfur coal, the increase in marginal cost is smaller, due to the smaller distance between the coal basin and the power plant. $C(z)$ is assumed convex, otherwise plants can blend coal with two different sulfur coal contents and achieve a lower cost. This implies $C'(z) < 0$, $C''(z) > 0$. I will use $C'(z)$ and "sulfur premium" interchangeably.

The first order condition is straightforward and the chosen emission level z^* will satisfy $C'(z)+p^z = 0$. If the two plants face the same sulfur premium, we should expect the two firms to choose the same emission rate. Now consider a realistic case where there are two power plants, 'Northeast' (H) and 'Midwest' (L). Since the coal basins for low sulfur coal are all situated to the West of the Mississippi River, the Midwest plant is geographically closer to the low-sulfur coal basins and therefore it pays a lower sulfur premium than its Northeast counterpart. Hence, $C'_H(z) < C'_L(z)$ for all levels of z.

Their marginal cost curves are illustrated in Figure 3.1. Points A^* and B^* denote the equilibria that the two plants choose under the ARP. From the first order conditions, those points are tangent to the line with slope $-p^z$. Denote these points by z^*_L and z^*_H, the optimal emission rates chosen by plants L and H respectively. From the assumption that $C'_H(z) < C'_L(z)$, the Northeast plant optimally selects a higher emission rate since it has to pay a higher sulfur premium – at the equilibrium the Northeast plant (plant H) chooses to demand more permits as permit prices are flat across plants H and L while sulfur premia (the slopes) are different for the two.

So what are the gains from trade? Consider a new policy where the two plants cannot purchase (or sell) permits to cover their emissions. Instead, each profit-maximizing power plant is now subject to a *uniform emission standard* $\bar{z}$ such that aggregate emissions are the same as before, i.e.

$$z_H^* x_H + z_L^* x_L = \bar{z}X \Rightarrow \bar{z} = \frac{1}{X} \times (z_H^* x_H + z_L^* x_L) \tag{3.3}$$

where $X = x_H + x_L$. The objective function becomes:

$$\max_{z,x}(p - c(z,x))q(z,x) \quad \text{s.t. } z \leq \bar{z} \tag{3.4}$$

So what are the gains from trade? Since $C(z)$ is assumed to be strictly decreasing[1], the objective function leads to the equilibrium that $z^* = \bar{z}$. Consider a simple scenario where the two firms are of identical size, and $\bar{z}$ is the average between points A^* and B^*. By looking at Figure 3.1, we can observe that the increase in the cost for the Northeast plant is going to be *higher* than the decrease in the cost for the Midwest plant. In other words, the total compliance cost will be higher under a uniform emission standard – that is where the cost effectiveness of the cap-and-trade program or the gains from trade are. The following theorem proves the general case where there are N firms of different sizes.

Cap-and-trade systems are superior to other policy instruments because they do not require knowledge of plant- or unit-specific parameters to determine optimal emissions. They let the emission market determine what they should do best. Also, by knowing how many allocations or 'caps' that are given out (or auctioned off),

[1]In some cases, for plants located near the sources of low sulfur coal, the cheapest coal may be the cleanest coal and therefore $C'(z)$ may be positive for some range of z. It is not going to change the central message of this chapter so I focus on the general case where $C(z)$ is strictly decreasing.

the agency also knows exactly what reductions are achieved. A uniform emission standard is often times considered as an alternative because it does not require prior knowledge about plants (because it is uniform) and also determines the size of emissions reductions.[2] Technology policies, such as mandating scrubber installation, were also discussed as alternatives. But they might lead to different aggregate emission reductions and will therefore be hard to compare with the cap-and-trade.

Theorem 3.1 *As long as $C''(z) \geq 0$, there are non-negative gains from trade under emissions trading. Gains are zero if and only if $C''(z) = 0$.*

Proof See Appendix A.

As shown in Theorem 3.1, gains from trade depend on the convexity of the marginal cost function. In other words, if the change in the sulfur premium is less rapid, we should expect a smaller cost savings. The intuition is that if sulfur premium does not vary much across z space, there will not be large gains from trading, as the change in the compliance cost will be minimal. One of the major determinants of the sulfur premium is cost of transporting coal – the lower the rate the lower the sulfur premium. Other determinants of the convexity include national variation in coal quality and abatement technology.

The above example serves as a simple illustration of the theory of gains from trade; however it does not represent reality. First, it is not necessary that the marginal cost function $C(z)$ is continuous. State-level regulations often favor certain

[2] In the case where there is over-compliance incentive (when $C(z)$ is not always decreasing or there are other incentives that will be discussed below), the government may not be able to match the exact emissions. However, it can re-adjust the uniform standard, in the case of perfect monitoring, such that the aggregate emissions will be the same.

compliance strategies over the others; for instance, they provide tax credits for the use of in-state coal. Therefore, we expect some *discrete* jumps in the compliance cost function $C(z)$. Second, scrubber installations, and even the adoption of low sulfur coal from the West, incur some upfront costs that lead to shifts in the cost functions. Accordingly in the following section, I provide an overview to the general discrete choice model where I allow for discrete jumps and estimate the costs and the effects of these policies on compliance choices.

3.2 Empirical Model of Compliance Choice

In this section I describe the structural model of compliance choice. I begin the section by describing the general framework. Then, I discuss the assumptions, the structure and identification of my random coefficients model in which each generating unit picks what types of coal to burn and whether to install a scrubber.

3.2.1 General Framework

The objective of the estimation procedure is to 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 estimate the magnitude of the cost savings, one has to know (1) the cost of compliance associated with observed choices, as well as (2) the emission rates and the compliance costs for other compliance choices. I estimate the cost functions associated with difference choices, allowing 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 the cost of retrofitting (modifying boiler to burn a different kind of coal), and the operating cost associated with low sulfur coal.

Many decisions made by power plants are discrete in nature. When power plants select their choice of coal, they decide which coal region they want to buy their coal from: located from East to West, different regions offer coal of different quality (sulfur and ash content), and are associated with different transportation costs. Investment in pollution control equipment, i.e., 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 function, also helps control for 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 represents a window between the 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.[3] 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 2.10, which shows survey data on compliance strategies by Phase I and II units, suggests 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 plants the flexibility to pick their emissions, taking into account a permit cost that increases with its desired emission rate. With the estimated model, I can also 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 compliance costs, which can be aggregated to estimate the cost savings achieved from emissions trading. By estimating a discrete-choice model, I can predict what the compliance choices are going to be under the constrained standard case, and can also predict the observed and unobserved compliance *cost*.

I choose to estimate a static rather than a dynamic model for two reasons. Despite the dynamic nature of the permit market, I did not pursue a dynamic model that explicitly models permit banking decisions (Zhang (2007)). In this paper, I am

[3] 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%.

not interested in studying permit banking and trading in equilibrium. Instead, each generating unit chooses a compliance strategy, which is associated with its desired SO_2 emission rate, that would implicitly take permit banking into account. My model estimates the shadow price of emissions and compare that to allowance prices. Permit prices are stable during the period of my analysis (see Figure 2.9) which suggests that the banking motive should not change over this period.[4]

In addition to the stability of permit prices, price trends for different kinds of coal did not fluctuate much over my study period. If this were not true, the snapshot in 2000–2002 might reflect a temporary change in coal prices in those years, and not necessarily the compliance choices that firms would otherwise make. Even if 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 arrangements. Figure 4.1 plots the minemouth prices for three regions – Appalachians, Interior (including Illinois Basin) and the West (sources of low sulfur coal) using data in U.S. Energy Information Administration (EIA). 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 in any of the regions. Therefore, current prices should act as a good proxy for the future prices and a static compliance cost function can represent long-run

[4]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.

compliance costs under the ARP.[5]

3.2.2 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 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 either the electricity or permit markets and produces a constant output. It therefore treats heat input (in MMBtu, and hence electricity output) as fixed.[6] This is a reasonable assumption as coal-fired power plants are often located at the lower portion of a electricity load curve and are base-load plants, because they are the least-cost producers. Fewer than 10 generating units indicate that they decreased utilization to comply with the ARP (as indicated by the EIA survey data in Figure 2.10). An emissions rate, as a function of the sulfur content of coal and the scrubber installation status, and compliance costs, can then be generated from the estimated model.

Plant location is the primary source of the observed heterogeneity in compliance cost. Plants in Michigan, which are closer to low sulfur coal in Wyoming and Colorado, will have a lower cost compared to plants in Pennsylvania due to transportation costs. The delivered price of coal, which is a sum of the minemouth

[5]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.

[6]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.

coal price and the transportation component, is included in the compliance cost functions. Each generating unit is also subject to state or local regulations that prohibit 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 cannot choose the kinds of coal that will violate the emission constraint. Therefore, each boiler minimizes the per MMBtu compliance cost subject to current emission standard:

$$\min_j C_i(j, \beta) \quad \text{s.t.} \quad (1 - \theta(j))SULFUR(j) \leq \overline{SULFUR}_i \tag{3.5}$$

where $C_i(j, \beta)$ is the weighted compliance cost per MMBtu for generating unit i choosing 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% percentile of observed sulfur and ash content. The weighted compliance cost per MMBtu takes the following parametric functional form:

$$
\begin{aligned}
C_i(j,\beta) = \beta^F COALPRICE_i(j) + \beta^A ASH(j) + \beta^S SULFUR(j) \\
+\beta^t SULFUR(j) \times (1-\theta(j)) + \mathbf{1}(j = PRB)(\beta_0^l + \beta_1^l AGE_i) \\
+\beta^z SCRUBCOST_i(j) + \beta^M MODIFY_i(j) + \varepsilon_i(j)
\end{aligned} \tag{3.6}
$$

β serves two purposes in the above equation. First, it represents the weights that each manager places on each category of costs (Fowlie (2010)) and reflects the possible non-cost minimizing motives that he may have with respect to each component. Second, it captures the capital and operating cos, as I discuss 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) (β^A).

The compliance cost functions in equation (3.6) consist of [1] coal prices ($\beta^F COALPRICE_i(j)$), [2] costs 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 θ 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 cost that is specific to each alternative j but not observed by the econometrician. I assume that $\varepsilon_i(j)$ follows a type-I generalized extreme value distributes and is identically and independently distributed across generating units i and alternatives j. I will discuss components [4], [5] and

[6] below.

The shadow price of permits will be estimated from the model based on the coefficient β^t. $(1-\theta(j))SULFUR(j)$ represents the emission rate and β^t in equation (3.6) is the shadow price of permits (as perceived by firms). To estimate β^S and β^t, I include the sulfur content of coal as well as an interaction term between sulfur and scrubber status. Theoretically these coefficients should differ by θ. I did not however impose this restriction in the estimation due to possible operating costs associated with the sulfur content of coal (represented by β^S) or different weighting of the two by the decision maker. In the counterfactual both β^S and β^t will be set equal to zero to indicate that there is no shadow price of permits in the emission standard case.[7]

Components [5] and [6] in the above equations are the two types of unobserved retrofitting costs that I model. 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 more quickly to achieve the same thermal efficiency). Second, there is a potential cost to modifying the source of the coal. This represents two types of costs – retrofitting costs that power plants incur when they modify the types of coal they use (as a boiler is often designed to burn only a subset of coal types) and the cost of building the required railroad 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

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

the retrofitting dummy equal to one if the coal type used in 2000–2002 differs from 1981–1983.

The weights, represented by the β'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 may favor the scrubber option because the scrubber is viewed as a capital investment included in the rate base. Therefore, estimating these parameters can capture non-cost minimizing behavior. This may cause cost savings to differ from estimates that assume a least-cost solution.

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

$$\beta^z = \beta_0^z + \beta_1^z KBIAS_i + \beta_2^z DEREG_i \tag{3.7a}$$

$$\beta^F = \beta_0^F + \beta_1^F MINEMOUTH_i(j) + \beta_2^F MATCH_i(j) + \beta_3^F DEREG_i \tag{3.7b}$$

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 due to state regulations. Plants that located in deregulated electricity markets 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 coefficients in equation (3.6) are identified using cross-sectional variation in the data. Observable components of cost include the price of coal and scrubbing cost, obtained from the survey forms gathered from the Energy Information Administration (more details in Section 4). The coefficients of observable cost components are identified using cross-sectional variation in 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 chosen.

The discrete nature of the cost function makes it difficult to estimate a discrete-continuous model, treating SO_2 emissions as a continuous decision variable (Dubin and McFadden (1984)). In such a framework, I would have to estimate a coal price equation as a function of sulfur emissions, which would require correcting for the PRB premium. For instance, I 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 retrofitting 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 in a continuous model as these represent discrete jumps in the pricing equation.

3.3 First Look at the Data

Appendix B describes the sources of the data in more detail. Table 3.5 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 to install scrubbers. Their compliance decisions were therefore not affected by the Acid Rain Program.[8] For the rest of the units, I either have no data on coal procurement or they buy coal from other than the six major basins on which I focus. 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 the 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 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 3.1 summarizes the actual coal prices observed in the data for the three major coal basins – Powder River (low sulfur), Central Appalachian (medium sulfur) and North Appalachian (high sulfur). Table 3.2 presents similar results based on imputed prices. Powder River Basin coal is often the cheapest coal available to coal plants. This might sug-

[8]There are different classes of NSPS units, 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.

gest that most coal-fired power plants would purchase coal from the Powder River Basin (PRB); however in practice, only a portion of them do. Units often incur additional costs to burn PRB coal, this includes operating costs to increase the speed of pumping coal into the boiler due to the lower heat content of PRB coal, plus additional retrofitting costs. Therefore it is empirically important to estimate the hidden cost (or premium) of using PRB coal.

The identification of compliance strategies relies on the geographical variation in (imputed) coal prices, variation in the sulfur and ash content of coal as well as the exogenous variation in local emission standards. The geographical distances between coal mines and plants determine the type of coal chosen, as we can see from the imputed prices in Table 3.2. 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 3.3. The bigger buyers are all very close by – Pennsylvania units buying buying from North Appalachian, Midwest (Michigan, Illinois, Missouri) units are getting PRB coal, while South Appalachian coal is bought only by the Alabama coal plants. Table 3.4 provides similar summary statistics looking at the coal procurement practice in each state.

Another important dimension of the compliance strategies is the decision to scrub. 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 3.6 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. In the simulations, I restrict 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 3.7 provides summary statistics for other variables including the cost of scrubbing. For my sample – the cost of scrubbing is of similar magnitude as the low sulfur premium observed in the data.

3.4 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 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.

3.4.1 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

$$\Pr(j|X_i, \beta) = \frac{\exp(-C(j, \beta; X_i))}{\sum_{j'=1}^{J} \exp(-C(j', \beta; X_i))} \tag{3.8}$$

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

$$\mathcal{L}(\beta|Y, X) = \sum_i \sum_j \mathbf{1}(Y_i = j) \ln \Pr(j|X_i, \beta) \tag{3.9}$$

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 unobserved heterogeneity will likely lead to an underestimation of the cost savings in my simulation. Therefore, a random coefficient logit model is used instead of the conditional logit model. Its log-likelihood function takes the following form:

$$l(b, \Sigma) = \sum_i \sum_j \mathbf{1}(Y_i = j) \ln \int_{-\infty}^{\infty} \frac{\exp(-C(j; b, X_i))}{\sum_{j'}^{J} \exp(-C_i(j'; b, X_i))} f(\beta|b, \Sigma) d\beta \tag{3.10}$$

where Y_i is the actual choice made by i, $f(\beta|b, \Sigma)$ is the probability distribution for the random coefficients and b, Σ 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. I will therefore use maximum simulated likelihood to estimate the parameters associated with equation (3.6).

I allow the coefficients on scrubbing cost, operating cost for using Powder River Basin coal and the implicit cost of retrofitting to depend on an idiosyncratic unobserved component φ where φ is assumed to be normally distributed with zero mean and a diagonal variance-covariance matrix Σ. I use the coefficient of coal price to scale all parameters to a dollar value. In the results below, I assume φ to be identically and independently distributed for each generating unit, although these coefficients may be correlated within a plant. [9]

3.4.2 Extension to allow within-region coal choices

As seen in Table B.1, each coal basin is associated with a range of sulfur contents. The mean sulfur content of coal will therfore be a poor measure of the sulfur content of coal actually purchased to comply with the Acid Rain Program. In this subsection I introduce an algorithm to take the within-basin 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.

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

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

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 minimizes the *same* compliance cost function as in equation (3.6)

$$\min_k C_i(k;j) \text{ for all } i \text{ and } j \tag{3.11}$$

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 obtain β^*.

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 (B.1) 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.

3.5 Cost Function Estimation Results

Table 3.8 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 3.1), it bears additional costs that deter units from using it. More importantly, older generating units incur a higher cost in switching to Powder River Basin coal. Based on the average age of 44, this is equivalent to a premium in the price of coal of around 50 cents. After adding the 50 cent premium to the 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 sources for Northeast units.

A second point to notice is that deregulated units are more sensitive to coal prices and scrubbing costs and tend to buy cheap coal. This result is also found in the literature on the effect of electricity market deregulation (Chan et al. (2013); Cicala (2013)) which finds 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 costs. Cicala (2013) in particular finds 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 have 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 find a large discount for minemouth units to use minemouth coal, which may reflect the value of long-term contracts.

The implied shadow price of a permit, based on the coefficient on the interaction of the sulfur content of coal and scrubber status, is about \$180 (per ton of emissions, constant 1995 dollars).[10] 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 operated efficiently.

Third, there is considerable heterogeneity in the impacts of the observables. Table 3.8 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, conditional on the observed choices (Train (2009)). Taking into account this 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

[10] 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.

predicted emissions are 8.70 million tons of SO_2, which is slightly larger 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 focus 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 generating units.

Therefore, I estimate the conditional mean of these unobserved cost terms (ε's) and incorporate them in the simulation. I first draw 40,000 shuffled Halton draws (Bhat (2001)) for each unit and each alternative, 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 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 3.2. 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 tons. From Panel B of Figure 3.2, the prediction errors seem to be centered around zero and the predicted emission rates appear not to be systematically different from the observed emission rates.

3.5.1 Comparison to other models

Table 3.9 compares my baseline model in Table 3.8 with two alternative specifications – a conditional logit model with 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 cost 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: the baseline model (without accounting for the conditional distribution of ϵ's) predicts emissions to be 8.7 million tons while themixed logit model predicts 10.6 million tons; actual emissions are 7.16

million tons, as documented in Table 3.5. 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.

Figure 3.1: Equilibrium in the Permit Trading Market

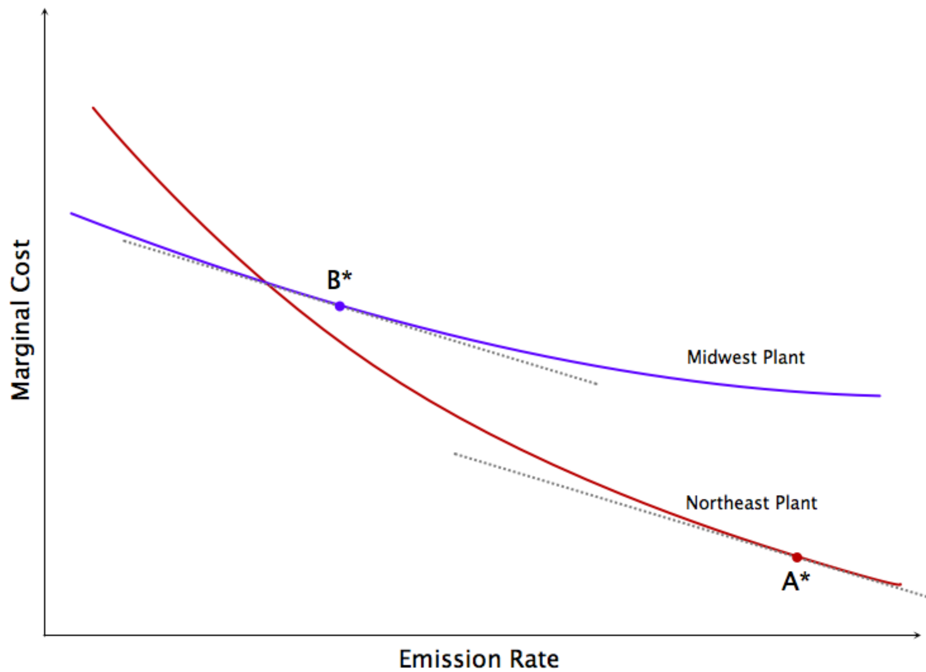
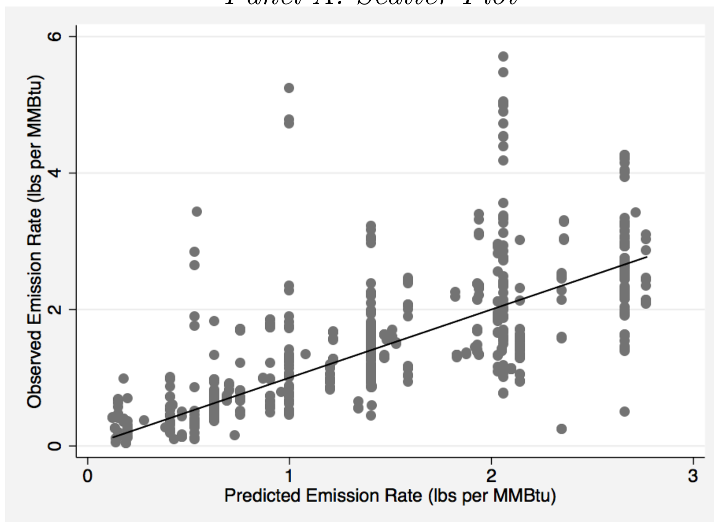


Figure 3.2: Predicted Emission Rate

Panel A: Scatter Plot



Panel B: Difference between Actual and Predicted Emission Rate

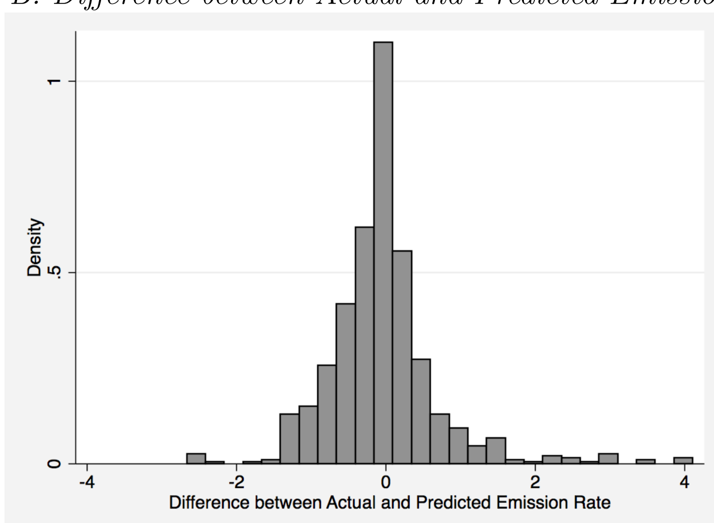


Table 3.1: Observed Delivered Coal Prices, in 1995 cents

	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 3.2: 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 3.3: Major Buyers from the Coal Basins

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

Table 3.4: Coal Procurement by Non-NSPS Units

State	Total	NA	CA	SA	IL	UB	PRB	Others
					(All in %)			
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 3.5: 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 3.6: 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 3.7: 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 3.8: 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			
Scrub Cost	0.1256*	Modif. Cost	1.8300***
	(0.0758)		(0.4627)
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. A positive coefficient implies that the cost is increasing in that component. 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 3.9: Comparison Across Models

	Baseline	Cond. Logit	Mixed Logit
Estimates			
Sulfur	6.3711***	2.9876***	3.9460***
	(0.9223)	(0.2265)	(0.3158)
Sulfur × 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 3.8, except for omitting the standard deviations for the random coefficients for conditional logit. 'Baseline' model uses the same specification as in Table 3.8 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.

Chapter 4: How Large are the Cost Savings from Emissions Trading?

In this chapter, I use the parameters in Chapter 3 to estimate the cost savings from the Acid Rain Program. To begin this chapter, I present the methodology. I use the estimates to predict the choices under the ARP and compute aggregate emissions and compliance costs. 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.

4.1 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 distributions is that they capture 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 a distributional assumption to compute the conditional distribution. The unobserved cost terms can lead to a smaller or larger estimates of the cost savings. Cost savings are smaller if they suggest that units are 'stuck' at an alternative that looks attractive to them but not to the econometrician based on mean values, or the savings can be larger because 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 to be the option with the highest probability and compute the implied aggregate emissions and *unweighted* compliance costs: I omit the coefficients and compute the inferred costs from the coal price equation, scrubbing cost equations, estimated operating costs, retrofitting costs, as well as the premium for 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, but 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 means. The compliance cost function that will used in the counterfactual scenario takes the following form:

$$
\begin{aligned}
COMPC_i(j) = {} & SCRUBCOST_i(j) + COALPRICE_i(j) \\
& + \underbrace{\mathbf{1}(j = PRB)(\mathbf{E}_i\beta_0^l + \beta_1^l AGE_i)/\beta^F}_{\text{Premium for PRB Coal}} \\
& + \underbrace{\beta^A ASH(j)/\beta^F}_{\text{Operating Cost}} + \underbrace{\mathbf{E}_i\beta^M(j)/\beta^F}_{\text{Retrofitting Cost}} + \underbrace{\varepsilon_i(j)/\beta^F}_{\text{Unobs. Cost}}
\end{aligned} \tag{4.1}
$$

In the counterfactual scenario in which the uniform emission standard is in place, the objective function (3.6) is the same except that the emissions components (both β^S and β^t) are removed. This implies that, under a uniform emission standard, generating units should have picked the type of coal with the lowest cost, taking into account all operating cost components. This is a different methodology compared to the one used in Keohane (2007) – while Keohane (2007) assumes the cheapest coal is selected under a uniform emission standard, he did not estimate the unobserved cost components.

I begin by setting a starting value for a uniform emission standard. The goal is to find a standard such that aggregate emissions match predicted aggregate emissions in the ARP. I assume that only the ARP is changed in the counterfactual and that the current local emission standards are still in place. In other words, the uniform emission standards is 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 the last chapter, I allow discrete jumps in aggregate emissions to help match the aggregate emissions under the two scenarios. 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. I am more confident in saying 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 more accurately predict the sulfur content of coal and hence emissions.

The following list summarizes the above steps in detail:

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

$$\mu_i(\beta|D_i = Y, X_i, b, \Sigma) = \frac{P(D_i = Y|X_i, \beta)f(\beta|b, \Sigma)}{P(D_i = Y|X_i, b, \Sigma)} \tag{4.2}$$

   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 unobserved costs, 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 emissions, based on

the predicted choice $\hat{j}_i$ for each unit

$$AGGCOMPC = \sum_{i=1}^{I} COMPC_i(\hat{j}_i)q_i \tag{4.3}$$

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 3.4.2 with coal types that violate a uniform emission standard $\bar{s}_{(0)}$ ruled out. Predict the optimal compliance strategy j that minimizes the new weighted compliance cost function, or maximizes the following probability

$$\widehat{\Pr}_i(j|X_i, b, \Sigma) = \int_{-\infty}^{\infty} \frac{\exp(-\tilde{C}(j; b, X_i))}{\sum_{j'}^{J} \exp(-\tilde{C}(j'; b, X_i))} \mu_i(\beta|X_i, b, \Sigma) d\beta \tag{4.4}$$

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 with $\bar{s}_{(t)} = \bar{s}_{(t-1)} - 0.01$ until the emissions are close to or lower than those in the previous iteration.

4.2 Simulation Results

Table 4.1 reports the simulation results. The implied abatement costs are all expressed in millions of 1995 USD to facilitate comparisons with the literature. 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) that achieve the same emissions. The implied abatement costs can be viewed as the average aggregate costs per year.

Table 4.1: 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 Costs in constant 1995 Million USD.

Table 4.1 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 having mean zero (implying that the unobserved effects are not permanent) while numbers in the second row assume that the unobserved costs are permanent and use the conditional means estimated in Step 2. After controlling for 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 choices are carried over to the uniform emission standard case, my model could have predicted a smaller cost savings as it implies less flexibility and less cost heterogeneity. On the other hand, from what we have seen in Table 4.1, after taking into account the unobserved cost differences, we achieve a larger estimate of cost savings due to a larger degree of heterogeneity.

In the simulation exercise I predict each unit's compliance choice under the uniform emission standard. Table 4.2 provides an overview of the number of units choosing each compliance strategy in the ARP and under the uniform emission standard. Generating units, under the uniform emission standard, cannot use coal from the Illinois Basin without installing a scrubber. Therefore, there is a huge shift in compliance choices from burning high sulfur coal (and obtaining more permits) to either blending high and medium sulfur coal or installing a scrubber. Out of the 171 units that switched their compliance choices, 125 of them were burning high sulfur coal under the ARP. 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.

4.3 Why Are the Cost Savings Low?

The estimated cost savings are much smaller than those in the existing literature. Carlson et al. (2000) predicted a cost savings of around $780 million i the long run (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.[1] 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 that the Acid Rain Program would achieve the least cost solution. There are several reasons why that may not be

[1]Normally we expect much higher cost savings in 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 dissertation.

the case. First, plants under cost-of-service regulation may not have incentives to minimize their costs. Second, state-level policies may magnify the value of certain options. State emission standards, although not as stringent as the ARP target, limits the compliance strategies that different generating units can use. It may not be viable for units to buy permits even if it is the cheapest option under the ARP. In my model I capture some of these differences by allowing the weights in the cost function to depend on 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) switching to low sulfur coal (PRB) or (2) installing 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.[2] I also compute a per ton cost of SO_2 removal for units that use PRB coal. 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 a permit is only \$180.

Two other reasons why we may see a lower cost savings are 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 (B.1) by dividing my sample into two periods: 1991-93 and 2001-03. The estimated coal transportation rates (in constant 1995 dollars) are shown in Table 4.3. The most

[2] I obtain similar numbers by looking only at scrubbers installed after 1995.

striking observation is that the transportation cost for Powder River Basin coal has been cut almost in half in 10 years time, while the minemouth prices follow almost the same trends for these coal basins (as shown in Figure 4.1). Since railroad deregulation under the Staggers Act of 1980, the transportation cost for coal has been drastically decreased (Christensen Associates (2008); Schmalensee and Stavins (2013)) – it implies that coal plants in Ohio do not have to pay as much if they intend to switch to Powder River Basin coal.[3] This also implies that the heterogeneity in compliance cost is smaller compared to the earlier literature which is based on the pre-1990 or early 90s levels.

Cost heterogeneity is also reduced through improvements in scrubber technology. Using the estimates in the scrubber operating cost equation, I plot the average operating cost over time in Figure 4.2. Year 1991 is the excluded category therefore all coefficients are relative to 1991. Clearly the operating cost for scrubbers is decreasing. The operating cost in 2000 is around 40% lower than the 1991 level. Bellas (1998) also found similar evidence of the technological advancement in scrubber technology using the same data source. It also suggests that the marginal abatement cost is lower than earlier estimates. This will lead to a decrease in both the compliance cost and predicted cost savings.

[3] Transportation to and from Powder River Basin is traditionally operated by two major rail lines (Busse and Keohane (2007)) and therefore the effect of increasing competition may have significantly decreased transportation costs for PRB coal compared to other kinds of coal (Pittman (2010)).

4.4 Summary, Implication and Unanswered Questions

In this project, I quantify the cost savings from a market-based instrument compared to a command-and-control instrument by using ex-post data from the first three years of Phase II of the Acid Rain Program (ARP). This enable me to model the optimal choice of coal as well as the scrubber installation decision. Cost heterogeneity arises primarily because of geographic variation in costs: some generating units are closer to 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 implement.

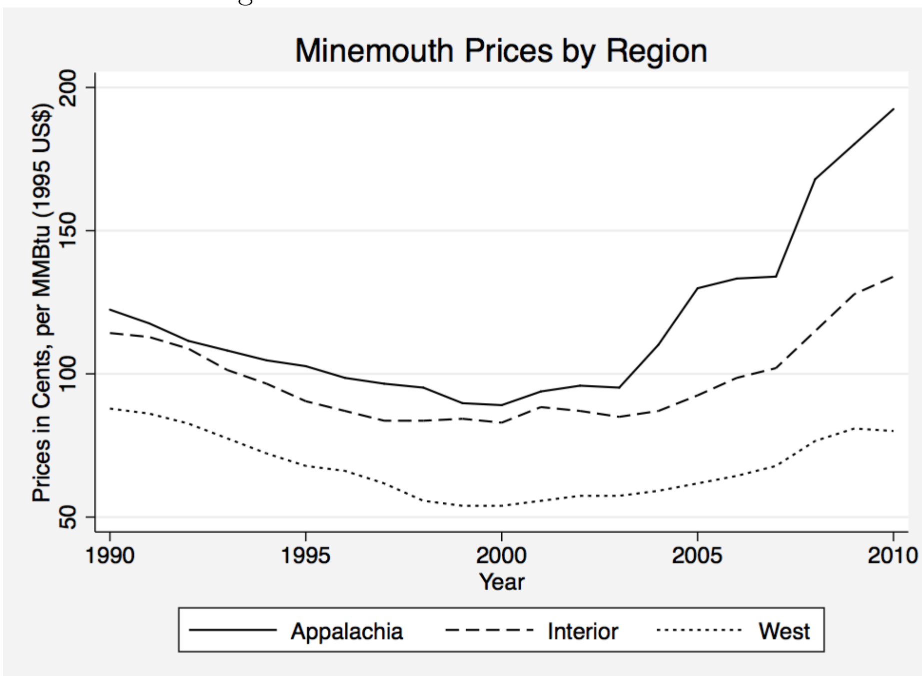
I proceed by first estimating a static random coefficient logit model to identify optimal compliance strategy for regulated generating units and recover parameters of the compliance cost function. I find economically and statistically significant unobserved components for retrofitting costs as well as additional costs for using Powder River Basin coal. This explains the puzzling fact that PRB coal is often the cheapest source of coal. By estimating a mixed logit model I can control for statistically significant variation in the impacts of covariates on the compliance cost function. 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 in the literature on electricity market restructuring, I find that deregulated units attach a greater weight to coal price and scrubbing cost, that leads them to act 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 permanent effects. Based on my estimated model, I simulate what would happen to the aggregate compliance cost under a uniform emission standard that achieves the same emissions reduction as the ARP. I find 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 my estimates: (1) lower transportation cost induces less cost heterogeneity across generating units, (2) technological improvement in scrubbing technology also lowers marginal abatement cost curves, (3) state policies, in particular state emission standards, might have limited choices and prevented coal-fired units from achieving the least cost solution.

This analysis helps us design environmental policies. It suggests that emissions trading program may not be always superior than other less flexible regimes. Often times political consideration in designing these programs impede the program from operating efficiently. One example is the failure of the Clean Air Interstate Rule (CAIR) in 2005, as discussed in Chapter 2. After the EPA learned that the interstate transport of pollutant affected upwind and downwind states differently (Fraas and Richardson (2010)), EPA proposed the CAIR to replace the ARP. The Courts ruled that the EPA had to re-design a new policy. It was struck down by the courts in 2008 because the rule allowed unconstitutional trades between states. Afterwards, the EPA proposed the Transport Rule which was also deemed unconstitutional in 2012 but was later reinstated by the Supreme Court. These rules generated uncertainty in the permit market. Uniform standards would have avoided this aspect of regulatory uncertainty.

While my results apply to the largest trading program in the U.S., the claim that emissions trading may not yield a large cost savings may not hold for other trading programs. My estimation is based on coal-fired electricity generators, and it is for this particular trading program. Other markets might be less influenced by other state or federal regulations; also, there may be larger cost heterogeneity across complying firms. In those cases, the cost savings from cap and trade may be larger. Further research is required in the ex post evaluations of policies. In general ex ante studies may over-estimate the gains from trade. Studying the effects of state-level policies on the efficiency on federal policies remain an important direction for future research.

Figure 4.1: Minemouth Price for Coal



Source: U.S. Energy Information Administration (EIA)

Figure 4.2: Predicted Operating Cost for Scrubbers

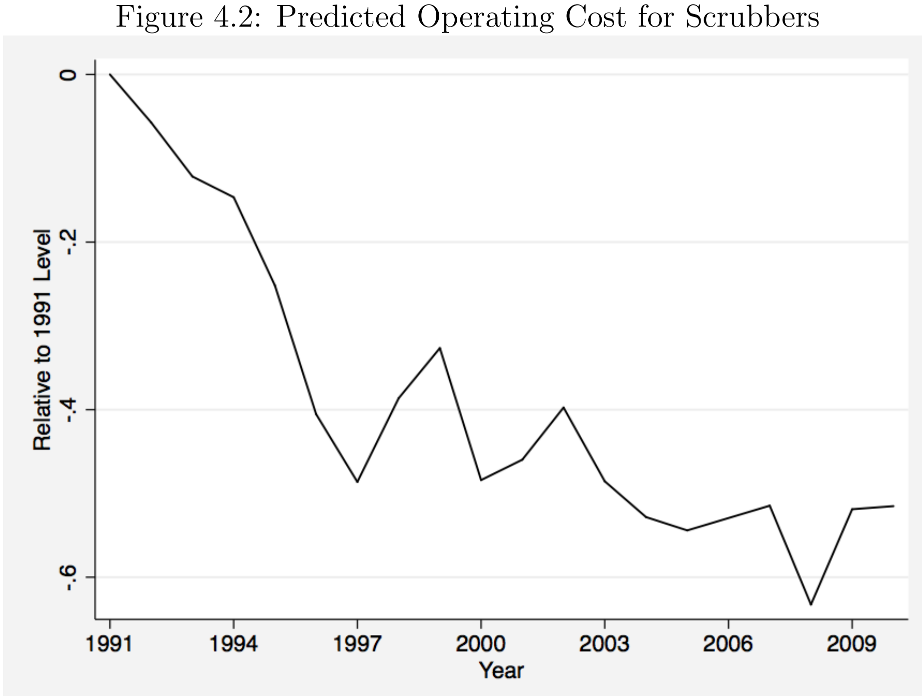


Table 4.2: Compliance Choice in ARP and Emission Standard

	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 4.3: 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

Chapter A: Proof of Theorem 3.1

What we want to prove is the following expression for the general case where there are nonidentical plants $i = 1, 2, ..., N$ each with heat input x_i:

$$\sum_i C_i(z_i^*)x_i \leq \sum_i C_i(\bar{z})x_i \tag{A.1}$$

Left hand side of equation A.1 represents the total compliance cost under the Acid Rain Program while the right hand side denotes the total cost under a uniform emission standard.

Performing a second-order Taylor series approximation on $C_i(\bar{z})$ around z_i^* for each i yields the following:

$$C_i(\bar{z}) = C_i(z_i^*) + C_i'(z_i^*) \times (\bar{z} - z_i^*) + \frac{C_i''(z_i^*)}{2} \times (\bar{z} - z_i^*)^2 \tag{A.2}$$

for each i.

Insert equations (A.2) into the right hand side of equation (A.1):

$$\sum_i C_i(\bar{z})x_i = \sum_i C_i(z_i^*) + \sum_i C_i'(z_i^*) \times (\bar{z} - z_i^*)x_i + \underbrace{\sum_i \frac{C_i''(z_i^*)}{2} \times (\bar{z} - z_i^*)^2 x_i}_{\Omega} \tag{A.3}$$

Using the equilibrium condition $C_i'(z_i^*) = -p^z$ for all i and the definition of $\bar{z}X = \sum_i z_i^* x_i$ where $X = \sum_i x_i$, the second term on the right hand side of equation (A.3) sums to zero:

$$\sum_i C_i'(z_i^*) \times (\bar{z} - z_i^*) = -p^z \left[\bar{z} \sum_i x_i - \sum_i z_i^* x_i \right] = 0 \tag{A.4}$$

Since we have $C_i''(z_i^*) \geq 0$, Ω in equation (A.3) is non-negative and it is zero if and only if $C_i''(z_i^*) = 0$. Therefore,

$$\sum_i C_i(\bar{z}) x_i = \sum_i C_i(z_i^*) x_i + \Omega \tag{A.5}$$

and Ω are the gains from using a market based instrument.

Q.E.D.

Chapter B: Data Appendix

This appendix 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 of scrubbing cost data. Regression results for imputing coal prices are then presented.

B.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. Also reported are heat, sulfur and ash content by weight, quantity of coal purchased, contract type, the mine from which the coal was bought 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 average coal procurement over 2000–2002.

There are three challenges regarding these data. The first challenge is to define the type of coal purchased. Figure B.2 summarizes the sulfur content of fuel (per MMBtu) of all coal transactions observed from 1991 to 2010. There are two spikes below a 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 B.1 shows the physical location of these coal basins. The summary statistics of their sulfur content are tabulated in Table B.1. 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 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.[1] I drop generating units that do not purchase any coal from the six regions. These plants mainly buying lignite coal from the Gulf Coast region or import bituminous coal from Colombia. I attempted to predict the price from Gulf Coast region but the estimated coal price implied most of the plants in my sample should have bought coal from this region. This imprecision is mainly driven by low number of observed transactions. These transactions are initiated by plants around thr Gulf Coast region.

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

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

the unit level: (1) for a plant with minimal difference in emission rates (gathered from the Continuous Emissions Monitoring System (CEMS) database) across its generating units, I assume all units burn same kind of coal. If they are buying a significant amount (more than 20%) from two basins, I assume that they mix the two kinds of coal (under an assumed 50-50 ratio); (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 plant with scrubbers installed in some but not all of their boilers, I assign the type of coal with higher sulfur content to the boilers with scrubbers installed.

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.

$$\begin{aligned}
&\ln(COALPRICE_{ijt} - \tau DISTANCE_{ij}) \\
&= \alpha_1 \ln SULFUR_{ijt} + \alpha_2 \ln ASH_{ijt} + \alpha_3 (\ln SULFUR_{ijt})^2 + \alpha_4 (\ln ASH_{ijt})^2 \\
&+ \alpha_5 (\ln SULFUR_{ijt}) \times (\ln ASH_{ijt}) + \alpha_6 SPOT_{ijt} + \delta_t + \varepsilon_{ijt} \qquad \text{(B.1)}
\end{aligned}$$

$COALPRICE_{ijt}$ is the observed real coal price (in cents per MMBtu) that plant i pays if i purchases from mine j at year t.[2] 'Mine' is defined as a specific

[2] All costs are expressed in 1995 dollars using the GDP deflator, downloaded from Federal

county from which the coal is transported. Mine-level information that would allow me to define mine-specific quality is incomplete. $DISTANCE_{ij}$ 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 δ_t is a time dummy. τ represents per ton per mile transportation cost in cents, and is estimated using nonlinear least squares, along with other coefficients. By subtracting the transportation cost component, the left hand side of equation (B.1) represents the predicted minemouth price.

I have also tried a different specification where sulfur and ash content (and their interaction) have a linear relationship with delivered coal prices. The estimation and simulation results do not change significantly. Due to concerns about the major policy changes (CAIR and CSAPR), I have also dropped observations beyond 2005. The predicted coal prices are very close to the ones predicted using the full sample: the correlation between the two samples is 0.99.

Results for all of the six major coal basins are displayed in Table B.2. 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 generating units, but the positive correlation

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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 the 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 coal prices at the mine level using the same algorithm.

B.2 Scrubbing Cost and Other Sources of Data

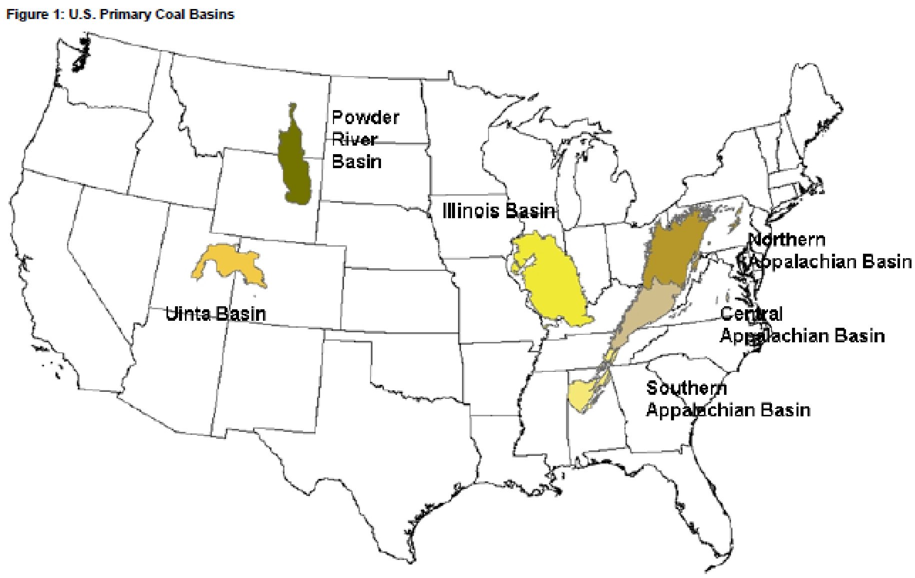
Operating and installation cost for scrubbers are recorded in "Steam-Electric Plant Operation and Design Report" (EIA-767). As for coal, I observe the scrubber operating cost and installation cost only for the scrubbed units so I estimate models similar to Lange and Bellas (2005) to impute scrubbing costs. I separately estimate two equations, one for operating cost and another equation for installation cost, using plant characteristics that include size, operating hours and physical location, as well as technical attributes of the scrubbers including age of scrubber, removal rate and percentage of gas entering the scrubber. Results are shown in Table B.3. For scrubber-specific regressors, average values are used to impute the scrubbing cost. In the simulation, I assume a scrubber removes 85% of total emissions.

To estimate equation (3.6), 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. As with the coal prices, all scrubbing costs 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. Heat input used is gathered from the CEMS database, cross-checed against data in the 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 EIA-767 is reported by fuel type. While EIA-767 data may appear more 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. I find no evidence that using different kinds of coal impacts the thermal efficiency of the boiler. When I run a fixed-effect regression of heat input on power generated, 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. Data on plant location, age of the boiler and NSPS regulation status come from EIA-767 and EIA-860 forms.[3]

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

Figure B.1: Coal Basins



Source: Enviroknow

Table B.1: 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 B.2: 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	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. 'Transport' variable is the per-mileton distance. All standard errors are robust standard errors. *, **, and *** indicate significance at the 10, 5, and 1 percent levels.

Figure B.2: Distribution of Sulfur Content

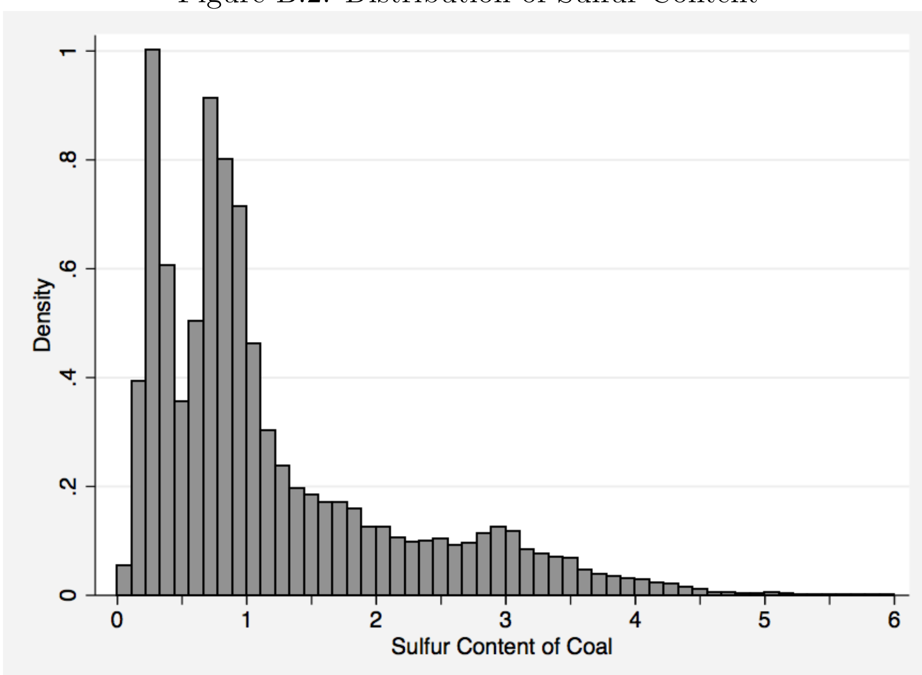


Table B.3: Cost Equation for Scrubbers

	(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.

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