Does Electricity Restructuring Work?
Evidence from the U.S. Nuclear Energy Industry[1]

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To present an empirical test of the effectiveness of electricity restructuring in improving the electricity generation efficiency, I analyze the variation in productivity of 73 investor-owned nuclear power plants in the United States from 1992-1998. I find consistent evidence that high-cost plants are more likely to be restructured. Accounting for this policy endogeneity, survival analysis and two-stage least squares are used to implement a "pseudo" randomization process to create exogenous variation in regulatory status. Overall, I find striking relationship exists between restructuring and the efficiency improvements, and that some efficiency gains have come about from the adoption in advanced technology.

I. Introduction

For just over a decade, the U.S. electricity industry has been undergoing drastic reform in the way it prices and delivers electricity to millions of households and businesses. After a century of government-sanctioned monopoly in the form of closely regulated utilities, this $220 billion industry is being restructured and opened to competition. At the federal level, the 1992 Energy Policy Act, followed by Order 888 and Order 889 from the Federal Energy Regulatory Commission (FERC) in 1996, opened access to the transmission grid for nonutility generators and initiated the restructuring of interstate wholesale markets. At the state level, as of July 1, 2004, 24 states and the District of Columbia had enacted legislation and/or passed regulatory orders that will allow consumers to choose their electricity providers (U.S. Energy Information Agency (EIA), 2003).

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Economic theory predicts that an important merit of market restructuring is to increase industry efficiency by creating incentives for cost savings and the adoption of new technologies (Laffont and Tirole, 1993). This prediction has been realized in the restructuring of a host of other industries—airline, banking, trucking and telecommunications (Baltagi, Griffin, and Rich, 1995; Avkiran, 2000; Rose, 1987; Olley and Pakes, 1996). As for electricity, inefficiencies that could be corrected by introducing competition were observed under traditional regulation (Pescatrice and Trapani, 1980; Hayashi et al., 1997; Koh et al., 1996). However, empirical studies of *ex post* efficiency gains from restructuring are sparse. To date, most of the academic literature regarding restructured electricity markets has assessed the exercise of market power in regional submarkets. Markiewicz, Rose, and Wolfram (2004) (Hereafter, MRW) Knittel (2002), Hiebert (2002), and Kleit and Terrell (2001) are the few papers that rigorously examine the impact of market restructuring on productivity in the context of the U.S. electricity industry. However, the study samples in these papers have only included fossil fuel-fired generating units.

The objective of this paper is to measure whether state-level restructuring improved the operating efficiency of nuclear power plants during the transition phase of regulatory change. The question is important because much of the motivation behind the restructuring efforts is to drive down costs and prices by eliminating inefficiencies. However, this rational does not get much attention in public discussions because these effects remain, for the most part, unquantified. As it is argued that restructuring contributed to the severity of the 2000–2001 California electricity crisis and the August 2003 blackout in the Northeast (Van Doren and Taylor, 2004), restructuring has been the focus of heated debate around the country. It is, therefore, important to identify and measure the size of the benefits from restructuring to respond to policy proposals that may emerge from these debates.

My particular interest in investigating the nuclear energy industry arises not only because it is an important component of the U.S. electricity supply – it is the second largest source, producing over one-fifth of the country's electricity—but also because it is an industry that has experienced substantial efficiency improvements since 1990s, the same time when restructuring got underway [3] .Ultimately, to what extent these improvements were induced by market restructuring remains an empirical question. In addition, the stable structure of the nuclear power industry—due to its huge entry and exit costs—offers a unique opportunity to test directly the relationship between competition and efficiency. Previous literature suggests that competition usually involves significant entry and exit. Therefore, it is difficult to examine whether increased competition forces efficiency improvements in incumbent plants because inefficient plants are often driven out of business, leading to a sample selection issue (Olley and Pakes, 1996; MRW, 2004).

[3]During the 1970s and 1980s, the operating and maintenance costs of nuclear power plants rose at an annual rate of 12% (EIA, 1988) and the commercial nuclear energy was written off as uneconomic and financially risky. This perspective changed over the past decade when the median industry capacity factor of nuclear power plants increased from 70.2% in 1990 to 90.5% in 2004; Annual electricity generation from the nuclear sector increased from 612.6 billion kilowatt hours in 1991 to 788.5 billion kilowatt hours in 2002. (EIA http://www.eia.doe.gov/cneaf/nuclear/page/nuc_generation/nugen_data.xls)

However, this type of selection is avoided in the situation studied in this paper. The nuclear power industry remains fairly stable even in a competitive environment. With the significant costs and barriers to the siting and permitting of new units, or the decommissioning of old ones, no applications for new nuclear plants were filed in the United States in the last 25 years, and only 5 out of 73 plants were retired after 1992.[4]

To measure the effects of restructuring on productivity, a counterfactual analysis is required to estimate the productivity changes solely attributable to restructuring that would not have occurred otherwise. Because restructuring at the retail level has been quite uneven across the states, the time series and geographical variation in regulatory status ostensibly provide an opportunity to construct a counterfactual to disentangle restructuring efficiency gains from those due to factors exogenous to restructuring, such as the increased power demand and plants' learning effects, etc. However, it is often hard to argue that restructuring process is a natural experiment (or random treatment). States that were expected to gain the most from restructuring are perhaps the ones that eventually adopted the policy. In that case, plants that were restructured differ from the counterfactual on the basis of productivity and a direct comparison would distort the estimation. This paper pays particular attention to this econometric identification problem and demonstrates how to provide a "pseudo" randomization device for the analysis of the influence of restructuring on productivity.

The study is based on plant-level panel data of power generation and costs from 1992 to 1998 for all 73 investor-owned nuclear power plants in the United States that were operational in 1992. The analysis takes advantage of the most detailed and comprehensive data on the restructuring process across the country, including the date of each landmark event toward restructuring at the state level. Using capacity factor and unit production cost as proxies of productivity, I find positive association between the multiple steps of restructuring and plant operating efficiency. Issuing a restructuring plan brings an average 9.1 percentage points increase in capacity factor; the regulatory approval of market restructuring yields an average 5.7 percentage points increase in capacity factor; when the probability of moving toward restructuring increases by 10%, plant unit production cost decreases an average 9.8%, *ceteris paribus*. In addition, states that have considered or implemented restructuring are more likely to see an investment in the adoption of new technology ("power uprates") and in a greater magnitude.

The remainder of the paper is organized as follows: Section II provides a brief background of electricity restructuring and its potential effects on the nuclear industry, Section III develops the empirical models, Section IV presents the data, while Section V discusses the estimation results, and Section VI concludes the paper.

II. Electricity Restructuring and Its Impact on Nuclear Industry

Historically in the United States, the three parts of the electricity supply—generation, transmission, and distribution—were assumed to be a natural monopoly and were

[4] The retired capacity represents only 4.6% of the total nuclear generation capacity.

operated by a single utility to exploit the economy of scale. Within a defined geographical area, one or a small number of firms have exclusive rights to serve retail customers. As these firms are partially exempt from competitive pressures, they are subject to rate-of-return regulation under the basic principle that electricity prices should be set equal to utilities' average production cost.

Under the traditional rate regulation, a firm receives a profit as a function of its capital expenditure. Beginning with Averch and Johnson (1962), a number of authors have proved theoretically and empirically that private, regulated monopolies tend to apply capital-intensive generation relative to the optimum (Atkinson and Halvorson, 1980; Granderson and Linvill, 2002; Rungsuriyawiboon and Stefanou, 2003). In addition, since the firm does not get to retain any benefits of cost reduction, its profits being limited to a "reasonable return," firms are less motivated for technology efficiency as well.[5]

With growing public pressure for correcting the economic inefficiency of the old regulatory system, electric restructuring proceeded at an ever-accelerating pace at both the federal and state levels in the 1990s. The Energy Policy Act of 1992 and Federal Energy Regulatory Commission Order (FERC) 888 opened transmission access to nonutilities, thereby establishing interstate wholesale competition. Many states also have encouraged nonutilities' entry into the electricity market and have adopted retail competition as the primary pricing mechanism for electricity generation.[6]

Competitive pricing provides firms with a powerful incentive to reduce costs. This is because restructured markets made firms residual claimants on all cost increases or decreases over time. Particularly in many restructured states, nuclear plants lost the ability to pass through the costs of repairs and replacement power to cover commitments during outrages.[7] This means that any extended downtime could lead to a large loss of revenue.[8] Secondly, the potential entry of low-cost generators increased competitive pressure. For nuclear power, the key challenge is to be directly competitive with other types of fuel generation on the marginal cost of operation (i.e., operating and maintenance [O&M] costs), including repair and refurbishment expenses, and fuel costs. Although the average O&M costs for nuclear are low compared to other energy sources, the cost is not low for all plants.[9] In fact, the plants in the high-cost quartile spend twice as much on O&M as the plants in the low-cost quartile and as large, coal-fired power plants. Rothwell (1998) estimates that 6.3% to 17.5% of current nuclear capacity is not

[5] Joskow (1974) points out that because regulators might not be active enough in the oversight of the firm, there is a "regulatory lag;" that is, the actual rates of return earned by electric utilities may be above or below the commission-determined fair rate of return at any instant. When prices are fixed, utilities can increase profits by cutting costs. But Joskow also admits that regulatory lag provides incentive for cost saving only on the margin.

[6] For a more comprehensive review of the drivers and process of electricity restructuring in the United States, see Joskow (1997), U.S. Energy Information Agency (EIA) (2000), and EIA (2003).

[7] Nuclear generation is baseload designed. Whenever a nuclear plant is out of service, replacement power has to be procured to satisfy continuous supply.

[8] An outage due to infrastructure failure typically would require 35 to 60 days of idling of plant operation. In 1999, Con Edison paid more than $100 million for replacement power during a non-routine shutdown of Indian Point 2 (Pace Law School, 2001, http://law.pace.edu/energy/NuclearAccountabilityProject.html).

[9] According to EIA data, in 1996 the average O&M costs for nuclear, coal, and gas were 1.91c/kWh, 1.81c/kWh, and 3.38c /kWh, respectively.

competitive and faces the risk of early retirement. Two other studies state that up to 40% of U.S. nuclear capacity could have marginal expenses that are higher than competitive market prices.[10]

To make a profit in a competitive market, baseload nuclear plants must attempt to (1) maximize total electricity output (MWh) during the year—that is, the capacity factor—to cover fixed O&M costs and to reduce replacement power costs and (2) minimize the operating cost per MWh ($/MWh) to compete with large, coal-fired plants. As expected, improvements that have already taken place in the nuclear industry took the form of fewer unplanned outages, shorter refueling times, and a reduced workforce. Anecdotal evidence suggests that much of these improvements in the operating performance of the nuclear sector by 1998 stemmed from reducing its use of contract personnel by bringing work in-house, training workers to perform multiple functions, and sharing best practices in the industry, and by successful power uprates (the practice of squeezing more power out of generators through advanced techniques).[11] Since these activities, especially staffing decisions and human capital training, take time to achieve, plants would have taken actions to prepare for competition even before being subject to true competition. As Eugene Grecheck, vice president of nuclear support services for Dominion Energy, Inc., pointed out, "The prospect of electricity market competition has been an important driver of this improvement in the industry."

There may be efficiency spillover effects from restructured to unrestructured plants through knowledge sharing or if cost reduction in restructured states puts pressure on rate adjustment in neighboring, unrestructured states. Without estimating the positive externality of restructuring, I only measure a lower bound of restructuring benefits.

III. Econometric Models

This paper is most related to MRW (2004), which analyzes the impact of electricity restructuring on the efficiency of fossil fuel-fired generating units. They estimate plant-level annual input demand functions for fuel and non-fuel expenses using restructuring indicator variables to pick up the shock from regulatory reform. They find plants affected by restructuring experienced 5–20% more cost reduction than unaffected plants.

Compared to MRW (2004), this study uses a different empirical strategy that is similar to Joskow and Schemalensee (1987). The latter assesses each observation of a plant's productivity at each given time as a function of a series of plant-specific attributes

[10] The two studies are "Need for Natural Gas Increases with More Nuclear Plant Shutdowns" by the Washington International Energy Group, Washington, DC, May 1998, and *Nuclear Week*, December 11 1997, p.6.

[11] After 1998, industry consolidation became the primary driver in improving the industry's operating performance. Single unit or small plants were sold to larger and more experienced nuclear operators that had the resources and management skills to run plants well. Since many plants were divested to nonutilities, plant cost data are incomplete after 1998 (nonutilities are not required to report operating cost data to FERC). Dropping these plants leads to nonorthogonal sample selection if divested plants systematically differ from the others. In light of this consideration, I confine my analysis to 1992–1998.

(such as the plant's age, vintage, scale, operating practices, and coal quality) and institutional characteristics. This approach provides measures of both allocation and technical efficiency without requiring a specific assumption for production behavior.

This study also is related to Marie (1996). Marie explores whether incentive regulation (IR) programs improve the operating performance of nuclear generating units during 1988–1992.[12] Marie finds that units with prior poor performance were more likely to have incentive regulation imposed upon them. He then uses the average production cost of the three-calendar-year before the imposition of incentive regulation as an instrumental variable for IR.[13] He did not find an inverse relationship between IR and plant production cost.

Other related studies include Knittel (2002), who estimates the effects of an IR program within a stochastic frontier framework using a dataset spanning 1981 to 1996 for fossil fuel-fired plants. He finds that an IR program potentially could save 9.53% to 17.57% of input costs. Kleit and Terrell (2001) use a Bayesian stochastic frontier model to compute the inefficiency measures for natural gas-fired plants using 1996 data. They conclude that plants potentially could reduce costs by up to 13% by restructuring.

III (i) Variables and the One-Stage Estimation

I use capacity factor (%) and annual per unit average production cost ($/MWh) as measures of operating efficiency. Capacity factor is defined as the actual generation divided by the product of nameplate capacity and the number of hours in the year. Per unit average production cost is the ratio of annual fuel cost plus O&M costs to annual output of that plant. Cost data were derived directly from FERC Form 1, which defines O&M costs as all nonfuel operating expenditures (labor, material, and services) excluding capital costs.[14]

Capital costs always present one of the major measurement difficulties in productivity studies. Being durable inputs that are not fully consumed in one period, the costs have to be depreciated over a lifetime. Given capital typically is chosen at the time of facility recovery or power uprates and it is changed relatively infrequently. Following MRW(2004), I combine information on plant major non-routine shutdowns and power uprates to define plant-epochs such that within each plant-epoch capital stock and its

[12] Since the late 1970s, many states have adopted an array of incentive regulation programs as alternatives to rate-of-return control, such as rate of return range programs that allow prices to fluctuate less proportionally with changes in costs or yardstick competition programs that determine a utility's prices based on the costs of comparable utilities. For a more detailed discussion of incentive regulation, see Joskow and Schmalensee (1986).

[13] It remains unclear whether this instrument can be treated as exogenous. Annual costs are likely to be serially correlated and jointly determined by unobservable plant-specific characteristics. In this case, the instrument is correlated with error term.

[14] According to Bowers et al. (1987), approximately 67% of the total reported O&M costs of nuclear plants are labor related (performing engineering, security, administrative, and managerial activities) and the remaining 33% of expenditures are for maintenance materials and supplies. However, because there are no reliable labor cost data available, it is not possible to analyze separately how different components of production cost vary with restructuring activities.

impact on plant efficiency are assumed to be approximately constant. [15]

In an effort to better approximate the variation in competitive pressure, I construct two dummy variables to differentiate three different regulatory statuses: “no action,” “consideration,” and “action.” Following Ando and Palmer (1998), a state moves from no action to consideration when any one of the following three things happen: (1) the public utility commission (PUC) initiates a formal inquiry into the possibility of allowing retail competition; (2) PUC-endorsed informal stakeholder discussions begin that are oriented toward policy recommendations and that either take place over a period greater than one month or produce a report that is taken up by PUC; or (3) a PUC staff report is issued with recommendations regarding retail competition. The state moves to action status when: (1) it issues a final order that contains a date by which all PUC-regulated utilities in the state must open their markets to retail competition; or (2) the PUC has required retail restructuring filings from its regulated utilities in preparation for competition by a particular date, even if it has not yet issued a final comprehensive order.

For plant-epoch i in year t, the following one-stage regression model is defined:

$$Y_{it} = \beta_0 + \beta_1 D_{it}^{con} + \beta_2 D_{it}^{act} + \gamma Z_i + \pi X_{it} + \sum_{t=1993}^{1998} \delta_t T_t + \sum_{j=1}^{30} \nu_j L_j + \alpha_i + \varepsilon_{it} \qquad (1.1)$$

where the dependent variable Y_{it} is either the capacity factor or log of the per unit average production cost of the plant-epoch i in year t. Hereafter, i indexes plant-epoch and t indexes the calendar year.

D_{it}^{con} and D_{it}^{act} are the two regulatory variables. D_{it}^{con} takes the value 1 when the plant is facing a restructuring plan (‘consideration’), 0 otherwise; D_{it}^{act} takes the value 1 when the plant is or to be restructured (‘action’), 0 otherwise.

I control a vector of time-invariant plant-epoch specific variables Z_i that determines the performance of a power plant. Z_i includes: $PWR_{i,,}$ a dummy variable equal to 1 if the plant uses pressured water reactor (PWR), 0 if it uses boiling water reactor; $VINTAGE_i$ is the capacity-weighted average of the vintages (the year of initial operation) of the units comprising the plant minus 1969—the year the first nuclear power unit in the country was brought online. I allow the variable $VINTAGE_i$ to enter with a flexible polynomial specification but find that a linear specification exhausts its explanatory power. $UNITS_i$ is the number of units comprising the plant. LnC_i is the log of a plant-epoch’s nameplate capacity in megawatts. LnC_i^2 is square of $LnC_{i.}$ The number of units and nameplate capacity are controlled to capture possible economies or diseconomies of scale.

X_{it} is a vector of time-varying variables that includes: $INCENTIVE_{it}$ is a dummy variable with value 1 if there is an IR program imposed on the plant-year. It is necessary to control for the effects of incentive programs since previous studies suggest incentive programs potentially can explain variations in productivity (Knittel, 2002).[16] AGE_{it} is

[15] Specifically, I assign a unique identifier i, to each plant. Any time the plant experienced a shutdown longer than half a year or a change in rated capacity, I created a new identifier and the corresponding new plant-epoch.

[16] There might be collinearity between the presence of incentive programs and regulatory status; that is,

calculated as the capacity-weighted average of the ages of the individual units comprising the plant. I estimate the model allowing AGE_{it} to enter with a quadratic specification.[17]

I include year-specific dummy variables T_t (t = 1993, 1994,…, 1998) to pick up exogenous effects common to the plants, such as technical progress or changes in Nuclear Regulatory Commission control. For completeness, I also control for state fixed effects that, as it turns out, deplete explaining power while changing the coefficients of interests only slightly.

α_i is assumed to be an unobservable plant-epoch level time-invariant fixed effect.[18] α_i controls plants' heterogeneity in initial design, construction, and other unobservable fixed characteristics that affect a plant's intrinsic productivity. ε_{it} is assumed to be an idiosyncratic shock to operating performance drawn from an identical and independent distribution $\varepsilon_{it} \sim N(0,\sigma^2{}_{\varepsilon})$.[19] Both α_i and ε_{it} are unobservable. $\beta_0, \beta_1, \beta_2, \gamma, \pi, \delta, \nu$ are coefficients.

III (ii) Policy Endogeneity and Instrumental Variables

A critical issue affecting the empirical analysis of public policy is the potential endogeneity of the policies under study. As stated in Section 2, retail rate disparity between states is one of the two major driving forces of market restructuring. California and many states in the Northeast, which were among the first to move toward restructuring, are also the states with prices well above the national average and with densely distributed nuclear power plants. The high concentration of nuclear power plants suggests that electricity prices are closely correlated with nuclear plants' performance. If the poor performance of nuclear power plants contributed to high prices, which is suggested by the estimation of Varley and Paffenbarger (1998), and in turn motivated restructuring, the restructuring decision was endoegenous and chosen partly on α_i. That is $E[\alpha_i \mid D^{con}{}_{it}, D^{act}{}_{it}] \neq 0$. A situation like this makes the "no action" group an invalid counterfactual.

A Hausman test can provide information about the correlation between α_i and the

states that adopted incentive regulation may be more or less likely to advocate restructuring. Collinearity will result in relatively large standard errors, and the coefficients of two collinear variables often will be statistically insignificant. However, this is not the case based on the empirical estimates shown in section V.

[17] On the one hand, experience associated with learning by doing can lead to improvements in operating performance as length of service increases. On the other hand, operating efficiency tends to deteriorate and the plant experiences higher maintenance costs as it ages. Given that the incremental advantage from learning is diminishing over time, while the disadvantages of older equipment are rising, I expect that operating performance increases in the early stages and begins to fall after some critical age level.

[18] α_i is allowed to change with facility repair and power uprates at the plant-level.

[19] Estimated average first-order autocorrelation coefficient ρ indicates ε_{it} is likely to be serially correlated. In capacity factor equation, ρ is 0.30 in OLS model. In the average production cost equation, ρ is 0.54 in OLS model. Likelihood ratio (LR) test shows evidence of cross-sectional heteroskedasticity. To obtain robust standard errors, I adjusted standard errors for clustering by plant in the following estimations.

other right-hand-side variables. If the Hausman test suggests that the cross-sectional error term α_i is correlated with at least one of the variables explaining the performance of plant *i*, both ordinary least squares (OLS) and general least squares (GLS) estimates would be biased and inconsistent. One can still obtain consistent coefficient estimates using a fixed effects model, although the estimation is inefficient.

At first glance, a fixed effects model seems able to avoid this policy endogeneity problem. Even if market restructuring was adopted in response to inefficient production, we can still ask the question how changing market structure influences efficiency changes in a time series context as the previous efficiency level has been differenced out in a fixed effects model. However, a fixed effects model has two important defects: (1) the within-group estimator is not fully efficient since it ignores variation across individuals in the sample; and (2) the more serious problem is that a fixed effects model can't difference out time-varying components of the disturbance that are correlated with policy variables. For example, if we utilize a first-differencing equation (1.1) to eliminate the time-invariant components, we get:

$$\Delta Y_{it} = \beta_1 \Delta D_{it}^{con} + \beta_2 \Delta D_{it}^{act} + \pi \Delta X_{it} + \sum_{t=1993}^{1998} \delta_t T_t + \Delta \varepsilon_{it} \tag{1.2}$$

Although previous heterogeneity in efficiency level α_i has been differenced out, if policy change ΔD_{it} is a year-to-year response to changes in the outcome variable ΔY_{it}, then $\Delta \varepsilon_{it}$ is not randomly distributed and fixed effects doesn't address the fundamental problem associated with endogenously determined policy. Furthermore, as Besley and Case (2000) point out, any policy choice is purposeful action and rarely can be treated as exogenous. Since fixed effects model studies state policies as right-hand side variables, a concern remains if any time-varying economic or political conditions that simultaneously influence policy variables and policy outcomes are omitted and absorbed in the error term. Generally, by treating time-varying policy choices as exogenous, a fixed effects model leaves estimates open to potential simultaneity and omitted variable bias.

Noting the pitfalls of a fixed effects model, I use instrumental variables to realize an alternative "pseudo" randomization device. The instrumental variables should be correlated with the restructuring decision but uncorrelated with α_i to create variation in regulatory status that is exogenous to a plant's inherent productivity. "Pseudo" randomization manipulates a treatment and affects the outcome only indirectly through its manipulation of the treatment. If instrumental levels are randomly assigned to individuals, then the instrument may permit a consistent estimation of the effects caused by the treatment, even though the treatment assignment itself is far from random (Angrist, Imbens and Rubin, 1996; Angrist and Krueger, 2001).

III (iii) Instrumental Variables and Hazard Model

Assume there are other major determinants, IV_j, of the market restructuring process in state *j*. If *IV* are uncorrelated with α, we can use *IV* as instrumental variables. Several papers analyzed the political economy of electricity restructuring (Ando and Palmer, 1998; White, 1996; Andrews, 1999). Following previous empirical results, I identify the instrumental variables as a set of time-varying and time-invariant variables described below.

The size of the industrial customers, $S_{jt,}$, is measured by the share of total utility sales to industrial customers in state j in year t. Industrial customers compose an important interest group that would potentially benefit from market restructuring. The larger the size of this group, presumably the greater pressure it may place on decision makers to pursue electricity restructuring.

The variable M_{jt} is the percentage of total electricity generation in state j in year t from municipal and rural cooperative utilities. This portion of generation is exempt from PUC regulation and would not be affected by market restructuring. The hypothesis is that the larger the M_{jt}, the less aggressive the PUC and large industrial consumers would be in promoting market restructuring.

The average share of generation from hydropower in state j from 1991 to 1998 is represented by $\overline{H}_j$. The different natural resource endowments of hydropower to some extent contribute to rate differences across states. The production cost of hydropower is typically less than one-third of that of coal or nuclear. States with a larger percentage of hydropower usually enjoy lower electricity prices and presumably are less enthusiastic to pursue electricity restructuring.

Republican control of state government, $R_{jt,}$ is a dummy variable coded 1 when Republicans control both the governorship and the legislature in state j in year t. Ideologically, jurisdictions under Republican control may favor market restructuring more than those under Democratic control.

A dummy variable PUC_{jt} equals 1 if the PUC in state j and year t is appointed and equals 0 if it is elected. Ando and Palmer (1998) suggest that an elected PUC is more likely to promote retail competition as a favor to the voters who elected them.

I also include the League of Conservation Voters' (LCV) rating of each state's federal senators and representatives from 1992 to 1998 based on their support for environmental initiatives. The size and strength of environmental groups may have an impact on the progress of market restructuring.

Retail electricity prices, the import and export electricity price gap, and the magnitude of stranded costs are all highly correlated with a state's rate of moving toward restructuring. However, these variables are potentially determined by plants' historical performance and thus, are correlated with the inherent productivity of nuclear power plants. They are excluded from the two-stage least squares (2SLS) model.

I use a multivariate discrete time proportional hazard model to approximate the probability of exiting the initial "no action" status in the first stage. There are two major reasons why this research issue cannot be addressed via probit or more straightforward OLS regression techniques. First, there is the problem of right censoring. Since the restructuring process is still very much ongoing, many states did not experience restructuring during the study period 1992 to 1998 or experience restructuring after the observation period. For a state that is subject to censoring, we cannot observe the exact duration of its initial status. The only thing we know from these states still in the initial state is that the duration lasted at least as long as the tracking period. A hazard model can handle the censored data using maximum likelihood estimation. The conditional likelihood for observation j can be written as:

$$f(t_j \mid x_j;\theta)^{d_j}[1-F(t_j \mid x_j;\theta)]^{(1-d_j)} \tag{1.2}$$

where d_j is the censoring indicator. $d_j = 1$ if uncensored; $d_j = 0$ if censored. $f(t_j \mid x_j;\theta)$ is the probability of state j exiting from the "no action" status in year t conditional on its characteristics x_j. $F(t_j \mid x_j;\theta)$ is the conditional cumulative distribution function (cdf). It is the probability that state j stays in "no action" status up to year t conditional on its characteristics x_j.

Given data on (t_j, d_j, x_j) for a sample of size N, the MLE estimator of θ is obtained by maximizing:

$$\sum_{j=1}^{N}\left\{d_j \log[f(t_j \mid x_j;\theta)] + (1-d_j)\log[1-F(t_j \mid x_j;\theta]\right\} \tag{1.3}$$

The MLE is consistent and asymptotically normal.

The second reason to use the hazard model is that probit and OLS analyses only help inform the patterns observed for a particular snapshot in time. They ignore the information we have about how long it took the states to reach the statuses they occupy in that snapshot; the hazard model can use some of that information.

Assume a hazard function is defined as $\lambda(t;W(t),V,\eta_t)$, where $W(t)$ and V are, respectively, the time-varying and time-invariant covariates described above, and η_t is the error term.[20] Let T denote the time until exit from the "no action" status (t is a particular outcome on T). We observe that T falls into one of the seven intervals $[a_0,a_1),[a_1,a_2),\ldots,[a_5,\infty)$, where $a_0 = 1992$ and $a_5 = 1998$. T is measured to the nearest year and treated as continuously distributed. I coded an unbalanced panel where each state-year observation is a vector of a binary indicator p_m, equal to 1 if the duration ends in the interval m, and 0 otherwise; a binary censoring indicator d equals to 1 if the duration is censored in interval 6, and 0 otherwise; along with covariates $W(t)$ and V. At each interval, the population is composed of states with a "no action" status. After exiting the initial status, I drop the state from the risk set.

The conditional hazard function of a state at time t is given by:

$$\lambda[t;W(t),V] = \frac{f(t \mid W(t),V)}{1-F(t \mid W(t),V)} \tag{1.4}$$

[20] To be able to include the time-varying variables in the survival estimation, *W(t)* needs to be well-defined whether or not the state is in the initial status, i.e., *W(t)* is exogenous to the survival path. All of the instrumental variables in this paper satisfy strict exogeneity assumption.

where $F(t|W(t), V)$ is the conditional cumulative distribution function (cdf) of T. $F(t)=P(T \leq t),\ t \geq a_0$. $f(t|W(t),V)$ is the conditional probability of leaving the "no action" status in the interval $[t, a_m)$ given survival up to t.

Assume λ is a proportional hazard of the form:

$$\lambda[t; W(t), V] = \phi[W(t), V]\lambda_0(t), \quad a_{m-1} \leq t \leq a_m \tag{1.5}$$

where $\phi(\cdot) > 0$ is a nonnegative function of $W(t)$ and V and $\lambda_0(t) > 0$ is the baseline hazard. The probabilities that states exit "no action" differ proportionately based on a function $\phi(W(t), V)$ of observed covariates. The baseline hazard is common to all states in the risk set. Assuming that the hazard of exiting "no action" status is increasing over time, due to federal influence or policy imitation effects (Andrews, 1999; Henisz, Zelner, Bennet, and Mauro, 2004), I specify the baseline hazard model as a Weibull function, which is the only distribution with an accelerating failure time and proportional hazard. Its cdf is given by $F(t) = 1 - \exp(-\gamma t^{\alpha})$, where γ and α are nonnegative parameters. Using maximum likelihood estimation, I am able to estimate the coefficients associated with W and V and to predict the hazard rate at each point time.

The proportional assumption assumes a log-linear relationship between the independent variables and the underlying hazard function. The 2SLS model is:

$$\log \lambda(t, W(t), V) = \varpi W_t + \upsilon V + \log \lambda_0(t) + \eta_t \tag{1.6}$$

$$Y_{it} = \beta_0 + \beta \overline{D}_{IV_{it}} + \gamma Z_i + \pi X_{it} + \sum_{t=1993}^{1998} \delta_t T_t + \sum_{j=1}^{30} \nu_j L_j + \alpha_i + \varepsilon_{it} \tag{1.7}$$

where W_t and V are instrumental variables used in the first stage, and $\overline{D}_{IV}$ is the predicted probability of the state where plant i is located moving from "no action" to "consideration" of market restructuring at time t, taking into account right censoring and how long the state has been with the initial status. Because both stages are linear in nature, the estimation of β is consistent.

IV. Data Sources and Descriptive Statistics

This study is based on an unbalanced panel dataset of plant-level output and production costs taken at yearly intervals, as well as a variety of plant-specific characteristics. The data are from the years 1992 to 1998 for all 73 investor-owned nuclear power plants in the United States and were collected from FERC Form 1. Production cost is adjusted to real terms using a 5% discount rate and presented in 1992 dollars. The data sources are described in Appendix A.

Table 1 reports the number of plants falling into "no action", "consideration," and "action" groups in each year. Table 1 shows there are rich variations in plants' regulatory status in both longitudinal and cross-sectional dimensions. Table 2 lists the summary statistics of the variables.

I divide the sample into three groups based on plants' regulatory status in 1998. Table 3a reports mean value and mean differences in plant characteristics between groups.

Although there are no statistically significant differences in most of the plant characteristics, “no action” plants were more often subject to incentive regulation and more likely to be PWR plants, leading to concerns about the fundamental differences in plants’ operating performance between “no action” and restructuring groups.[21] Table 3b reports mean, mean differences in capacity factor and per unit average production cost before and after restructuring, the corresponding percentage change, and the differences in percentage changes among the three groups. The larger percentage increase in the capacity factor of restructuring plants (“consideration” and “action”) is significant at 5%, and the greater decrease in per unit average production cost of restructuring plants is significant at 1%. Notably, there is no preexisting difference in capacity factor between the “no action” group and the “action” group, while the “action” group has a statistically significant higher per unit average production cost in the pre-restructuring period. These aggregate statistics provide suggestive evidence of: (1) the positive relationship between restructuring and improvements in operating efficiency; and (2) a selection process based on previous cost performance.

Table 4 presents the summary statistics of instrumental variables. The instrumental variables are designed to capture the variation in states’ political and economic conditions that result in different rates of restructuring. However, the variation of instruments in the time series is not as rich as that in the cross-sectional dimension. Consequently, these instrumental variables may not be able to separately identify for each state the change in status from “consideration” to “action.” Thus, in the instrumental variable model, I estimate the effects of a regulatory status change from “no action” to restructuring (“consideration” and “action”).

V. Empirical Estimates

V (i) Conventional One-Stage Estimates

Tables 5 and 6 report the results from estimating equation (1.1) via OLS, GLS, and a fixed effects model with capacity factor and the natural logarithm of unit production cost as the dependent variables, respectively.

When using capacity factor as the dependent variable, the estimation results are largely insensitive to the choice of model. It is not surprising that the Hausman test fails to reject the hypothesis that the unobserved variable α_i is uncorrelated with the other independent variables at the 1% level, implying that unobservable plant heterogeneity is uncorrelated with virtually all other observable determinants of operating efficiency. In this case, α_i can be considered part of the error term and a random effects specification yields consistent and efficient estimation.

The dummy variables D^{act} and D^{con}, indicating the regulatory and market structure, emerge as the two main explanations for the cross-state and time variation in capacity

[21] Knittel (2002) finds an inverse relationship between input costs and an IR program. Most of the IR programs became effective in mid-1980s. Marie (1996) finds BWR’s operating and maintenance expenditures are higher on average.

factor. Specifically, the results suggest that restructuring or the positive prospect of market restructuring increases operating efficiency as measured by the plant's capacity factor. Conditioning on other exogenous variables, the adoption of restructuring yields an average 9.1 percentage points increase in capacity factor, *ceteris paribus*; the positive consideration of restructuring yields an average 5.7 percentage points increase in capacity factor, *ceteris paribus*.

Estimates from the fixed effects model are lower than those of the random effects model. This is because a fixed effects regression identifies variation from within-group and ignores between-group (cross-section) variation; thus, it picks up only the performance change of the same plant before and after regulatory status change (time series). In contrast, random effects report the average effect of regulatory status change within the same plant and across groups.

As seen in Table 6, when the natural logarithm of unit production cost is the dependent variable, the dummy variable estimates are very sensitive to model specification and occasionally have an unanticipated sign. A Hausman test suggests that the cross-sectional error term is correlated with at least one of the explanatory variables, indicating that estimates from the OLS and the random effects model are biased and inconsistent. The OLS and cross-sectional models' dummy variable coefficient estimates are lower in absolute value than those of the fixed effects model. This is noteworthy because it provides yet more evidence of a selection process based on historical cost performance. This is proven below. Assume that if a plant is being restructured, we observe the cost y_{it}^1, otherwise we observe y_{it}^0. Here, we try to measure the treatment effect of restructuring (the specifications below are the same as in Section 5):

$$E(y_i^1 \mid X_i, Z_i, \alpha_i) - E(y_i^0 \mid X_i, Z_i, \alpha_i) = y^1(X,Z) - y^0(X,Z) \tag{1.8}$$

However, for cross-sectional comparison, we have only:

$$E(y_i^1 \mid X_i, Z_i, \alpha_i, D=1) - E(y_j^0 \mid X_j, Z_j, \alpha_j, D=0) \tag{1.9}$$

where D is the indicator variable. D = 1 if a plant is restructured, and D = 0 if a plant is not restructured.

From Table 6, we see that the restructured and control groups have similar values in all the observable plants' specific characteristics. Thus, equation (1.9) can be further written as:

$$\begin{aligned} &E(y_i^1 \mid X_i, Z_i, \alpha_i, D=1) - E(y_j^0 \mid X_j, Z_j, \alpha_j, D=0) \\ &= y^1(X,Z) - y^0(X,Z) + E(y_i^1 \mid \alpha_i, D=1) - E(y_j^0 \mid, \alpha_j, D=0) \end{aligned} \tag{1.10}$$

The right-hand side of equations (1.8) and (1.10) are the same if:

$$E(y_i^1 \mid \alpha_i, D=1) = E(y_j^0 \mid \alpha_j, D=0) \tag{1.11}$$

However, if α is a selector variable which determines a plant's cost performance such that if it falls into some region, a state would consider or implement restructuring; if it falls into the complement, no action for restructuring. If α associated with the restructured group systematically induced a higher cost than that induced by the α that is associated with the control group, i.e., $E(y_i^1 \mid \alpha_i, D=1) - E(y_j^0 \mid \alpha_j, D=0) > 0$, the estimation of the treatment effect based on OLS or GLS is biased downward. The fact that estimates from the OLS and the cross-sectional model are lower than those from the fixed effects model suggests that the assignment to treatment and control is dependent on the plant's unobservable determinants of cost (α), and the treatment group historically had a higher level of production cost.

In this case, only the fixed effects model provides unbiased estimation on the subpopulation of the treatment group, although the estimates are inefficient and the effects of time-invariant variables are all absorbed. Because the key variables of interest are the two time-varying dummy variables D^{con} and D^{act}, the focus in the remainder of the paper will be only on the fixed effects model when considering the correlation between restructuring and cost performance.

Interpreting the results from the fixed effects model, the coefficient estimates for the dummy variables D^{con} and D^{act} imply that on average a 10% cost saving can be achieved by positively considering restructuring and another 10% cost saving can be realized by implementing restructuring.[22] However, the effects are not statistically significant.

Dropping outliers based on cost information, I report year effects of unit production cost for groups "no action" and "restructured" respectively in figure 1. The vertical axis is year-by-year change in natural log of unit production cost. They are the residual values from re-estimating equation (1.1) for each group separately without including the regulatory status dummy variable and fixed-year effects dummy variables. Figure 4 suggests an industry-wide improving trend in cost performance since 1991, a period when the industry was facing increasing competitive pressure due to market restructuring. Figure 4 also shows that comparing to the "no action" group, the "restructured" group is associated with a higher rate of improvement.

Although we can observe visually in Figure 1 the difference between the restructured and the control group in the change of cost performance, the estimates on the dummy variables are not statistically significantly different from 0. One explanation is that the average effect of restructuring on reducing costs may vary in the population. Due to policy endogeneity, a one-stage, regression-adjusted association between the plant's cost and restructuring is weak because we estimate only the effect on the subpopulation that is at an inherent disadvantage in improving cost performance.

The estimates of plant-specific effects largely are consistent with previous studies. Incentive programs have a significant positive effect on a plant's capacity factor but not on cost. The estimates of *AGE* and AGE^2 show that the performance improves over the range of ages of the plants included in the data; however, it might improve at a declining rate, implying diminishing returns. Estimated coefficients of *VINTAGE* demonstrate that technological improvements induce higher operating efficiency over time. Multi-unit plants have better performance on the basis of cost estimates. Finally, there is evidence to suggest economies of scale as larger nameplate capacity induces a higher capacity factor

[22] I use [exp(β)-1]*100 to approximate the percentage effect of D^{con} and D^{act} on unit production cost.

and lower average production cost, although the effect is decreasing with the increasing of the scale.

V (ii) Hazard Model and 2SLS Estimates

Taking into account the policy endogeneity problem and the pitfall of the fixed effects model, I use 2SLS (IV/2SLS) for cost analysis.[23] The results from the first-stage hazard model analysis are reported in Table 7, and the 2SLS estimates are reported in Table 8.

In the first-stage hazard model analysis, the estimation of the Weibull parameter is greater than 1 ($P = 2.28$), which means the hazard (the probability of being restructured) is monotonically increasing (the hazard everywhere exhibits positive duration dependence). Provided we believe that the restructuring process was actively being pushed forward across the country from 1992 to 1998, the assumptions inherent in the Weibull distribution seem reasonable for capturing duration dependence.

After using instrumental variables to address the endogeneity problem, the coefficient estimates for the restructuring effort dummy variable show a statistically significant impact on cost saving. Plants that are more likely to be restructured have on average a statistically significant lower unit production cost. Specifically, the result indicates that when the probability of moving toward restructuring ("consideration") increases by 10%, the unit production cost decreases on average 8.3%. However, the results reflect only the local average treatment effects based on the variance present in the sample.

V (iii) Source of Productivity Improvements

In this section, I estimate the relationship between regulatory status and the investments on power uprates. I argue that one source of post-restructuring productivity improvements is the increased adoption of advanced technology.

I aggregate plant-level power uprates data into state-level data and control for state GDP, population, median household income, and fixed-year effects. I conduct a random effects and probit analysis using the magnitude and frequency of power uprates from 1992 to 1998 as dependent variables. To indicate state regulatory status, first I include in the model two dummy variables, D^{con} and D^{act}, with the same definition as before. Second, I use only one dummy variable, D^{Dereg}, which equals 1 if the state is either considering or has passed a restructuring plan and 0 otherwise. The results are reported in Table 9. In both analyses, the dummy variables indicate a positive relationship between restructuring and the probability and magnitude of power uprates. A state moving toward restructuring increases capacity 1.09 percentage points higher than a state that is less likely to be restructured and has a statistically significant higher probability of investment in power uprates, *ceteris paribus*. The positive relationship between the adoption of advanced technology and restructuring can partially explain the mechanism through which restructuring improved operating efficiency.

[23] I also use IV/2SLS to estimate the effect of restructuring on capacity factors. The estimates show the expected sign, although it is insignificant. This is possibly explained by the selection problem not being salient to capacity factor performance and the variance in the sample being reduced by using instruments.

V (iv) Robust Check

A. Regression to the Mean

In this subsection, I test whether the above results can be explained by a regression to the mean phenomenon—that is, if plants' capacity factor or unit production costs are normally distributed, inefficient plants tend to catch up to better operated plants, and they both revert to the mean. If this is true, we should observe cross-section dispersion diminishing over time. As a straightforward test, I examine directly the cross-section distributions of operating performance over time. I normalize the capacity factor and production cost of each plant by dividing them by the industry average value of that year. If a plant performs at the average level, it should have an index equal to 1. The kernel density distribution of the normalized capacity factor and production cost of different years is shown in Figure 2. The key message from the figures is that the cross-section distributions do not appear to be collapsing. This is especially distinct in the case of capacity factor: the industry continues to display significant cross-sectional dispersion, with more plants moving away from the mean. If there were a regression to the mean phenomenon, we would not expect to see this sequence of change in capacity factor and unit production cost.

B. Alternative Specification of Regulatory Status

In addition to use the two dummy variables D^{con} and D^{act} to proxy a plant's expectation of restructuring, I also use some alternative measures of the change of market structure in the one-stage regression as provided in Equation (1.1) (using capacity factor as the dependent variable in a random effects model and using natural log of unit production cost as the dependent variable in a fixed effects model). The first row of Table 10 shows the coefficient estimates for a variable "*lawdate,*" which represents the calendar year when the state's restructuring law was passed. The second row shows estimates for the variable "*time*", which measures the number of years left to pass a restructuring law. The estimates show the same sign as the measures in tables 5 and 6, although the magnitude is smaller because it ignores other signals of regulatory change, such as formal hearings by the PUC or a utility shareholder restructuring initiative that may also influence a plant's expectations of market structure change and its operating behavior.

C. Utility-Level Results

The previous specification assumes that each plant-level observation is an independent observation. However, it is likely that operational decisions are made at the utility level and plants operated by the same utility have similar operating efficiency. The performances of those plants owned by the same utility are likely to be strongly correlated. This correlation would suggest that estimating efficiency at the plant level and treating each observation as independent would tend to understate the standard errors. If plants owned by the same utility are strongly correlated, treating each plant observation as independent would tend to reduce the standard error. In addition, "labor sharing" could be an issue of measurement error if labor was shared across multiple plants of a utility but was reported as belonging to one particular plant. To account for these, I use utility-level data for robust checks. To account for this, I estimate the previous models using utility-level data. Specifically, I crosslink the FERC Form 1 and EIA-860 data set to identify the utility to which a plant belongs. I sum output and cost across commonly owned plants for a given utility and year to create a utility-level observation for each year. I then use these data to estimate the correlation between regulatory status and operating efficiency. The estimates are reported in Table 12, which demonstrates that the conclusions from the plant-level analysis are robust. [24]

D. Attrition

Five nuclear power plants have been permanently shut down from 1992 to 1998. If the five plants dropped from the sample had been systematically lower in efficiency relative to the other plants in the sample, it is possible another selection bias may contaminate the estimates. To assess the impact of attrition, I re-estimate previous specifications based on a balanced panel data, in which case the sample was restricted to plants that were in the data set in 1998. The results for this sample are for the most part very similar to the results for the full sample, suggesting that there is no selection bias due to this amount of attrition.

VI. Conclusion

To provide a new perspective on the debate on the efficacy of electricity market restructuring, this paper complements the existing literature by providing the first empirical evidence of operating efficiency gains in the nuclear power industry during and after electricity market restructuring in the U.S. This paper highlights policy endogeneity problem for evaluating regulatory reform that has received little attention from previous literature in electricity industry. Based on the most detailed data available on the restructuring process in the U.S., the paper also distinguishes between the regulatory difference “no action” and “consideration”.

It is demonstrated that market restructuring does deserve some credit for the U.S. nuclear power industry’s resurgence after 1990. Using generation, cost, and regulatory status data for each plant from 1992 to 1998, I calculate a 9.1 percentage points and 5.7 percentage points increase in capacity factor for the plants in states restructured and soon to be restructured, respectively. This increase in capacity factor implies a net generation gain of 629 billion kilowatt hours during the study period. After controlling for nonrandom adoption of restructuring, a 8.3% cost saving is significantly correlated with a 10% increase in the probability of moving toward restructuring. This means a total cost saving of $3.8 billion over the seven study years. Restructuring has also had an intriguing effect on promoting technology adoption in the form of power uprates. Plants in restructured states are more likely to apply for uprates and, on average, adopt larger magnitude of power uprates.

[24] Some utilities’ service territory spreads to more than one state. I found separately characterizing “mixed” regulation had very little impact on the results.

Based on the above analysis, electricity market restructuring has achieved some remarkable successes. However, whether it is successful in achieving its original goals depends on how much of this productivity improvement resulted in consumer benefits. This will be an interesting topic for further research.

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Figure 1. Year Effects of Unit Production Cost by Regulatory Status

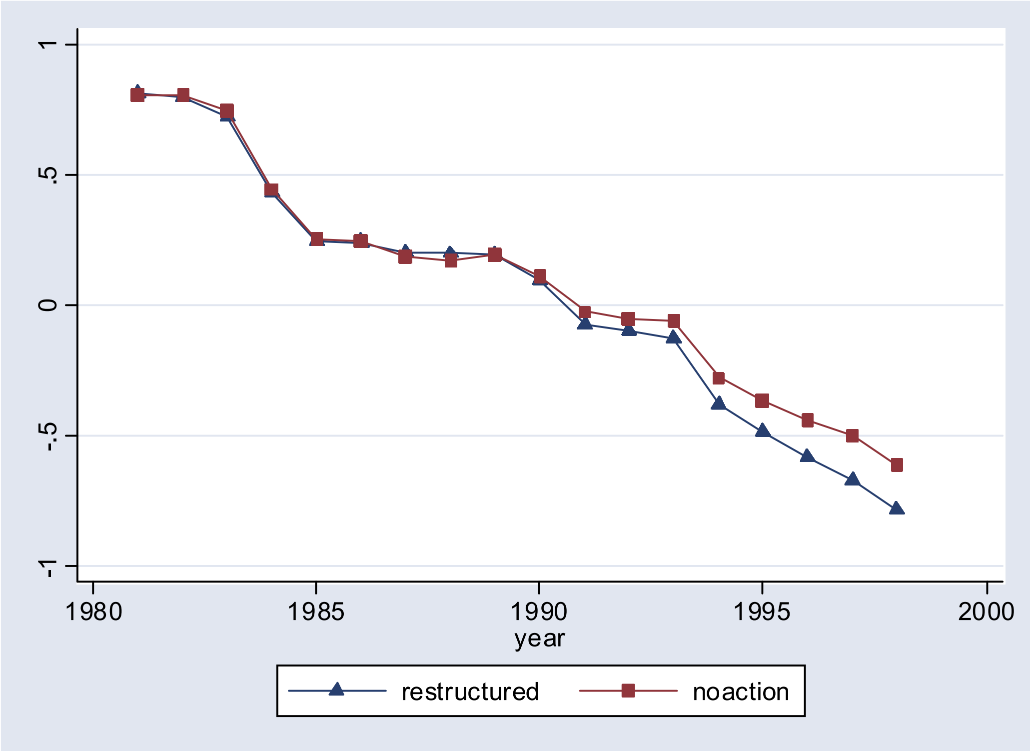

Figure 2. Density of Normalized Capacity Factor and Unit Production Cost—1982, 1992, 1995, 1998

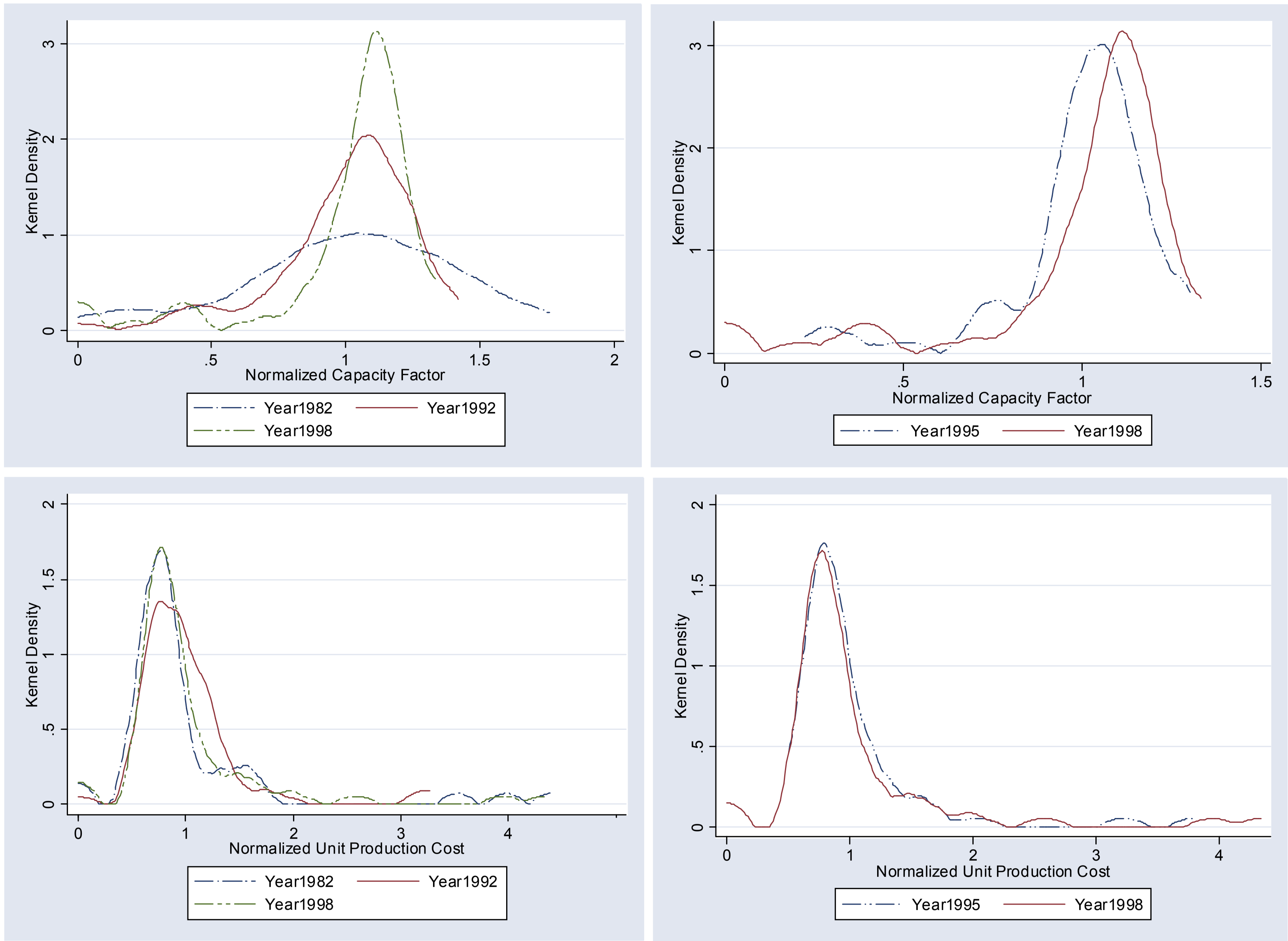

Table 1. Regulatory Status: Plant-Year Observation

Year	Obs.	No Action	Consideration	Action
1992	**72**	**70**	**2**	**0**
1993	**71**	**65**	**6**	**0**
1994	**71**	**38**	**31**	**0**
1995	**71**	**19**	**50**	**2**
1996	**72**	**16**	**45**	**11**
1997	**70**	**14**	**31**	**25**
1998	**68**	**14**	**30**	**24**

Table 2. Summary Statistics of Plant-Level Data

Variable	Mean	Std. Dev.	Min	Max
Capacity Factor (%)	0.71	0.17	0.06	0.98
Average production cost ($/MWh)	22.36	29.35	8.04	525.65
Incentive Regulation	0.59	0.49	0	1
PWR Reactor	0.65	0.48	0	1
Units	1.57	0.64	1	3
Vintage	1978	6.84	1963	1996
Nameplate Capacity (MWh)	1520.59	777.73	75	4210
Age (year)	15.96	7.05	0	34
Obs.			483	

Table 3a Plant Characteristics by Regulatory Status in 1998

Variable	Mean			Differences in Means		
	No Action	**Consideration**	**Action**	N vs. C (1)	N vs. A (2)	C vs. A (3)
Incentive Regulation	.71 (.46)	.57 (.50)	.61 (.04)	-.14**	-.11	.02
PWR Reactor	.75 (.43)	.69 (.46)	.52 (.50)	-.11	-.23**	-.17**
Units	1.65 (.63)	1.65 (.66)	1.52 (.65)	-.005	-.13	-.13
Vintage	1979.7 (5.6)	1980.2 (6.6)	1978.8 (7.1)	1.04	-.006	-1.38
Nameplate Capacity (MWh)	1625.5 (801.5)	1556.5 (661.5)	1483.6 (883.9)	-69.0	-141.9	-72.9
Age (year)	15.9 (5.8)	14.8 (6.9)	16.2 (7.2)	-1.1	.3	1.4

Table 3b Mean Capacity Factor and Average Production Cost by 1998 Regulatory Status

Time	**Mean Capacity Factor** (%)			**Differences in Means** (Percentage Points)		
	No Action	**Consideration**	**Action**			
	Obs. N=13 n = 130	Obs. N=30 n = 251	Obs. N=24 n= 218	N vs.C (1)	N vs. A (2)	C vs. A (3)
1981-1991	55.79 (14.12)	60.28 (9.66)	55.07 (9.96)	4.49**	-0.72	-5.20**
	Obs. N = 13 n = 91	Obs. N = 30 n = 210	Obs. N = 24 n = 168	N vs.C	N vs. A	C vs. A
1992-1998	67.89 (13.17)	74.64 (8.7)	71.44 (11.57)	6.89**	3.55**	-3.12**
Change	27.96% (0.3414)	29.39% (0.1895)	33.91% (0.3365)	1.43**	5.95*	4.52*
Time	**Mean Average production cost** ($/MWh)			**Differences in Means** ($/MWh)		
	No Action	**Consider**	**Action**			
	Obs. N = 13 n = 130	Obs. N= 30 n = 282	Obs. N = 24 n = 228	N vs.C (1)	N vs. A (2)	C vs. A (3)
1981-1991	30.91 (9.13)	32.73 (14.95)	42 (20.29)	1.82	11.09***	9.26***
	Obs. N = 13 n = 91	Obs. = 30 n = 210	Obs. = 24 n = 167	N vs.C	N vs. A	C vs. A
1992-1998	19.69 (9.04)	17.35 (10.82)	19.46 (6.36)	-2.34	-0.23	2.11**
Change	-33.83% (0.2406)	-44.85% (0.2483)	-45.67% (0.2372)	-11.01***	11.82***	-0.82

Note: Plants are categorized into three subgroups “no action” (N), “consideration” (C) and “action” (A), based on their regulatory statuses in 1998. Standard errors are in parentheses. Column (1) of “Differences in Means” presents mean difference in the values between plants which fall into “no action” and “consideration” category in 1998; Column (2) and (3) report the analogous calculations for plants in “no action” and “action” group; and “consideration” and “action” group respectively. Using (ANOVA) models for multiple-comparison test, *** indicates significant at the 1% level; ** indicates significant at the 5% level,*indicates significant at the 10% level. Using a 5% discount rate, costs are in 1992 dollars.

Table 4. Summary Statistics of Instrumental Variables

Variable		Mean	Std. Dev.	Min	Max
Year	overall	1995	2.00	1992	1998
Industry Consumer (%) *(IndSize)*	overall	.327	.100	.099	.550
	between		.097	.105	.496
	within		.022	.170	.459
Republican Control *(Repub)*	overall	.222	.416	0	1
	between		.282	0	1
	within		.305	-.634	1.079
PUC Appointed (*PUC*)	overall	.851	.357	0	1
	between		.349	0	1
	within		.059	.422	1.421
LCV Rating *(LCV)*	overall	.514	.209	.07	.97
	between		.189	.144	.892
	within		.093	.033	.862
Hydroelectricity (%) *(Hydro)*	overall	.064	.117	0	.853
	between		.138	0	.795
	within		.014	-.039	.155
Municipal Electricity (%) (*Muni*)	overall	.213	.214	.014	1
	between		.222	.014	1
	within		.025	-.025	.330
Obs.			395		

Table 5. Determinants of Capacity Factor

Independent Variables	Coefficients OLS	Fixed Effects	Random Effects
Dummy variable D^{con}	.0521 **	.0484*	.0568**
	(0.0254)	(.0293)	.0268
Dummy variable D^{act}	.0783 **	.0797*	.0912**
	(.0254)	(.0438)	(.0399)
PWR	.0485**	NA	.0528*
	(.0196)	--	(.0311)
VINTAGE	.0103	NA	.0078
	(.0066)	--	(.0073)
UNITS	.0142	NA	.0186
	(.0275)	--	(.0479)
INCENTIVE	.0451**	.0500	.0409*
	(.0182)	(.0415)	(.0248)
LnC	-.0619	-.0188*	-.0678*
	(.0362)	(.2504)	(.0649)
AGE	.0137	.0156	.0137
	(.0092)	(.0114)	(.0112)
AGE^2	-.0002	-.0003	-.0003
	(.0002)	(.0003)	(.0003)
Year 1993	.0065	.0035	.0050
	(.0264)	(.0261)	(.0234)
Year 1994	.0063	.0064	.0045
	(.0278)	(.0259)	(.0265)
Year 1995	.0169	.0190	.0153
	(.0279)	(.0267)	(.0248)
Year 1996	-.0090	-.0048	-.0060
	(.0299)	(.0259)	(.0233)
Year 1997	-.0652	-.0619**	-.0618
	(.0389)	(.0266)	(.0244)
Year 1998	NA	NA	NA
	--	--	--
Constant	-19.5076	.6274	-14.4623
	(13.0365)	(1.785)	(14.4540)
Adjusted R-Squared	0.0724	0.0435	NA
Obs.		495	

Note:

1. Standard errors clustered by plant in parentheses.
2. ** significant at the 5% level, * significant at the 10% level.

Table 6. Determinants of Natural Logarithm of Unit Production Cost

Independent Variables	Coefficients OLS	Fixed Effects	Random Effects
Dummy variable D^{con}	-.0852	-.1049	-.0853
	(.0601)	(.0616)	(.0711)
Dummy variable D^{act}	.0430	-.1045	-.0057
	(.0827)	(.0994)	(.0976)
PWR	-.1170**	NA	-.1406**
	(.0410)	--	(.0616)
VINTAGE	-.0830***	NA	-.0886
	(.0128)	--	(.0126)
UNITS	-.0730	NA	-.1255
	(.0778)	--	(.0988)
INCENTIVE	-.0415	-.1341	-.0239
	(.0382)	(.0929)	(.0498)
LnC	-.0685	.1493	.0154
	(.1002)	(.5572)	(.1387)
AGE	-.1004***	-.0928**	-.1280***
	(.0188)	(.0257)	(.0203)
AGE^2	.0010**	.0012	.0019***
	(.0005)	(.0007)	(.0006)
Year 1993	.0754	.0663	.0820
	(.0587)	(.0583)	(.0504)
Year 1994	-.0264	-.0452	-.0073
	(.0519)	(.0583)	(.0378)
Year 1995	.0568	.0194	.0375
	(.0761)	(.0596)	(.0760)
Year 1996	.0146	-.0050	-.0108
	(.0701)	(.0585)	(.0546)
Year 1997	.0619	.0729	.0576
	(.0748)	(.0615)	(.0472)
Year 1998	NA	NA	NA
	--	--	--
Constant	169.2733***	3.082	179.8735 ***
	(25.4742)	(3.9707)	(24.9557)
Adjusted R-Squared	0.2575	0.1473	NA
Obs.		495	

Note:
1. Standard errors clustered by plant in parentheses.
2. *** indicates significant at the 1% level, ** indicates significant at the 5% level,

Table 7. Estimates of Instrumental Variables in Hazard Model

	Hazard Model	
Independent Variables	**Hazard Ratio**	**Coefficient**
Municipal and Co-op	.0017**	-6.3993**
	(.0045)	(2.7032)
PUC Appointed	.4215	-.8640
	(.3859)	(.9157)
Repub. Legislature Control	1.6173**	.4808**
	(.9765)	(.1422)
LCV Rating	.9253	-.0777
	(.0641)	(.0693)
Hydropower	6.2903	0.1839
	(7.6531)	(1.2166)
Industrial Customer Share	2.41e-06***	-12.9354***
	(9.33e-06)	(3.8700)
Constant		-3.5531***
		(.8726)
Obs.	181	

Note:
1. Standard errors in parentheses.
2. *** significant at the 1% level, ** significant at the 5% level

Table 8. Estimates of IV/2SLS Model for Cost Analysis

Independent Variables	**Ln(cost) Coefficient**
$\bar{D}_{IV_{it}}$	-.0086** (.0042)
PWR	-.1030* (.0621)
VINTAGE	-.0848** (.0121)
UNITS	-.0912 (.0703)
INCENTIVE	-.2127** (.0992)
LnC	.1325 (.5554)
AGE	-.1083*** (.0260)
AGE^2	.0011* (.0007)
Year 1993	.0736 (.0578)
Year 1994	-.0818 (.0580)
Year 1995	-.0287 (.0596)
Year 1996	-.0382 (.0588)
Year 1997	.0561 (.0611)
Year 1998	NA --
Constant	3.5053 (3.9531)
Obs.	481

Note:
1. Standard errors in parentheses.
2. *** significant at the 0.01 level, ** significant at the 0.05 level, * significant at the 0.1 level.

Table 9. Impact of Market Restructuring on Investments on Power Uprates

	Coefficient	
Variable	**Probability of Power Uprates**	**Magnitude of Power Uprates**
D^{Dereg}	.480**	1.094**
	(.229)	(.508)
D^{con}	.399	.838**
	(.318)	(.392)
D^{act}	.929	1.559
	(.438)	(1.167)
Obs.	357	

Note:

1. Standard errors in parentheses.
2. ** indicates significant at the 5% level

Table 10. Alternative Specification of Regulatory Status

	Coefficient	
Variables	***CF***	***Ln(Cost)***
V(lawdate)	- .028 *	.033
	(.015)	(.033)
V(time)	-.020**	.045**
	(.008)	(.018)

Note:

1. Standard errors clustered by plant in parentheses.
2. ** indicates significant at the 5% level, * indicates significant at the 10% level.

Table 11. Restructuring Effects at Utility-Level

	Coefficient	
Variables	***CF***	***Ln(Cost)***
D^{con}	- .067 **	-.256**
	(.023)	(.054)
D^{act}	-.047	-.175**
	(.032)	(.077)

Appendix A Data Sources

Plant-level generation and production cost, plant size, capacity factor, year built, and number of units were taken from FERC Form 1. Missing generation data were supplemented with EIA Form 906 and 920. Information on nuclear reactor design (PWR or BWR) was obtained from EIA web site. Data on incentive programs were collected from Appendix I of Marie (1996) and the state incentive regulation dataset provided by Resources for the Future. Data on regulatory status were collected from *Retail Wheeling & Restructuring Report*, a state-by-state reporting of regulatory commissions, state legislations, and utilities' activities related to retail competition published quarterly by the Edison Electric Institute. These data are cross-checked with the *LEAP Letter* published bimonthly by William A. Spratley & Associates and the National Regulatory Research Institute web site. The original report of the Edison Electric Institute provided monthly data on the progress of state-level market restructuring. To make it compatible with the plant-level panel data, I converted monthly data into yearly data by taking the regulatory status in the last month of each year as the regulatory status for the state in that year. The share of industrial consumption was obtained from the EIA historical dataset for electricity retail revenues and sales from 1992 to 1998 by state. Municipal and rural cooperative generation and percentage of hydroelectricity were compiled from EIA's *Electric Sales and Revenue* and *Electric Power Annual* for their respective years. Data regarding Republican control was obtained from *Statistical Abstract of the United States*. Data for PUC appointed or elected and LCV rating were provided by Resources for the Future and were composed from the National Association Regulatory Utility Commissioners' *Profiles of Regulatory Agencies of the U.S. and Canada* Yearbook and the League of Conservation Voters' *National Environmental Scorecard*.