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Emissions Trading, Electricity Industry Restructuring, and Investment in Pollution Abatement*

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Abstract

Policy makers are increasingly relying on emissions trading programs to address environmental problems caused by air pollution. If polluting firms in an emissions trading program face different economic regulations and investment incentives in their respective industries, emissions markets may fail to minimize the total cost of achieving pollution reductions. This paper analyzes an emissions trading program that was introduced to reduce smog-causing pollution from large stationary sources (primarily electricity generators) in 19 eastern states. I develop and estimate a random-coefficients discrete choice model of a plant's environmental compliance decision. Using variation in state-level electricity industry restructuring activity, I identify the effect of economic regulation on pollution permit market outcomes. There are two important findings. First, plants in states that have restructured electricity markets are less likely to adopt more capital intensive compliance options. Second, this economic regulation effect, together with a failure of the permit market to account for spatial variation in marginal damages from pollution, have resulted in increased health damages. Had permits been defined in terms of units of damages instead of units of emissions, more of the mandated emissions reductions would have occurred in restructured electricity markets, thereby avoiding on the order of hundreds of premature deaths per year.

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1 Introduction

When the U.S. federal government first began regulating major sources of air pollution in the 1960s, the conventional approach to meeting air quality standards involved establishing maximum emissions rates or technology-based standards for regulated stationary sources. At that point, the idea of establishing a cap on total permitted emissions, distributing tradeable pollution permits to regulated sources, and letting a market coordinate pollution reduction among regulated firms was just beginning to take hold among a small group of economists (Coase, 1960; Crocker, 1966; Dales, 1968; Baumol and Oates, 1971). Over the past few decades, the environmental regulatory landscape has changed dramatically. Today, the "cap and trade" approach to regulating point sources of pollution is the centerpiece of air pollution regulation in the United States, and it is a key component of the proposed policy response to global climate change (Foss, 2005).

Economists have long pointed out that an efficient pollution permit market minimizes the total social cost of meeting an exogenously determined cap on emissions. In the first-best permit market equilibrium, each firm chooses a level of pollution abatement such that the marginal cost of reducing pollution is set equal to the social marginal benefit from emissions reduction at the firm. There are two important assumptions underlying economic arguments for the efficiency of permit markets that are unlikely to be satisfied by many existing and proposed cap and trade (CAT) programs.[1] The first pertains to the objectives of the firms regulated under CAT programs; the second to the terms of permit trading. I assess the consequences of violating these two assumptions in practice using a unique data set from a major U.S. Nitrogen Oxide (NOx) emissions trading program (the NOx State Implementation Plan (SIP) Call). I find that inter-state variation in economic regulation, together with the failure of the permit market to account for spatial variation in marginal damages from pollution, have distorted investment in pollution controls away from the first-best, thereby reducing the efficiency of the CAT approach.

In a formal proof of the existence of a cost effective permit market equilibrium, it is typically assumed that all firms have the same objective function (Montgomery, 1972). Although firms are assumed to differ in terms of the price they receive for their products, costs of production, and costs of reducing emissions (indeed, it is this heterogeneity that gives rise to gains from permit trading), it is assumed that all firms are essentially solving the same cost minimization problem when deciding how to comply with CAT regulation.

In fact, firms in the same pollution permit market may approach the choice of how to comply with a CAT program very differently. The vast majority of the emissions regulated under CAT

[1] Several assumptions are required to demonstrate the efficiency of cap and trade programs. These include: zero transaction costs, perfectly competitive permit markets, perfect enforcement and compliance, perfectly competitive product markets and profit maximizing (or cost minimizing) behavior. In a multiple-receptor, non-uniformly mixed pollutant case, economists further assume an "exposure" or damage based permit system.

programs come from electricity generators.[2] The recent wave of electricity industry restructuring in the United States has resulted in significant inter-state variation in electricity industry economic regulation. Thus, in addition to having different production and abatement costs, generators in the same CAT program face different economic regulation and investment incentives depending on the nature of their electricity market.

Hence, the first question I address: have differences in electricity market regulation affected how coal plant managers chose to comply with a multi-state NOx emissions trading program?[3] I develop and estimate a random-coefficients logit (RCL) model of the firm's compliance choice that controls for unit-level variation in compliance costs and allows for correlation across choices made by the same plant manager. I find that plants in restructured electricity markets were less likely to choose more capital intensive compliance options as compared to similar plants operating in regulated electricity markets. More capital intensive compliance options are associated with significantly greater emissions reductions. Unfortunately, because of relatively poor air quality in states with restructured electricity markets, these are precisely the states where pollution reductions are most needed.

These results are particularly troubling because pollution permit markets, as they are currently designed, fail to reflect considerable spatial variation in marginal benefits from pollution reductions. Currently, all major cap and trade programs are "emissions-based": a permit can be used to offset a unit of pollution, regardless of where in the program region the unit is emitted. Designing a program in this way presumes that the health and environmental damages resulting from the permitted emissions are independent of where in the regulated region the emissions occur. A growing body of scientific evidence indicates that this is not the case for NOx, which is classified as a "non-uniformly mixed" pollutant because damages from increased NOx emissions depend on the location of the source (Lin et al., 2002; Mauzerall et al., 2005).

This leads to the second key assumption underlying the efficiency of permit market equilibria that is often violated in practice. Economists have traditionally assumed that CAT programs regulating non-uniformly mixed pollutants will be "exposure-based" (i.e., permits will be defined in terms of units of damages) rather than emissions-based (Montgomery, 1972; Tietenberg, 1974). In the second part of the paper, I evaluate the consequences of violating this assumption in a case where inter-state variation in electricity market regulation has the potential to exacerbate the inefficiencies associated with emissions-based trading. The estimates of the RCL compliance

[2] All of the emissions regulated under the Acid Rain Program and over 90% of the emissions regulated under the NOx SIP Call come from electricity generators. The cap and trade program laid out in the proposed Mercury Rule applies exclusively to the electricity sector.

[3] The paper focuses exclusively on the compliance decisions of coal-fired electricity generators. Although only 31% of the units regulated under the SIP Call are coal plants, 85% of the point source NOx emissions regulated under the program comes from coal plants.

choice model are used to assess whether an exposure-based market design would have significantly affected the spatial distribution of NOx emissions permitted under the SIP Call. I derive parameters of conditional distributions specific to each plant manager. Drawing from these conditional distributions, I predict the compliance choices that these plant managers most likely would have made had the NOx emissions market been designed to reflect spatial heterogeneity in marginal damages from pollution.

I find that the decision to adopt an emissions-based program (versus a damage-based permit market designed to achieve the same total emissions) has substantially increased daily NOx emissions in areas where air quality problems are most severe. Epidemiological studies consistently find a statistically significant association between NOx related air quality problems and increased mortality and morbidity (Grypares, 2004; WHO, 2003). In a recent study, Mauzerall et al. (2005) estimate that shifting 11 tons of NOx emissions per day from a relatively "low damage" location (North Carolina, a state that has not restructured its electricity market) to a "high damage" area (Maryland, a state that has restructured its electricity industry) over ten days will result in the loss of approximately one human life. I find that exposure-based permit trading would have moved as much as 300 tons of NOx per day out of high damage areas and into low damage areas where the pollution does less damage.[4]

These findings are relevant to three related areas of the literature. First, a number of authors have asked the broad question: how effective are existing U.S. cap and trade programs? Most have focused exclusively on the Acid Rain Program (ARP) that was established in 1990.[5] This is, to my knowledge, the first paper to evaluate the performance of the "next generation" of major US CAT programs, the NOx SIP Call, which is second only to the ARP in terms of size and scope.

Second, strands of both the industrial organization and environmental economics literatures have considered the effects of economic regulation and industry structure on firms' investment decisions.[6] Previous empirical work that considers how economic regulation in electricity markets has affected firms' CAT compliance choices has focused predominantly on the Acid Rain Program.[7] Because the Acid Rain Program started before restructuring began, these papers use

[4] This daily shift in NOx emissions would only occur during "ozone season" (May-September) when the the NOx SIP Call is in effect. Firms do not need to purchase permits to offset uncontrolled emissions occuring outside ozone season because NOx related air quality problems are less severe during the cooler months of the year.

[5] Papers analyzing the operation and performance of the Acid Rain Program include: Joskow et al.(1998), Schmalansee et al.(1998), Stavins (1998) and Keohane (2005).

[6] Hannan and McDowell (1984) and Genesove (1999) find that increased competition slows the adoption of new technologies, whereas Levin et al.(1987) find that increasing competitive pressures has a positive effect on the rate of technology adoption and diffusion. In the environmental economics literature, several papers have illustrated how, in theory, economic regulation can undermine the ability of a pollution permit market to operate efficiently (see Bohi and Burtraw, 1992; Carlson et al., 1998; Coggins and Smith, 1993; Fullerton et al., 1997).

[7] Mansur (2004) is an exception. He considers how market concentration in restructured electricity markets affects firms' short run compliance decisions under the Ozone Transport Commission's NOx Budget program.

more subtle variations in cost recovery rules and coal protection measures to identify an effect of electricity market regulation on compliance choices. Results have been mixed.[8] I revisit this question post-restructuring, now that there is significantly more interstate variation in electricity industry regulation and investment incentives, and thus increased potential for variation in economic regulation to undermine the efficiency of the permit market.

Finally, there is a growing literature that considers non-uniformly mixed pollution permit trading.[9] In previous empirical work, deterministic models of the compliance decision that assume strict cost minimization on behalf of all firms have been used to assess ex ante the merits of imposing spatial constraints on NOx permit trading.[10] The analysis presented here allows for a more realistic ex post evaluation of alternative, exposure-based permit market designs. Unlike previous studies, I find that the adoption of exposure-based NOx permit trading would have delivered significant health benefits. This result is particularly relevant to the debate that is currently taking place over the design of future emissions trading programs.[11]

The next two sections describe the emissions trading program, electricity market regulation, and restructuring in the United States. Section 4 describes the data and presents summary statistics. Section 5 introduces a model of the firm's compliance decision. Estimation results are presented in Section 6. In Section 7, I use the model to simulate compliance decisions under exposure-based trading. Section 8 concludes.

2 The NOx State Implementation Call

The NOx State Implementation Plan (SIP) Call was introduced by the U.S. Environmental Protection Agency (EPA) in 1998 to facilitate cost effective emissions reductions of NOx from large stationary sources through the introduction of an emissions trading program. NOx emissions contribute to the formation of ozone.[12] High ambient ozone concentrations have been linked to increased mortality, increased hospitalization for respiratory ailments, irreversible reductions in

[8] Bailey (1998) tests whether permit market participation (measured at the state level) is affected by how favorable an electricity market regulator has been to shareholder interests. She finds very limited evidence. Keohane (2005) finds no discernable effect of economic regulation on the decision to install a scrubber. Conversely, Arimura (2002) and Sotkiewicz (2003) do find evidence that economic regulations affected ARP compliance decisions.

[9] Analytical papers that consider imposing spatial constraints on trading and related alternative market designs include Duggan and Roberts (2002), Hahn (1990), and Krupnick et al. (1983).

[10] Farrell et al. (1999) consider imposing geographic constraints on NOx permit trading in the Northeast and conclude that the benefits do not justify the costs. Krupnick et al.(2000) argue that there is no clear benefit to spatially differentiated NOx trading.

[11] In March of 2005, the EPA issued two new, large scale emissions trading programs, both of which regulate non-uniformly mixed pollutants and are emissions-based. One of these programs, the Mercury Rule, has been particularly controversial because the proposed market fails to reflect spatial variation in damages from pollution.

[12] NOx reacts with carbon monoxide and volatile organic compounds (such as hydrocarbons and methane) in the presence of sunlight to form ozone in the lower atmosphere.

lung capacity, reductions in agricultural yields and increased susceptibility of plants to disease and pests. Recent epidemiological studies indicate that health impacts increase linearly with increasing ozone concentrations (US EPA, 2003; Steib et al., 2003, as cited in Mauzerall et al., 2005).

The NOx SIP Call was designed to help northeastern states come into attainment with the Federal 1-hour and 8-hour federal ozone standards of 120 ppb and 80 ppb respectively. Figure 1 illustrates how, during high ozone episodes, significant portions of the northeast can fail to attain the Federal standard (OTAG, 1997). The dashed line outlines the 19 state region regulated under the NOx SIP Call. The arrows represent transport wind vectors. Surface ozone concentrations are a function of both in situ ozone production and pollutant transport; both are significantly affected by prevailing meteorological conditions. Many states that are in attainment with Federal ozone standards were included in the SIP Call program because their NOx emissions contribute to the non-attainment problems of downwind states. Although some states contribute significantly more than others to the ozone non-attainment problem, the NOx SIP Call applies uniform stringency across all 19 states.

The NOx SIP Call mandated a dramatic reduction in average NOx emissions rates.[13] In the period between when the SIP Call was upheld by the US Court of Appeals (March 2000) and the deadline for full compliance (May 2004), firms had to make costly decisions about how to comply with this new environmental regulation.[14] To comply, firms can do one or more of the following: purchase permits to offset emissions exceeding their allocation from other firms, install one of several types of NOx control technology, or reduce production at dirtier plants during ozone season.

Two factors that are likely to figure significantly in a manager's compliance decision are the up-front capital costs associated with retrofitting a plant with a particular NOx control technology, and the anticipated variable compliance costs. The capital costs, variable operating costs, and emissions reduction efficiencies associated with different compliance alternatives vary significantly, both across NOx control technologies and across generating units with different technical characteristics.

Figure 2 is a graphical illustration of the compliance choice faced by one particular unit in the sample. Each of the eight points plotted in fixed cost ($/kW) variable cost (cents/kWh) space corresponds to a different compliance "strategy". With the exception of the "no retrofit" option (i.e., the firm will rely entirely on the permit market to comply with the program), all of the

[13] Pre-retrofit emissions rates at affected coal plants were, on average, three and a half times the emissions rate on which the aggregate cap was based (0.15 lbs NOx/mmbtu).

[14] Coal plants in 9 Northeastern states had to achieve compliance by May 2003; plants in the Southeastern states had to comply by May 31 2004.

compliance strategies involve some sort of technology retrofit.[15] Variable costs include the costs of operating the control technology plus the costs of purchasing permits to offset uncontrolled emissions.[16]

There are two important things to note about this choice set, which is very typical of choice sets in the sample. First, compliance strategies differ significantly in terms of costs and emissions reductions. Second, the most capital intensive compliance options (i.e., those incorporating selective catalytic reduction technology) are associated with significantly greater emissions reductions.

The specific control technologies available to a given unit, the number of choices in a unit's choice set, and the costs associated with each compliance option vary considerably across coal-fired units of different vintages and boiler types. Compliance options that incorporate Selective Catalytic Reduction (SCR) technology can reduce emissions by up to ninety percent. NOx emissions rates can be reduced by thirty-five percent through the adoption of Selective Non-Catalytic Reduction Technology (SNCR). Pre-combustion control technologies such as low NOx burners (LNB) or combustion modifications (CM) can reduce emissions by fifteen to fifty percent, depending on a boiler's technical specifications and operating characteristics.

3 Electricity Industry Restructuring and the Compliance Decision

In this section, I briefly describe the process of electricity industry restructuring in the United States, and I introduce the hypothesis that the type of electricity market in which a coal plant is operating (i.e., restructured versus regulated) significantly affects the choice of how to comply with the NOx SIP Call.

[15] In restricting the choice set to the points in this figure, I implicitly assume that the unit will not achieve compliance by reducing production, and that the unit will comply perfectly with the program. Because all units are equipped with continuous emissions monitoring equipment, it is reasonable to assume full compliance; compliance among coal-fired units was 100 percent in 2004 (EPA, 2005). The assumption that production levels at these coal-fired units will not be significantly affected by this environmental regulation also finds empirical support. This assumption is discussed in detail in Section 6.3.

[16] Using detailed unit-level data, estimates of capital costs and variable compliance costs can are generated for each unit, for each NOx control technology. These calculations assume a permit cost of \$2.25/lb NOx. This was the average futures permit price (per lb NOx) in the years leading up to the SIP Call. Permits started trading in early 2001 in anticipation of the SIP Call Rule. A discussion of how these cost estimates are generated is included in Section 4.

3.1 Regulation in the US Electricity Industry

Until the mid 1990s, over ninety percent of electricity in the United States was generated by vertically integrated investor-owned utilities (IOUs), most of whom were operating as local monopolies regulated by state public utility commissions (PUCs) (Markiewicz et al., 2004). The remainder was supplied by government entities or cooperatives. Traditionally, the most widely used form of regulation has been "rate of return" regulation. In lengthy rate hearings, the PUC sets rates so as to allow the utility to recover prudently incurred operating costs and earn a "fair" rate of return on its rate base (the value of assets less depreciation).

In their seminal paper, Averch and Johnson (1962) illustrate how, under certain conditions, a firm subject to rate of return regulation will find it profitable to employ more capital relative to variable inputs (including labor and fuel) than is consistent with cost minimization. A significant share of the regulation literature has since been devoted to elaborating upon and testing this result.[17] Attempts to empirically test the AJ effect using data from the US electricity industry have met with mixed results. Courville (1974), Spann (1974) and Hayashi and Trapani (1976) find support for the hypothesis, whereas Boyes (1976) does not.

Partly in response to the debate over the AJ capital bias, the nature of electricity market regulation began to change. "Incentive" or "performance based" regulation (PBR) became increasingly common throughout the 1970s, 1980s and early 1990s in an effort to strengthen incentives for increased efficiency.[18] Electricity industry restructuring was initiated in the early 1990s. Proponents of restructuring argued that replacing rate hearings and fuel adjustment clauses with the discipline of a competitive market would increase efficiency and bring rates down.

Ownership structure and operating incentives have dramatically changed in states that have restructured their electricity industries. In the interest of encouraging competition among generators, state restructuring legislation has required or encouraged utilities to divest the majority of their thermal generation assets to non-utility generation companies that are not subject to cost of service regulation. Generators submit bids (prices and quantities) that they are willing to produce in a given hour; Independent System Operators (ISOs) combine these bids and intersect the

[17] Joskow(1974) provides an excellent survey of the earlier Averch and Johnson literature. He argues that the AJ model does not "capture the *essence* of actual regulatory processes". He concludes that empirical evidence is often inconsistent with the AJ model, although he notes that "during periods of rising average costs, A-J type biases may begin to become important." This study considers such a period: the introduction of the NOx SIP Call raised the average cost of generating electricity at coal plants significantly.

[18] Performance based regulation is a broadly defined concept that refers to any regulatory mechanism that attempts to link profits to desired performance objectives (such as improved operating efficiency, improved environmental performance or cost minimizing procurement). Ratemaking under PBR is typically a two-step process. First, rates are established based on the utility's prudently incurred and projected costs; firms are still entitled to earn a fair rate of return. Second, the utility is given financial incentives to reduce these costs and increase operating efficiency.

aggregate supply curve with demand in order to determine the wholesale market clearing price. In states that have introduced retail choice, local utilities no longer have monopoly over local customers.

All fifty states held hearings to assess the benefits of restructuring. In the end, only nineteen states restructured their electricity industries. Several factors determined a state's decision. First, most states that decided against restructuring had less to gain because their rates were relatively low to begin with. Rates were low because these states had access to low cost hydro and coal generation, had made little or no investment in nuclear power, and had fewer long-term fixed price contracts with independent power producers that had been encouraged under the 1978 Public Utility Regulatory Policy Act (Bushnell and Wolfram, 2005; Van Doren and Taylor 2004). Ando and Palmer (1998) find evidence that the availability of profitable nearby export markets also increased the probability that a state would pass restructuring legislation. Finally, California's high profile energy woes raised serious doubts among those states who had yet to pass restructuring legislation as to whether restructuring would deliver a net gain (politically or otherwise). Momentum behind restructuring fell flat after the California electricity crisis in 2000.

3.2 Compliance Choices in Regulated Markets

In regulated electricity markets, the environmental compliance decisions of regulated firms were likely influenced by PUC regulations governing capital and variable cost recovery. In each of the seven states that fall under the SIP Call and that have not enacted electricity industry restructuring, firms have successfully sought rate base adjustments in order to recover costs of capital required to invest in NOx control equipment, and to allow shareholders to earn a return on equity.[19] Firms have also won approval for various kinds of rate adjustment clauses or rate freezes which allow them to recover costs associated with purchasing NOx permits, operating pollution control equipment, and pre-approved construction work in progress.[20]

Although state regulators have allowed electricity generators to earn a positive rate of return on capital investments in pollution control equipment and recover the average costs of operating pollution controls and purchasing permits (profits from the sale of permits are also passed through to rate payers), the *opportunity* costs of using or holding allocated allowances are not reflected in regulated rates. Regulated firms have an incentive to choose compliance options that require more

[19]In a recent survey, regulators report allowing up to three additional points on the return of shareholder equity for investment in pollution reduction equipment at coal plants, in addition to what would otherwise be earned on prudent investments (NARUC 2004).

[20]For details on PUC rulings in these case, see: Charleston Gazette, 2004; Electricity Daily, 2003; Megawatt Daily, 2003; NARUC, 2004; Platts Utility and Environment Report 1999, 2000a, 2000b, 2001a, 2001b, 2002a, 2002c, 2002d, 2002f; PR Newswire, 2002; Southeast Power Report, 2000.

capital investment relative to pollution permit “inputs” than is consistent with cost minimization.

3.3 Compliance Choices in Restructured Markets

Responses to a recent survey of electricity market regulators are illustrative of the differences in how compliance costs, and large investments in pollution control technology in particular, are recovered in restructured versus regulated electricity markets (NARUC, 2004).[21] When asked about regulating or supporting improvements in the environmental performance of existing coal-fired electricity generation, commissioners in regulated electricity markets indicated that their role is to “allow regulated utilities to recover costs of compliance with applicable Federal, State and local environmental requirements.” In response to the same question, commissioners in states with restructured electricity industries stated that it was not their job to regulate generation facilities: “We have no current direct statutory obligation to support improved environmental performance of generation facilities.”

In the absence of a regulator willing to guarantee that large investments in pollution control equipment will be recovered, the consequences of making such investments are very uncertain in restructured electricity markets. Since restructuring began, concerns have been raised about whether restructured wholesale energy and operating reserve markets would allow generating companies to recover fixed costs of production (Joskow 2003).[22] During the period when these compliance decisions were being made (2000-2004), it was unclear how difficult it would be to recover investments in pollution controls in restructured wholesale electricity markets.

The effect of the NOx SIP Call on average wholesale prices in a restructured electricity market is a function of the variable (per kWh) compliance costs among the price-setting or “marginal” generating units. Because coal-fired units typically have low operating costs relative to other units in the electricity market, they are typically inframarginal.[23] The generating units that most often set the wholesale electricity price (gas and oil plants) tend to have significantly lower environmental compliance costs as compared to coal. Average wholesale electricity prices during ozone season

[21] 60 public utility commissioners in 19 states were surveyed. The survey was conducted in 2003 by the National Association of Regulatory Utility Commissioners (NARUC), the National Association of State Energy Officials (NASEO) and the Environmental Council of States (ECOS). The stated purpose of the survey was " to collect and describe different state approaches and/or incentives for improved environmental performance of fossil-based electricity generators" (NARUC, 2004).

[22] In some markets, market-power mitigation policies, price caps, and other market interventions have kept wholesale prices below the level needed to stimulate investment in new capacity (Bushnell, 2005). Several ISOs have had to introduce side payments to help generators recover their capital investments in generating capacity.

[23] A unit will generally operate when its marginal costs of production are less than or equal to the last unit dispatched to serve the load. Because coal-fired units typically have low operating costs relative to other units in the electricity market, they are normally operated to serve the minimum load of a system; they run continuously and produce electricity at an essentially constant rate. Increases in variable environmental compliance costs at these "base load" plants will not significantly affect the wholesale electricity price or the plants’ capacity factors.

will not increase to reflect the average coal-fired unit's environmental compliance costs. As one industry analyst has observed "coal plants will still be dispatched, but their (profit) margins will be less."[24]

The concept of "option value" has been developed in the context of irreversible investment decisions when the future consequences of making the investment are uncertain (Dixit and Pindyck, 1994; Arrow and Fisher, 1974; Fisher and Hanemann, 1987). Investments in capital intensive pollution control equipment such as SCR are, for all practical purposes, irreversible. Consider a simple case where a coal plant manager in a restructured electricity market faces a binary choice of investing in SCR or relying on the permit market to offset uncontrolled emissions. Once the investment in SCR has been made, it cannot be reversed, regardless of the information that the manager will later obtain regarding future electricity prices and his ability to recover environmental compliance costs. Conversely, if the manager chooses to rely on the permit market for compliance, he has much more control over the environmental compliance costs he will incur going forward. In hours when electricity prices are too low to allow him to recover variable environmental compliance costs, he can choose not to operate. He can also choose to invest in SCR later on, once some of the regulatory and price uncertainty has been resolved (in fact, because of over-investment in SCR in the years leading up to the SIP Call, no further investment in pollution controls will be required to comply with the program). This flexibility creates economic option value in restructured markets, but not in regulated electricity markets where firms are allowed a positive rate of return on their investments.

In addition to the uncertainty about recovering environmental compliance costs, higher costs of capital made securing financing for a large capital investment in NOx control technology relatively more costly for firms in restructured electricity markets (Business Wire 2003; Platts Utility Environment Report, 2002e). Credit rating changes in the energy sector were overwhelmingly negative over the time period in which plant managers were having to make their compliance decision.[25] This negative trend has affected generators operating in restructured industries disproportionately. Whereas the ratings of merchant energy companies and some companies with a significant degree of non-core activities have fallen drastically, most regulated utilities have been affected to a far lesser extent (Business Wire, 2001; Business Wire, 2004a; Business Wire, 2004b).

[24] "High Coal Costs Put the Squeeze On Power Plants."Matthew Dalton; *The Wall Street Journal*; June 29, 2005.

[25] Downgrades outnumbered upgrades 65 to 20 in 2000; that ratio was up to 182 to 15 in 2002. In 2003, 18 percent of firms were non-investment grade (Senate Committee on Energy and Natural Resources, 2003).

3.4 Industry Structure and Environmental Compliance

Firms in regulated electricity markets have incentives to adopt more capital intensive pollution control equipment. In restructured markets, considerable uncertainty about future electricity market conditions and poor credit ratings have reduced the appeal of capital intensive compliance options. The hypothesis that type of electricity market in which a coal plant is operating will significantly affected the choice of how to comply with the NOx SIP Call follows directly from these differences in economic regulation and investment incentives.

Ideally, in the interest of empirically testing for a relationship between economic regulation and the environmental compliance decision, coal plants would be randomly assigned to either a restructured or a regulated electricity market. This would guarantee that the type of electricity market in which a coal plant is operating was pre-determined and completely exogenous to firms' environmental compliance decisions. Although this controlled experiment did not occur, two important factors make it possible to causally relate differences in economic regulation to differences in compliance choices.

First, the timing of the NOx SIP Call and electricity industry restructuring was such that a state's restructuring status was completely pre-determined. All 19 states that were ultimately included in the NOx SIP Call held hearings to consider restructuring their respective electricity industries between 1994 and 1998. By 1999, restructuring bills had been passed in 12 of these states and D.C. By 2000, the remaining 7 states had all officially resolved not to move forward with electricity restructuring (EIA).[26] Consequently, when the courts upheld the NOx SIP Call and the terms of environmental compliance were finally established, plant managers knew what type of electricity market they would be operating in.

Second, the coal plants serving restructured markets are extremely similar to those serving regulated markets. Because the circumstances that determined a state's electricity industry restructuring status were independent of the operating characteristics of existing coal generation, there is no reason to expect that physical factors affecting coal plants' NOx control costs (such as plant age or boiler technology type) should differ significantly across electricity market types. Empirical analysis presented in the following section demonstrates the physical similarities between the two sub-populations of coal plants.

[26] Of the 19 states that are affected by the NOx SIP Call, 12 have restructured their electricity industries: CT, DE, IL, MA, MD, MI, NJ, NY, OH, PA, RI and VA. The remaining 7 chose not to go forward with restructuring: AL, IN, KY, NC, SC, TN, WV.

4 A First Look at the Data

4.1 Data description

The data set includes the 702 coal-fired generating units that are regulated under the NOx SIP Call. Of these, 322 are classified as "regulated" for the purpose of this analysis. Regulated plants include those subject to PUC regulation in states that have chosen not to restructure their electricity industries, and any state or municipally owned and operated facilities in restructured markets. The results presented here are generated using data from 632 units. Compliance costs for the remaining 70 coal fired units cannot be generated due to data limitations.[27]

I do not directly observe the variable compliance costs and fixed capital costs or the post-retrofit emissions rates that plant managers anticipated when making their decisions. I can, however, generate detailed, unit-specific engineering estimates of these variables using detailed unit-level and plant-level data. In the late 1990s, to help generators prepare to comply with market-based NOx regulations, the Electric Power Research Institute[28] developed software to generate cost estimates for all major NOx control options available to coal-fired boilers, conditional on unit and plant level characteristics. The software has been used not only by plant managers, but also by regulators to evaluate proposed compliance costs for the utilities they regulate (Himes, 2004; Musatti, 2004; Srivastava, 2004). For the purpose of this research, I obtained a license to use this software (EPRI, 1999b).

Cost estimation requires detailed data on over 80 unit and plant level operating characteristics (such as boiler dimensions, pre-retrofit emissions rates, plant operating costs, etc.). With these data inputs, the software can be used to generate boiler-specific variable costs and fixed cost estimates for each viable compliance option. Post-retrofit emissions rates are estimated using the EPRI software, together with EPA's Integrated Planning Model (US EPA 2003). A detailed data appendix is available on the author's website (http://are.berkeley.edu/~fowlie).[29]

[27] These units appear on states' lists of coal-fired units in the NOx SIP Call, but appear only sporadically in EPA, EIA and Platts databases. These units appear to be significantly smaller and younger on average. The mean capacity is 22 MW compared to the sample average capacity of 252 MW (only 22 of the excluded units reporting). The mean age is 14 years, compared to a sample average of 36 years (only 4 of the excluded units reporting).

[28] The Electric Power Research Institute (EPRI) is an organization that was created and is funded by public and private electric utilities to conduct electricity industry relevant R&D.

[29] Sources of these data include EPA's Continuous Emissions Monitoring System (CEMS) database, the EPA's National Electric Energy System (NEEDS) database, the Energy Information Administration (forms 423, 767, 860 and 861), Platts Basecase database, Alstom Engineering, Babcock Power, Riley Power Inc., Raftelis Financial Consultants and the Bureau of Labor Statistics.

4.2 Summary Statistics

Figures 3a and 3b summarize the observed compliance choices for units in restructured and regulated electricity markets in terms of MW of installed capacity (87,828 MW in regulated markets and 88,370 MW in restructured markets).[30] A significantly larger proportion of the coal capacity in unrestructured markets has been retrofit with SCR (the control option that is the most capital intensive and delivers the most significant emissions reductions). Conversely, in restructured markets, a greater proportion of capacity has either not been retrofitted, or has been retrofitted with controls that can achieve only moderate emissions reductions (such as combustion modifications or SNCR). These data are consistent with, but not proof of, the hypothesis introduced in the previous section.

There are several reasons why we might observe differences in compliance strategy choices across electricity market types. Perhaps the most appealing explanation would be that this permit market is efficiently coordinating investment in pollution controls such that the plants with the lowest control costs are installing control equipment, and that SCR costs happen to be relatively high in restructured markets. Put differently, it is possible that these differences can be explained by differences in unit-specific compliance costs.

Table 1 presents summary statistics for unit-level operating characteristics that significantly affect compliance costs: nameplate capacity, plant vintage, pre-retrofit emissions rates, pre-retrofit heat rates and pre-retrofit summer capacity factor. Overall, these two groups of coal generators look extremely similar. The one dimension in which these two groups do differ somewhat is the pre-retrofit emissions rate which is lower on average among units in restructured markets. This is to be expected; because of persistent air quality problems in the Northeast, these plants have historically been subject to more stringent pollution regulation prior to the SIP Call.

Table 2 presents means and standard deviations of the capital and variable costs (estimated at the unit level) for the most commonly adopted NOx control technologies. There are no significant differences in average costs across the two electricity market types. Average costs are slightly higher for units in more regulated electricity markets. This is likely due to the fact that plants with higher pre-retrofit emissions rates tend to have higher retrofit costs.

These summary statistics indicate that the unit characteristics that help determine compliance costs, and the compliance costs themselves, are distributed similarly within the two subpopulations of coal fired units. Consequently, it is unlikely that variation in compliance costs

[30] Units are required to report what type of NOx control technology they will be using to comply with the NOx SIP Call to two federal agencies (the EIA and EPA).Units in these two different groups were equipped with very similar NOx controls at the time the SIP Call was promulgated. Over 80% of capacity in both types of markets had some type of low NOx burners. 5% of capacity in restructured markets and 7% of capacity in regulated markets had installed some type of combution modification or overfire air ports. Only 1% of capacity in restructured markets had been retrofit with SCR as of 2000. No SCR retrofits had taken place in regulated markets.

across these two groups is sufficient to explain the observed differences in compliance strategy choices.

5 An Empirical Model of the Compliance Choice

In this section, I develop an empirical model of a plant manager's choice between mutually exclusive approaches to complying with this emissions trading program. The purpose of specifying the model is twofold. First, it provides a framework to test whether economic regulation affects the environmental compliance choice. Second, the model provides a means to evaluate how these plant managers would have responded to a permit market designed to reflect spatial variation in marginal damages from pollution (see Section 6).

This analysis focuses exclusively on the compliance choices that were made in the years leading up to the compliance deadline (2000-2004).[31] Put differently, it is the decision of how to achieve compliance during the early years of the NOx SIP Call that is modeled. Because it is difficult to identify the precise point in this four year period at which this decision was made, these compliance choices are modeled as static decisions.[32] There is arguably a dynamic component to the compliance strategy choice that is ignored by this specification. Plants could postpone the decision to invest in pollution controls until after the NOx SIP Call program has taken effect, once more information is available about permit market conditions and rivals' investment in pollution control equipment. However, due to over-investment in SCR in anticipation of the SIP Call, the decisions analyzed here will likely determine regional emissions patterns to a significant extent for the foreseeable future (Natural Gas Week, 2004).

The manager of unit n faces a choice among J_n compliance strategy alternatives (indexed by $j,\ j = 1...J_n$). The observed outcome of this choice is y_n, a scalar indicating the chosen compliance strategy. Plant managers are assumed to choose the compliance strategy that minimizes the unobserved latent variable C_{nj}. The deterministic component of C_{nj} is a weighted sum of expected annual compliance costs v_{nj}, the expected capital costs K_{nj} associated with initial retrofit and

[31] Past research has cautioned against trying to identify differences in the underlying propensity to adopt a new technology using choices observed over a short time period. Particularly in the case of a "lumpy", capital intensive technology, the pattern of technology diffusion across firms can be driven by differences in opportunities to adopt (Rose and Joskow, 1984). Fortunately, the NOx SIP Call eliminates temporal variation in technology adoption opportunity by design; every coal plant manager was forced to make a decision of how to comply with the program during the four years between when terms of compliance were officially established and when full compliance was required of all plants.

[32] Because of labor shortages and a limited number of towercranes needed to complete SCR retrofits, many plants reported delays of several years between when they made their compliance decision and when the pollution control retrofit was completed (Cichanowicz, 2004; Midwest Construction, 2005). Consequently, the dates when pollution control retrofits are completed or when NOx control choices are reported to the press or to Federal agencies (which I can observe) are noisy measures of when the compliance decision was actually made.

technology installation, and a constant value α_j that varies across technology types :

$$\begin{aligned} C_{nj} &= \alpha_j + \beta_n^v v_{nj} + \beta_n^K K_{nj} - \varepsilon_{nj}, \qquad (1) \\ where \quad v_{nj} &= (V_{nj} + \tau m_{nj}) Q_n \qquad (2) \end{aligned}$$

The variable cost (per kWh) of operating the control technology is V_{nj}. The variable costs associated with offsetting emissions (per kWh) with permits is equal to the permit price τ multiplied by the post-retrofit emissions rate m_{nj}.[33] Expected average annual compliance costs are obtained by multiplying estimated per kWh variable costs by expected seasonal production Q_n.

Expected seasonal electricity production at a unit is assumed to be independent of the compliance strategy being evaluated. Anecdotal evidence suggests that managers used past summer production levels to estimate future production, regardless of the compliance choice being evaluated (EPRI, 1999a). I adopt this approach and use the historical average of a unit's past summer production levels ($\bar{Q}_n$) to proxy for future ozone season production. Empirical support for this assumption is presented in section 6.3.

It is likely that the compliance choice characteristics that are relevant to the compliance decision are not limited to observable cost characteristics. Technology constants α_j capture unobserved, intrinsic technology preferences or biases such as widely held perceptions regarding the reliability of a particular type of NOx control technology. A stochastic component ε_{nj} is included in the model to capture the idiosyncratic effect of unobserved factors.

My objective is to test whether the type of electricity market in which a firm is operating has significantly affected the compliance decision. This reduced form model has just enough structure to capture the differences in responsiveness to capital costs and policy sensitive variable costs across units, and across electricity market types more generally. An alternative approach would involve using a more detailed theoretical model of the firm's compliance decision to motivate the empirical specification. This would allow for a more structural interpretation of the estimated parameters. However, it is not clear what model would most accurately capture the salient features of the average firm's compliance decision. This model is sufficiently general to accommodate a variety of possible objectives.[34]

[33] The unit-specific, compliance strategy-specific estimates of K_{ni} and V_{ni} are generated using the EPRI cost estimation software described in section 4.1. Emissions rates (which also vary across units and control technologies) are estimated using the software and accompanying documentation and EPA's IPM model (US EPA 1998d), in addition to other sources in the technical literature which are discussed in the data appendix.

[34] For example, in the case of regulated plants, it is most common to assume that managers maximize profits subject to regulatory constraints (Averch and Johnson, 1962; Bohi and Burtraw, 1992). However, several alternative management objectives have been suggested, including maximizing returns on investment, maximizing output, maximizing revenues and maximizing reliability of supply (Bailey and Malone, 1970).

5.1 The Conditional Logit Model

I first estimate a conditional logit (CL) model of the compliance decision; conditional on observed unit characteristics, coefficients are not permitted to vary across plants. The ε_{nj} are assumed to be iid extreme value and independent of the covariates in the model. This stochastic term is subtracted from (versus added to) the deterministic component of costs in order to simplify the derivation of choice probabilities implied by this model.[35]

The closed form expression for the probability (conditional on the vector of coefficients β and the matrix of covariates X_n) that the n^{th} firm will choose compliance strategy i is:

$$P(y_n = i|X_n, \beta) = \frac{e^{-\beta' X_{ni}}}{\sum_{j=1}^{J_n} e^{-\beta' X_{nj}}}. \tag{3}$$

This conditional choice probability is derived in Appendix 1. The number of choices in the n^{th} unit's choice set is J_n. Choice sets vary across units depending on the type of NOx controls the unit had installed prior to the NOx SIP Call and the boiler type (not all NOx control technologies are appropriate for all boilers). Although fifteen different compliance strategies are observed in the data, the most alternatives available to any one unit is ten. With the obvious exception of the "no retrofit" option, all of the observed compliance strategies chosen by plant managers involve some combination of eight different NOx control technologies.

5.2 The Random Coefficient Logit Model

The advantage of the CL model is its simplicity; choice probabilities can be evaluated analytically. Unfortunately, this simplicity comes at a cost. First, this model does not account for random variation in tastes or response parameters; conditional on observed plant characteristics, the coefficients in the model are not allowed to vary across choice situations. However, these generating units are very heterogeneous. There are likely to be factors affecting how plant managers weigh compliance costs in their decision-making that we do not observe. Examples include a plant's costs of capital, managerial attitudes towards risk, contractual arrangements, and subtle variations in PUC cost recovery rules. To the extent that there is significant variation in unobserved determinants of the compliance choice, errors will be correlated and CL coefficient estimates will be biased.

[35] These choice probabilities are very similar to the standard logit choice probabilities derived under assumptions of random utility maximization (McFadden, 1973). The assumption that the error term is subtracted (versus added) from the deterministic component of the model greatly simplifies the derivation of choice probabilities (see Appendix 1).

The second limitation has to do with the panel structure of data used to estimate the model. While I only observe one compliance choice for each coal-fired boiler or "unit", an electricity generating facility or "plant" can consist of several physically independent generating units, each comprising of a boiler (or boilers) and a generator. Some plants only have one boiler, but there can be as many as ten boilers at a given plant. It seems reasonable to assume that the same manager made compliance decisions for all boilers at a given plant. The CL model cannot accommodate this correlation across choice situations associated with the same decision maker.

Finally, the functional form assumptions underlying the CL model (i.e., the assumption that the stochastic term is iid extreme value) imply the infamous "independence of irrelevant alternatives" (IIA) property. The associated substitution patterns are very restrictive and unrealistic.

The random-coefficient logit (RCL) model, a generalization of the CL model, does a better job of accommodating unobserved response heterogeneity and relaxes the troublesome iid error structure assumption. This specification allows one or more of the model parameters to vary across plants. I assume that the variable cost coefficient (β^v) and the capital cost coefficient (β^K) are distributed in the population according to a bivariate normal distribution. Allowing these coefficients to vary randomly across plants accommodates unobserved heterogeneity in responses to changes in compliance costs.

I maintain the assumption that the unobserved stochastic term ε_{nj} is iid extreme value and independent of β and X_{nj}. To accommodate the panel nature of the data, the (unobserved) β vectors are allowed to vary across managers according to the density $f(\beta|b, \Omega)$, but are assumed to be constant over the choices made by a manager.[36] Thus, the coefficient vector for each manager (indexed by m) can be expressed as the sum of the vector of coefficient means b and a manager-specific vector of deviations η_m. Because the η_m are assumed to be equal across choices made by the same manager (at the same plant), the unobserved component of anticipated costs is correlated within a plant. This does not imply that the errors corresponding to all choices faced by a single manager are perfectly correlated; the extreme value error term still enters independently for each choice.

Conditional on β_m, the probability that a manager of a plant comprised of T_m units makes the observed Y_m compliance choices is:

[36] Alternatively, beta vectors could be held constant across all units, and across all plants owned by the same parent company. Interviews with industry representatives indicate that it is sometimes the case that environmental compliance decisions are made or influenced by the parent company (Whiteman, 2005). In future work, I will estimate a model where cost coefficients are allowed to vary across parent companies, but not across plants.

$$P(Y_m = \boldsymbol{i}|X_m, \beta_m) = \prod_{t=1}^{T_m} \frac{e^{-\beta'_m X_{mit}}}{\sum_{j=1}^{J_{mt}} e^{-\beta'_m X_{mjt}}}, \tag{4}$$

where $\boldsymbol{i}$ is a $T_m * 1$ dimensional vector denoting the set of observed choices. Here, the n subscript denoting the unit has been replaced by a unique mt pair. Unconditional choice probabilities $P(Y_m = \boldsymbol{i})$ are derived by the integrating conditional choice probabilities over the assumed bivariate normal distribution of the unobserved random parameters.

The standard RCL specification assumes that the random coefficients in the model are independently distributed. It seems plausible that some plant managers might be more or less cost sensitive in general; plant managers who weigh capital costs more (less) heavily in their compliance decisions might also be more (less) sensitive to variation in variable operating costs. The model is parameterized in terms of the Cholesky factor L of the covariance matrix Ω, so as to allow the two random cost coefficients to be correlated.[37]

The unknown vector of coefficient means b and covariance matrix Ω (easily recovered from estimates of L) describe the distribution of the β_m in the population. Parameter estimates are those that maximize the following log likelihood function:

$$LL(b, \Omega) = \sum_{m=1}^{M} \ln \int_{-\infty}^{\infty} \prod_{t=1}^{T_m} \frac{e^{-\beta'_m X_{mit}}}{\sum_{j=1}^{J_{mt}} e^{-\beta'_m X_{mjt}}} f(\beta|b, \Omega) d\beta. \tag{5}$$

Because this integral does not have a closed form solution, unconditional probabilities are approximated numerically using simulation methods. The RCL estimates are those that maximize the simulated likelihood function. For each decision maker, 1000 two-dimensional vectors of independent standard normal random variables are drawn. To simulate a random draw from the bivariate normal density $f(\beta^v, \beta^K|b, \Omega)$, each vector of standard normals is multiplied by the matrix L and the resulting product is added to the vector b. To increase the accuracy of the simulation, pseudo-random Halton draws are used (Bhat 1998; Train, 2001).[38]

The value of the integrand [4] is calculated for each decision maker, for each draw. The results are averaged across draws. The maxlik algorithm in Gauss is used to find estimates of the parameters in b and L that maximize the simulated likelihood of the observed compliance choices.

[37] Because the covariance matrix is positive definite, it can be expressed as the product of the lower triangular matrix L and its transpose.

[38] Researchers have found that using Halton draws (versus random draws) provide more uniform coverage over the domain of the integration spaceand results in more accurate computation of probabilities for a given number of draws. Bhat finds that 125 Halton draws produces more accurate estimates than 2000 random draws.

Gauss code is based on that developed by Train, Revelt and Ruud (1999). The derivation of the analytic gradient that was used in these simulations is included in Appendix 2.

5.3 Manager Specific Parameters

The RCL estimates of b and Ω provide information about how the capital and variable cost coefficients are distributed in the population, but tell us nothing about where one manager lies in the distribution relative to other managers. It seems we should be able to infer something about the position of a particular manager in the population distribution based on the choices we observe that manager making. Recent work has demonstrated how simulated maximum likelihood estimates of random-coefficient, discrete choice models can be combined with information about observed choices in order to make inferences about where in the population distribution a particular agent most likely lies (Allenby and Rossi, 1999; Revelt and Train, 2000; Train, 2003).[39] Conditioning on agents' observed choices has been found to considerably improve predictions in new choice situations (Revelt and Train, 2000).

Following Train (2003), let the density describing the distribution of β in the population of managers be denoted $g(\beta|b,\Omega)$. The probability of observing the m^{th} manager making the choice he does when faced with the compliance decision described by the matrix of covariates X_m is given by [4]. This probability is conditional on information we cannot observe (β_m). The marginal probability of observing this outcome is $P(Y_m|X_m,b,\Omega) = P(Y_m = \boldsymbol{i}|X_m,\beta)g(\beta|b,\Omega)$. Let $h(\beta|\boldsymbol{i},X_m,b,\Omega)$ denote the distribution of β_m in the sub-population of plant managers who, when faced with the compliance choice set described by X_m would choose the series of strategies denoted $\boldsymbol{i}$. Using Bayes rule, this manager specific, conditional density of β_m can be expressed as:

$$h(\beta|\boldsymbol{i},X_m,b,\Omega) = \frac{P(Y_m = \boldsymbol{i}|X_{m,}\beta)g(\beta|b,\Omega)}{P(Y_m = \boldsymbol{i}|X_m,b,\Omega)}. \tag{6}$$

These conditional distributions are implied by the maximum likelihood estimates of the population distribution parameters and the choices we observe. To illustrate this more explicitly, [6] can be reformulated as:

[39] Alternatively, a finite mixture logit (FML) model could have been estimated in order to obtain information about where in the larger population distribution a particular type of manager lies. FML models accommodate systematic heterogeneity by assigning the economic agents to separate behavioral groups/types or latent segments. One limitation of these models is that they often cannot adequately capture all of the heterogeneity in the data (Allenby and Rossi, 1999; Rossi et al. 1996). Consequently, I choose to estimate a RCL model and derive conditional, manager-specific coefficient distributions.

$$h(\beta|\boldsymbol{i}, X_m, b, \Omega) = \frac{\prod_{t=1}^{T_m} \frac{e^{-\beta'_m X_{mit}}}{\sum_{j=1}^{J_{mt}} e^{-\beta'_m X_{mjt}}} g(\beta|b, \Omega)}{\int_{-\infty}^{\infty} \prod_{t=1}^{T_m} \frac{e^{-\beta'_m X_{mit}}}{\sum_{j=1}^{J_{mt}} e^{-\beta'_m X_{mjt}}} g(\beta|b, \Omega) d\beta}. \tag{7}$$

These conditional distributions can be used to derive conditional expectations of functions of β. For example, we are interested in knowing how the compliance choices made by these managers would have differed had the permit market been designed to reflect spatial variation in marginal damages from pollution. The expected probability that alternative i will be chosen by the m^{th} manager in this counterfactual choice situation (denoted by $T + 1$) can be expressed as:

$$E[P(y_{m,T+1} = i|Y_m, X_m, b, \Omega)] = \frac{\int_{-\infty}^{\infty} \prod_{t=1}^{T_m+1} \frac{e^{-\beta'_m X_{mit}}}{\sum_{j=1}^{J_{mt}} e^{-\beta'_m X_{mjt}}} g(\beta|b, \Omega)}{\int_{-\infty}^{\infty} \prod_{t=1}^{T_m} \frac{e^{-\beta'_m X_{mit}}}{\sum_{j=1}^{J_{mt}} e^{-\beta'_m X_{mjt}}} g(\beta|b, \Omega) d\beta}. \tag{8}$$

A simulated approximation to this expectation is obtained by first drawing from the estimated population distribution $g(\beta|b, \Omega)$ and then simulating conditional values of the counterfactual choice probability for each draw. Because this approach involves integrating over the estimated distribution of the random coefficients in the population, this formulation accounts for sampling and simulation error in estimates of b and Ω. Integrals are simulated in the same way as for the unconditional RCL choice probabilities.

6 Estimation

Tests of the hypothesis introduced in Section 3 can be formulated as a test of whether the coefficients in the model differ significantly across electricity market types. The two most common approaches to comparing coefficient estimates across groups involve either estimating a single model that includes interactions between a dummy variable indicating group membership and the covariates of interest, or estimating the models separately for the two groups.

There are problems with using the first approach in this application. In order to identify the logit model, all coefficients have been scaled by the variance of the extreme value error term. Consequently, pooling the data to estimate a single equation forces this variance to be equal across groups (Allison, 1999). It is likely that the true variances of the extreme value terms differ across market types.[40] Monte Carlo experiments have illustrated that the most likely outcome of estimating a single equation with interaction terms when the residual variances differ across groups is that the slope coefficients will be found not to differ even if they actually do, but it is also possible to find an effect when no effect exists (Hoetker, 2003). Thus, the results from estimating the model using pooled data are not emphasized here, although they are consistent with the results obtained when separate models are estimated.[41]

The advantage of estimating the model separately for the two sup-populations of units is that coefficient estimates and standard errors are consistent within each group. Within a model, tests of the significance of a given coefficient are valid; the ratio of the coefficient and the variance of the unobserved stochastic term will only be zero if the coefficient is zero. While direct comparisons of coefficients across groups are still confounded by the logit identification assumption, such comparisons can be informative if the pattern of coefficient significance varies across groups.

In addition to the variable compliance costs and capital compliance costs variables, an interaction term between capital costs and demeaned plant age is included in the model. Older plants will likely use shorter investment time horizons; they can be expected to weigh capital costs more heavily (i.e., the coefficient on this interaction term is expected to be negative).[42] To estimate standard errors, the robust asymptotic covariance matrix estimator is used (Mc Fadden and Train, 2000).

[40] The unobservable factors that affect the compliance choice (and that are captured by the extreme value term) are likely to differ across restructured and regulated electricity markets. For example, variation in firms' (unobserved) cost of capital is likely an important determinant of the compliance choice in restructured electricity markets, but not so important in regulated markets where there is less variation in costs of capital, and where capital costs are passed directly through to customers. Subtle variations in cost recovery rulings likely affect compliance choices in regulated markets; this is not an issue in restructured markets. Because the error term captures different unobserved variables in the restructured and regulated cases, the variance of this unobserved disturbance term is also likely to differ across electricity market types.

[41] A single model is estimated using pooled data. Interactions between cost variables and a dummy variable indicating a restructured electricity market are included in this model. Whereas the coefficient on the uninteracted capital cost variable is not statistically significant, the estimated coefficient on the interaction between capital costs and the restructured market indicator is significant at the 5% level and has the expected negative sign. These results are consistent with the results discussed below.

[42] Several other specifications were also tried. For example, in the model estimated using data from restructured electricity markets, cost variables were interacted with a dummy indicating that the plant had been divested. In the regulated model, cost variables were interacted with dummy variables indicating whether the unit was a government owned or investor owned plant. None of these interaction terms significantly improved the fit of the model.

6.1 Conditional logit model results

The first two columns of Table 3 report estimates for the more restrictive CL specification in which coefficient values are not permitted to vary across plant managers. In both the restructured and regulated cases, a nested likelihood ratio test of this specification against a benchmark specification that includes only technology specific constants indicates that including variable and capital cost variables significantly improves the fit of the model.[43] The test statistics reported in the last row of Table 3 are larger than the χ^2 statistic with 3 degrees of freedom and a p-value of 0.001.

All of the technology type constants are negative and significant at the 1 percent level, regardless of whether the CL model is estimated using data from regulated or restructured markets.[44] One interpretation of this result is that, relative to the baseline option of no control technology retrofit, managers were biased against retrofits in general (controlling for costs). These constants are consistently larger in absolute value when the model is estimated using data from regulated electricity markets. This could be due to a stronger average bias against technology retrofits among regulated firms, a smaller variance of the unobserved residual among regulated firms, or some combination of these two factors.

The coefficient on variable compliance costs is statistically significant at the 1 percent level and has the expected negative sign in both the regulated and restructured electricity market cases. These results indicate that expected variable compliance costs are an important factor affecting the plant's compliance choice.

When the model is estimated using data from restructured electricity markets, the coefficient on capital costs is statistically significant and has the expected negative sign. An increase in the capital cost of a compliance option decreases the probability that the option will be chosen by a plant in a restructured electricity market. However, when the model is estimated using data from regulated electricity markets, the coefficient estimate is positive and is not statistically significantly different from zero, suggesting that capital costs might not be an important factor in the compliance decisions regulated plants.

One way to get around the scaling problem that confounds direct comparisons of these coef-

[43] The fit of the nested (or more restricted) model can be evaluated using a chi-square statistic. This test statistic is calculated by taking twice the absolute difference in the log likelihoods for the two models. If significant, (degrees of freedom are equal to the difference in the number of parameters between the two models), the nested model should be rejected (Bhat, 1998).

[44] I include only three technology fixed effects for the three major categories of NOx controls: Post-combustions pollution control technologies (SNCR and SCR), Combustion Modifications (CM) and Low NOx Burner (LNB) technologies. Although cost estimates and emissions reduction estimates were generated for sub-classes of these categories (for example, there are four different types of low NOx burners in the data), including a more complete set of technology fixed effects did not improve the fit of the model.

ficients across groups is to compare ratios of coefficients.[45] The $\beta^v : \beta^K$ ratio has a particularly intuitive interpretation. Totally differentiating [1] and setting it equal to 0, we see that this ratio can be interpreted as a measure of capital bias; it is the amount that a manager is willing to pay in increased up-front capital costs in order to avoid a one dollar increase in annual variable compliance costs. The point estimate of the difference in the ratios implied by the two sets of CL coefficients indicates that firms in restructured markets are, on average, more biased against capital intensive compliance options.[46]

6.2 Random Coefficient Logit Results

Results from estimating the RCL model are presented in the third and fourth columns of Table 3. Estimated standard deviations of the two random coefficients are statistically significant. The results of a nested likelihood ratio test imply that, in both the restructured and regulated cases, allowing for response heterogeneity significantly improves the fit of the model. The significant increase in the absolute value of the variable and capital cost coefficient estimates is further evidence that the variation in random parameters constitutes a significant portion of the variance in (unobserved) anticipated compliance costs.[47] These results suggest that cost coefficients do vary significantly across managers in regulated and restructured markets, even after unit age is controlled for. These RCL estimates are robust to various optimization routines and variation in the number of pseudo-random draws used in the simulations.

When the model is estimated using data from restructured markets, the means of both the capital and variable compliance cost coefficients are negative and significant at the 1 percent level. The estimated standard deviations are also large in absolute value and statistically significant, indicating that there is unobserved variation in responsiveness to changes in compliance costs.[48]

[45] In linear models, the Wald test is typically used to test the equality of two sets of coefficients. Although a Wald test statistic was calculated (the test statistic is 35.75 with a p-value < 0.0001), it is of very limited use. In the linear case, the corresponding test statistic will have an asymptotic chi-square distribution with degrees of freedom equal to the number of restrictions eing tested. However, the asymptotic chi-square distribution provides a poor approximation to the test statistic associated with the same test in a discrete choice model context. Furthermore, differences in these vectors of coefficients could be driven by differences in scale factors.

[46] Because the estimate of the capital cost coefficient among regulated plants is imprecisely estimated and indistinguishable from zero, the estimated $\beta^v : \beta^K$ ratio is hard to interpret.

[47] In the RCL specification, unobserved variation is decomposed into an extreme value stochastic term and variance of the random parameters. In the CL model, all unobserved variation in anticipated costs is captured by the extreme value stochastic term. Consequently, normalizing coefficients by the variance of the extreme value component of the disturbance will make RCL parameters larger in absolute value if a portion of unobserved variation is captured by the random parameter variances.

[48] There are several possible explanations for this variation, including variation in costs of capital and variation in managers' risk aversion. In an effort to attribute some of this variation to observable plant characteristics (such as plant size and whether or not the plant had been divested), other interactions were also tested, but none improved the fit of the model.

The negative and significant coefficient values on the capital cost/age interaction term indicates that older plants weighed capital costs more negatively in their compliance decision, presumably because of shorter investment time horizons.

Different results are obtained when the model is estimated using data from regulated markets. The point estimate for the capital cost coefficient is substantially smaller than the point estimate obtained using data from restructured markets, and is not statistically significant at the 1 percent or 5 percent level. Because less of the unobserved variation is captured by the extreme value disturbances in the RCL model, differences in coefficients across models are less likely to be driven by differences in residual variances.[49] The standard deviation of the coefficient is significant, suggesting that there is unobserved heterogeneity in how responsive managers are to variation in capital costs. The capital cost/age interaction term is significant and has the expected negative sign. Among older regulated plants, the capital cost coefficient does become significant, possibly because regulators are unlikely to approve a major capital investment in pollution control equipment if the plant is very old and expected to retire soon. The variable cost coefficient is also statistically significant and negative when the model is estimated using data from regulated electricity markets.

The RCL estimates of the moments of the distribution of β in the population are combined with the observed choices in order to derive the parameters of manager specific conditional distributions. The population parameter estimates $\hat{b}$ and $\hat{\Omega}$ are substituted into [7] and the first and second moments of these conditional distributions are calculated (using the same matrix of Halton draws that were used to estimate [5]). Table 4 presents the summary statistics for the estimated moments of these 221 manager-specific distributions.

If the model is correctly specified, the average of the means of the manager specific conditional distributions (the $\bar{\beta}_m s$) should be very close to the estimated population means. This is true in most cases, suggesting that the normality assumptions are appropriate, with the possible exception of the variable cost coefficient in restructured markets. Model specifications that assumed a log-normal distribution for this coefficient failed to converge.[50] The standard deviations of the

[49] It is also worth noting that the estimated technology constants are larger in absolute value when the model is estimated using data from regulated markets, as compared to restructured markets. These constants are meant to represent average biases for or against a particular technology type; there is no reason to expect managers in a regulated market should be any more biased against, for example, low NOx burner technology, as compared to a manager of a similar plant in a restructured electricity market. A likely explanation for the differences in the coefficient estimates is that the variance of the residual variation captured by the extreme value error term is smaller in regulated electricity markets. If this is the case, the observed absolute difference in cost coefficient estimates across models will *under* estimate the difference in the true cost coefficients.

[50] It is common in the literature to assume that cost coefficients are lognormally distributed, so as to ensure the a priori expected negative domain for the distribution (costs enter the model as negative numbers). Hensher and Greene(2002) discuss some of the drawbacks of assuming a lognormal distribution. Several other researchers report having problems with log-normal specifications (see Revelt and Train, 1998; Brownstone and Train, 1999).

conditional means are significantly larger than zero, suggesting that variation in the conditional means captures a significant portion of the total estimated variation (Revelt and Train, 2000).

The elasticities implied by the model estimates provide a more intuitive characterization of the responsiveness of compliance decisions to changes in compliance costs. Table 5 presents average elasticities with respect to both own capital costs and own average ozone season variable compliance costs for the most commonly observed compliance choices. Elasticities for each choice situation are calculated using point estimates of the means of the corresponding manager-specific conditional distributions. These summary statistics indicate that choice probabilities in restructured markets are significantly more sensitive to changes in compliance costs in general, and capital costs in particular. For example, the model predicts that a one percent increase in the capital cost of an SCR retrofit, holding all else equal, will result in a 5.7 percent decrease in the probability that SCR will be chose by the unit in a restructured electricity market, versus a 1.3 percent decrease if the unit is in a regulated market. The corresponding variable cost elasticities are 1.8 and 1.3 respectively.[51]

As in the CL case, the ratios of the RCL estimates of the cost coefficients $\beta^v : \beta^K$ are compared across electricity market types. A direct comparison of ratios of coefficients across groups is possible because the scale parameter cancels out. Recall that this ratio can be interpreted as a measure of willingness to pay (WTP) in increased, up-front capital costs for a one dollar decrease in annual compliance costs. Using the RCL model estimates of the average population parameters, the point estimates of this ratio are \$2.29 and \$5.96 in restructured and regulated markets, respectively. On average, managers in restructured electricity markets were willing to tolerate higher variable operating costs in order to avoid having to make larger up-front investments as compared to managers in regulated electricity markets.

Making statistical inferences about the difference between these two WTP estimates requires estimating the variances of these ratios. Unfortunately, standard approaches to estimating the variance of a function of random variables (such as using the delta method or a bootstrap) are inappropriate here.[52] Given two normally distributed random variables $\hat{\beta}^v$ and $\hat{\beta}^K$, both with

Specifications that assumed log normally distributed cost coefficients were tested, but resulted in a failure to reach convergence.

[51] Because these elasticities are nonlinear functions of the levels of the explanatory variables and the parameter estimates, comparisons of these effects across market types are also confounded by the normalization of the logit coefficients by potentially unequal error variances.

[52] The delta method is often used to estimate the standard error of ratio statistics, based on a first order Taylor series expansion of the ratio centered at the mean of b. The delta method estimates are \$0.17 and \$4.24 for the standard errors of the restructured and regulated ratios respectively. These estimates are invalid, however, because the variance of $\beta^v : \beta^K$ is not well-defined. The same problem arises if a bootstrap is used to estimate the standard errors of these WTP estimates. The estimated distribution of β^K for both restructured and regulated electricity markets overlaps zero. With enough samples, the bootstrap eventually generates estimates of β^K that are arbitrarily close to zero, implying infinitely large WTP estimates.

significant densities at zero, the density of the ratio $\hat{\beta}^v : \hat{\beta}^K$ can be expressed as a product of a Cauchy density and a second, more complicated function (Marsaglia, 1965; Hinkley, 1969). Because the integral of a Cauchy distribution does not converge, the density of this ratio does not have a well-defined variance.[53]

This WTP measure can also be estimated at the unit level using manager-specific coefficient estimates. The ratio $\beta_m^v : (\beta_m^K + \beta_m^{KA} \cdot A_{nt})$ is estimated for each unit. Two distributions of ratio estimates are generated, one for each market type. The mean and standard deviation of this WTP for an incremental reduction in annual compliance costs among units in restructured markets is \$2.22 (σ = \$12.61); the mean and standard deviation of the ratio in regulated markets is \$6.58 (σ = \$16.58). On average, managers in restructured electricity markets are more biased against capital intensive compliance options; they are less willing to make larger up-front investments in order to avoid higher annual compliance costs.[54]

6.3 Further Robustness Tests

A final test pertains to how plant managers formed their expectations about future production. In the preceding analysis, I have assumed that production expectations are independent of the compliance alternative being evaluated; the average of a unit's past summer production levels in the years preceding the compliance decision $\bar{Q}_n$ is used to proxy for expected ozone season production. Because coal generation tends to serve load on an around-the-clock basis, the capacity factors of most coal plants are unlikely to be significantly affected by a compliance-related change in variable operating costs.[23] However, if $\bar{Q}_n$ consistently under (or over) estimates what managers actually expected, the variable operating cost measures will be biased.

It is impossible to know whether all plant managers used $\bar{Q}_n$ to approximate Q_n in their

[53] In a 1978 paper, Zellner introduces a Minimum Expected Loss (MELO) estimator as a way to deal with the problem of estimating ratios of population means and regression coefficients. When these MELO estimates are viewed as estimators, they are found to have finite second moments. I use a relative squared error lost function to generate estimates of this ratio using population parameter estimates. The ratio estimates are \$3.36 ($\sigma = 2.20$) and \$2.46 ($\sigma = 2.22$) for the regulated and restructured markets respectively. These results are also consistent with a larger negative capital bias among managers in restructured electricity markets.

[54] In the past, researchers have made some simplifying but restrictive assumptions in order to circumvent problems associated with estimating the parameters of the distribution of a ratio of random parameters. One common approach involves assuming that the coefficient in the denominator is fixed (Hensher et al, 2004; Layton and Brown, 2000). This way, the distribution of the ratio is simply the distribution of the numerator rescaled. However, recent work by Sonnier et al. (2005) shows that constraining the coefficient in the denominator to be fixed in order to get a ratio that is normally distributed results in an overestimate of the variance of the ratio, even when the true variance is small. Other reseachers have reparameterized the RCL model so as to identify the ratio directly. Reparameterization is accomplished by making alternative identification assumptions. Rather than set the scale parameter to one, one of the coefficients in the model is restricted to equal one (Train and Weeks, 2004; Sonnier et al. 2005). This approach is inappropriate for this application, where the capital cost and variable cost coefficients are likely to differ across models.

decision making.[55] However, unit level production data from the first ozone season can be used to assess how well $\bar{Q}_n$ predicts the electricity production we do observe.[56] The following equation is estimated:

$$Q^*_{n,04} = \theta_0 \bar{Q}_n + \theta_j \sum_{j=1}^{J_n} D_{jn} \cdot \bar{Q}_n + u_n, \tag{9}$$

where $Q_{n,04}$ is the observed production at unit n during the 2004 ozone season, D_{jn} is an indicator for whether unit n adopted pollution control technology j, and u_n is a random error term. A robust covariance matrix estimator that accounts for within plant correlation in the error terms is used.[57] If unit-level production was significantly affected by firms' compliance decisions, one or more of the θ_j will be statistically significant. A positive (negative) θ_j indicates that, on average, firms choosing compliance strategy j increased (decreased) their production relative to those units who chose to rely entirely on the permit market for compliance.

I estimate the model separately for restructured and regulated markets. Results are reported in Table 6. The coefficient on $\bar{Q}_n$ is 1.03 when the model is estimated using data from the regulated markets and very precisely estimated, whereas none of the interaction terms are significant. This implies that unit level production, on average, increased slightly in regulated markets once the NOx SIP Call took effect, but was not significantly affected by the compliance strategy chosen. When the model is estimated using data from plants in restructured markets, the coefficient on $\bar{Q}_n$ is 1, also with a small standard error. Only the SCR interaction term is positive and significant at the five percent level; the SNCR coefficient is significant at the 10% level. This is an interesting, but not surprising result. In restructured markets, units installing SCR slightly increased their ozone season production on average, where as production levels at all other plants were generally unchanged. Put differently, those plants whose variable operating costs increased by relatively less are called upon to generate relatively more often.

In regulated electricity markets, these results are supportive of the model assumptions. If managers correctly anticipated how compliance decisions would affect future production, they used past ozone season production as a proxy for future production in their evaluation of all compliance options. In restructured markets, managers who correctly anticipated that adopting SCR (and possibly SNCR) could result in increased production (by a quantity denoted by ΔQ_n) would have changed their production expectations accordingly. This would increase annual compliance costs

[55] Anecdotal evidence indicates that managers used past summer production levels to estimate future production, regardless of the compliance choice being evaluated (EPRI, 1999a).

[56] The first ozone season in which all coal-fired units had to comply was 2004. This is the only year for which emissions data are currently available.

[57] There are several reasons why the error terms might be correlated across units in the same facility. For example, an facility-wide outtage would affect the production of all units at a plant.

associated with SCR by $\Delta v_{n\ SCR} = (V_{n\ SCR} + \tau \cdot m_{n\ SCR})\Delta Q_n$.[58] Per kWh compliance costs are relatively low for SCR (see Figure 2), so $\Delta v_{n\ SCR}$ should be small. Because it is hard to know whether managers correctly anticipated this increase, and because the increase is likely to be small, the same assumptions regarding expected production are maintained for all units, for all compliance strategies.

6.4 Summary of Estimation Results

There are two important implications of the empirical results discussed in this section. First, unobserved heterogeneity in how plant managers respond to variation in compliance costs has played a significant role in determining environmental compliance choices under the NOx SIP Call. Second, the coefficient on capital costs appears to be substantially more negative among firms in restructured electricity markets, as compared to similar plants in regulated electricity markets who are guaranteed a positive rate of return on their capital investments in pollution control equipment. Unfortunately, because of the identification assumptions underlying the logit model and the difficulties associated with estimating the variance of a ratio of two random variables, there is no completely satisfying way to formally demonstrate that capital cost coefficients differ across electricity market types. However, all of the empirical evidence strongly suggests that the negative coefficient on capital costs is substantially larger in absolute value when the model is estimated using data from restructured electricity markets. Whereas we can easily reject the null hypothesis that the capital cost coefficient is greater than or equal to zero in the restructured market case, we fail to reject this hypothesis when the model is estimated using data from regulated electricity markets. When the ratio of the variable and capital cost coefficient estimates are compared (hereby eliminating the scale parameter that confounds direct comparisons of coefficients across market types), we find further support for the hypothesis that plants in restructured electricity markets weigh capital costs more heavily in their compliance decisions.

[58] In fact, this increase in per kWh compliance costs would potentially be offset by increased revenues. Under the assumption that expected production is independent of the compliance choice, revenues from the sale of electricity do not vary across compliance alternatives and therefore drop out of the discrete choice model. If expected production is higher conditional on adopting SCR, revenues will increase by an amount equal to $\sum_{t_{n\ SCR}=1}^{T_{nSCR}} q_{nt_{nSCR}} P_{nt_{nSCR}}$,where t_{nSCR} indexes the additional hours in which the n^{th} unit would operate if it installed SCR, and P_{nt} is the electricity price the n^{th} unit expects to receive in hour t.

7 Implications of the Results

Estimation results suggest that economic regulation in the electricity market significantly affected how plant managers chose to comply with the NOx SIP Call, and that managers in restructured markets are more biased against more capital intensive compliance options, as compared to their more regulated counterparts. Because capital intensive compliance options are associated with significantly greater emissions reductions, this implies that plants in restructured markets chose "dirtier" compliance options. This section addresses the policy implications of these findings.

7.1 Implications for Permit Market Design

Ozone non-attainment problems are significantly more severe in states that have restructured electricity markets, largely because of differences in levels of industrial activity, population densities, and meteorological conditions. Consequently, the health benefits from reducing NOx pollution are significantly greater in these states.[59] Consider the health effects of choosing to install selective catalytic reduction (SCR) technology (the most capital intensive NOx control option) at a unit in a regulated electricity market versus a unit in a restructured electricity market. An average unit in the sample emitted 15 tons of NOx per day in 1999; retrofitting a *single unit* with SCR technology results in daily NOx reductions of 12 tons on average. A recent study finds that shifting 11 tons of NOx emissions per day from a relatively "low damage" location (North Carolina, a state that has not restructured its electricity market) to a "high damage" area (Maryland, a state that restructured its electricity industry) over a ten day period results in the loss of approximately one human life (Mauzerall et al., 2005).

Under the first-best pollution permit market outcome, the total social cost of achieving mandated emissions reductions is minimized. At each generating facility, the marginal cost of reducing emissions is set equal to the damage caused by an incremental change in emissions at that facility; pollution controls are installed where they deliver the greatest net benefit. There are two factors that can potentially distort equilibrium investment in pollution control equipment away from first best. First, results presented in Section 6 indicate that plants in restructured electricity markets are less likely to invest in pollution control equipment, as compared to similar plants in regulated electricity markets. The efficiency costs of this negative capital bias in restructured markets are exacerbated by a second factor: the permit market's failure to reflect spatial variation in marginal damages from pollution. The NOx SIP Call, like all major CAT programs in the United States, is emissions-based. The regulatory constraint is defined in terms of pounds of pollution; a permit

[59] A cross-agency U.S. Government website, AIRNow, provides a good summary of the health effects of ozone exposure: http://airnow.gov/index.cfm?action=static.ozone2#3.

is worth a pound of emissions, regardless of where the pound is emitted. Because the permit market fails to reflect spatial variation in benefits from reducing NOx emissions, there will likely be insufficient incentives for efficient levels of investment in the regions where pollution controls would deliver the largest health and environmental benefits.

Whereas environmental regulators have no control over the first factor (electricity market regulation), they do have control over how pollution permit markets are designed. An alternative approach designing permit markets involves setting a cap on total damages and establishing trading ratios that determine the terms of interregional permit trading. To set up such a system, the marginal damages resulting from increased NOx emissions in different regions of the regulated area must be estimated. The trading ratio R corresponding to a particular region is set equal to the estimated damages for that region divided by the damages in a designated numeraire region. These regions can be as small as the available data on marginal damages allows. In the extreme case, ratios would be set at the facility level.

The anticipated compliance costs defined in [1] can be rewritten as follows:

$$\begin{aligned} C_{nj} &= \alpha_j + \beta_n^v v_{nj} + \beta_n^K K_{nj} - \varepsilon_{nj}, \\ where \quad v_{nj} &= (V_{nj} + R_n \cdot \tau \cdot m_{nj})\bar{Q}_n \end{aligned} \tag{10}$$

Under emissions-based trading, $R_n = 1 \ \forall \ n$. The introduction of trading ratios that reflect spatial variation in marginal damages increases the marginal cost of polluting in areas where pollution does the most damage, thereby increasing the incentives to install pollution controls in relatively high damage areas. The effect of trading ratios on compliance decisions, and thus patterns of emissions, will depend on how responsive firms' compliance choices are to changes in variable compliance costs. If the bias of managers against capital intensive compliance options is sufficiently strong in high damage areas, it could be that the use of trading ratios would not have affected compliance choices.

The EPA received over 50 responses when, during the planning stages of the NOx SIP Call, it solicited comments on whether the program should incorporate trading ratios or other restrictions on interregional trading in order to reflect the significant differential effects of NOx emissions across states(FR 63(90): 25902). Most commentors supported unrestricted trading and expressed concerns that "discounts or other adjustments or restrictions would unnecessarily complicate the trading program, and therefore reduce its effectiveness" (FR 63(207): 57460). These comments, together with a simulation exercise which indicated that imposing spatial constraints on trading would not significantly affect the location of emissions (US EPA, 1998a), led regulators to design a single jurisdiction trading program in which all emissions are traded on a one-for-one basis.

In this section, I assess whether the benefits of NOx trading ratios could have justified the added complexity ex post. Drawing from the manager-specific distributions of cost coefficients implied by the RCL estimates, I simulate the compliance choices that these managers most likely would have made had the NOx emissions market been designed to reflect spatial heterogeneity in marginal damages from pollution. Unlike previous studies,[60] I find that the decision to adopt an emissions-based versus an exposure-based permit market has significantly affected the spatial distribution of permitted emissions.

7.1.1 Simulating Exposure-Based Trading

Defining trading ratios

Several assumptions had to be made in setting up the simulation of exposure-based NOx permit trading. The first set of assumptions pertain to how the trading ratios are defined. Although there was discussion of imposing spatial constraints on permit trading during the planning stages of the NOx SIP Call, a complete proposal of appropriate jurisdictional boundaries or trading ratios was unfortunately never established. However, there are two papers in the literature which estimate marginal damages from incremental increases in NOx emissions in the Eastern United States that provide some information on how these ratios might have been defined. Krupnick et al.(1998) generate trading ratios for a subset of the states affected by the NOx SIP Call.[61] Averaged across typical episodes, ratios range from 1 in low damage areas to 1.5 in high damage areas. I use this ratio in simulating a more conservative exposure-based trading program. Less conservative ratio estimates are provided in a more recent paper (Mauzerall et al., 2005).[62] Based on this work, I also consider an exposure-based trading system in which 5 permits are needed for every pound of NOx emitted in high damage areas.

Ideally, trading ratios would incorporate all available information on how marginal damages from NOx pollution vary across counties, municipalities, or even facilities. I was unable to obtain

[60] Farrell et al. (1999) consider imposing geographic constraints on NOx permit trading in the Northeast and conclude that the benefits do not justify the costs. Krupnick et al. (2000) argue that there is no clear benefit to spatially differentiated NOx trading.

[61] This paper looks at controlling NOx emissions in the Chesapeake Bay. The authors use an urban airshed model to link regional changes in NOx emissions in different regions to regional, population weighted changes in ozone concentrations. They use emissions and meteorological data from three "typical" five day ozone episodes in 1990 to estimate trading ratios. The authors note that 1990 was a "good" ozone year; their estimates of typical changes in ozone concentrations attributable to sources are conservative.

[62] Mauzerall et al (2005) use a comprehensive air quality model (CAMx) to quantify the variable impacts that a fixed quantity of NOx emitted from individual point sources can have on downwind ozone concentrations and resulting population weighted health damages. Simulations were carried out using data from a 10 day period in 1995 (July 7-17). Considering fatality effects only (i.e. ignoring morbidity) and using "off the shelf" estimates of the value of a statistical life, the estimated damage per ton of NOx emissions ranges from 1995 $10,700 to $52,800 depending on ambient temperature and location. This suggests that the appropriate trading ratios in high damage areas could be as large as 5:1. Ratios that take morbidity and environmental damages into account would be even larger.

marginal damage estimates at this level of detail. "Low damage" states are defined to be those that are either completely or marginally in attainment with the federal one hour and eight hour ozone standards (according to the US EPA's "Green Book"). "High damage" states are those that include counties classified as moderate, severe or serious under the one hour and eight hour standards (EPA Green Book). Under exposure-based trading, I assume that a permit is required to offset a pound of NOx in low damage areas; 1.5 permits (or 5 permits in the second scenario) are required in high damage areas.

Defining the baseline

A second set of assumptions have to do with establishing a baseline or benchmark against which to compare simulated emissions under exposure-based trading. We are interested in knowing how different spatial patterns of emissions would have been under exposure-based versus emissions-based permit trading. One approach would be to use observed NOx emissions from coal-fired units as a benchmark.[63] However, because of significant discrepancies between observed emissions during the first ozone season[64] and emissions predicted by the model under emissions-based permit trading, this is not an appropriate basis for comparison.

Table 7 compares observed emissions from the first ozone season of the NOx SIP Call (2004) to the emissions predicted by the model. The second and third columns report predicted emissions conditional on observed choices and conditioned on simulated choices, respectively. Although the model is reasonably accurate in predicting compliance choices, it does a poor job of predicting emissions. Predicted emissions (based on predicted compliance choices) are 34% higher than observed emissions overall and over 40% higher in states with restructured electricity markets.

A closer look at the data reveals three reasons for these discrepancies. First, the model assumes that emissions rates (measured in lbs NOx/mmbtu) for those units that choose not install any pollution controls will equal the unit's average ozone season emissions rate over the period 1999-2002. In fact, emissions rates at units that chose to rely entirely on the permit market for compliance fall by an average of 21% in the first ozone season, relative to past summers. This relationship (between expected and observed emissions rates among plants who did not install pollution controls) does not differ significantly across electricity market types.[65] Emissions rates

[63] Because approximately 85% of emissions regulated (and permits allocated) under the program come from coal-fired generators, I capture the majority of the market when emissions from non-coal-fired units are considered exogenous to the model. In future versions of the paper, this assumption will be released by assuming a range of elasticities of permit supply/demand for the market segment that is not explicitly represented in the simulation (i.e.,oil and gas-fired generators and industrial boilers). This simulation also treats the number of banked permits as exogenous.

[64] Data is not yet available for subsequent ozone seasons. This first, full-compliance ozone season was only 122 days long. Future ozone seasons will be 153 days (May-September).

[65] The average decrease in NOx rates is 22% (with a standard deviation of 26%) in regulated markets and 19% in restructured markets (with a standard deviation of 21%).

at these plants were likely reduced by changing boiler conditions so as to reduce NOx formation during combustion.

Second, the unit-specific, technology-specific, post-retrofit NOx removal rates assumed by the model also appear to have been conservative. These are the same estimates that were made available to plant managers while they were making their compliance decisions. Among units that adopted some pollution control technology other than SCR, observed post-retrofit NOx emissions rates are, on average, 27% below predicted post-retrofit NOx rates. Among units adopting SCR, observed post-retrofit emissions rates are, on average, 41% below predicted rates in restructured electricity markets and 28% below predicted rates in regulated markets. The reason for the difference across electricity market types is that several plants installing SCR reportedly were unable to complete their SCR retrofits in time for the first ozone season; most of these are in regulated electricity markets. Consequently, observed NOx rates in the summer of 2004 greatly exceeded the predicted NOx rates at these plants. The emissions rates at these plants, and the proportion of permitted NOx emissions in states with regulated electricity markets, should decline in future ozone seasons as SCR retrofits are completed.

Finally, assumptions about unit-level heat rates (measured in mmbtu/kWh) also underestimate ex post observed unit-level performance. The model assumes that future unit-level heat rates will equal those observed in previous summers. On average, units performed more efficiently in the summer of 2004 than in past ozone seasons. When observed heat rates are regressed on predicted heat rates and NOx control technology dummies, the coefficient on predicted heat rates is 0.91 with a standard error of 0.01. None of the technology dummies are statistically significant. Results do not change when regression equations are estimated separately for regulated and restructured markets.

Because observed emissions are significantly lower than the emissions predicted by the model, comparing emissions predicted under counterfactual exposure-based policy simulations with observed emissions would be uninformative and misleading. Instead, baseline emissions (i.e., the emissions associated with the observed, emissions-based permit trading program) are simulated in the same way that emissions under counterfactual, exposure-based trading are simulated. The simulation procedure is described below.

Defining the cap

Under emissions-based trading, the number of permits distributed equals the total cap on emissions. Assuming perfect compliance, the regulator has complete control over the total amount of pollution that is emitted. Under a trading ratio system, the regulator cannot directly cap emissions. The number of permits distributed equals the permitted damages. The total quantity of permitted emissions will depend on which firms use permits, and which firms invest in pollution reduction. If more permits are used in low (high) damage areas, the total amount of pollution will be greater (smaller) for a given cap.

To facilitate a comparison between emissions-based and exposure-based permit market designs, I assume that the cap is defined in terms of emissions in both cases. Put differently, I simulate compliance choices and emissions under an exposure-based and emissions-based permit markets that are designed to deliver the same total quantity of seasonal emissions (in terms of pounds of NOx).

The baseline cap used in all simulation exercises is estimated as follows. The means of the manager specific conditional distributions and the permit price that prevailed during the years in which these compliance decisions were being made ($2.25/lb) are used to generate point estimates of choice probabilities [4] under the baseline case of emissions-based permit trading (i.e., $R_n = 1$ for all n). For each unit, the compliance strategy with the largest choice probability is assumed to be the chosen alternative. The corresponding estimates of unit-level ozone season emissions are summed across units. The resulting quantity (measured in pounds of NOx per ozone season) is the cap that is used in all of the simulation exercises described below.

7.1.2 Simulation

The econometric model is used to predict emissions under emissions-based and exposure-based permit trading as follows:

1. The permit price τ is initially set equal to the price that prevailed during the years in which firms were making their compliance decision ($2.25/lb).
2. A vector of coefficients b^r is drawn from the distribution of the random coefficients in the population; r denotes the repetition ($r = 1...1000$).
3. For each unit, the expected choice probabilities as defined in [8] are approximated for all compliance available choices, conditional on the price τ, the draw from the population distribution, the character and outcomes of previously observed choices of the corresponding manager (X_m, Y_m), and the assumed trading ratio R_m.
4. Unit level compliance choices for all choice situations faced by each manager are predicted. Each unit is assumed to choose the compliance strategy with the highest expected choice probability.
5. Seasonal emissions (measured in lbs of NOx) corresponding to the predicted choices are calculated and summed across units.
6. If the total quantity of emissions equals the assumed cap, τ is the equilibrium price and the simulation stops. Equilibrium emissions in high damage areas and low damage areas are

calculated.

7. If the total quantity of emissions exceeds (is less than) the cap, τ is increased (decreased) by \$0.01. Steps 3-6 are repeated.[66]

This procedure is repeated 1000 times under the baseline case (emissions-based trading), the conservative exposure-based trading case where $R = 1.5$ in high damage areas, and the less conservative exposure-based trading case where $R = 5$ in high damage areas. Distributions of predicted equilibrium emissions are generated for each scenario. Summary statistics are reported in Table 8.

The model predicts an average reduction of 131 tons per day (6 percent) in emissions in the high damage states under the first case, and an average reduction of 446 tons per day (22 percent) in high damage states under the second, less conservative case. These results suggest that the health damages that have resulted (and that will continue for the foreseeable future) from the decision to adopt an emissions-based permit design are non-negligible. Allowing for the fact that the model does over-predict emissions, a 6 to 22 percent decrease in observed emissions in high damage areas translates to moving 123-452 tons of NOx emissions *per day* out of high damage areas into low damage areas, depending on the chosen trading ratios. Recall that it has been estimated that the number of lives lost due to ozone exposure can be reduced by moving only 11 tons per day over a period of 10 days out of high damage areas into low damage areas (Mauzerall et al., 2005).

7.2 Implications for policy analysis

The planning models that are conventionally used by federal and state-level policy makers to analyze proposed air pollution regulations make the simplifying assumptions that all firms minimize costs when choosing how to comply with a CAT program, and that all firms minimize the same cost function. Estimation results presented in the previous section are not supportive of these assumptions. I find that there is significant heterogeneity in how plant managers weigh costs in their compliance decisions, and that responsiveness to costs varies with electricity market type.

Appendix 3 describes a second simulation exercise which examines the consequences of ignoring both variation in electricity market regulation, and heterogeneity in response to cost changes in the analysis of proposed air pollution regulations. The Integrated Planning Model (IPM) is a dynamic linear programming model of fuel markets, emission markets, and electricity markets that is used extensively by the EPA, state air regulatory agencies, utilities and other public and private

[66] If this iterative procedure arrives at a point where adding or subtracting a cent delivers aggregate emissions on either side of the cap, the price that delivers the quantity of emissions just below the cap is chosen to be the equilibrium price. Equilibrium emissions are calculated and the simulation stops.

sector institutions to analyze proposed air pollution regulations. I use a deterministic model that incorporates the relevant IPM assumptions and parameters to predict compliance choices and NOx emissions under emissions-based trading. These emissions are compared against baseline emissions (as defined in section 7.1). This deterministic model of cost minimizing plant managers significantly over-predicts investment in pollution controls in restructured electricity markets. Predicted daily NOx emissions are 260 tons below baseline emissions in high damage areas.

8 Summary and Conclusions

I have estimated a model of how plant managers chose to comply with a major U.S. NOx emissions trading program. I find that economic regulation in the electricity market in which a power plant is operating has significantly affected the environmental compliance decision. Plants in restructured electricity markets are found to be less likely to install capital intensive pollution control technology as compared to similar plants in regulated electricity markets who are allowed to earn a positive rate of return on their investments in pollution control equipment.

This effect of electricity market economic regulation on pollution control technology adoption affects permit market efficiency in two ways. First, because the plants with the lowest pollution control costs are not always the ones installing pollution controls, the permit market may fail to minimize the total economic cost of meeting the exogenously determined emissions cap. Second, because air quality problems are more severe in states that have restructured their electricity markets, this effect exacerbates the inefficiencies associated with emissions-based trading of a non-uniformly mixed pollutant. Thus, the total social cost associated with the permitted emissions is not minimized.

The NOx SIP Call, like all major emissions trading programs in the United States, defines permits in terms of emissions. In theory, exposure-based permit trading could reduce the efficiency costs of the negative capital bias in restructured electricity markets. The econometric model is used to predict how technology adoption, and thus emissions, would have been different under an exposure-based trading program designed to meet the same total emissions cap. The model predicts that 6-22 percent of permitted emissions (or 123-452 tons of NOx per day, based on observed emissions in 2004) would have been moved out of high damage areas and into low damage areas under a generally defined exposure-based program, relative to an emissions-based program. Recent epidemiological research suggests that a spatial shift in emissions of this magnitude could reduce premature deaths from ozone exposure by hundreds each year. There would also be additional benefits, including reduced morbidity and reduced environmental damages. While this analysis is somewhat limited in how accurately it can measure the precise number of tons of NOx that would move out of high damage areas and into low damage areas under exposure-based trading, the inefficiency of emissions-based permit trading is clear.

There are two important policy implications of this research. First, when there is significant spatial variation in marginal damages from pollution, permit markets should be designed to reflect this variation. This is particularly critical in situations where variation in economic regulation across electricity markets is already reducing the probability that pollution controls will be installed in the areas where they deliver the greatest social benefits.

Second, when policy makers are forecasting permit market outcomes, variation in economic regulation and investment incentives across the affected industries should be taken into account. The models currently used by federal and state agencies to evaluate proposed air pollution regulations make the simplifying assumptions that all electricity generators operate in perfectly competitive electricity markets, and that all firms minimize the same cost function when choosing how to comply with environmental regulations. Results presented here demonstrate how these inaccurate assumptions can result in over-prediction of investment in pollution controls in restructured electricity markets.

The permit market inefficiencies identified here will likely plague future CAT programs. The Mercury Rule and the Clean Air Interstate Rule, both finalized in March of 2005, are scheduled to take effect in 2010. The former regulates mercury emissions from all U.S. coal plants. The latter, meant to subsume the Acid Rain Program and the NOx SIP Call, regulates SO_2 and NOx. Both will affect electricity generators in restructured and regulated electricity markets. Both propose to use an emissions-based permit market to regulate a non-uniformly mixed pollutant.

This paper makes important preliminary steps in its empirical investigation of the merits of exposure-based permit trading. More detailed data on spatial variation in marginal damages from NOx pollution would allow for the simulation of compliance decisions under more informative trading ratios. The work could also be extended to evaluate other spatial restrictions on permit trading that have been proposed, such as zonal trading systems. These areas of inquiry are left for future research.

Finally, I am working to incorporate the discrete choice model developed here into a more comprehensive, discrete-continuous choice model of the firm's environmental compliance decisions. With each passing ozone season, I am collecting unit-level emissions, production and fuel use data. A discrete-continuous model of production and pollution decisions made once pollution control technologies are installed and the environmental regulation constraints are binding will allow for a more detailed analysis of how the incentives created by CAT programs affect firm decision making in both the long *and* the short run.

Appendix 1: Deriving the Conditional Logit Choice Probabilities Implied by Cost Minimization

It is straightforward to show that for additive, iid extreme value (Type I) errors, the assumption of cost minimization does not yield the standard CL choice probabilities due to the asymmetry of the assumed distribution. In the standard Random Utility Maximization (RUM) logit model, the assumption of an additive extreme value error term is motivated by a desire for simple closed-form expressions for choice probabilities. Here I show that, in the context of cost minimization, assuming that the extreme value term is subtracted from (versus added to) the deterministic component implies equally convenient expression for choice probabilities. This closely follows the derivation of the standard RUM choice probabilities in Train(2003).

The unit (denoted n) chooses from among J_n compliance alternatives. The cost that the unit associates with each alternative is comprised of a deterministic component and a stochastic component:

$$C_{ni} = \beta_m X_{ni} - \varepsilon_{ni},$$

where ε_{ni} is assumed to be independently, identically distributed type I extreme value. To derive the choice probabilities, I assume that the unit chooses the compliance option that minimizes anticipated compliance costs.(For ease of notation, the n subscript on the coefficient vector β is dropped). Let P_{ni} be the probability that unit n chooses alternative i :

$$\begin{aligned} P_{ni} &= \text{Prob } (\beta' X_{ni} - \varepsilon_{ni} < \beta' X_{nj} - \varepsilon_{nj} \quad \forall\ j \neq i) \\ &= \text{Prob } (\varepsilon_{nj} < \beta' X_{nj} - \beta' X_{ni} + \varepsilon_{ni} \quad \forall\ j \neq i) \end{aligned}$$

The expression for the conditional choice probability :

$$\begin{aligned} P_{ni}|\varepsilon_{ni} &= \prod_{j\neq i} F(\beta' X_{nj} - \beta' X_{ni} + \varepsilon_{ni}) \\ &= \prod_{j\neq i} \exp(-\exp(-(\beta' X_{nj} - \beta' X_{ni} + \varepsilon_{ni}))) \end{aligned}$$

Unconditional choice probabilities are obtained by integrating over the distribution of ε_n :

$$\begin{aligned} P_{ni} &= \int_{\varepsilon=-\infty}^{\infty} \prod_{j\neq i} \exp(-\exp(-(\beta' X_{nj} - \beta' X_{ni} + \varepsilon_{ni}))f(\varepsilon_n)\ d\varepsilon_n \\ &= \int_{s=-\infty}^{\infty} \prod_{j\neq i} \exp(-\exp(-(\beta' X_{nj} - \beta' X_{ni} + s))\exp(-s)\exp(-\exp(-s))\ ds \end{aligned}$$

Note that $\exp(-\exp(-(\beta' X_{nj} - \beta' X_{ni} + s))) = \exp(-\exp(-s))$. Making this substitution:

$$\begin{aligned}
P_{ni} &= \int\limits_{s=-\infty}^{\infty} \prod_j \exp(-\exp(-(\beta' X_{nj} - \beta' X_{ni} + s)) \exp(-s) ds \\
&= \int\limits_{s=-\infty}^{\infty} \exp - \sum_j \exp(-(\beta' X_{nj} - \beta' X_{ni} + s)) \exp(-s) ds \\
&= \int\limits_{s=-\infty}^{\infty} \exp(-\exp(-s)) \sum_j \exp(-(\beta' X_{nj} - \beta' X_{ni})) \exp(-s) ds
\end{aligned}$$

We define a variable t such that $t = \exp(-s) \Rightarrow dt = -\exp(-s)ds$. Making this substitution:

$$P_{ni} = \int\limits_{s=0}^{\infty} \exp(-t \sum_j \exp(-(\beta' X_{nj} - \beta' X_{ni}))dt$$

Evaluating this integral, we are left with:

$$P_{ni} = \frac{1}{\sum_j \frac{\exp(\beta' X_{ni})}{\exp(\beta' X_{nj})}}$$

An alternative way of expressing this conditional choice probability:

$$P_{ni} = \frac{\frac{1}{\exp(\beta' X_{ni})}}{\sum_j (\frac{1}{\exp(\beta' X_{nj})})} = \frac{\exp(-\beta' X_{ni})}{\sum_j \exp(-\beta' X_{nj})}$$

Appendix 2: Analytical Gradients of the Likelihood Function

Here, the analytic derivatives of the simulated log-likelihood function (SLL) with respect to the means of the random parameters and the elements of the lower triangular cholesky matrix (the c_{kl}) are derived. The contribution of the mth manager to the simulated log likelihood function is:

$$\begin{aligned} SLL_m(\theta) &= \ln \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_m} \frac{\exp(-\beta^{r\prime} X_{mi_t t})}{\sum_{j=1}^{J_m} \exp(-\beta^{r\prime} X_{mj_t t})} \\ &\equiv \ln \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_m} L_{mi_t t}(\beta^r) \end{aligned} \tag{11}$$

The derivative of [11] with respect to a draw of the kth element of the vector of random parameters β^r is:

$$G_{nk}(\beta) = \frac{\partial \left[\ln \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_m} L_{mi_t t}(\beta^r) \right]}{\partial \beta_k^r} = \frac{\partial \left[\frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_m} L_{mi_t t}(\beta^r) \right]}{\partial \beta_k^r} \cdot \left[\frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_m} L_{mi_t t}(\beta^r) \right]^{-1}$$

Let y_{mjt} be an indicator variable that =1 if firm m chooses alternative i in choice situation t, 0 otherwise. To simplify the differentiation, the choice probability $L_{m\mathbf{i}}(\beta^r)$ is rewritten:

$$\prod_{t=1}^{T_m} L_{mi_t t}(\beta^r) = \frac{\exp\left(\sum_{t=1}^{T_m} \sum_{j=1}^{J_m} y_{mj_t t}(-\beta^{r\prime} X_{mj_t t}) \right)}{\sum_{j=1}^{J_m} \exp\left(\sum_{t=1}^{T_m} -\beta^{r\prime} X_{mj_t t} \right)}$$

Differentiating this choice probability with respect to β_k^r :

$$\begin{aligned} \frac{\partial \left[L_{m\mathbf{i}}(\beta^r) \right]}{\partial \beta_k^r} &= \frac{\sum_{j=1}^{J_m} \exp\left(\sum_{t=1}^{T_m} -\beta^{r\prime} X_{mj_t t} \right) \sum_{t=1}^{T_m} \sum_{j=1}^{J_m} y_{mj_t t}(-x_{mj_t tk}) \left(\exp\left(\sum_{t=1}^{T_m} \sum_{j=1}^{J_m} y_{mj_t t}(-\beta^{r\prime} X_{mj_t t}) \right) \right)}{\left[\sum_{j=1}^{J_m} \exp\left(\sum_{t=1}^{T_m} -\beta^{r\prime} X_{mj_t t} \right) \right]^2} - \\ & \frac{\exp\left(\sum_{t=1}^{T_m} \sum_{j=1}^{J_m} y_{mj_t t}(-\beta^{r\prime} X_{mj_t t}) \right) \sum_{t=1}^{T_m} -x_{mj_t tk} \sum_{j=1}^{J_m} \exp\left(\sum_{t=1}^{T_m} -\beta^{r\prime} X_{mj_t t} \right)}{\left[\sum_{j=1}^{J_m} \exp\left(\sum_{t=1}^{T_m} -\beta^{r\prime} X_{mj_t t} \right) \right]^2} \end{aligned}$$

Simplifying this expression:

$$
\begin{aligned}
\frac{\partial\left[L_{m\mathbf{i}}(\beta^r)\right]}{\partial\beta_k^r} &= \prod_{t=1}^{T_m} L_{mi_tt}(\beta^r)\left[\frac{\sum_{j=1}^{J_m}\exp\left(\sum_{t=1}^{T_m}-\beta^{r\prime}X_{mj_tt}\right)\sum_{t=1}^{T_m}\sum_{j=1}^{J_m}y_{mj_tt}(-x_{mj_ttk})}{\sum_{j=1}^{J_m}\exp\left(\sum_{t=1}^{T_m}-\beta^{r\prime}X_{mj_tt}\right)}\right. \\
&\quad\left.-\frac{\sum_{t=1}^{T_m}-x_{mj_ttk}\sum_{j=1}^{J_m}\exp\left(\sum_{t=1}^{T_m}-\beta^{r\prime}X_{mj_tt}\right)}{\sum_{j=1}^{J_m}\exp\left(\sum_{t=1}^{T_m}-\beta^{r\prime}X_{mj_tt}\right)}\right] \\
&= \prod_{t=1}^{T_m} L_{mi_tt}(\beta^r)\left[\sum_{j=1}^{J_m}\left(\sum_{t=1}^{T_m}y_{mj_tt}-\prod_{t=1}^{T_m}L_{mj_tt}(\beta^r)\right)(-x_{mj_ttk})\right]
\end{aligned}
$$

Substituting into the original derivative:

$$
G_{nk}(\beta)=\frac{\frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{T_m}L_{mi_tt}(\beta^r)\left[\sum_{j=1}^{J_m}\left(\sum_{t=1}^{T_m}y_{mj_tt}-\prod_{t=1}^{T_m}L_{mj_tt}(\beta^r)\right)(-x_{mj_ttk})\right]}{\frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{T_m}L_{mi_tt}(\beta^r)}
$$

I take a similar approach to find an expression for the analytic derivative of [11] with respect to an element of the cholesky factor of the covariance matrix:

$$
G_{nk}(c_{kl}^r)=\frac{\frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{T_m}L_{mi_tt}(\beta^r)\left[\sum_{j=1}^{J_m}\left(\sum_{t=1}^{T_m}y_{mj_tt}-\prod_{t=1}^{T_m}L_{mj_tt}(\beta^r)\right)(-x_{mj_ttk})(\eta_{ml}^r)\right]}{\frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{T_m}L_{mi_tt}(\beta^r)},
$$

where η_{ml}^r is the element of the matrix of pseudo-random draws from the standard normal distribution that corresponds to manager m, coefficient l and repetition r.

Appendix 3 : Simulations Using the IPM Based Deterministic Model

The Integrated Planning Model (IPM) is a dynamic linear programming model of fuel markets, emission markets, and electricity markets that is used extensively by the EPA, state air regulatory agencies, utilities and other public and private sector institutions to analyze proposed air pollution regulations. The model determines the least-cost method of meeting energy demands and peak energy requirements subject to existing and proposed regulatory constraints.

The assumptions of the IPM model are very well documented.[67] All electricity generators are assumed to operate in perfectly competitive wholesale markets. Firms are assumed to minimize the costs of meeting electricity demand, subject to resource availability and other operating and environmental regulation constraints. With respect to financing investments in pollution controls, the two most important parameter values in model are the discount rate (5.34% for all firms) and the capital charge rate (12% for all firms). The discount rate is used for calculation of net present values. The capital charge rate takes into account the cost of debt, return on equity, taxes and depreciation. All firms are assumed to use a corporate financing structure when evaluating investments in environmental retrofits. The assumed lifespan of a coal plant is 65 years.

I combine these assumptions and parameter values with the unit-specific compliance cost estimates and choice sets that were used in the estimation of the econometric model to calculate net present value (NPV) compliance costs for each unit, for each compliance option. To reiterate, implicit in these NPV estimates is the assumption that all firms minimize the same cost function, and that the parameters of this cost function are those assumed by the IPM model.

Emissions predictions under an emissions-based permit trading program are simulated as follows:

1. The permit price τ is initially set equal to the price that prevailed during the years in which firms were making their compliance decision ($2.25/lb).
2. Compliance costs are predicted for all choices in a unit's choice set, conditional on τ and the assumed parameters of the cost function (which do not vary across units). Each unit is assumed to choose the compliance strategy that minimizes the net present value of compliance costs.
3. Seasonal emissions (measured in lbs of NOx) corresponding to the predicted choices are calculated and summed across units.
4. If the total quantity of emissions equals the assumed cap, τ is the equilibrium price and the simulation stops. Equilibrium emissions in states with restructured electricity markets and states with regulated electricity markets are calculated.
5. If the total quantity of emissions exceeds (is less than) the cap, τ is increased (decreased) by $0.01. Steps 3-6 are repeated.[68]

Results are presented in the table below. Relative to the benchmark case, this model under-predicts emissions in high damage areas by 260 tons per day.

[67] The specific parameters and assumptions of the IPM model can be found at http://www.epa.gov/airmarkets/epa-ipm.

[68] If this iterative procedure arrives at a point where adding or subtracting a cent delivers aggregate emissions on either side of the cap, the price that delivers the quantity of emissions just below the cap is chosen to be the equilibrium price. Equilibrium emissions are calculated and the simulation stops.

Table A1: Simulation of Emissions-Based Trading Using IPM Assumptions

	Baseline	Deterministic IPM-based model
High damage area	2053	1791
NOx emissions (tons/day)	(55)	
Low damage area	2295	2555
NOx emissions (tons/day)	(55)	
Total	4347	4345
NOx emissions (tons/day)	(6)	
% NOx emissions in	47%	41%
high damage area	(1)	

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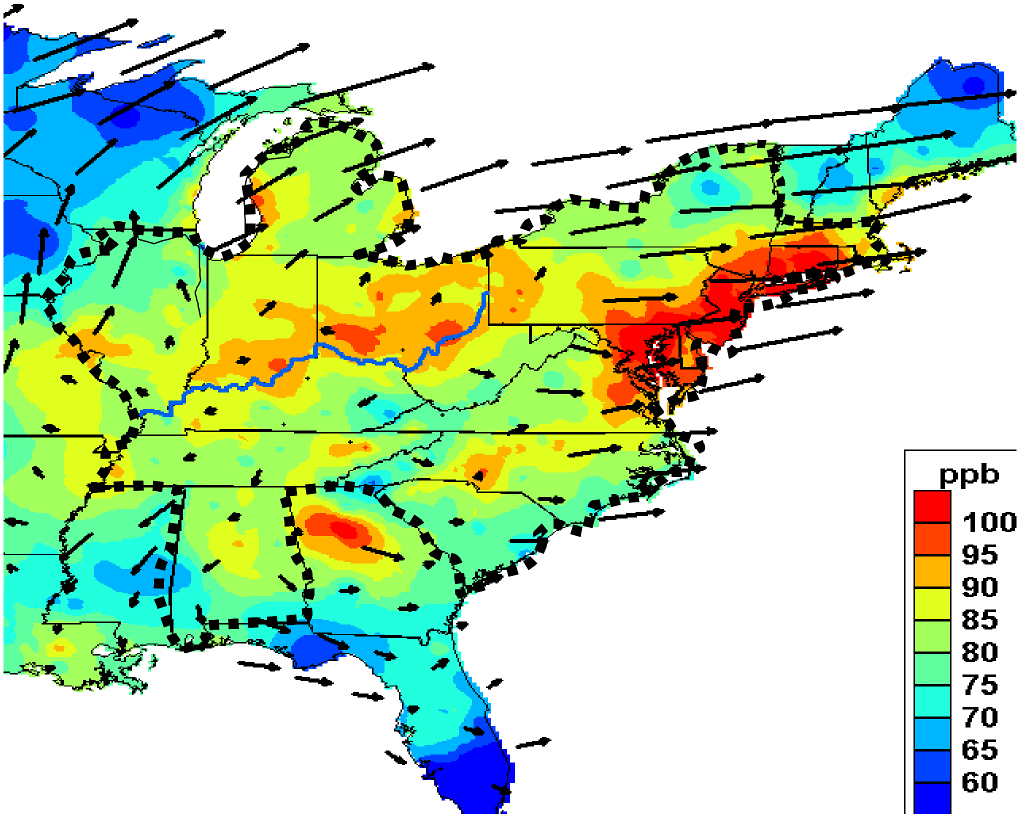

Figure 1: Ozone Transport and Non-Attainment (OTAG 1997)

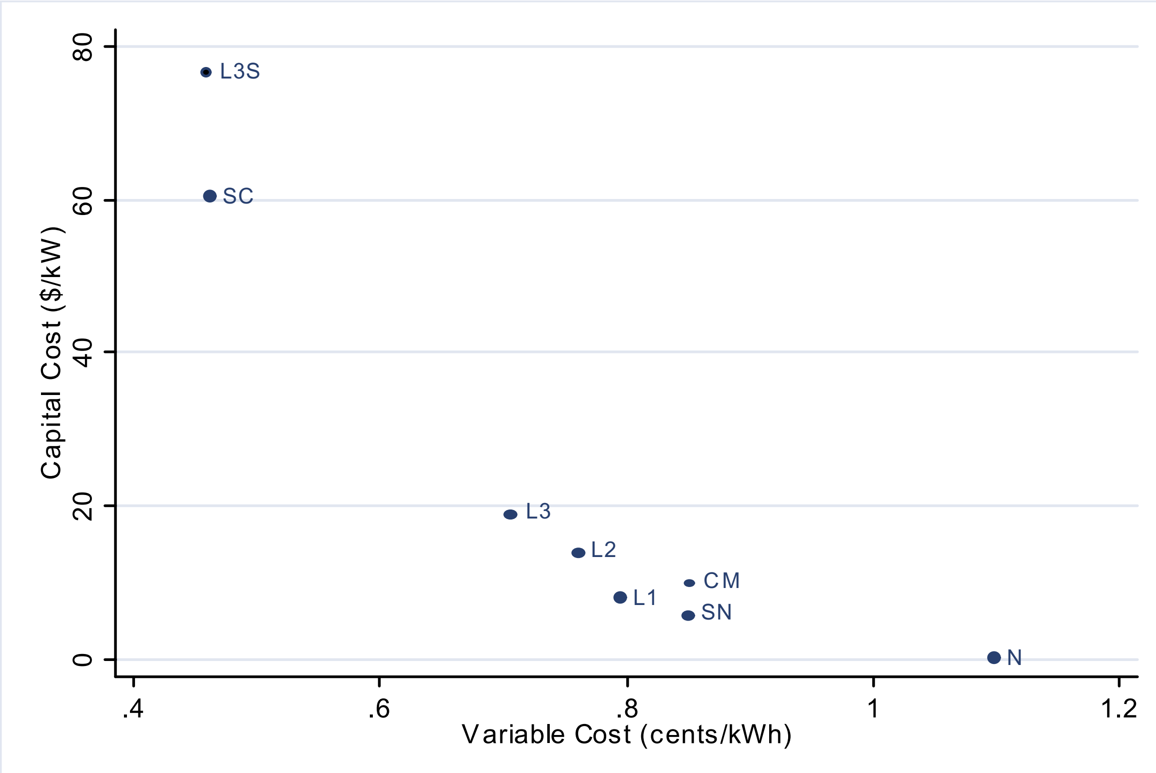

Figure 2: Estimated NOx Control Costs for a 512 MW T-Fired Boiler

Strategy code	Technology	lbs NOx/mmBtu
N	No Retrofit	0.42
SN	Selective Non-Catalytic Reduction (SNCR)	0.34
CM	Combustion Modification	0.33
L1	Low NOx Burners with overfire air option 1	0.31
L2	Low NOx Burners with overfire air option 2	0.28
L3	Low NOx Burners with overfire air options 1&2	0.26
SC	Selective Catalytic Reduction (SCR)	0.13
L3S	L3 + SCR	0.11

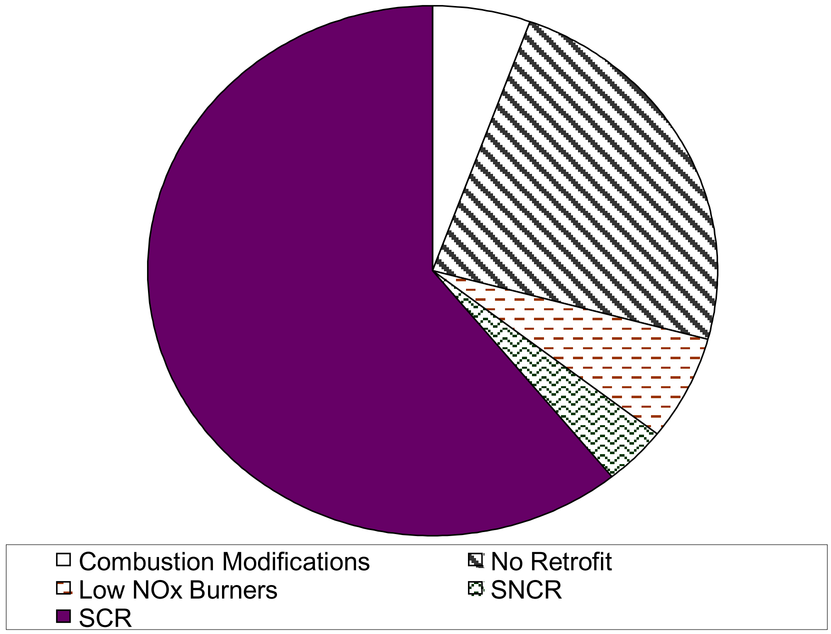

Figure 3a: Compliance Choices of Units in Regulated Markets

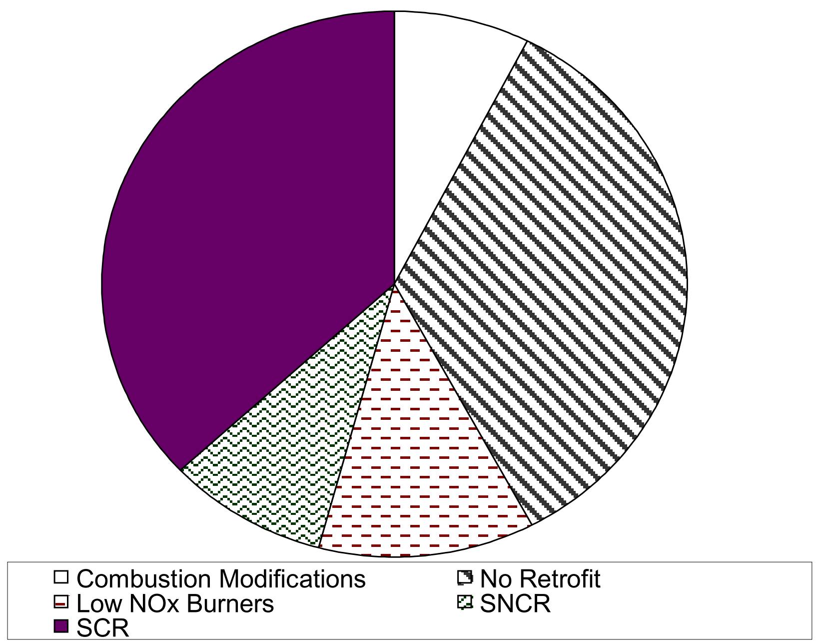

Figure 3b: Compliance Choices of Units in Restructured Markets

Table 1: Summary Statistics by Electricity Market Type

Variable	Restructured	Regulated
# Units	310	322
# Facilities	113	108
Capacity (MW)	275	268
	(243)	(258)
Pre-retrofit NOx emissions (lbs/mmBtu)	0.50	0.54
	(0.21)	(0.22)
Pre-retrofit summer capacity factor (%)	64	67
	(16)	(13)
Pre-retrofit heat rate (kWh/btu)	11,376	11,509
	(2153)	(1685)
Unit Age (years)	37	36
	(11)	(11)

Notes: Standard deviations in parentheses. Summary statistics generated using the data from the 632 units used to estimate the model.

Table 2: Compliance Cost Summary Statistics for Commonly Selected Control Technologies

Technology	Capital Cost ($/kW)		Per kWh operating costs (cents/kWh)	
	Restructured	Regulated	Restructured	Regulated
Combustion Modification	12.61 (4.87)	12.21 (4.24)	0.94 (0.38)	1.06 (0.39)
Low NOx Burners w/ OFA	29.72 (13.83)	31.16 (20.55)	0.64 (0.20)	0.64 (0.16)
SNCR	16.60 (14.41)	19.16 (21.88)	0.97 (0.41)	1.03 (0.38)
SCR	70.36 (21.02)	72.90 (25.52)	0.52 (0.31)	0.54 (0.19)

Notes: Standard deviations are in parentheses.

Table 3. Conditional and Random Parameters Logit Results

	Conditional Logit Model		RCL Model	
	Restructured	Regulated	Restructured	Regulated
	Technology Type Constants			
α_{POST}	-1.89**	-2.63**	-1.35*	-3.39**
	(0.34)	(0.38)	(0.52)	(0.59)
α_{CM}	-1.81**	-2.20**	-1.87**	-2.48**
	(0.26)	(0.28)	(0.30)	(0.32)
α_{LNB}	-1.86**	-2.15**	-1.55**	-2.49**
	(0.33)	(0.29)	(0.37)	(0.31)
	Cost Variables			
Annual compliance	-0.30**	-0.31*	-1.21**	-1.00**
costs (V)	(0.09)	(0.15)	(0.26)	(0.21)
($100,000)				
Capital cost	-0.06**	0.02	-0.53**	-0.16
(K)	(0.02)	(0.06)	(0.12)	(0.10)
($100,000)				
K*Age	-0.003	-0.002	-0.22**	-0.11*
	(0.002)	(0.003)	(0.06)	(0.05)
Cholesky 1	–		-1.42**	-0.51**
(σ_V)	–		(0.30)	(0.16)
Cholesky 2	–		0.30**	0.14**
(σ_K)			(0.08)	(0.05)
Cholesky 3	–		0.04	0.04
(off diagonal)			(0.11)	(0.07)
# units	310	322	310	322
# facilities	113	108	113	108
Log-likelihood	-431.2	-387.1	-359.4	-326.3
LR Test	compare to technology constants		compare to logit	
	103.94**	211.71**	143.66**	121.64**

Notes: Robust standard errors are in parentheses. *Indicates significance at 5%. **Indicates significance at 1%.

Table 4: Expected Means and Standard Deviations of Manager Specific Coefficient Distributions

Coefficient	Restructured		Regulated	
	Population parameter estimate	Average of conditional parameter estimates	Population parameter estimate	Average of conditional parameter estimates
Annual operating cost (V) ($100,000)	-1.21**	-1.13 (1.00)	-1.00**	-1.00 (0.33)
Capital cost (K) ($100,000)	-0.53**	-0.54 (0.19)	-0.16	-0.16 (0.10)
Elements of the Cholesky factor L of Ω				
Cholesky 1 (σ_V)	-1.42**	-0.94 (0.30)	0.51**	0.40 (0.07)
Cholesky 2 (σ_K)	0.30**	0.23 (0.04)	0.14**	0.11 (0.02)
Cholesky 3 (off diagonal)	0.04	0.07 (0.04)	0.04	0.002 (0.01)
# plants		113		108

Notes: Standard deviations are in parentheses. *Indicates significance at 5%. **Indicates significance at 1%.

Table 5: Average Own Capital Cost and Own Annual Compliance Cost Elasticities for Commonly Selected Technologies

Technology	Own capital cost elasticities		Own annual cost elasticities	
	RESTRUCTURED	REGULATED	RESTRUCTURED	REGULATED
Combustion Modification	-1.03	-0.25	-4.63	-4.40
Low NOx Burners with overfire air	-1.25	-0.49	-3.75	-2.18
No retrofit	–	–	-10.02	-8.19
SCR	-5.74	-1.33	-1.75	-1.34
SNCR	-1.07	-0.27	-7.56	-6.96

Notes: These elasticities are calculated using the point estimates of the means of the conditional coefficient distributions.

Table 6: Testing the Independence of Ozone Season Production and Compliance Strategy Choice

	Restructured	Regulated
Past ozone season	1.00**	1.03**
production	(0.04)	(0.01)
(average kWh)		
Past production x	-0.12	-0.04
Combustion modification	(0.07)	(0.04)
Past production x	0.04	-0.04
low NOx burners	(0.07)	(0.05)
Past production x	0.09*	-0.00
SCR	(0.05)	(0.03)
Past production x	0.08	0.02
SNCR	(0.05)	(0.02)
Observations	310	322
R-squared	0.97	0.97

Notes: Dependent variable is observed unit level production in June-September 2003. Standard errors robust to within plant correlation are in parentheses.*Indicates significance at 5%. **Indicates significance at 1%.

Table 7: Observed and Predicted Average NOx Emissions (tons per day) by Market Type

	Observed (2004 season)	Predicted | Observed Choices	Predicted | Predicted Choices (BASELINE)
Restructured markets NOx emissions (tons/day)	1662	2272	2349 (64)
Regulated markets NOx emissions (tons/day)	1592	2022	1999 (64)
Total NOx emissions (tons/day)	3254	4294	4348 (6)
% Emissions in restructured markets	51%*	53%	54% (0.5%)

Notes: Standard deviations are in parentheses.

*This distribution of emissions across regulated and restructured electricity markets may not be indicative of patterns in future ozone seasons. Several units did not complete their SCR retrofits in time for the 2004 ozone season. NOx emissions rates at these units, most of whom are located in regulated electricity markets, will decline significantly in future ozone seasons.

Table 8: Exposure-Based Trading Simulation Results

	BASELINE CASE	Trading Ratio Case I (1:1.5)	Trading Ratio Case II (1:5)
High damage area NOx emissions (tons/day)	2053 (55)	1924 (78)	1596 (146)
Low damage area NOx emissions (tons/day)	2295 (55)	2423 (78)	2750 (146)
Total NOx emissions (tons/day)	4347 (6)	4347 (7)	4346 (8)
% Emissions in High Damage Area	47% (1)	44% (1)	37% (3)

Notes: Standard deviations are in parentheses.