American Economic Review 100 (June 2010): 837–869
http://www.aeaweb.org/articles.php?doi=10.1257/aer.100.3.837

Emissions Trading, Electricity Restructuring, and Investment in Pollution Abatement

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This paper analyzes an emissions trading program that was introduced to reduce smog-causing pollution from large stationary sources. Using variation in state level electricity industry restructuring activity, I identify the effect of economic regulation on pollution permit market outcomes. There are two main findings. First, deregulated plants in restructured electricity markets were less likely to adopt more capital intensive environmental compliance options as compared to regulated or publicly owned plants. Second, as a consequence of heterogeneity in electricity market regulations, a larger share of the permitted pollution is being emitted in states where air quality problems tend to be more severe. (*JEL* L51, L94, L98, Q53, Q58)

When the US 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. However, economists have long maintained that an emissions permit market could more efficiently coordinate pollution abatement activities provided a series of assumptions are met. Over the past few decades, market based "cap and trade" (CAT) approaches to regulating emissions from industrial point sources have become a centerpiece of environmental regulation in the United States.

In the theoretical first-best permit market equilibrium, the total social cost of meeting an emissions cap is minimized. Each firm chooses a level of pollution abatement such that its marginal cost of reducing pollution is set equal to the social marginal benefit from emissions reduction. In practice, preexisting distortions in product markets that are subject to CAT regulation may interfere with the emissions permit market's ability to operate efficiently. This paper studies the effects of electricity market regulation on permit market outcomes in the context of a major US emissions trading program (the NO_x Budget Program). The recent wave of electricity industry restructuring in the United States has resulted in significant interstate variation in economic regulation. Consequently, facilities in the same CAT program face very different economic regulation and investment incentives in their respective electricity markets. Whereas rate base regulated plants are guaranteed to earn a rate of return on prudent investments in pollution abatement equipment, "deregulated" plants operating in restructured electricity markets are offered no such

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assurances. This could lead regulated plants to invest relatively more heavily in capital intensive environmental compliance options.

The central question addressed by this paper: has heterogeneity in electricity market regulation affected how coal plant managers chose to comply with a regional NO_x emissions trading program? I estimate a random coefficients logit model of the firm's environmental compliance decision that controls for unit level variation in choice sets and compliance costs and accommodates correlation across choices made by the same decision maker. I find that deregulated plants in restructured electricity markets were less likely to choose more capital intensive compliance options (which are associated with more significant emissions reductions) as compared to physically similar plants that are either subject to rate regulation or publicly owned. These results are robust to alternative specifications and assumptions about how environmental compliance decisions are made.

In the second part of the paper, I assess the practical implications of interactions between economic regulation and environmental compliance. The econometric model is used to simulate the environmental compliance decisions that plant managers most likely would have made if all electricity generators had faced the same economic regulatory regimes in their respective electricity markets. Two counterfactuals are constructed: one in which all coal plants in the emissions trading program are subject to electricity rate regulation, and one in which all facilities operate as deregulated entities supplying restructured electricity markets. This exercise allows me to isolate the effects of economic regulation in the electricity industry on emissions permit market outcomes.

An immediate finding is that deregulated facilities in restructured electricity markets account for a smaller share of permitted emissions in equilibrium when the distortionary effects of asymmetric economic regulation are removed. This has two potentially important implications for permit market efficiency. First, if economic regulation plays a significant role in determining which plants invest in pollution control equipment, plants with relatively low abatement costs may not be the plants investing in abatement. Consequently, total compliance costs may not be minimized. However, simulation results indicate that neither comprehensive rate regulation nor comprehensive deregulation would have significantly reduced compliance costs in aggregate.

The second cause for concern pertains to the nature of the pollution problem. Epidemiological studies consistently find a statistically significant association between NO_x related air quality problems and increased mortality and morbidity (Michelle L. Bell et al. 2004; World Health Organization 2003). Because NO_x is a "nonuniformly mixed" pollutant, health and environmental damages caused by NO_x emissions depend significantly on the location of the source. Consequently, although the total quantity of NO_x emissions is exogenously determined by the emissions cap, the total damages will depend on the spatial distribution of the permitted emissions.[1]

Simulation results indicate that asymmetric economic regulation in the electricity industry may have increased the health and environmental damages caused by NO_x emissions permitted under the NO_x Budget Program. The vast majority of deregulated electricity producers are located in the Northeast and Mid-Atlantic regions where ozone nonattainment problems are particularly severe. Simulated levels of investment in capital intensive compliance options increase among deregulated facilities when asymmetries in economic regulation are eliminated. This shifts more than 100 tons of daily NO_x emission (or approximately 2-4 percent of permitted emissions) out of relatively high damage areas and into regions where the pollution will likely

[1] The NO_x Budget Program does not explicitly account for spatial variation in marginal damages from emissions; a permit can be used to offset a unit of NO_x emissions, regardless of where in the program region the unit is emitted.

cause less damage.[2] To put this in perspective, a recent study finds that shifting 11 tons of NO_x emissions from a "high damage" area (a location in Maryland) to a "low damage" area (a location in North Carolina) over a 10-day period could avoid the loss of approximately one life on average (Denise L. Mauzerall et al. 2005).

This paper contributes to our understanding of how electricity producers in different industry environments respond to incentives created by market-based environmental regulation. In controversial court rulings, federal proposals to achieve further reductions in electricity sector emissions using market based policy instruments have recently been the source of much controversy. At issue in much of this litigation is the appropriateness of emissions permit trading when damages vary significantly across states. In the particular case of NO_x, federal regulators have been asked to reanalyze proposed interstate trading programs "from the ground up" and carefully reevaluate whether emissions in each affected state would remain below a level that avoids "significant contribution" to nonattainment.[3] The analysis presented here demonstrates the importance of representing economic regulation and industry structure when modeling permit market outcomes and associated damages. A failure to do so will likely result in underestimation of the share of emissions permits flowing to restructured electricity markets.

These findings are also germane to strands of both the industrial organization and environmental economics literatures that consider the effects of economic regulation and industry structure on firms' investment decisions.[4] 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 (see, for example, Toshi Arimura 2002; Elizabeth M. Bailey 1996; Nathaniel O. Keohane 2006; Paul M. Sotkiewicz 2003). Because the Acid Rain Program started before restructuring began, these papers use 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. I revisit this question postrestructuring, 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 academic literature that considers market based regulation of nonuniformly mixed pollutants. Studies that evaluate the merits of designing CAT programs to account for spatial variation in emissions damages typically assume strict cost minimization on behalf of all firms (Alex Farrell, Roger Raufer, and Robert Carter 1999; Alan J. Krupnick et al. 2000; US EPA 1998c). Findings presented here imply that variation in industry structure and economic incentives are an important consideration when analyzing how alternative permit market designs might affect spatial patterns of investment and emissions.

The following section introduces the NO_x Budget Program. Section II provides an overview of electricity market regulation and restructuring in the United States. Section III describes the data and presents summary statistics. Section IV introduces a model of the firm's compliance decision. Estimation results are presented in Section V. In Section VI, I use the econometric model to assess the practical implications of the relationship between economic regulation and environmental compliance. Section VII concludes.

[2] During the design and ex ante analysis stages of the NO_x Budget Program, the US Environmental Protection Agency identified states that contributed more to the ozone transport problem. Seven states were identified as having particularly high ozone-related damages (CT, DE, MA, MD, NJ, NY, PA) as compared to other states in the program (US Environmental Protection Agency (US EPA) 1998c).

[3] North Carolina v. US EPA, No. 05-1244 (D.C. Cir. Jul. 11, 2008).

[4] In the environmental economics literature, previous work has demonstrated that, in theory, economic regulation can undermine the ability of a pollution permit market to operate efficiently (see Douglas R. Bohi and Dallas Burtraw 1992; Jay S. Coggins and Vincent H. Smith 1993; Don Fullerton, Shaun P. McDermott, and Jonathan P. Caulkins 1997).

I. The NO_x Budget Program

The NO_x Budget Program (NBP) is an emissions trading program that limits emissions of NO_x from large stationary sources in 19 eastern states. These NO_x emissions contribute to the formation of ozone.[5] High ambient ozone concentrations have been linked to increased mortality, increased hospitalization for respiratory ailments, irreversible reductions in lung capacity, and ecological damages (Bell et al. 2004; US EPA 2006).

The NBP was primarily designed to help Northeastern and Mid-Atlantic states attain federal ozone standards. When the NBP was promulgated, significant portions of the Northeast, Mid-Atlantic, and parts of the Midwest were failing to meet federal standards (Ozone Transport Assessment Group (OTAG) 1997). Several states that were in attainment with federal ozone standards when the NBP was introduced were included in the program because their NO_x emissions contribute to the nonattainment problems of downwind states.[6] Although some states contribute significantly more than others to ozone nonattainment problems, the NBP applies uniform stringency across all 19 states. A pollution permit can be used to offset a ton of NO_x emissions, regardless of where the emissions occur.

The NBP mandated a dramatic reduction in average NO_x emissions rates.[7] In the period between when the rule 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 regulation. To comply, firms can do one or more of the following: purchase permits to offset emissions exceeding their allocation, install one or more NO_x control technologies, or reduce production at dirtier plants during ozone season.

Two factors that are likely to significantly influence a manager's choice of environmental compliance strategy are the up-front capital costs and anticipated variable compliance costs (i.e., compliance costs incurred per unit of electricity produced). The capital costs, variable operating costs, and emissions reduction efficiencies associated with different compliance alternatives vary significantly, both across NO_x control technologies and across generating units with different technical characteristics. The specific NO_x control options available to a given unit also vary across units of different vintages and boiler types. Compliance options that incorporate Selective Catalytic Reduction (SCR) technology can reduce emissions by up to 90 percent. NO_x emissions rates can be reduced by 35 percent through the adoption of Selective Non-Catalytic Reduction Technology (SNCR). Precombustion control technologies such as low NO_x burners (LNB) or combustion modifications (CM) can reduce emissions by 15 to 50 percent, depending on a boiler's technical specifications and operating characteristics.

Figure 1 provides a graphical illustration of the compliance choice set corresponding to one particular unit (or boiler) in the data. 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 compliance strategies involve retrofitting the unit with a NO_x control technology or combination of technologies. Variable costs v include the costs of operating the control technology plus the costs of purchasing permits to offset uncontrolled emissions. The broken

[5] NO_x emissions also contribute to the formation of particulate matter, contribute to acid rain in some mountain regions, and exacerbate eutrophication problems. However, it was ozone nonattainment problems that served as the primary impetus for the NBP.

[6] Surface ozone concentrations are a function of both in situ ozone production and pollutant transport; both are significantly affected by prevailing meteorological conditions.

[7] Preretrofit emissions rates at affected coal plants were, on average, three and a half times higher than the emissions rate on which the aggregate cap was based (0.15 lbs NO_x/mmbtu).

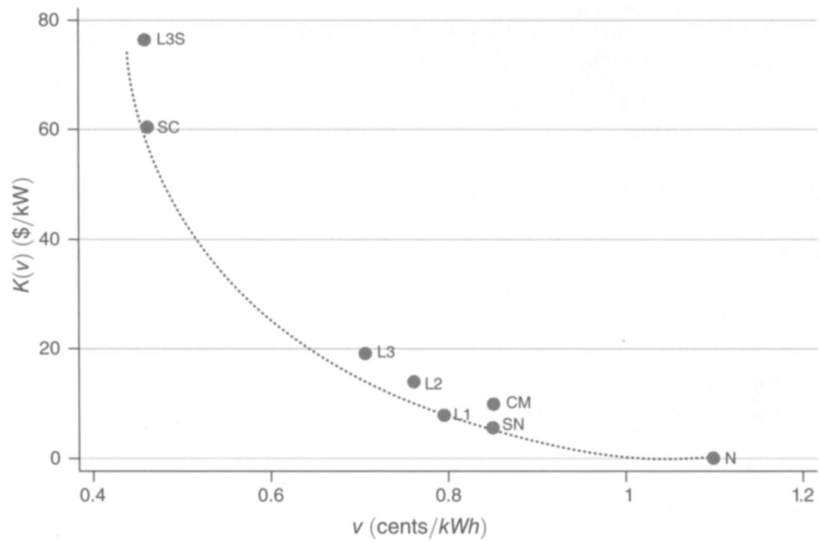

Figure 1. Estimated NO_x Control Costs for a 512 MW T-Fired Boiler

Notes: In generating this figure, I assume that the unit will achieve perfect compliance. This assumption finds empirical support (US EPA 2005). I further assume that compliance will not be achieved through reductions in output. Support for this assumption is provided in the Web Appendix. Section III includes a detailed discussion of how these cost estimates are generated.

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

line represents a quadratic frontier or envelope function $K(v)$ fit to the points in this choice set that minimize capital costs K given v. Points to the right of the frontier are not cost minimizing.

II. Electricity Industry Restructuring and the Environmental Compliance Decision

Until the mid 1990s, over 90 percent of electricity in the United States was generated by vertically integrated investor owned utilities (IOUs), most of which were operating as local monopolies regulated by state public utility commissions (PUCs). The remainder was supplied by government entities or cooperatives. Traditionally, the most widely used form of regulation has been "rate of return" regulation: rates are set by regulators so as to allow the utility to recover prudently incurred operating costs and earn a "fair" rate of return on its rate base (i.e., the value of assets less depreciation).

Proponents of electricity industry restructuring argued that replacing rate hearings and fuel adjustment clauses with the discipline of a competitive market would increase efficiency and reduce electricity prices. In the 1990s, large discrepancies in electricity rates across states stimulated initiatives to restructure the power generation sector. All 50 states held hearings to assess the benefits of restructuring. By 2001, 19 states with relatively high electricity rates had passed restructuring legislation. After the California's electricity crisis, momentum behind restructuring broke down.

A. *Environmental Compliance Choices at Regulated Plants*

In regulated (or unrestructured) electricity markets, firms' environmental compliance decisions were likely influenced by PUC regulations governing capital and variable cost recovery. Harvey Averch and Leland Johnson (1962) illustrate how, under certain conditions, a firm subject to rate of return regulation may find it profitable to employ more capital relative to variable inputs (including labor and fuel) than is consistent with cost minimization.[8] Firms participating in the NBP that are subject to economic regulation in their respective electricity market might be relatively more inclined to pursue more capital intensive environmental compliance options.

In each of the seven states in the NBP that did not enact electricity industry restructuring, firms have successfully sought rate base adjustments in order to recover costs of capital required to invest in NO_x control equipment and to allow shareholders to earn a return on equity.[9] Regulated utilities operating plants in restructured electricity markets have also won approval from state regulators for rate adjustment clauses or rate freezes that allow them to recover costs associated with purchasing NO_x permits, operating pollution control equipment, and preapproved construction work in progress.

B. *Environmental Compliance Choices at "Deregulated" Plants*

In the absence of a regulator willing to guarantee cost recovery, the consequences of making large capital investments in pollution control equipment were highly uncertain. I use the term "deregulated" to refer to plants in restructured electricity industries who must recover capital investments in wholesale electricity markets. In several of the states that have passed restructuring legislation, deregulated nonutility generators own and operate the majority of coal fired capacity.

The introduction of the NBP increased wholesale electricity prices through its effect on the variable (per kWh) compliance costs of the price setting or "marginal" generating units. Because coal fired units typically have low operating costs relative to other units supplying the market, they are typically inframarginal. Price setting (or marginal) generating units tend to be oil and gas plants with significantly lower environmental compliance costs as compared to coal. Managers of coal units in restructured electricity markets anticipated that the NBP induced increases in average wholesale electricity prices would not fully reflect their relatively high environmental compliance costs. As one industry analyst observed "coal plants will still be dispatched, but their (profit) margins will be less." [10]

[8] Paul L. Joskow (1974) provides an excellent survey of the earlier Averch and Johnson (AJ) literature. Attempts to empirically test the AJ effect using data from the US electricity industry have met with mixed results. Leon Courville (1974), Robert Spann (1974), and Paul M. Hayashi and John M. Trapani (1976) find support for the hypothesis, whereas William Boyes (1976) does not.

[9] These rate cases tend to be very comprehensive; they cover costs of maintaining and upgrading infrastructure, providing customer service, and attracting a competent workforce, in addition to costs related to environmental compliance. 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 (National Association of Regulatory Utility Commissioners 2004). For details on specific PUC rulings in these cases, 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.

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

In general, all restructured electricity markets have been characterized by uncertainty about future market conditions and the ease with which capital investments can be recovered. In the midst of this uncertainty, compliance strategies that rely to a significant extent on purchasing permits (versus making large capital investments) have option value. If a manager chooses to rely on the permit market for compliance, she has more control over the environmental compliance costs she will incur going forward.[11] This option value did not exist at regulated plants that were guaranteed to recover compliance costs.

Finally, higher costs of capital made securing financing for a large capital investment in NO_x control technology relatively more costly for many firms in restructured electricity markets (Business Wire 2003; *Platts Utility Environment Report* 2002e).[12] 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.[13] 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 noncore activities have fallen drastically, most regulated utilities have been affected to a far lesser extent (Business Wire, 2001; Business Wire, 2004a; Business Wire, 2004b; Mergent Online, all years).[14]

C. *Environmental Compliance Choices and Public Power*

Thirteen percent of the coal fired generation regulated under the NBP is owned and operated by public entities, including municipal utilities, public utility districts, rural cooperatives and the Tennessee Valley Authority (TVA). These agencies operate on a nonprofit basis and are controlled by an elected or appointed board. The environmental compliance decisions of these agencies were likely affected by operating conditions and mandates unique to public power.

Public power enjoys significant cost of capital advantages. There are several reasons for this. First, public power agencies generally operate in a very low risk environment, particularly as compared to their deregulated counterparts in restructured electricity markets. Second, federal utility debt carries with it an implicit US Treasury guarantee, while state and local public power agencies are often eligible for low interest long term loans from the federal government. Finally, all state and local power agencies are authorized to issue tax exempt bonds to construct and improve their infrastructure. Federal taxpayers, through reduced tax revenues, effectively subsidize a share of the interest costs on these bonds.[15]

The hypothesis that the type of economic regulatory regime in which a coal plant is operating will significantly affect the choice of how to comply with the NBP follows directly from the preceding discussion of asymmetries in electricity industry regulation and investment incentives. A more formal economic model of the relationship between economic regulation and environ-

[11] For example, in hours when electricity prices are too low to allow variable compliance costs to be recovered, the firm can choose not to operate.

[12] *Business Wire*. 2003. "Fitch Revises Northeast Utilities' Rating Outlook to Negative." May 19. *Platts Utility Environment Report*. 2002e . "IP&L granted 8 percent rate of return on \$260M clean coal projects." November 29, 4.

[13] 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).

[14] *Business Wire*. 2001. "Fitch Expects to Rate PSI Energy First Mortgage Bonds 'A-.'" June 18. *Business Wire*. 2004a. "Fitch Ratings Affirms Cinergy & Subsidiaries; Outlook Stable." April 13. *Business Wire*. 2004b. "Fitch Upgrades Alabama Power Company Sr Unsecured Rating to 'A+'." November 12.

[15] This subsidy could potentially affect the environmental compliance decisions of public power authorities. Whereas tax exempt bonds can be used to finance investment in pollution control equipment, permit purchases are likely to be ineligible for the same preferential tax treatment. The IRS explicitly prohibits earning arbitrage profits on tax exempt bonds. Issuing tax exempt bonds to cover expected variable costs before they are actually realized increases arbitrage potential. Consequently, tax exempt bonds cannot be issued until variable costs are fixed or determinable (Gary Bornholdt, Joint Committee on Taxation. Personal communication. September 2007).

mental compliance is presented in Appendix A. This model assumes managers minimize costs subject to regulatory constraints; this assumption might not hold true for all firms in the sample.[16] The model is presented as a possible, but not essential, motivation for the empirical analysis.

D. *Identifying an Effect of Economic Regulation on the Compliance Decision*

Ideally, in the interest of empirically testing for a relationship between economic regulation and the environmental compliance decision, coal fired generators would be randomly assigned to economic regulatory regimes. This would guarantee that the type of electricity market environment in which a coal plant is operating was predetermined and completely exogenous to firms' environmental compliance decisions. Clearly, this controlled experiment did not occur. Although electricity industry restructuring did generate an unprecedented amount of variation in how electricity producers are regulated, the restructuring process was not random. However, three factors make it possible to causally relate differences in economic regulation to differences in environmental compliance choices.

First, the timing of the NBP and electricity industry restructuring was such that a state's restructuring status was completely predetermined. All 19 states that were ultimately included in the NBP 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 DC. By 2000, the remaining seven states had all officially resolved not to move forward with electricity restructuring (Energy Information Administration 1999a).[17] Consequently, when the courts upheld the NBP and the terms of environmental compliance were finally established, all plant managers knew what kind of economic regulation they would face for the foreseeable future.

Second, the factors that determined a state's restructuring decision are independent of the factors that determine environmental compliance costs at coal fired generating units. In particular, states that elected not to restructure had relatively low electricity rates to begin with, such that the potential gains from restructuring were questionable (James B. Bushnell and Catherine D. Wolfram 2005). Low rates were a consequence of having access to cheap hydro and coal generation, limited sunk investments in nuclear power, or fewer long term fixed price contracts with independent power producers that had been encouraged under the 1978 Public Utility Regulatory Policy Act. The availability of profitable nearby export markets also appears to have increased the probability that a state would pass restructuring legislation (Amy W. Ando and Karen L. Palmer 1998). Finally, California's experience with electricity industry restructuring was enough to dissuade any states who had yet to pass legislation. Momentum behind restructuring fell flat after California's electricity crisis in 2000.

Third, there is significant overlap in the distribution of the variables that determine environmental compliance costs at coal fired generation facilities. This facilitates comparisons between plants in different economic regulatory regimes with very similar operating characteristics and compliance costs. Empirical analysis presented in the following section demonstrates these physical similarities.

Almost all of the states that did not pass industry restructuring legislation are southern states. One might be concerned that uncontrolled for differences across northern and southern NBP

[16] Cost minimization may not be an accurate representation of the objectives of all managers in the data. Several alternative management objectives have been suggested in the literature, including maximizing returns on investment, maximizing output, maximizing revenues, and maximizing reliability of supply (Elizabeth M. Bailey and John C. Malone 1970).

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

states might explain observed differences in compliance choices. It is therefore worth considering what potentially significant variables are omitted from the analysis and what sort of bias their omission might introduce. One potentially important factor is politics. By most measures, northeastern states are ranked more highly than southeastern and many midwestern states in terms of political commitment to making environmental quality improvements. Stronger political support for environmental quality improvements in the Northeast would likely result in more investment in pollution abatement in these states, hereby introducing bias *against* the null hypothesis. A second possible difference that could introduce bias in the opposite direction has to do with rates of return. If rates authorized by southern public utility commissions are relatively high, this would suggest that regional differences in capital investments in NO_x abatement technologies would have persisted even in the absence of restructuring. To investigate this possibility, authorized rates of return at natural gas utilities in the states subject to the NBP are examined over the study period. Although average authorized rates are slightly higher among southern states, the difference is neither economically nor statistically significant.[18]

III. A First Look at the Data

The data set includes the 702 coal fired generating units that are regulated under the NO_x Budget Program. Units are classified as regulated, deregulated, and public.[19] "Regulated" units are investor owned and subject to rate regulation. These units are located in both restructured and unrestructured states. The "deregulated" units are owned and operated by non–rate regulated, private entities and are located in states that have passed restructuring legislation. Units classified as "public" are owned and operated by cooperatives, municipal agencies, state power authorities, or the Tennessee Valley Authority.

I do not directly observe the variable compliance costs and fixed capital costs or the postretrofit emissions rates that plant managers anticipated when making their decisions. I can, however, generate 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 NO_x regulations, the Electric Power Research Institute (EPRI) developed software to generate cost estimates for all major NO_x control options available to coal fired boilers, conditional on unit and plant level characteristics.[20] The software has been used not only by plant managers, but also by regulators to evaluate proposed compliance costs for the utilities they regulate (Richard Himes 2004; Daniel Musatti 2004; Ravi Srivastava 2004).[21] I use this software to estimate capital and variable compliance costs at the unit level (EPRI, 1999b).

[18] *Public Utilities Fortnightly* published annual surveys of authorized rates of return for state regulated energy utilities over the period 1999–2005. Rates of return were approved in natural gas rate cases in all NBP states except West Virginia. The average authorized rate of return over this period was slightly higher in southeastern states (10.98 percent) versus northern states (10.64 percent), although the difference between the two averages is not statistically significant (the p-value for the one-sided hypothesis test is 0.06). This evidence is far from conclusive. However, it does help to diminish concerns that regional differences in authorized rates of return would have yielded the observed differences in compliance choices.

[19] To determine the regulatory status of each unit, data were collected from several sources. First, data were extracted from the "Electricity utility plants that have been sold and reclassified as nonutility plants" tables in the *Electric Power Monthly*, March volumes, published by the Energy Information Administration (various years). Additional data were compiled from the 8-K form that many investor owned utilities were required to file with the Securities and Exchange Commission once restructuring legislation took effect in their states. These forms often explain the how assets would be regulated in a restructured environment. If there was any ambiguity about regulatory treatment of a facility, clarification was made with the appropriate Public Service Commission.

[20] 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.

[21] Himes, Richard. Electric Power Research Institute. Telephone conversation. July 12, 2004. Musatti, Daniel. US Environmental Protection Agency. E-mail correspondence. June 7, 2004. Srivastava, Ravi. US Environmental

Cost estimation requires detailed data on over 60 unit and plant level operating characteristics (such as boiler dimensions, preretrofit emissions rates, plant operating costs, etc.). The software is used to identify which NO_x control technologies are compatible with which boilers, and to generate boiler specific variable costs and fixed cost estimates for each viable compliance option. Postretrofit emissions rates are estimated using the EPRI software, together with EPA's Integrated Planning Model (US EPA 2003). These data and cost estimation methods are described in detail in the Data Appendix.

A. *Summary Statistics*

Figure 2 summarizes the NO_x control technology retrofits reported by coal fired electricity generators in the NBP between 2000 and 2004. These graphs are generated using data from 632 regulated, deregulated, and publicly owned units.[22] Note that a significantly larger proportion of the coal capacity owned by regulated utilities and public agencies has been retrofit with SCR (the control option that is the most capital intensive and delivers the most significant emissions reductions). Conversely, a greater proportion of capacity owned by deregulated firms has not been retrofitted. These units presumably rely entirely on the permit market to achieve compliance. Alternative approaches to reducing NO_x emissions, such as combustion modifications or SNCR, are 75–80 percent less capital intensive than SCR technologies, but they are much less effective at reducing NO_x emissions. These more intermediate NO_x control options were relatively more popular among deregulated units. The 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 the three groups of units. One appealing explanation is 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 among deregulated and publicly owned plants.

A closer look at the data suggests this is not the case. Table 1 presents summary statistics for unit level operating characteristics that significantly determine compliance choice sets and costs: nameplate capacity, plant vintage, preretrofit heat rates, preretrofit emissions rates, and preretrofit summer capacity factors. Overall, these unit level characteristics are distributed similarly within each of the three subpopulations of coal fired units. Table 2 summarizes the engineering estimates of NO_x control costs (estimated at the unit level) for the most commonly adopted NO_x control technologies and the "no retrofit" option.[23] Note the considerable overlap in the distributions of these costs across the three groups.

A second possible explanation for differences in technology adoption patterns has to do with preexisting differences in environmental regulatory stringency. Table 1 indicates that preretrofit NO_x emissions rates were lower on average among deregulated plants. Because of persistent air quality problems in the Northeast, several states with restructured electricity markets have historically been subject to more stringent environmental regulations prior to the NBP. If generators in restructured markets were more likely to have carried out pollution control retrofits prior to 2000, this could explain differences in compliance decisions observed after 2000.

Protection Agency. Telephone interview. May 12, 2004.

[22] Compliance costs for the remaining 80 coal fired units cannot be generated due to data limitations. These units appear on states' lists of coal fired units in the NO_x SIP Call but appear only sporadically in EPA, EIA and Platts databases. These units appear to be smaller on average. The mean capacity is 52 MW compared to the sample average summer capacity of 272 MW (all 80 of the excluded units reporting). The mean age is 21 years, compared to a sample average of 36 years (only 75 of the excluded units reporting).

[23] These calculations assume a permit cost of \$2.25/lb NO_x. Permits started trading in early 2001 in anticipation of the NBP. Futures permit prices in the years leading up to the NBP averaged \$2.25/lb NO_x.

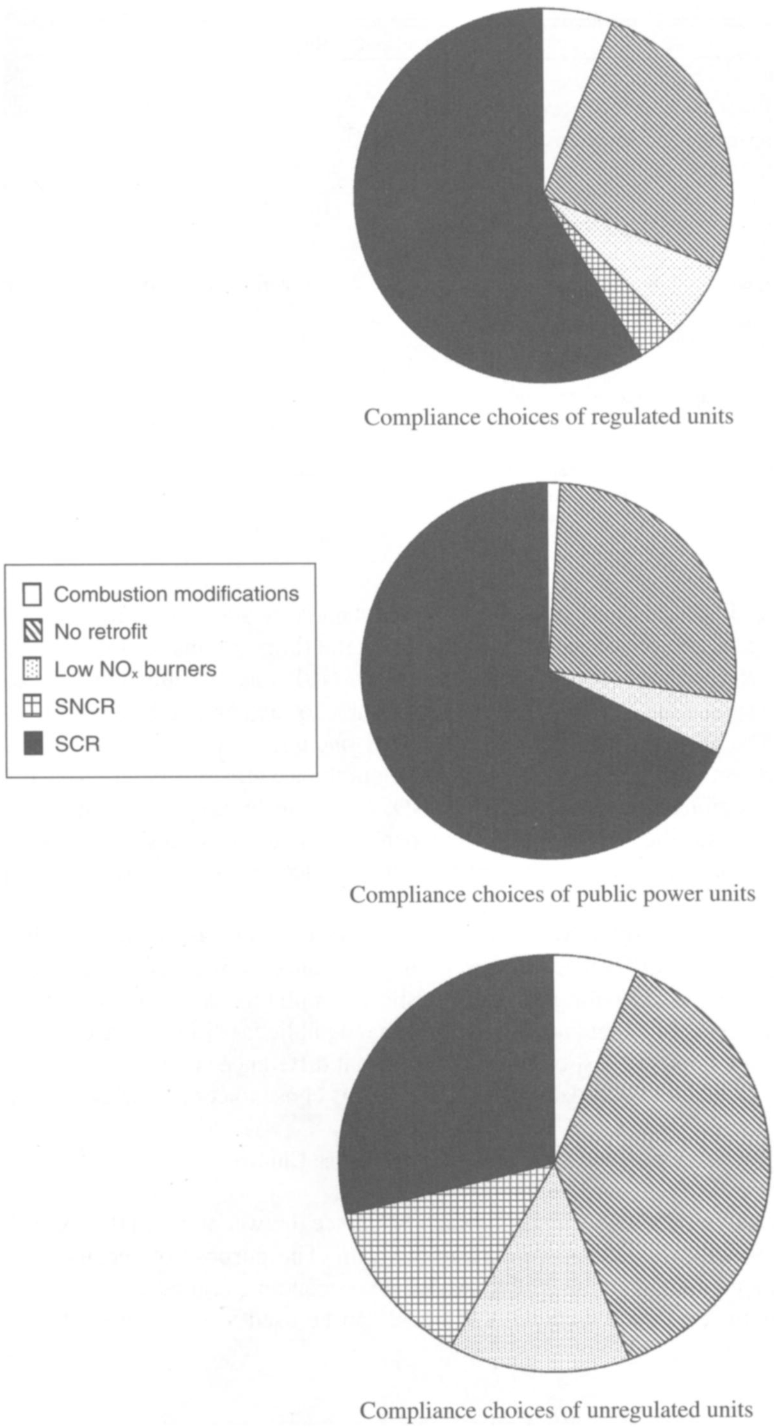

FIGURE 2. COMPLIANCE CHOICES BY REGULATORY REGIME

(*as a percentage of MW installed capacity*)

Table 1—Summary Statistics by Unit Type

Variable	Deregulated	Regulated	Public
Number of units	227	292	113
Number of facilities	86	100	34
Number of companies/public agencies	35	33	16
Capacity (MW)	248	314	208
	(212)	(279)	(227)
Unit age (years)	37	36	36
	(11)	(11)	(11)
Pre-retrofit heat rate (kWh/btu)	12,120	11,866	12,184
	(4,747)	(5,956)	(1,898)
Pre-retrofit NO_x emissions (lbs/mmBtu)	0.48	0.54	0.55
	(0.21)	(0.22)	(0.23)
Pre-retrofit summer capacity factor (percent)	63	67	68
	(17)	(14)	(13)

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

The data indicate that it is unlikely that differences in technology adoption patterns can be explained by differences in compliance choice sets. In fact, the three groups of units are very similar in terms of the NO_x controls installed at the time the NBP was promulgated.[24] Table 3 summarizes information about the NO_x control options available to each unit at the time the NBP was officially upheld. The most alternatives available to any one unit is ten.[25] 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 NO_x control technologies. Although compliance choice sets do vary significantly across units (depending on unit operating characteristics and preexisting NO_x controls), the average size and content of choice sets are very similar across subpopulations.

Taken together, these data suggest that variation in compliance costs and available compliance options cannot entirely explain differences in observed compliance choices across electricity market regimes. Because physical operating characteristics, compliance costs, and choice sets are similarly distributed across rate regulated, deregulated, and public facilities, these covariates can be controlled for in an empirical test of the hypothesis that differences in economic regulatory incentives play a significant role in determining how plants chose to comply with the NBP.

IV. An Empirical Model of the Compliance Choice

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 has affected the environmental compliance choice. Second, the model can be used to assess the efficiency implications of the empirical findings.

[24] Only two units, both deregulated, had installed SCR prior to 2000. These two units are excluded from the analysis as there was no longer a compliance choice to make.

[25] In total, 15 different compliance strategies are observed in the data. These strategies are: combustion modification, combustion modification combined with low NO_x burners, four different types of low NO_x burner technologies, low NO_x burners combined with SCR, overfire air, overfire air combined with low NO_x burners, SCR, SNCR, SCR with overfire air, SNCR with overfire air, low NO_x burners, SCR and overfire air, no retrofits.

TABLE 2—COMPLIANCE COST SUMMARY STATISTICS FOR COMMONLY SELECTED CONTROL TECHNOLOGIES

	Capital cost ($/kW)			Operating costs (cents/kWh)		
	Deregulated	Regulated	Public	Deregulated	Regulated	Public
Combustion modification	12.63	12.46	11.85	0.91	1.05	1.08
	(4.19)	(5.02)	(4.20)	(0.37)	(0.39)	(0.38)
Low NO_x burners	19.10	17.20	18.79	0.83	0.86	0.85
	(5.89)	(3.16)	(4.20)	(0.30)	(0.23)	(0.21)
SNCR	17.36	15.69	25.24	0.95	1.00	1.06
	(14.45)	(14.59)	(30.85)	(0.42)	(0.36)	(0.23)
SCR	71.21	68.38	81.01	0.53	0.50	0.59
	(22.17)	(19.91)	(30.90)	(0.35)	(0.16)	(0.22)
No retrofit	0	0	0	1.25	1.34	1.50
				(0.58)	(0.57)	(0.67)

Note: Standard deviations are in parentheses.

This empirical analysis focuses exclusively on the compliance choices that were made in the years leading up to the compliance deadline (2000–2004).[26] Because it is difficult to identify the precise point in this four-year period at which an environmental compliance decision was made, these choices are modeled as static decisions.[27]

The manager of unit n faces a choice among J_n compliance strategy alternatives (indexed by $j, j = 1, \ldots, J_n$). Plant managers are assumed to choose the compliance strategy that minimizes the unobserved latent value 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 technology installation, and a constant term α_j that varies across technology types:

$$C_{nj} = \alpha_j + \beta_n^v v_{nj} + \beta_n^K K_{nj} + \beta_n^{KA} K_{nj} Age_{nj} + \varepsilon_{nj}, \tag{1}$$

$$\text{where} \quad v_{nj} = (V_{nj} + \tau m_{nj}) Q_n.$$

An interaction term between capital costs and demeaned plant age is included in the model because older plants can be expected to weigh capital costs more heavily as they have less time

[26] 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 (Nancy Rose and Paul L. Joskow 1984). Fortunately, the NO_x Budget Program eliminates temporal variation in technology adoption opportunity by design; every coal plant manager was forced to make a decision on 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.

[27] Because of labor shortages and a limited number of tower-cranes 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 (John E. Cichanowicz 2004; *Midwest Construction*. 2005. "Top Projects Completed." June 1, 15). Consequently, reported retrofit dates are a very noisy measure of when the compliance decision was actually made. 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 NO_x SIP Call program had taken effect. However, because more pollution control equipment was installed than is needed to comply with SIP Call, the decisions analyzed here will determine regional emissions patterns to a significant extent for the foreseeable future (*Natural Gas Week*. 2004. "Extra Credits Will Keep Fuel Switching Down." April 23.).

TABLE 3—CHOICE SET SUMMARY STATISTICS BY UNIT TYPE

	Deregulated	Regulated	Public
# Choices	6.8	6.6	6.4
	(1.9)	(2.0)	(2.0)
NO_x Control Technology	percent choice sets including technology		
Combustion modification/ overfire air	96%	98%	97%
LNB	67%	60%	46%
SNCR	90%	96%	92%
SCR	100%	100%	100%

Notes: Standard deviations in parentheses. Percentages indicate the percentage of units that had a particular type of technology in their feasible choice set.

to recover these costs. The variable cost (per kWh) of operating the control technology is V_{nj}. The variable cost associated with offsetting emissions with permits is equal to the product of the permit price τ and the postretrofit emissions rate m_{nj}. Expected average annual compliance costs are obtained by multiplying estimated per kWh variable costs by expected seasonal production Q_n.[28]

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 NO_x control technology. A stochastic component ε_{nj} is included in the model to capture the idiosyncratic effect of unobserved factors.

This reduced form model has just enough structure to capture the differences in responsiveness to capital costs and variable costs across units. It is straightforward to map the parameters in this empirical model to the parameters of a more structured theoretical model introduced in Appendix A. More precisely, the cost coefficients can be viewed as functions of a plant's cost of capital, cost recovery parameters, and the scale parameter of the extreme value distribution.

A. *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 units. The ε_{nj} are assumed to be *iid* extreme value and independent of the covariates in the model.[29]

Let y_n be a scalar indicating the observed compliance choice, $y_n \in \{1, \ldots, J_n\}$. 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} unit will choose compliance strategy i is:

$$P(y_n = i \mid X_n, \beta) = \frac{e^{\beta' X_{ni}}}{\sum_{j=1}^{J_n} e^{\beta' X_{nj}}}. \tag{2}$$

[28] Expected seasonal electricity production (Q_n) 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 (EPRI 1999a). I adopt this approach and use the historical average of a unit's past summer production levels ($\overline{Q}_n$) to proxy for expected ozone season production. Empirical support for this assumption is presented in the Web Appendix.

[29] 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. These choice probabilities are very similar to the standard logit choice probabilities derived under assumptions of random utility maximization (Daniel L. McFadden 1973).

B. *The Random Coefficient Logit Model*

The CL model, although a good starting point, is not the best choice for this application. 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. In fact, there are likely to be factors affecting how plant managers weigh compliance costs in their decision-making that we do not observe. To the extent that variation in unobserved determinants of the compliance choice is significant, errors will be correlated and CL coefficient estimates will be biased.[30]

The second limitation has to do with the panel structure of data used to estimate the model. While I observe only 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 a boiler (or boilers) and a generator. There can be as many as ten boilers at a given plant. The 632 boilers in the sample represent 221 power plants owned by 84 different companies or public agencies. Presumably, the same plant managers made compliance decisions for all boilers at a given plant. It is also possible that compliance decisions could be correlated across facilities owned by the same parent company. The CL model cannot accommodate this correlation across choice situations associated with the same decision maker.

The random-coefficient logit (RCL) model, a generalization of the CL model, does a better job of accommodating unobserved response heterogeneity and relaxes the *iid* error structure assumption. 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, thereby accommodating any unobserved heterogeneity in responses to changes in compliance costs.[31]

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 β vectors are allowed to vary across managers according to the density $f(\beta \mid b, \Omega)$ but are assumed to be constant across choices made by the same manager.[32] 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.

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

$$P(Y_m = \mathbf{i} \mid X_m, \beta_m) = \prod_{t=1}^{T_m} \frac{e^{\beta_m' X_{mit}}}{\sum_{j=1}^{J_{mt}} e^{\beta_m' X_{mjt}}}, \tag{3}$$

where $\mathbf{i}$ is a $T_m \times 1$ dimensional vector denoting the set of observed choices made by manager m. Here, the n subscript denoting the unit has been replaced by a unique mt pair. Unconditional

[30] Examples of potentially significant omitted factors include plants' costs of capital, managerial attitudes towards risk, contractual arrangements, and PUC cost recovery rules. All of these factors are likely to vary across facilities.

[31] 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 (with costs entering the model as negative numbers). Model specifications that assumed a log-normal distribution for cost coefficient failed to converge. Problems with using log-normal distributions are well documented in the literature (David Brownstone and Kenneth E. Train 1999; David A. Hensher and William Greene 2002; David Revelt and Train 1998).

[32] Alternatively, beta vectors can be held constant across all units and 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 (Chad Whiteman 2005). A model where cost coefficients are allowed to vary across parent companies, but not across plants owned by the same parent, is also estimated. Results from estimating this model are summarized in the Web Appendix.

choice probabilities $P(Y_m = \mathbf{i})$ are derived by the integrating conditional choice probabilities over the assumed bivariate normal distribution of the unobserved random parameters.

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

$$(4) \qquad l(b,\Omega) = \sum_{m=1}^{M} \ln \int_{-\infty}^{\infty} \prod_{t=1}^{T_m} \frac{e^{\beta_m' X_{mit}}}{\sum_{j=1}^{J_{mt}} e^{\beta_m' X_{mjt}}} f(\beta \mid b,\Omega) d\beta.$$

Unconditional choice probabilities are approximated numerically using simulation methods. The RCL estimates are those that maximize the simulated likelihood function. For each decision maker, I simulate 1,000 draws from the distribution of β. The value of the integrand in (4) is calculated for each decision maker, for each draw. To increase the accuracy of the simulation, I take pseudo-random Halton draws from the distribution $f(\beta \mid b,\Omega)$ (Chandra Bhat 1998; Train 1999). 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.[33] To estimate standard errors, the robust asymptotic covariance matrix estimator is used (McFadden and Train 2000).

C. *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. Previous work demonstrates how these simulated maximum likelihood estimates 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 (Greg M. Allenby and Peter E. Rossi 1999; Revelt and Train 2000; Train 2003).

Let the density describing the distribution of β in the population of managers be denoted $f(\beta \mid b,\Omega)$. The probability of observing the m^{th} manager making the choice she 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 $P(Y_m \mid X_m, b, \Omega) = \int P(Y_m \mid X_m, \beta) g(\beta \mid b, \Omega) d\beta$. Let $h(\beta \mid Y_m, X_m, b, \Omega)$ denote the distribution of β_m in the subpopulation of plant managers who, when faced with the compliance choice set described by X_m, would choose the series of strategies denoted $\mathbf{i}$. Applying Bayes's rule, this manager specific, conditional density of β_m can be expressed:

$$(5) \qquad h(\beta \mid Y_m, X_m, b, \Omega) = \frac{P(Y_m \mid X_m, \beta) f(\beta \mid b, \Omega)}{P(Y_m \mid X_m, b, \Omega)}.$$

These conditional distributions, which are implied by the simulated maximum likelihood estimates of the population distribution parameters and the choices we observe, are used to evaluate how functions of model parameters are distributed in the population.

[33] Gauss code is based on that developed by Train, Revelt, and Paul A. Ruud (1999).

V. Estimation

Tests of the hypothesis introduced in Section II can be formulated as tests of whether the model coefficients differ significantly across regulated, deregulated, and publicly owned plants. Unfortunately, these tests are complicated by the fact that neither the CL nor the RCL models are completely identified. The standard approach to estimating these models involves normalizing the scale parameter of the extreme value distribution to one. If in fact the residual variance differs across groups, the coefficient estimates to be compared are confounded with scale factor differences.

Unobserved factors affecting compliance decisions likely vary across regulated, deregulated, and publicly owned electricity generating units. For example, unobserved differences in PUC cost recovery rules potentially influenced compliance decisions of regulated facilities, whereas unobserved differences in costs of capital and debt:equity ratios could have played a more important role in explaining the compliance decisions of deregulated facilities. Differences in coefficient estimates across groups could be indicative of differences in residual variances, differences in the impact of covariates on the compliance choice, or some combination of the two.

There are at least two approaches to addressing this identification problem. Both will be implemented here. The first involves reparameterizing the underlying model so as to allow residual variation to vary across groups (Joffre D. Swait and Jordan J. Louviere 1993). The scale parameter s_n is defined to be:

$$s_n = 1 + \delta^{DEREG} D_n^{DEREG} + \delta^{PUB} D_n^{PUB}, \tag{6}$$

where $D_n^{DEREG} = 1$ if unit n is deregulated and zero otherwise. The variable D_n^{PUB} indicates public ownership. The standard normalization is adopted for regulated plants (i.e., $s_n = 1$ for all regulated units). The parameters δ^{DEREG} and δ^{PUB}, estimated jointly with the model coefficients, determine the relative scale of the residual variance across groups.

Estimation of a model that allows the scale parameter to vary across groups facilitates a test of the null hypothesis that both the residual variances and the model coefficients are equal across subgroups. Paul D. Allison (1999) proposes a test to determine whether the heteroskedasticity parameters differ sufficiently across groups so as to render conventional comparisons of coefficient vectors inappropriate. Results from this test are summarized below. Unfortunately, these results are difficult to interpret because testing proceeds under the assumption that the values of the underlying coefficients in the model do not differ across groups (i.e., the assumption that we ultimately want to test).

A second approach to investigating whether coefficients differ across groups involves estimating the model separately for each group. Because tests of the significance of a given coefficient are valid within each group, it is possible to learn something from a comparison of separately estimated models.

A. *Conditional Logit Model Results*

The CL model is first estimated using pooled data from all units. The most restrictive specification forces all parameters to be equal across all groups. Less restrictive specifications allow the scale parameters and/or cost coefficients to vary across groups. The null hypothesis that both the scale parameters and the model coefficients are equal across groups is rejected (p-value < 0.01). Column (1) in Table 4 reports results from a specification which includes the two scale parameters and an interaction between capital costs and the deregulated dummy variable.[34] The inclusion of additional interaction terms does not significantly improve the model fit.

All of the technology fixed effects are negative and significant at the one percent level.[35] This suggests that, relative to the baseline option of no retrofit, managers were biased against retrofits in general (controlling for costs). The coefficient on variable compliance costs is statistically significant at the one percent level and has the expected negative sign, indicating that expected variable compliance costs are an important factor affecting firms' compliance choices.

The capital cost coefficient is positive and statistically indistinguishable from zero (p-value $= 0.67$). However, the interaction between capital costs and D^{DEREG} is statistically significant and negative. When an interaction term between the capital cost variable and D^{PUB} is included in the model, the coefficient is not statistically significantly different from zero.[36] These results are consistent with the hypothesis that capital costs play a more important role in determining compliance decisions of deregulated plants, as compared to their regulated or publicly owned counterparts. The capital cost/age interaction term is also negative and statistically significant at the five percent level suggesting that older plants with shorter investment horizons weighed capital costs more heavily in their compliance decision.

The second and third columns of Table 4 report results from estimating the model separately for regulated and deregulated units.[37] A likelihood ratio test favors this less restrictive approach over the specification in column (1) (p-value < 0.01). Note that the vectors of coefficients corresponding to regulated and deregulated plants differ by more than a multiplicative scalar. This suggests that differences in residual variances cannot account for all differences in coefficient estimates.

The coefficient on variable compliance costs is statistically significant at the one percent level and has the expected negative sign for both groups of facilities. When the model is estimated using only data from deregulated plants, the coefficient on capital costs is statistically significant and has the expected negative sign. When the model is estimated using data from regulated units (who are presumably more certain of capital cost recovery) the capital cost coefficient estimate is positive and is not statistically significantly different from zero.

[34] The inclusion of the two heteroskedasticity parameters improves the fit of the model significantly (the LR test statistic is 16.91 with 2 d.f.). The estimates of the δ^{DEREG} and δ^{PUB} parameters are 0.32 and -0.33, respectively. One interpretation of these results is that the residual variance among unregulated plants is 32 percent larger than that of regulated plants, whereas the residual variance among publicly operated plants is 33 percent smaller. If the equality constraints imposed by this specification are incorrect, the estimates of δ^{DEREG} and δ^{PUB} will be biased.

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

[36] Untestable identification assumptions make it difficult to meaningfully interpret these coefficients. For example, if the residual variances do not actually differ, the inclusion of δ_{UNREG} and D_{PUB} will bias estimates of differences in coefficients across groups downward. 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, although it is also possible to find an effect when no effect exists (Glen Hoetker 2003).

[37] The model was also estimated using data from public units only. Because of the small number of units (only 34 facilities) these results are less emphasized. Estimation results are qualitatively similar to the regulated case. The estimated capital cost coefficient is -0.08 with a standard error of 0.09 (i.e., not statistically significant). The variable cost coefficient is -1.57 with a standard error of 0.34.

Table 4—Estimation Results

	Conditional logit			Random parameter logit		
	Pooled (1)	Deregulated (2)	Regulated (3)	Pooled (4)	Deregulated (5)	Regulated (6)
Technology type constants						
α_{POST}	−2.31***	−1.50***	−2.67***	−2.46***	−0.41	−3.15***
	(0.21)	(0.37)	(0.39)	(0.30)	(0.61)	(0.60)
α_{CM}	−2.06***	−1.54***	−1.91***	−2.06***	−1.48***	−2.08***
	(0.16)	(0.29)	(0.26)	(0.18)	(0.39)	(0.29)
α_{LNB}	−2.03***	−1.55***	−2.21***	−1.97***	−0.96	−2.42
	(0.19)	(0.37)	(0.30)	(0.22)	(0.46)	(0.31)
Annual compliance costs ($100,000)						
Mean	−0.31***	−0.19***	−0.28***	−0.96***	−1.21***	−0.72***
β^V	(0.05)	(0.07)	(0.12)	(0.14)	(0.25)	(0.14)
Capital cost ($100,000)						
Mean	0.01	−0.06**	0.01	−0.23***	−0.78***	−0.11
β^K	(0.02)	(0.03)	(0.06)	(0.05)	(0.21)	(0.07)
K × Age	−0.02**	−0.04	−0.02	−0.14***	−0.25***	−0.09**
	(0.01)	(0.02)	(0.03)	(0.02)	(0.07)	(0.04)
K × D^{DEREG}	−0.06***	—	—	−0.11 **	—	—
	(0.01)			(0.05)		
σ^V	—	—	—	0.68***	1.68***	0.42***
				(0.11)	(0.35)	(0.11)
σ^K	—	—	—	0.23***	0.52***	0.10***
				(0.05)	(0.13)	(0.03)
δ^{DEREG}	0.32**	—	—	0.19	—	—
	(0.15)			(0.14)		
δ^{PUB}	−0.33***	—	—	−0.51***	—	—
	(0.08)			(0.07)		
Number of units	632	227	292	632	227	292
log-likelihood	−808.1	−339.1	−359.7	−685.6	−276.1	−320.7

Notes: Robust standard error are in parentheses.
*** Indicates significance at 1 percent.
** Indicates significance at 5 percent.

B. *Random Coefficient Logit Results*

In the RCL model specifications, the coefficients β^K and β^v are permitted to vary randomly across plant managers.[38] Column 4 of Table 4 presents results from estimating a specification that allows the scale parameter to vary across subgroups and permits the capital cost coefficient to differ between deregulated and regulated or publicly owned plants using pooled data.[39] Columns 5 and 6 report results from estimating the RCL model separately using data from regulated and deregulated

[38] Here, I assume that the two random coefficients are independent. In the Web Appendix, a less restrictive specification that can accommodate correlated random parameters is estimated. The null hypothesis of independence cannot be rejected.

[39] Alternative specifications were also estimated. For example, models that included interactions between group indicator variables and variable costs, and interactions between the D^{PUB} and capital costs, were evaluated. The model presented in Table 6 outperformed these other specifications in nested LR tests.

units, respectively.[40] The two model specifications can be compared using a nested likelihood ratio test. The more restrictive model is rejected in favor of the specification that allows all coefficients to vary across groups.[41] Estimates of the standard deviations of the two random coefficients are statistically significant across all specifications, suggesting that there is unobserved variation in how plants weigh variable operating costs and capital costs in their compliance decisions.[42]

Consistent with the CL estimation results, the null hypothesis that both the scale parameters and the model coefficients are equal across groups is easily rejected. When all coefficients are constrained to be equal across all groups but scale parameters are allowed to vary, both heteroskedasticity parameters are statistically significant at the one percent level. A comparison of columns 5 and 6 of Table 4 suggests that it is unlikely that scale parameter differences can fully explain differences in coefficient estimates; coefficients differ by more than a multiplicative scalar. The mean of the variable compliance cost coefficient is negative and significant at the one percent level across all RCL model specifications. The capital cost/age interaction term is also consistently negative and significant, suggesting that capital costs more significantly affected compliance decisions at older units, presumably due to shorter investment time horizons.

These RCL parameter estimates offer further support for the hypothesis that capital costs factored more significantly into the environmental compliance decisions of deregulated plants. In model (4), the interaction between the D^{DEREG} indicator and the capital cost variable is statistically significant and negative. When the model is estimated using data from regulated markets, the point estimate is -0.11 and is not statistically significantly different from zero (p-value 0.12). Conversely, when the model is estimated using data from deregulated units, the point estimate for the capital cost coefficient is -0.78 and statistically significant at the one percent level.

The estimated technology fixed effects vary considerably across RCL specifications. In particular, the postcombustion control indicator is significantly more negative among regulated facilities. One possible explanation is that managers of regulated plants are inherently more biased against postcombustion NO_x control technology retrofits, although there is no obvious reason why this should be the case. To investigate this result further, specifications (5) and (6) are reestimated subject to the restriction that the postcombustion fixed effect are equal across groups. The capital cost coefficient remains statistically significant and negative among deregulated plants. This coefficient is not statistically significant among regulated plants.

The RCL estimates of the moments of the distribution of β in these subpopulations of units are combined with data on observed compliance choices in order to derive the parameters of manager specific conditional distributions. The population parameter estimates $\hat{b}$ and $\hat{\Omega}$ are substituted into (5) and the first and second moments of these conditional distributions are calculated (using the same matrix of Halton draws that were used to estimate (4)). Table 5 presents the summary statistics for the estimated moments of these 222 manager specific distributions using both sets of RCL coefficient estimates presented in Table 4.

If the RCL models are correctly specified, the average of the means of the manager specific conditional distributions (the $\overline{\beta}_m s$) should be close (if not equal) to the estimated population means. These results offer no evidence to suggest that the normality assumptions are inappropriate. The standard deviations of the conditional means are significantly larger than

[40] When only data from public units were used to estimate the model, the small sample size (and presumably insufficient variation) results in nonconvergence.

[41] To carry out this test, specification (4) is estimated using pooled data from deregulated and regulated units. The likelihood ratio test value is 177, which is larger than the chi-square statistic with one degree of freedom at any reasonable level of significance.

[42] 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.

TABLE 5—MEANS AND STANDARD DEVIATIONS OF MANAGER SPECIFIC COEFFICIENT DISTRIBUTIONS

Coefficient	Model (4)		Model (5)		Model (6)	
	Population parameter estimate	Conditional parameter estimates	Population parameter estimate	Conditional parameter estimates	Population parameter estimate	Conditional parameter estimates
Regulated units						
β^v	−0.96	−0.89	—	—	−0.72	−0.71
	(0.68)	(0.39)			(0.42)	(0.24)
β^K	−0.23	−0.24	—	—	−0.11	−0.11
	(0.20)	(0.11)			(0.08)	(0.05)
Deregulated units						
β^v	−0.81	−0.76	−1.21	−1.13	—	—
	(0.57)	(0.34)	(1.68)	(1.14)		
β^K	−0.28	−0.25	−0.78	−0.82	—	—
	(0.17)	(0.13)	(0.52)	(0.36)		
Publicly owned units						
β^v	−1.98	−2.18	—	—	—	—
	(1.39)	(0.71)				
β^K	−0.48	−0.40	—	—	—	—
	(0.70)	(0.32)				

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

C. *A More Intuitive Interpretation of the Coefficient Estimates*

Coefficient ratios eliminate the scale factor that confounds direct comparisons of coefficient estimates across groups. The ratio $\beta^K : \beta^v$ is of particular interest as it can be interpreted, under certain assumptions, as an estimate of the discount rate (see Appendix A). Ideally, one would want to formally test whether this ratio of cost coefficients differs significantly across subpopulations. However, because the supports of the estimated distributions of the β^v parameter overlap zero for both subpopulations, the variance of this ratio is not well defined. Consequently, conventional approaches to estimating the standard error of ratio statistics cannot be used.[43]

I compute this ratio using the estimated means of the manager specific conditional distributions (versus the estimated parameters of the population distribution). Point estimates of this ratio are 0.48 and 0.21 among managers of deregulated and regulated units, respectively. Although these estimates differ by a substantial margin, they are too noisy to be meaningfully compared (standard deviations are 5.2 and 0.29, respectively).

[43] Neither the delta method nor bootstrap methods can be used because the variance of the ratio is not well defined. One common approach to circumventing these problems involves assuming that the coefficient in the denominator is fixed (David I. Layton and G. Brown 2000). However, Train and Garrett Sonnier (2005) show 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 researchers have reparameterized the RCL model so as to identify the ratio directly. Rather than set the scale parameter to one, one of the coefficients in the model is restricted to equal one (Train and Malvyn Weeks 2005). This approach is inappropriate for this application, where the capital cost and variable cost coefficients are likely to differ across groups.

The elasticities implied by the parameter estimates provide another intuitive measure of the responsiveness of firms' environmental compliance decisions to changes in operating and capital costs. Elasticities for each choice situation are calculated using the point estimates of the means of the corresponding manager specific conditional distributions. Table 6A presents average own-cost elasticities with respect to both capital costs and average ozone season variable compliance costs for the most commonly observed compliance choices. Elasticities reported in the top panel are those implied by parameter estimates from specifications (5) and (6).

On average, estimated choice probabilities among deregulated plants are more sensitive to changes in compliance costs in general, and capital costs in particular. Most striking are the differences associated with more capital intensive compliance options. For example, a one percent increase in the capital cost of an SCR retrofit, holding all else equal, is associated with a 9.7 percent in the probability that SCR will be chosen among deregulated units. This elasticity averages less than one percent among regulated plants. Note that the corresponding variable operating cost elasticities are more similar across groups (−2.15 and −1.02, respectively). Table 6B reports the elasticities implied by the more restrictive RCL specification (4) which forces technology fixed effects to be equal across groups. The implied own-capital cost elasticities are still larger in absolute value among deregulated plants, although the differences across groups are less striking.[44]

Finally, the RCL coefficient estimates are used to simulate predicted choice probabilities. A representative choice set is constructed using the average capital and variable costs associated with the seven compliance options that are most prevalent among observed choices. Predicted choice probabilities are generated using the RCL coefficient estimates associated with both rate regulated and rate deregulated regimes. In the rate regulated case, RCL coefficient estimates imply choice probabilities of 21 percent and 23 percent for SCR retrofits and no retrofit, respectively. Choice probabilities associated with deregulated units are 12 percent and 33 percent for SCR retrofits and the no retrofit option, respectively. Similar results are obtained when estimates from column (4) are used to simulate these (and other) compliance choice probabilities.[45]

D. *Further Robustness Tests*

Results from the main model specifications presented above are robust to the choice of optimization routine, the number of draws used in simulations, and alternative assumptions about what level of management presides over environmental compliance decisions. I have also estimated model specifications in an effort to tease apart the relative importance of different factors that may explain why rate regulated plants might be more likely to adopt more capital intensive compliance options. Finally, I have ascertained that results are robust to the presence of preexisting SO_2 reduction technologies. The Web Appendix summarizes these results from estimating alternative specifications and additional robustness tests in detail. This appendix also presents results from estimating less restrictive specifications of the RCL model and provides empirical support for the assumption that production levels are independent of the chosen compliance alternative.

[44] Recall that the technology fixed effects take on very different values when the model is estimated separately using data from regulated and deregulated units. If these differences have more to do with the multicollinearity of capital costs and technology fixed effects than with true differences in technology specific biases across groups, the elasticity estimates reported in Table 6A will overstate the true differences in capital cost elasticities across regulated and deregulated units.

[45] The probability of adopting SCR is 23 percent for the deregulated coefficients and 11 percent using rate regulated coefficients. The probability of relying entirely on the permit market for compliance is 23 percent for both groups.

TABLE 6A—OWN-CAPITAL COST AND ANNUAL COMPLIANCE COST ELASTICITIES
(*Unrestricted RCL Model*)

	Own capital cost elasticities		Own annual cost elasticities	
Technology	Deregulated	Regulated	Deregulated	Regulated
Combustion modification	−1.21	−0.12	−3.47	−2.25
	(1.43)	(0.19)	(6.96)	(3.50)
Low NO_x burners	−1.65	−0.18	−1.39	−0.87
	(2.51)	(0.37)	(3.52)	(2.25)
No retrofit	—	—	−8.32	−6.30
			(14.71)	(9.06)
SCR	−9.73	−0.90	−2.15	−1.02
	(9.32)	(1.08)	(3.95)	(0.78)
SNCR	−1.43	−0.16	−4.53	−5.48
	(1.10)	(0.27)	(8.92)	(7.16)

TABLE 6B—OWN-CAPITAL COST AND ANNUAL COMPLIANCE COST ELASTICITIES
(*Restricted RCL Model*)

	Own capital cost elasticities		Own annual cost elasticities	
Technology	Deregulated	Regulated	Deregulated	Regulated
Combustion modification	−0.36	−0.29	−2.17	−2.84
	(0.49)	(0.39)	(3.00)	(4.73)
Low NO_x burners	−0.50	−0.36	−0.78	−1.12
	(0.80)	(0.90)	(1.56)	(3.08)
No retrofit	—	—	−3.98	−8.39
			(6.70)	(12.65)
SCR	−2.98	−2.04	−1.41	−1.24
	(2.71)	(2.20)	(1.47)	(1.24)
SNCR	−0.45	−0.37	−3.00	−6.99
	(0.41)	(0.46)	(3.80)	(10.14)

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

VI. Simulating Counterfactual Environmental Compliance Choices

Empirical results presented in the previous section suggest that the economic regulatory regime significantly affects plants' environmental compliance decisions. In particular, compliance choices at deregulated plants appear to have been substantially more sensitive to capital cost considerations (as compared to regulated and publicly owned plants).

These results raise two potential policy concerns. First, heterogeneity in economic regulation may lead to deviation from the first-best cost minimizing set of compliance choices. The second potential problem has to do with the fact that NO_x is a nonuniformly mixed pollutant. The health and environmental damages caused by a unit of NO_x emissions vary significantly with the location of the source (Cynthia Y.C. Lin, Daniel Jacob, and Arlene Fiore 2001; Mauzerall et al. 2005). Ozone nonattainment problems tend to be more severe in states that have restructured electricity markets, largely due to preexisting differences in levels of industrial activity, population densities, and meteorological conditions. When the NBP was upheld by the courts in 2000, 16 percent of counties in the states that had passed restructuring legislation were failing to attain federal ozone standards. In the NBP states that did not restructure their electricity industries, only two percent of counties were out of attainment. Consequently, health and environmental benefits associated with NO_x reductions at deregulated plants are likely to be larger on average as compared to regulated plants.

In this section, I use the econometric model to assess the extent to which heterogeneity in economic regulation has undermined the effectiveness of market based environmental regulation. I simulate the compliance choices that these plant managers most likely would have made in three scenarios: a benchmark scenario that assumes the observed economic regulatory structure, a counterfactual scenario that assumes all units are subject to rate regulation, and a second counterfactual scenario that assumes all units are deregulated.

The simulations involve several steps:

1. To account for sampling error, Z random draws from the estimated sampling distribution of the appropriate set of parameters are taken. Let Θ^z represent the z^{th} draw.[46]

2. For each manager, for each parameter vector Θ^z, R random draws of β from the appropriate subpopulation density $f(\beta \mid \theta^z)$ are taken. Once this step is complete, there are a total of $Z \times R$ coefficient vectors $\mathbf{b}_{mrk}$ for each manager.

3. Equilibrium outcomes are simulated for each of $Z \times R$ matrices of coefficients. Simulations begin by setting the permit price τ equal to 0.

4. For each unit, choice probabilities are approximated for all available compliance choices. These probabilities are conditional on the prevailing permit price τ, the coefficient vector b_{mrk}, and the observed choice characteristics X_{mit}.

5. Unit level compliance choices for all choice situations faced by each manager (*firm*) are predicted. Managers are assumed to choose the compliance strategies with the highest estimated probability.

6. Ozone season emissions (measured in lbs of NO_x) and engineering estimates of compliance costs associated with the predicted choices are calculated and summed across units.

7. If the total quantity of emissions equals the cap, τ is the equilibrium price and the simulation stops.

8. If the total quantity of emissions exceeds (is less than) the cap, τ is increased (decreased) by \$0.01. Steps 4–6 are repeated.[47]

This procedure is repeated $Z \times R$ times for each of three scenarios. Equilibrium outcomes are summarized in Table 7.

Several results from these simulation exercises are worth highlighting. First, the permit price required to induce sufficient investment in pollution abatement is highest in the counterfactual

[46] Θ^z is a vector of parameters. For example, if the compliance choice of a regulated unit is being simulated, Θ contains the technology fixed effects and the coefficient on the interaction between age and capital cost that correspond with regulated units and a draw of cost coefficients from the distribution of β^V and β^K in the subpopulation of regulated units.

[47] If this iterative procedure arrives at a point where it is vacillating around 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 7—COMPLIANCE COSTS AND EMISSIONS ASSOCIATED WITH OBSERVED AND COUNTERFACTUAL COMPLIANCE CHOICES

	Implied by observed choices	Benchmark simulation	All deregulated simulation	All regulated simulation
Permit price	$2.25	$2.54	$4.91	$2.18
($/lb NO_x)		($0.36)	($1.45)	($0.26)
Regulated units				
NO_x emissions	2,171	2,139	2,370	2,285
(tons/day)		(90)	(125)	(73)
NPV costs	$6.3	$6.5	$5.7	$6.0
($1,000,000,000)		($0.31)	($0.36)	($0.28)
Deregulated units				
NO_x emissions	1,583	1,607	1,377	1,461
(tons/day)		(90)	(124)	(73)
NPV costs	$1.9	$1.9	$2.8	$2.5
($1,000,000,000)		($0.28)	($0.46)	($0.26)
Total (regulated + deregulated)				
NPV costs	$8.2	$8.4	$8.5	$8.5
($1,000,000,000)		($0.23)	($0.40)	($0.18)
NO_x emissions	3,754	3,746	3,747	3,746
(tons/day)				

Note: Simulations use sampling distributions of RCL coefficients estimated separately for regulated and deregulated units.

scenario that assumes all facilities are deregulated. When all agents are relatively biased against capital intensive compliance options, a higher permit price is required to incentivize sufficient capital investment in pollution controls. Conversely, when all facilities are assumed to be subject to rate regulation (and presumably guaranteed recovery of prudent capital investments in pollution control equipment), a lower permit price induces sufficient investment in abatement equipment.

Somewhat surprisingly, simulated aggregate compliance costs are not significantly affected by heterogeneity in economic regulation. Estimates of the total cost of achieving the cap in the counterfactual scenarios are all very similar. In the simulations that assume all units are subject to rate regulation, simulated compliance choices are more capital intensive relative to the set of compliance choices that are consistent with pure cost minimization. Conversely, in the simulations that assume all units are deregulated, there is an overreliance on the less capital intensive compliance choices (vis-à-vis pure cost minimization).

Perhaps the most important implication of the results presented in Table 7 is that heterogeneity in economic regulation substantially affects the spatial distribution of permitted NO_x emissions. Simulated emissions at deregulated units are ten to 15 percent lower under symmetric economic regulation as compared to the benchmark (symmetric) case. To more clearly illustrate the potential health implications of these findings, Table 8 summarizes these results in terms of "high" and "low" damage areas. In the design stages of the NBP, regulators identified states that they believed would contribute the most to ozone nonattainment problems (US EPA 1998c).[48] I

[48] When promulgating the rules that created the NO_x Budget Program, regulators considered dividing the affected region into trading zones in order to make a distinction between states that contribute more to the ozone transport problem and those whose wind patterns would be less likely to exacerbate nonattainment problems. Seven states were identified as being associated with particularly high ozone related damages: Connecticut, Delaware, Massachusetts,

Table 8—Distribution of Simulated Emissions across "High" and "Low" Damage Areas

	Benchmark simulation 6.8	All deregulated simulation	All regulated simulation
High damage	1,641	1,419	1,496
	(90)	(122)	(73)
Low damage	2,105	2,328	2,250
	(90)	(124)	(73)
Percent in high damage	44 percent	38 percent	40 percent
	(2.4 percent)	(3 percent)	(2 percent)

Notes: "High damage" states are: CT, DE, MA, MD, NJ, NY, PA. These are states identified by the US EPA as having the most significant contribution to ozone nonattainment problems. These are also states that suffered disproportionately from ozone nonattainment problems at the time the NBP was introduced.

separate the emissions occurring in these seven "high damage" states from those occurring in the remaining 12 states. Under symmetric economic regulation, daily NO_x emissions in the high damage region are between 145 and 220 tons below the benchmark emissions levels.[49] Put differently, when heterogeneity in economic regulation is removed, roughly two to four percent of permitted emissions shift from high to low damage regions.

Precisely estimating the health and environmental implications of the simulation results is well beyond the scope of this paper. The photochemical reactions that convert NO_x to ozone, the meteorological conditions that determine patterns of ozone transport, and the epidemiological relationships between ozone exposure and adverse health impacts are both complex and controversial. However, findings from past studies can help put these simulation results in perspective. First, a comprehensive regulatory impact analysis carried out by the US EPA in 1998 estimated that reducing daily ozone season NO_x emissions in the Eastern United States by 6,100 tons per day would reduce premature deaths by approximately 370 annually (US EPA 1998). A more recent study by Mauzerall et al. (2005) estimates that a shift of 11 tons of NO_x per day from a relatively high damage area (Maryland) to a lower damage location (North Carolina) over a 10- day period results in the loss of approximately one human life on average. Taken together, this evidence suggests that shifting more than 100 tons of NO_x emissions each day (throughout ozone season) from high to low damage areas could reduce the mortality and morbidity effects of the permitted emissions.

VII. Conclusion

In the four years between the ratification of the NO_x Budget Program (NBP) and the deadline for full compliance, managers of over 700 rate regulated, deregulated, and publicly owned coal fired generating units had to make costly environmental compliance decisions. Plant managers could choose from a menu of compliance options that varied significantly in terms of capital intensity and emissions reduction efficiency. Because the NBP was introduced following a piecemeal restructuring of the electricity industry, facilities with very similar physical operating

Maryland, New Jersey, New York, and Pennsylvania (US EPA 1998). These states also had higher ozone monitor readings, on average, as compared to other states in the program. To generate the results in Table 8, I define these seven states as "high damage" and the rest as "low damage."

[49] The effects of heterogeneity in economic regulation on the level of emissions in high and low damage areas may be overestimated. The emissions predicted conditional on observed choices overpredict actual emissions. Appendix B investigates these discrepancies in detail.

characteristics and NO_x control options made their environmental compliance choices in very different electricity market environments. This creates an unusual opportunity to investigate the effects of economic regulation and electricity market structure on firms' technology adoption decisions and emissions permit market outcomes

Using detailed data from the NO_x Budget Program, I estimate an econometric model of the environmental compliance decision which controls for unit level variation in NO_x control options and compliance costs. The model allows firms subject to different forms of economic regulation to weigh variable and capital costs differently in their environmental compliance choices. I find that deregulated generators in restructured electricity markets were less likely to install more capital intensive pollution control technologies as compared to similar plants that are either subject to rate regulation or publicly owned and operated. These results are robust to a variety of specifications and assumptions about how environmental compliance decisions are made.

The econometric model is used to investigate the broader implications of these empirical findings. I simulate permit market equilibria under observed economic conditions (the benchmark) and under scenarios in which the distortionary effects of asymmetric economic regulation are removed (the counterfactuals). Somewhat surprisingly, the total cost of meeting the emissions cap does not decrease under either counterfactual scenario relative to the benchmark case. However, the spatial distribution of investment in pollution abatement (and thus emissions) is substantially affected by asymmetries in economic regulation. Counterfactual emissions among deregulated units are ten to 14 percent lower than benchmark emissions; well over 100 tons of daily NO_x emissions shifts from deregulated facilities to rate regulated or publicly owned facilities. This implies that asymmetric economic regulation in the electricity industry has likely increased the total damages caused by permitted NO_x emissions.

It is worth being explicit about what this analysis does and does not imply for existing and future market based environmental regulation of the electricity sector. We can conclude that heterogeneity in electricity sector regulation played an important role in determining pollution abatement decisions in the NBP. Furthermore, simulation results suggest that asymmetric economic regulation had an impact on the spatial distribution of investment in abatement and permitted emissions. Health and environmental damages would likely have been less under symmetric economic regulation, with relatively more of the permitted NO_x emitted in relatively low damage areas.

Based on this analysis alone, we cannot ascertain which of the two counterfactual scenarios (i.e., comprehensive industry restructuring or comprehensive rate regulation) would have led to greater total social benefits under the NO_x Budget Program. Finally, one should certainly not conclude from this analysis that the NO_x Budget Program is, on balance, a failed program. On the contrary, the program has reduced daily NO_x emissions in the Eastern United States by an estimated 5,700 tons per day, yielding significant health and environmental benefits at lower than expected costs (US EPA 2007).

Appendix A: A Model of Compliance Cost Minimization

For all units in the sample, $K_n'(v) < 0$; $K_n''(v) \geq 0$. For ease of exposition, the compliance decision is represented as a choice of a point on the continuous, convex cost frontier $K_n(v)$.

The Compliance Choice of a Deregulated Firm in a Restructured Electricity Market.—Three independent system operators operate centralized power markets in the region regulated by the NBP.[50] Real time and day ahead wholesale energy markets operate as uniform price auctions

[50] These are the New York ISO, the New England ISO and the "PJM" (Pennsylvania, New Jersey, and Maryland) ISO.

wherein the price is set by the marginal bidder. The manager's compliance choice of v_n can affect the unit's position in the dispatch order (relative to other units supplying the market). If the unit is never the marginal (price setting) unit, an increase in v_n will have no effect on the wholesale electricity price.

Let $\overline{P}_n$ represent the average wholesale electricity price paid to unit m. Let ψ_n represent the fraction of variable compliance costs that is not reflected in $\overline{P}_n$:

$$1 - \frac{\partial \overline{P}_n}{\partial v_n} = \psi_n. \tag{A1}$$

The compliance choices of plants in this sample will rarely affect the average electricity price $\overline{P}_n$ that the firm receives in the wholesale market because coal fired generating units are typically inframarginal. For a unit that is never marginal, $\psi_n = 1$.

I assume that the manager chooses v_{ni} to minimize levelized annual compliance costs subject to the constraint that the chosen compliance strategy must lie on the least cost compliance frontier $K_n(v_{ni})$:

$$\min_v LAC_n = \psi_n v q_n + l_n K_n(v), \tag{7}$$

$$l_n = \frac{r_n(1 + r_n)^{T_n}}{(1 + r_n)^{T_n} - 1}. \tag{8}$$

The initial capital investment $K_n(v)$ is multiplied by the levelized annual cost factor l_n. This yields the annual capital amortization over a period T_n. The annuity interest rate r_n is a weighted average of the cost of debt and the opportunity cost of equity (i.e., the firm's cost of capital).

Minimization of the above constrained optimization problem implies:

$$K_n'(v) = -\frac{\psi_n Q_n}{l_n} \tag{A3}$$

The manager will want to choose the point on the compliance cost frontier such that the (negative) slope is equal to the ratio of the cost of an incremental change in variable compliance costs and the cost of an incremental change in fixed compliance costs.[51] This ratio can be interpreted as approximately equal to the firm's discount rate r_n scaled by ψ_n when the firm's investment is infinitely long:

$$\frac{dK_n(v)}{dv} = \psi_n \frac{(1 + r_n)^{T_n} - 1}{r_n(1 + r_n)^{T_n}} \tag{9}$$

$$\lim_{T_n \to \infty} \frac{dK_{nj}}{dV} = \psi_n r_n.$$

[51] This implies that an increase in the cost of capital will, ceteris paribus, be associated with a less capital intensive compliance choice. Similarly, a decrease in ψ_n would lead to a less capital intensive compliance choice. This assumes that restructured markets are closely monitored, so that sellers need to justify bids with operating costs.

For a plant that is always inframarginal and that has an infinitely long investment horizon, the ratio of the variable cost and capital cost coefficient is equal to the firm's discount rate r_n.

The Compliance Choices of a Regulated Investor Owned Utility.—I assume that managers at regulated utilities comply with environmental regulations while minimizing compliance costs borne by shareholders (or taxpayers in the case of government owned facilities). Following the example of Fullerton et al. (1997), I define parameters that describe how compliance costs are shared between ratepayers and shareholders. Let θ_n^V represent the portion of variable compliance costs born by the utility and its shareholders versus the ratepayers. Similarly, let θ_n^K be the portion of capital investments in NO_x control technology that the utility cannot pass through to ratepayers.

I assume that the manager chooses v to minimize levelized annual compliance costs subject to the constraint that the chosen compliance strategy must lie on the least cost compliance frontier $K_n(v)$:

$$\min_v LAC_n = \theta_n^v v Q_n + \theta_n^K l_n K_n(v). \tag{A5}$$

Minimization of the above constrained optimization problem implies:

$$K_n'(v) = -\frac{\theta_n^v Q_n}{\theta_n^K l_n}. \tag{A6}$$

Assuming an infinitely long time horizon, the manager will want to locate at the point on the compliance cost frontier where the slope is equal to r_n scaled by the ratio of the cost recovery parameters:

$$\frac{dK}{dV} = \frac{\theta_n^V}{\theta_n^K l} = \frac{\theta_n^V}{\theta_n^K}\frac{(1+r_n)^{T_n}-1}{r_n(1+r_n)^{T_n}}$$

$$\lim_{T\to\infty}\frac{dK}{dV} = \frac{\theta_n^v}{\theta_n^K}\, r_n.$$

If variable and capital costs are treated symmetrically by regulators, this will be r_n. If cost recovery rules favor capital intensive compliance options, this ratio will exceed r_n.

The Compliance Choices of a Public Power Agency.—I assume that public power agencies choose the compliance strategy that maximizes the welfare of their consumers subject to the environmental compliance constraint. I assume that customers bear variable compliance costs in full. Capital investments in pollution control equipment are financed by tax exempt bonds; the implicit subsidy per dollar of financing is s_n.

I assume that the agency chooses v_{ni} to minimize levelized annual compliance costs subject to the constraint that the chosen compliance strategy must lie on the least cost compliance frontier $K_n(v_{ni})$:

$$\min_v LAC_n = vQ_n + (1 - s_n)l_n K_n(v). \tag{A7}$$

Table A1—Observed and Predicted Average NO_x Emissions (*tons per day*)

	Observed	Predicted | Observed choices	Predicted | Predicted choices
Regulated units NO_x emissions (tons/day)	1,811	2,171	2,139 (90)
Deregulated units NO_x emissions (tons/day)	1,305	1,583	1,607 (90)
Publicly owned units NO_x emissions (tons/day)	475	550	—
Regulated + deregulated NO_x emissions (tons/day)	3,116	3,754	3,746 (8)

Notes: Standard deviations are in parentheses. The predicted emissions associated with observed choices defines the cap for the simulations. Simulated emissions are not allowed to exceed this cap. Thus, on average, simulated emissions associated with simulated choices are slightly below emissions associated with observed choices.

Minimization of the above constrained optimization problem implies:

$$K_n'(v) = -\frac{Q_n}{(1-s_i)\,l_n}. \tag{A8}$$

Assuming an infinitely long time horizon, the manager will want to locate at the point on the compliance cost frontier where the slope is equal to r_n scaled by the ratio of the cost recovery parameters:

$$\frac{dK}{dV} = \frac{1}{(1-s_i)\,l_n} = \frac{1}{(1-s_i)}\,\frac{(1+r_n)^{T_n}-1}{r_n(1+r_n)^{T_n}}$$

$$\lim_{T\to\infty}\frac{dK}{dV} = \frac{r_n}{(1-s_n)}.$$

Appendix B: Comparing Predicted and Observed Emissions

Significant discrepancies exist between emissions observed during the 2004–2006 ozone seasons (the first two years during which full compliance was mandated under the NBP) and emissions predicted by the model conditional on observed compliance choices. Table A1 summarizes observed emissions (averaged across the 2004 and 2005 seasons) and predicted emissions for the three subpopulations of units.

The second and third columns report predicted emissions conditional on observed choices and conditioned on simulated choices, respectively. Although the model performs well in predicting compliance choices, it does a relatively poor job of predicting emissions. Predicted emissions (based on predicted compliance choices) are 20 percent higher than observed emissions overall.

A closer look at the data suggests there are three reasons behind these discrepancies. First, the model assumes that emissions rates (measured in lbs NO_x/mmbtu) for those units that choose not to install any pollution controls will equal the unit's average, historic ozone season emissions rate (i.e., emissions rates observed during the ozone seasons of 1999–2002). In fact, emissions rates at units that chose to rely entirely on the permit market for compliance fall by an average of 31 percent in the ozone seasons of 2004–2006 relative to past summers. This relationship does not differ significantly across subgroups.[52] Emissions rates were likely reduced by changing boiler conditions so as to reduce NO_x formation during combustion.

Second, the unit specific, technology specific, postretrofit NO_x removal rates assumed by the model appear to have been conservative. Note that 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, postretrofit NO_x emissions rates observed over 2004–2006 are, on average, ten percent below predicted postretrofit emissions rates. Among units adopting SCR, observed postretrofit emissions rates are, on average, 12 percent below predicted.

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 operated more efficiently in the summer of 2004 than in past ozone seasons. When historic heat rates are regressed on the heat rates observed during the 2004–2006 ozone seasons and NO_x control technology dummies, the coefficient on observed heat rates is 1.08 and highly statistically significant (p-value < 0.01). None of the technology dummies are statistically significant.

Because observed emissions are significantly lower than the emissions predicted by the model, comparing emissions simulated under counterfactual simulations that assume symmetric economic regulation with observed emissions would be misleading. Instead, baseline emissions are simulated in the same way that emissions under counterfactual, exposure based trading are simulated.

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[52] The average decrease in NO_x rates is 32 percent among regulated units, 32 percent among unregulated units, and 29 percent among publicly operated units.

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