Has Restructuring Improved Operating Efficiency at US Electricity Generating Plants?

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Abstract

This paper assesses whether impending electricity industry restructuring in an investor-owned utility's home state encourages the utility to improve efficiency at its generating plants. Under cost-plus regulation, utilities have little incentive to reduce operating costs since they can pass them directly to ratepayers. Restructuring programs increase utilities' exposure to competitive markets for wholesale electricity and ultimately, to competition for their retail customers. Many restructuring programs have been preceded or accompanied by transitional rate freezes, essentially placing the utility under price cap regulation. We test the impact of these changes on the operating efficiency of electric generating plants. Using annual plant-level data, we compare changes in non-fuel operating expenses and the number of employees in states that moved quickly to deregulate wholesale markets to those in states that have not pursued restructuring. Our results suggest that utilities in states enacting restructuring may have reduced nonfuel operating expenses; evidence on employment is mixed. Production function estimates suggest no significant changes in fuel efficiency, and provide mixed evidence of changes in the efficiency of labor and maintenance activity.

Until the mid-1990s, over ninety percent of the electricity in the US was sold by vertically-integrated investor-owned utilities (IOUs), most operating as regulated monopolists within their service areas. These utilities met demand primarily by dispatching their own plants, though there was some wholesale power traded among utilities, or purchased from a small but growing number of independent power producers (IPPs). A series of policy reforms over the past decade have dramatically altered this picture. Today, roughly a quarter of generation capacity nationwide is owned by non-utility generators, and IOUs in many states may own only a small fraction of total generating capacity and operate in a partially deregulated structure that relies heavily on market-based incentives or competition. While federal policies have encouraged some of this movement, the dominant policy shift has been at the state level. By 1998, every jurisdiction (50 states and the District of Columbia) had initiated formal hearings to consider restructuring their electricity sector, and by 2000, almost half had approved legislation introducing some form of competition including retail access.[1]

The diffusion of restructuring in this sector appears dominated by the quest for lower electricity prices. While studies of state-level electricity restructuring suggest politicians may have been motivated in large part by rent-seeking (e.g., White, 1996, and Joskow, 1997), many proponents of restructuring argued that replacing traditional regulatory rate-setting with more competitive, market-based outcomes would yield efficiency gains that could ultimately reduce electricity costs and retail prices. These arguments were supported by analyses of the substantial variation in efficiencies across regulated electric utilities, as well as by advances in the economic theory of regulation under asymmetric information (see Laffont and Tirole, 1993). While the most significant savings are likely to be associated with long-run investments in new capacity, there may be opportunities for modest reductions in operating costs of existing plants (see Joskow, 1997). The ultimate effect of potential efficiencies from restructuring on electricity prices will depend upon their realized magnitude, as well as possible offsetting effects from restructuring costs, the loss of coordination and network economies within vertically integrated systems, and the exercise of market power in unregulated generation markets.

The considerable body of academic work on electricity restructuring within the US and abroad has thus far focused on assessing the performance of competitive wholesale markets, with particular attention to the exercise of market power (see for example Borenstein, Bushnell and

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[1] In the aftermath of California's electricity crisis in 2000-2001, restructuring has become less popular and many states have delayed or suspended restructuring activity, including six that had previously approved retail access legislation. See US Energy Information Administration (EIA), 2003.

Wolak, 2002 and Joskow and Kahn, 2002). Relatively little effort has been made to quantify the ex post operating efficiency gains of restructuring, if any, although a few studies have analyzed the efficiency effects of alternative regulatory schemes within the electricity sector, see, for example, Knittel (2002).[2] There is suggestive work from other industries on efficiency gains associated with deregulation, particularly with respect to labor use (see for example, Bailey's (1986) overview; Kole and Lehn (1997) and Park et al. (1998) on airlines).[3] Our study attempts to fill this gap by exploring the extent of realized operating gains by utility generators in restructured electricity markets.

The relatively brief time period since restructuring policies have been enacted limits current measurement to the medium-run efficiency gains that Joskow (1997, p. 214) posits "may be associated with improving the operating performance of the existing stock of generating facilities and increasing the productivity of labor operating these facilities." The results of this work indicate that plant operators most affected by restructuring reduced some operating expenses, and provides some evidence of modest efficiency gains. However, the results are sensitive to how input productivity is identified, and to which control group of plants restructured plants are compared.

The remainder of the paper is organized as follows: Section 1 describes the pre-restructuring regulatory structure and incentives and discusses how restructuring might alter plant operations. Sections 2 details our empirical methodology for testing these predictions, focusing on our strategy for identifying restructuring effects. the data are described in Section 3. Sections 4 and 5 report the results of the empirical analysis, and Section 6 concludes.

1. Why Might Restructuring Affect Generator Efficiency?

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[2] One exception is Hiebert (2002), who includes indicators for regulatory orders or legislative enactment of restructuring reforms in 1996 and in 1997 in stochastic frontier production function estimates of generation plant efficiency over 1988-1997. While he finds significant reductions in mean inefficiency associated with restructuring laws in 1996 for coal plants, he finds no effects for gas plants, nor for either fuel type in 1997. Our work uses a longer time period, richer characterization of the restructuring environment and dating of reforms consistent with the U.S. Energy Information Administration, and an alternative technology specification that allows for more complex productivity shocks and treats possible input endogeneity biases. Joskow (1997) describes the significant labor force reductions that accompanied restructuring in the UK, as the industry moved from state-owned monopoly to a privatized, competitive generation market, although these mix restructuring and privatization effects.

[3] Some hint of this possibility in electricity is provided by Primeaux (1977), who compared a sample of municipally owned firms facing competition to a matched sample of municipally owned firms in monopoly situations and found a significant decrease in costs per kWh for firms facing competition.

It has long been argued that traditional cost-of-service regulation does relatively well in limiting rents but less well in providing incentives for cost-minimizing production.[4] For an investor-owned utility operating under traditional cost-of-service regulation, the revenue it receives increases proportionally with the costs of its plants, with little direct dependence on the efficiency or performance of those plants. An investor-owned utility files a rate case with the appropriate state Public Utilities Commission (PUC), and the PUC determines allowed rates. The aggregate revenue that the utility is allowed to collect has four basic components: (1) total rate base; (2) allowed rate of return; (3) non-fuel expenses and (4) fuel expenses. The total rate base reflects the depreciated cost of the utility's physical plant, including, for instance, generating plants, transmission towers and distribution lines. The allowed rate of return is set at the weighted average cost of capital, and the only component over which regulators have much discretion is the cost of equity. Occasionally, the allowed return on equity may be set low to penalize inefficient operation or high to reward good performance, although the range within which regulators can work typically is modest. Regulators determine allowable non-fuel expenses, such as labor costs, using actual costs over a test period. Rate hearings are held to adjust rates based on components (1) through (3) at most annually, although nearly every state has separate fuel adjustment clauses to change rates as frequently as every three months based on changes in fuel procurement costs. The costs of purchasing power from other utilities or IPPs are usually included with fuel costs.[5]

Since the (PUC-approved) costs of the utilities are passed directly through to customers, reductions in the cost of service yield at most short-term profits, because rates would be revised to reflect the new lower costs at the next rate case.[6] Similarly, inefficient behavior by managers that raises costs of operation in principle would be reflected in increased rates and passed through to customers. Joskow (1974) and Hendricks (1975) demonstrate that frictions in cost-of-service regulation, particularly those arising from regulatory lag (time between price-resetting hearings), may provide some incentives at the margin for cost-reducing effort. Their impact generally is limited, however, apart from periods of rapid nominal cost inflation (see Joskow, 1974).

Restructuring fundamentally changes the way plant owners are paid for their output. At the wholesale level, plants sell either through newly-created spot markets or through long-term contracts that are presumably based on expected spot prices. In the spot markets, plant owners submit bids indicating the prices at which they are willing to supply power from their plants.

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[4] Stigler (1962) notwithstanding; see Peltzman (1993).

[5] For analysis regarding the efficiency implications of the fuel adjustment clause, see Gollop and Karlson (1978) and Baron and De Bondt (1979).

Dispatch order is set by the bids and the bid of the marginal plant is paid to all plants that are dispatched. This gives the plant operators an incentive to reduce costs, to move higher in the dispatch order, increasing dispatch probability, and to increase the profit margin between plant costs and the expected market price.

Most restructuring programs have also changed the way retail rates are determined and the way in which retail customers are allocated. States have used a variety of approaches to link retail rates under restructuring to wholesale prices in the market. Over the short-term, most states implemented rate freezes. For instance, Massachusetts regulators mandated that the incumbent utilities offer all customers a "standard offer service" which reflected a ten percent reduction off pre-restructuring rates. These decouple a utility's revenue from its costs, so that the company can keep the difference between its rates and any savings it can squeeze out of its fuel costs, for instance. Some states, such as Pennsylvania, are aggressively trying to encourage entry by competitive energy suppliers, who may contract directly with retail customers. Retail access programs may increase the intensity of cost-cutting incentives, leading to even greater effort to improve efficiency.

Economists have long-argued that replacing cost-of-service regulation, with its relatively dull incentives for reducing costs, with higher-powered regulatory incentive schemes or increased competition may enhance cost efficiency.[7] This paper attempts to measure the extent of that possible improvement for the existing stock of electricity generating plants in the U.S. The implicit null hypothesis is that, before restructuring, operators were minimizing their costs, given the capital stock available in the industry. Under the null, there should be no change in plant-level efficiency measures associated with restructuring activity. We discuss below our method for identifying deviations from this hypothesis.

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[6] Rates are constant between rate cases, apart from certain specific automatic adjustments (such as fuel adjustment clauses), so changes in cost would not be reflected in rates until the next rate case.

[7] See, for example, Laffont and Tirole (1993).

2. Identification Strategy

Assessing the effects of restructuring requires specification of how generating plants would have been operated absent the policy change. Constructing this counterfactual is crucial, but difficult. There is substantial heterogeneity across plants, utilities and states, and the economic environment in which utilities operate may change considerably over time. In addition, restructuring is not randomly assigned across political jurisdictions—earlier work suggests that it is strongly correlated with higher than average electricity prices in the cross-section.[8] Fortunately, we have a database rich in variation available in this sector. There are thousands of generating plants operated by hundreds of utilities subject to regulation by dozens of political jurisdictions each setting their own legal and institutional environment. This allows us to construct benchmarks that we believe control for most of the potentially confounding variation, as described below.

Consider a general production function:

$$Q_{isrt} = F(\underline{I}_{ist}; \underline{\beta}; \varepsilon_{isrt})$$

where Q is output, $\underline{I}$ is a vector of inputs, $\underline{\beta}$ is a parameter vector, and $\underline{\varepsilon}_{isrt}$ is a vector of productivity shocks associated with plant *i* in state *s* operating under regulatory regime *r* in year *t*. We consider a rich structure of potential productivity shocks,[9] denoted by

$$\underline{\varepsilon}_{isrt} = \{\alpha_i , \delta_t , \gamma_r , \eta_{isrt}\}$$

The plant-specific shock, α_i, measures the efficiency of plant *i* relative to other plants in the sample. These shocks may be associated with differences in plant technology type and vintage, ownership (government v. private utilities), and time-invariant state effects on productivity. The year-specific shock, δ_t, measures the efficiency impact of sector-level shifts over time, such as secular technology trends, macroeconomic fluctuations or energy price shocks. Restructuring effects on plant productivity correspond to a non-zero γ_r. The heterogeneity in the timing and outcomes of state-level restructuring activity, as well as variation across utilities within a state on

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[8] The significant role of sunk capital costs in regulatory ratemaking mean that high prices do not necessarily imply high operating costs for generation facilities within a state, however. See Joskow (1997) for a discussion of the contributors to price variation across states.

[9] At this point, we are agnostic about whether these shocks are Hicks-neutral or factor-specific, and hence require a factor superscript. This question is addressed in the development of our specific production function model.

the applicability of restructuring, allow the data to distinguish between temporal shocks and restructuring effects. While all states held hearings on possible restructuring, the earliest was initiated in 1993, and the latest in 1998. There is considerable variation in the outcome of those hearings, as well, with just under half the jurisdictions (23 states and the District of Columbia) enacting restructuring legislation between 1996 and 2000.[10] The remainder considered and rejected, or considered and simply did not act on, such legislation. This variation allows us to use changes in efficiency at plants in states that did not pass restructuring legislation to identify restructuring separately from secular changes in efficiency of generation plants over time.[11] Finally, because restructuring applies to private investor-owned utilities but not to publicly-owned municipal or federal plants within a given state, the difference in restructuring shocks across ownership types implicitly nets out any differential in efficiency evolution over time between restructuring and non-restructuring states. We therefore consider two alternative benchmarks for plants operated by investor-owned utilities in restructuring regimes: all plants in non-restructuring regimes, and government- or cooperatively-owned plants in restructuring regimes.

3. Data & Summary Statistics

The analysis in this paper is based on annual generating plant-level data for U.S. electric utilities. Plants are comprised of at least one, but typically several, generating units, which may be added to or retired from service over the several-decade life of a typical generating plant. While an ideal data set would allow us to explore efficiency at the generating unit level, inputs other than fuel are not available at the generating unit level, and some, such as employees, are not assigned at the unit level as they are shared across units at the plant.[12] We therefore use a plant-year as an observation. To minimize the effect of changes in generating units at a plant over time, we define plant-epochs as a plant during a period in which there are no significant changes in capacity. When there are significant changes in capacity, as occurs if generating units at the plant are

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[10] We collected information on state restructuring legislation from various Energy Information Administration and National Association of Regulatory Utility Commissioners publications and state public utility commission websites. Since 2000, no additional states have enacted restructuring legislation, and several have delayed or suspended restructuring activity in response to the California crisis.

[11] There is some possibility that control group plants altered their behavior over this period, due perhaps to a mix of the introduction of incentives within states that did not enact restructuring, an expectation of potential restructuring that did not occur, and spillovers from restructuring movements in other states (e.g. if regulators updated their information about the costs necessary to run plants of a certain type). To the extent this occurs, our comparison will understate the magnitude of any efficiency effect of restructuring.

[12] Indeed, some labor may be shared across multiple plants, though assigned to one particular plant in our data. This will lead induce measurement error, particularly in the plant employment variable.

retired or added, a new plant-epoch is defined. Plant-specific shocks are defined at this plant-epoch level.

The Federal Energy Regulatory Commission (FERC) collects data for investor-owned utility plants annually in the FERC Form 1, and the Energy Information Administration (EIA) and Rural Utilities Service (RUS) collect similar data for municipally-owned plants and rural electric cooperatives, respectively. These data include operating statistics such as size of the plant, fuel usage, percentage ownership held by the operator and other owners, number of employees, capacity factor, operating expense, year built, and many other plant-level statistics. Our base data set includes all large steam and combined cycle generating turbine (CCGT) generating plants for which data were reported to FERC or EIA over the 1981 through 1999 period.[13] We excluded smaller plants, defined as those for which gross capacity exceeded 100 megawatts for fewer than three of our sample years. We also excluded approximately 1,500 observations where data were missing, and dropped several hundred observations based on diagnostic tests to screen for sensitivity to individual observations. Further details on the data are provided in the Appendix.

We supplement the operational plant data with information on state-level restructuring activity. For each state, we have identified the date at which formal hearings on restructuring began, the enactment date for legislation, if any, restructuring the state's utility sector, and the implementation date for retail access under that legislation. Testing for restructuring-specific shocks requires a determination of how to match this information with firm decisions: when were plant operators in a given state likely to have begun responding to a policy change? Our reading of these events suggests that utilities may have acted in advance of final outcomes. The legislative and regulatory process leading up to state restructuring typically lasted a number of years, allowing utilities to anticipate the coming change, and alter their behavior in advance. For example, Boston Edison's 10-k filed in March 1994 discussed Massachusetts' consideration of restructuring, stating "The Company is responding to the current and anticipated competitive pressure with a commitment to cost control and increased operating efficiency without sacrificing quality of service or profitability" (p. 6).[14] Early action may have begun to phase in input

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[13] One unfortunate consequence of restructuring is that available data on plants sold by utilities to non-utility generators are extremely limited after the sale, due to changed reporting requirements. This means that plants will be excluded from the dataset after such sales.

[14] In a 1993 article outlining PECO's cost saving accomplishments and strategies for the future, Chairman and CEO Joseph Paquette discussed restructuring of the utility industry and was quoted as stating, "we have been focusing on our strategic plans to enhance our abilities to satisfy our customer needs by becoming more competitive." PECO initiatives cited in the article included improving the cost effectiveness of all operations. One particular accomplishment noted was the reduction in total employment from 18,700 to 12,900.

changes, such as those involving labor and particularly unionized workers that require lead-time to implement. Moreover, as policy changes were discussed, rates were frozen in many states, either explicitly by policy makers or in effect by implicit PUC decisions not to hear new rate cases, enabling utilities to capture immediately the savings from incremental cost reductions.

In this work, we test for restructuring effects beginning with the opening of formal hearings on restructuring. The primary variable of interest, *RESTRUCTURED*, is an indicator variable that turns on with the start of formal proceedings in a state that eventually passed restructuring legislation (as of 2000). A second variable, *HEARINGS*, indicates the start of formal hearings in states that did not pass legislation. A third variable, *RETAIL ACCESS*, indicates the start of retail access for plants in the four states that implemented retail competition during the sample.[15] Table 1 reports the number of plants in our database each year that were in states that had begun formal proceedings and the number of plants in states that had started retail access by 1999.

Comparing changes associated with *RESTRUCTURED* to those associated with *HEARING* only provides information on the differential impact of being in a state that approves restructuring as opposed to just considering a policy change. If utilities do not respond until restructuring legislation or regulation is enacted, and the uncertainty resolved, *RESTRUCTURED* will underestimate the true effect. To evaluate this possibility we introduce a fourth variable, *LAW PASSED*, an indicator equal to one beginning in the year the state passes restructuring legislation.[16] Similarly if actual implementation of retail access and the associated wholesale market reforms is important to efficiency gains, it will be reflected in an incremental effect of *RETAIL ACCESS*.

The data are summarized in Tables 2a and 2b. Table 2a reports summary statistics for all observations in our database across all years. Table 2b reports the mean and standard deviation for plants in restructuring and non-restructuring states for the year 1990. From this table, it is evident that the plants from these two groups of states do not look like random draws from the same population. The first three variables measure employees and non-fuel operating expenses, scaled by the plant's capacity, and fuel expenses, scaled by the plant's output. In 1990, before state-level restructuring initiatives were considered, plants in states that eventually restructured

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[15] While *RESTRUCTURED* indicates approval of retail access legislation, the specified phase-in of retail access was often slow. Only five states implemented retail access during our sample period: Rhode Island in 1997; California, Massachusetts, and New York in 1998, and Pennsylvania in 1999 (US EIA, 2003). Because we have no valid observations on Rhode Island plants in 1997 or beyond, retail access effects will be determined by the 4 states implementing in 1998 or 1999.

[16] There is on average about a 2.6-year lag between the initiation of hearings and the passage of the law.

had higher intensities of all three inputs, although the difference is significant only for non-fuel expenses. *BTU EXPENSE* and *HEAT RATE* decompose the fuel expenses into the efficiency with which the plant converts the energy in fuel to electricity and the expense of the energy in the fuel. The last five variables in Table 2b describe the stock of plants in the two types of states. Plants are very similar in size, but in restructuring states, plants were older, more likely to use gas, and less likely to use coal. The empirical analysis controls for these differences directly with plant-level fixed effects, and we have analyzed many of the relationships separately for different fuel types.

If plant operators achieved efficiency improvements when facing impending restructuring of the generation sector, one would expect to see a relative decrease in the cost of generation for affected companies, and little difference in the change in transmission and distribution costs between the affected and not affected states since restructuring programs leave transmission and distribution comparatively untouched. If restructuring did not affect operating efficiency in the generation sector, we might expect either (1) the change in generation expenses would not be statistically difference between restructuring and non-restructuring companies, or (2) we would see the same pattern of change in costs for the transmission and distribution sectors as for the generation sector.[17]

Table 3a and 3b display the difference in mean tests for companies in restructuring and non-restructuring states for a change in costs between 1990 and 1996. Table 3a reports the percentage change in total costs for each category of cost, and Table 3b reports the percentage change in costs per MWh. The larger decrease in generation costs at restructuring companies is significant at the 1% level, and the result for generation costs per MWh is significant at the 6% level. The difference in costs for companies in restructuring and non-restructuring states is not significant for either the transmission or distribution costs. These aggregate statistics provide preliminary support for the expectation that the portion of the utility company faced with competition (the generating sector) responded with a decrease in costs, while other sectors and companies not faced with competition did not share this response.

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[17] For the analysis comparing costs of generation, transmission, and distribution services, we rely on data reported annually by utility companies to the Federal Energy Regulatory Commission (FERC) in the FERC Form 1, page 320, 321, and 322 respectively. We use a balanced sample composed of all companies with data reported for all three sectors in both 1990 and 1996. This amounts to 50 companies in states that did not deregulate and 74 in states that did deregulate for the comparison of costs, and 48 and 72 respectively for the comparison of costs per MWh. Using costs per MWh necessitates the exclusion of a few companies for which MWh data was not available in one of the two years.

4. Input use effects of restructuring

In this section, we describe the correlation of restructuring with three variable inputs to electricity production: labor, materials, and fuel. Raw state-level aggregates suggest a possible inverse correlation between restructuring activity and input use. Figures 1, 2, and 3 compare the average generating plant employees per MW, average non-fuel operating expenses per MW, and fuel expenses per MWh, respectively, for investor-owned plants in states that passed restructuring legislation to those in states that did not.[18] These graphs suggest some divergence in the relative efficiencies of the two groups of plants after the early 1990s, when restructuring began, for employees and non-fuel expenses. Consistent with the summary statistics in Table 2b, plants in restructuring states seemed to use more employees and have higher nonfuel operating expenses prior to the early 1990s. In both series, input use in restructuring states converges to, then dips below, that in non-restructuring states by the end of the sample period. The effects of restructuring are not readily apparent in the fuel expense graph, although divergent price changes across fuels may confound this series. While these graphs suggest that plants that faced restructuring may have reduced some input use, they do not control for variations in plant attributes or changes in plant mix that could alter input intensity, nor do they link changes directly to the timing of restructuring activity. We therefore use regression analysis to more precisely identify possible restructuring effects in the data. We focus on the labor and nonfuel expense inputs.

As described earlier, differences in efficiency following restructuring are identified by comparing changes in performance for plants subject to the regulatory changes to changes in performance for those not subject to restructuring, controlling for general industry, state, and plant characteristics. The control group consists of two types of plants: those in states that did not restructure their electricity generating sector, and government- or cooperatively-owned plants in states that restructured. We will refer to the latter group as "municipal" plants, while recognizing that the group is broader than the label. The general form of the model is:

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[18] For the figures and the regression analysis that follows, plants are assigned to the state in which they are regulated. A plant located in one state may be owned by a company with exclusive service territory in a different state, and that second state is the state by which the regulatory policy is measured. Some plants are owned by a company with service territory in more than one state and some plants are owned by several companies that are regulated by different states. In the regression analysis, we found that separately characterizing "mixed" regulation and "shared" plants had very little impact on our results

$$Input\ Usage_{kist} = f[Restructured_{ist,}, Plant\ Attributes_{ist}] + e_{kisrt} \qquad (1)$$

for input *k* used by plant *i,* in state *s*, year *t* and restructuring regime *r*.

For this analysis, we model the error term, e_{kisrt}, as

$$e_{kisrt} = \alpha_{\mathrm{ki}} + \delta_{\mathrm{kt}} + \eta_{\mathrm{kisrt}}$$

where α_{ki} is a time-invariant error component at the plant level, which may contain a state-specific effect that will not be separately identified, δ_{kt} is an industry-level effect for input k in year t, and η_{kisrt} is assumed to be a time-varying mean zero i.i.d. shock for input *k* at plant-epoch *i* in state *s* at time *t*. As a Hausman test rejects the exogeneity assumption for the plant effects, we report results using plant-epoch fixed-effects to control for time-invariant unobservable differences between the plants.[19]

The basic regression is:

$$\begin{aligned}\ln(\mathrm{Input}_{\mathrm{kist}}) = {} & \beta_{1k}\ln(MWh_{\mathrm{it}}) + \beta_{2k}AGE_{\mathrm{it}} + \beta_{3k}FGD_{\mathrm{it}} + \gamma_{\mathrm{IOU}}\, IOU{*}RESTRUCTURED_{\mathrm{isrt}} \\ & + \gamma_{\mathrm{MUNI}}\, MUNI{*}RESTRUCTURED_{\mathrm{isrt}} + \alpha_{\mathrm{ki}} + \delta_{\mathrm{kt}} + \eta_{\mathrm{kisrt}}\end{aligned}$$

We consider two measures of input use: First is the number of employees working at the plant during the year, *EMPLOYEES.* The second measure is total non-fuel operating expenses, *NONFUEL EXPENSE,* which includes all non-fuel operations and maintenance expenses, such as expenses for coolants, maintenance supervision and engineering expenses.[20] The latter measure includes the wage bill for the employees counted in *EMPLOYEES*, although that expense is not separately delineated in the data. Plant-epoch fixed effects control for much of the expected variation in input use across plants arising from heterogeneous technologies, state or regional fixed factors, and basic efficiency differences. They also control for differences in the plant mix between restructuring and non-restructuring states by comparing each plant to itself over time, removing any time-invariant plant effects.

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[19] This use of fixed effects is similar to the work of Joskow and Schmalensee (1987), who used generating unit-level data to explore the relationship between operating performance and unit characteristics. Our fixed effects are actually finer than plant-level, as we permit α_i to change with unit additions or retirements, and other significant changes in rated plant capacity.

Even with this level of detail in plant fixed effects, two important characteristics vary over time:. *FGD,* which records the presence of a flue-gas desulfurziation system (also called scrubbers) to reduce sulfur-dioxide emissions in some coal plants; and *AGE*, the age of the plant in year t, dated from the installation date of the oldest operating generating unit at the plant.[21]

Input use over time will vary with the level of plant operation, which is measured in these specifications as the net generation by the plant in megawatt-hours (MWh). Two problems arise in estimating its effect. First, as described earlier, staffing decisions and much of the nonfuel operating budget are likely to be set in advance of utilization realizations and remain relatively fixed over a year's horizon. Deviations from predetermined employment and maintenance budgets may be caused by unanticipated breakdowns that require increased labor and repair expenditures and result in lower output. In addition, there may be a simultaneity problem: shocks to input use may be correlated with output, if, for example, if managers choose to operate their more efficient plants more, increasing both input and output. We treat this by instrumenting for output with state demand (the log of total state electricity sales, and this variable squared). These instruments affect the likelihood that a given plant in the state will be dispatched more over the year, but are not influenced by the characteristics of the plant or the choices of individual plant operators.

We consider specifications that include the four restructuring indicator variables described in section 3: *RESTRUCTURED, HEARINGS, LAW PASSED,* and *RETAIL ACCESS*. As described earlier, these variables are equal to zero prior to the initiation of formal restructuring hearings for the first two variables, or the date of enactment or implementation for the latter two variables, and equal to one for all years following the relevant event. In some specifications, a counter variable equal to the number of years since the initiation of hearings is also employed. In the input regressions, a negative coefficient on the restructuring variables would imply reduced input use associated with the regulatory reform.

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[20] Fuel is considered in the production function specification. We also have explored specifications that decompose fuel costs per Mwh into a price component (fuel cost per Btu of fuel input) and fuel efficiency component (heat rate, equal to Fuel Input in Btus/Mwhs).

[21] We considered using load type (base, cycle, or peak plant designations) as a control for expected usage intensity, but these designations appear to be poorly defined and are not generally reported in our data after 1993. We estimate some models separately for those units we can identify as base units throughout the sample.

The core results for the input analysis are presented in Tables 4 for *EMPLOYEES* and Table 5 for *NONFUEL EXPENSES*. As described above, all regressions include year and plant-epoch fixed effects.[22] Column 1 of each table reports a simple OLS formulation, in which *IOU*RESTRUCTURED* captures the mean differential in input use for investor-owned utilities in states that eventually pass restructuring legislation, measured over the period following the first restructuring hearings, relative to utilities in non-restructuring states, without controlling for output levels. This corresponds to the mean within-plant shift in input use, output independent. The results suggest statistically and economically significant declines in inputs during restructuring. Employment declines by almost 8% (2%) and nonfuel expenses decline by about 17% (2%). These do not seem to reflect unmeasured state-level trends, as the estimated change in input use of municipally-owned utilities in these states is positive for employment and indistinguishable from zero for nonfuel expenses during the restructuring period.[23] Controlling for plant output reduces the estimated impact of restructuring slightly, though the effects remain large and statistically distinguishable from zero (see column 2 of each table), at -6% (2%) for employment and -13% (2%) for nonfuel expenses. Again, IOU plants reduce inputs by more than do municipal plants within restructuring states, and the differences are statistically distinguishable from zero. Measuring restructuring effects from the enactment date of legislation does little to change the conclusions (see column 3 in each table.).

This finding hints at the first surprise in our data: same-plant output declines on average in restructured regimes, which is why estimated input use reductions associated with restructuring are smaller in the presence of output controls. Some of this might be expected: if these plants were less efficient prior to restructuring, as the raw input and price data suggest may have been the case, they may be used less in a more competitive environment. If restructuring encourages entry by non-utility or exempt generators, this might further reduce output at less efficient plants. What is more surprising, however, is that the decline also appears in state-level sales data, suggesting that electricity consumption is lower in restructured regimes, all else equal. Given that restructured regimes are measured in our data only through 1999, the height of the economic boom, this decline is unexpected, if not dubious. Whether it is an artifact of data collection and tabulation methods used by the U.S. Energy Information Administration, or reflects real decreases in electricity consumption, remains an open question.

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[22] All equations were estimated correcting for a non-diagonal error correlation matrix within a plant. The regression sample excludes observations that were identified as overly influential using a set of regression diagnostic tools in Stata.

Given the importance of controlling for output in assessing restructuring effects, we next turn to instrumental variables estimates of the input equations, which attempt to control for potential measurement error and simultaneity bias. The fourth column of each table explores the impact of instrumenting for output using the log of total electricity sales in the state and its square. The effect in each case is to increase the magnitude of the coefficient on output, and to further reduce the magnitude of the coefficient on the *IOU*RESTRUCTURING* variable, to less than half its magnitude in the OLS regressions. Employment is estimated to decline by a little more than 2% (1% standard error) with restructuring for IOUs, relative to all plants in non-restructuring regimes (column 4, table 4). Nonfuel expenses decline by a little more than 6% (2% standard error; column 4, table 5). Measuring restructuring by *LAW PASSED* leads to estimated declines of 3.5 – 4.0% in each input (column 5).

These columns highlight the next surprise in our data: government-owned and cooperative plants in restructuring regimes, which were in general not subject to the same competitive pressures as IOUs in those states, use more inputs, all else equal, relative to plants in non-restructuring regimes. This divergence leads to an estimated gap of roughly 15% in input use between IOU plants and the public and cooperative plants in restructuring regimes. Thus, the conclusion of whether restructuring leads to substantial reductions in input use depends importantly on the counterfactual: has input use declined modestly, as implied by the comparison to plants in non-restructuring regimes, or were there factors in the restructuring states that would have led to even greater input use (as reflected by the MUNI coefficients) for IOU plants had they not been subject to restructuring pressures?

In columns 6 and 7, we add the *HEARINGS* and *RETAIL ACCESS* variables. For employment, neither hearings alone nor *IOU*RESTRUCTURED* has any discernable effect, with point estimates that are indistinguishable from zero. In the specification that measures restructuring from the legislative enactment date, *IOU*LAW PASSED* maintains its earlier estimated effects, of about a 3% decline in employment. Surprisingly, however, the move to retail access is associated with an estimated *increase* in employment of almost 14% (5% standard error). The gap between IOU and municipal plants is maintained, apart from the retail access impact. The addition of years since hearings were begun in column (8) has little real impact on the pattern of results.

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[23] Tests of the equality of the *RESTRUCTURED* coefficients across IOUs and MUNIs reject the hypothesis of equality at tight significance levels for both regressions.

These results contrast to those for nonfuel expenses in Table 5. Hearings alone are associated with declines of about 4.5% (2% standard error) in nonfuel expense, somewhat smaller than the estimated impact of roughly 7.5% (2%) for hearings that lead to legislative action. Both effects are much smaller, and statistically indistinguishable from zero, in column (7), which measures restructuring at the legislative enactment date. Retail access is associated with substantial declines in nonfuel expenses, on the order of almost 20% (though estimated somewhat imprecisely, with a standard error approaching 7%). Including the number of years since hearings were initiated in column (8) suggests a 3% (1%) decline per year in the nonfuel expense regressions, suggesting more pronounced expense reductions over time and as restructuring becomes more certain. In all of columns (6) through (8), IOUs reduce nonfuel expenses relative to utilities in non-restructuring regimes and even more relative to municipal plants in their same states.

We explore three more variants of the input use specifications in tables 6 through 8. Table 6 introduces an alternative measure of competitive pressure, based on an indicator (*HIGH NUGS)* that turns on in 1993 if the plant is in a state that has above median penetration of non-utility generation as of 1995. Columns 1 and 3 replace the policy-based measures with this variable; columns 2 and 4 include the variable *BOTH*, which interacts the *RESTRUCTURED* and *HIGH NUGS* variables. The estimated impact of non-utility generation on nonfuel expenses (columns 1 and 2) is indistinguishable from zero, though it is correlated with an estimated 5% (1%) reduction in employment.

In table 7, we explore results for two subsamples: baseload coal plants and baseload gas combined cycle (CCGT) plants. The results for *IOU*RESTRUCTURED* in columns (1) and (3) suggest that restructuring is associated with declines of about 8% (3%) in nonfuel expenses for coal plants, but no effect on employment. Note that the estimated output elasticities are considerably higher for these subsamples than for the universe of plants in the earlier tables. The results for gas plants in columns (2) and (4) suggest no effect on nonfuel expenses, and an almost 6% (3%) *increase* in employment, relative to plants in non-restructuring states. This result may be possibly confounded by the prevalence of gas plants in restructured states, making it more difficult to identify input use relative to non-restructuring state plants. We continue to explore this puzzle.

Finally, in table 8, we consider the evidence for possible regression to the mean: whether plants in restructuring states are able to increase efficiency because they are low efficiency plants, and would be expected to improve through some regression to the mean effect. To examine this, we identify high and low cost plants to investigate whether efficiency gains at the higher cost plants are offset by efficiency losses at low cost plants. To separate plants into "cheap" and "expensive" categories, we run an OLS regression on data for the pre-restructuring period, 1981 – 1993, regressing the input measure on plant, state, and industry characteristics (excluding plant fixed effects). We calculate the mean residual for each plant and classify plants with mean residuals above zero as "expensive" and those below zero as "cheap." We then interact these expensive and cheap indicators with the restructuring variables (which are post-1993), and re-run the fixed effects regressions using these more detailed restructuring variables. Results are presented in Table 8. The results suggest that expensive IOU plants in restructuring states reduced both labor and nonfuel expenses, by 5% to 8%. Cheap IOU plants also reduced nonfuel expenses, though the point estimates are below those for expensive IOU plants, and held employment inputs constant. These results provide little evidence of mean reversion for IOU plants, unlike the roughly 20% increases in input use for cheap municipal plants in restructuring regimes.

5. Production Function Estimates of Efficiency

We next turn to a structural model of efficiency. For a single-output production process, productive efficiency can be assessed by estimating whether a plant is maximizing output given its inputs and whether it is using the best mix of inputs given their relative prices. Production functions describe the technological process of transforming inputs to outputs and ignore the costs of the inputs. Cost minimization assumes that, given the input costs, firms choose the mix of inputs that minimizes the costs of producing a given level of output. A firm could be on the production frontier, but not minimizing its costs if, for instance, labor was cheap relative to materials, yet a firm was using a high materials to labor mix of inputs. Even if the firm were producing the maximum output possible from its given workers and materials, it would not be efficient if it could produce the same level of output less expensively by substituting labor for materials.

An ideal approach would be to estimate cost functions and assess how restructuring changes firms' positions relative to the cost frontiers. Cost functions subsume technical efficiency (output maximization for a fixed set of inputs) and optimal input use. Unfortunately, while we have plant-level data on employees, fuel inputs and prices, and non-fuel operating expenses, we lack micro data on materials prices and wages facing plant managers. Moreover, some earlier work, such as Hendricks (1975), suggests that regulatory inefficiencies may take the form of not bargaining aggressively over input prices, such as wages. These both argue against cost function estimation.[24] We therefore explore the impact of restructuring on the efficiency using a production function approach.

We confront a number of difficulties implementing this approach First is measuring output. While generating plant output frequently is summarized by the net energy the generating units produce over some period (measured in megawatt-hours per year in our data), output in reality is multidimensional, and most dimensions are not recorded in the plant data. For example, generating plants may also provide reliability services (such as spinning reserves, when the plant stands ready to increase output at short notice), voltage support and frequency control. While the production process varies considerably across these different outputs, only net generation is well-measured in the data.[25] Moreover, electricity output is not a homogenous product. Because electricity is non-storable, electricity produced at 5PM on the first Friday in July is a separate output from electricity produced at 5AM on the second Sunday in March. Firms must decide how to balance the costs associated with taking their plant down to do maintenance against the probability that a poorly maintained plant will fail during peak demand hours, and the availability of the plant may be an important modifier of output quality. Changes in incentives associated with restructuring may have altered firms' assessments of these tradeoffs, although the expected direction of the effects are theoretically ambiguous.[26] Hourly output prices and output from individual plants might allow us to better assess this. Lacking such data, we rely on a single output dimension, but acknowledge its limitations.

The second issue we confront is how to specify the form of the production function. Actual output from a generating plant will in general be the lesser of the output the plant is capable of producing, given its available inputs, and the output called for by the system dispatcher. This is further complicated by the fact that some inputs are determined far in advance of demand realizations. From the perspective of our problem, capital is set far in advance of production, and at the plant level is changed relatively infrequently. We use plant-epochs, and treat capital as a

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[24] Other studies have looked at cost minimization using noisy proxies for wages. For instance, Kleit and Terrell (2001) use the average wage for workers in the same two-digit SIC code as utilities in the county where the power generating plant is located. We find this approach unconvincing.

[25] The inputs required to produce a given level of energy (MWh) from a specific plant also will depend on whether the plant runs continuously or intermittently and on its average capacity utilization. Starting a plant frequently and running it at low capacity utilization rates typically use more inputs (particularly fuel) than running a plant continuously at its rated capacity.

[26] For instance, under traditional regulation, utilities may have faced strong political incentives to avoid blackouts or brownouts, leading to investment in greater capacity to increase reserve margins and in greater maintenance resources to increase plant reliability. On the other hand, firms producing in restructured wholesale markets may face even stronger incentives to be available when demand peaks because this is when prices are highest.

fixed input from the perspective of the utility. Utilities hire labor and set operating and maintenance expenditures in advance, based on expected demand. While these can be adjusted over the medium-run, staffing decisions as well as most maintenance expenditures are not tied to short run fluctuations in output.[27] We will therefore treat these as set in advance of actual production, and determining a target level of available output, Q^A. Fuel, on the other hand, is varied in real time as the plant dispatching changes. While labor, materials, and capital may be to some extent substitutable to produce available output, the generation process does not typically allow for these to substitute for fuel in the short-run. We therefore posit a Leontief production process of the following form:

$$Q = \min[\, g(E, \beta^E, \varepsilon^E),\ Q^A(K, L, M, \underline{\beta}, \varepsilon^A)]$$

where Q is actual output; inputs are denoted by E for energy (fuel) input, K for capital, L for labor, and M for maintenance; β denotes parameter vectors, and ε denotes vectors of unobserved (to the econometrician) shocks. Capital, measured by the nameplate generating capacity of the plant, is relatively fixed. Significant changes in capacity at the generating plant level occur primarily through unit additions or retirements, which are infrequent events, and in our dataset will define a new plant-epoch over which capacity is essentially constant. Labor and maintenance (materials) decisions are made in advance of production, but after the level and productivity of the plant's capital is observed. This reflects the quasi-fixity of these inputs over time: staffing decisions and maintenance plans are designed to ensure that the plant is available when it dispatched, Q^A. In contrast, fuel input decisions are made in real time, after the manager has observed any shock associated with the pre-assigned inputs or planned output, and after observing the energy-specific productivity shock for the plant in the current period. This specification of the production function is similar to that used by Van Biesebroeck (2003) to model automobile plant production.

We model the energy component, which will in general hold with equality, as:

$$\text{(PF1)} \qquad Q_{irst} = g(E_{irst}, \beta^E, \varepsilon^E_{irst}) = E_{irst}^{\beta 1E} \exp(X_{irst}\beta_2^E) \exp(\gamma_r^E + \alpha_i^E + \delta_t^E + \eta_{isrt}^E)$$

for plant i in restructuring regime r, state s, and year t. X is a vector of time-varying plant characteristics.

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[27] In fact, over a short time period, maintenance and repair expenditures will be inversely related to output since the boiler needs to be cool and the plant offline for most major work. We deal with this potential

We model available output using a Cobb-Douglas function of labor and materials, embedding capital effects in a constant ($Q_0(K)$) term, and allowing actual output to deviate from available output in a given period through the multiplicative error, η_{irst}^{A}. This yields the specification:

(PF2) $$Q_{irst} \le Q_0(K) \cdot (L_{irst})^{\beta L} \cdot (M_{irst})^{\beta M} \cdot \exp(X_{irst}\beta^{A}) \cdot \exp(\gamma_r^{A} + \alpha_i^{A} + \delta_t^{A} + \eta_{irst}^{A})$$

Both of these specifications model the restructuring effect as a proportional shift in the production frontier, although we explore some specifications that allow restructuring to shift the marginal productivity of the inputs.[28]

One issue in estimating these equations is the possibility that the productivity shocks are correlated with the input levels. This is particularly likely to occur if input decisions are made after a plant's manager observes the plant's efficiency—positive efficiency shocks may lead managers to increase desired output, implying increased input use. We control directly for plant-specific efficiency differences and for secular productivity shocks in a given year, but must consider the impact of the remaining idiosyncratic errors, η_{isrt}^{E} and η_{isrt}^{A}. The estimates may also be subject to selection bias if exit decisions driven by these unobserved productivity shocks are correlated with inputs. Neither of these problems is unique to our setting, and they have been raised in many earlier papers.[29]

Consider first the simultaneity issue. We face a potential simultaneity problem if, for instance, a malfunctioning piece of equipment reduces the plant's efficiency, leading the utility to reduce its operation of that plant and consequently to use less fuel. A variety of methods have been used to

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simultaneity bias below.

[28] Note that given the specifications of the production function derived thus far, the input demand equation for, for example, labor is:

$$L = (\lambda\beta^{L}Q^{A})/W$$

where W is the wage level and λ is the Lagrangian on the production constraint. Taking logs, this equation is similar to the one we estimate in Section 4 if the year-effects and plant fixed-effects capture relevant wage movements. This suggests that another interpretation of the *RESTRUCTURED* effect is to shift the shadow value of satisfying the production constraint.

[29] Nerlove (1963) provides an early discussion of simultaneity bias in production functions. Olley and Pakes (1996) propose a structural approach to addressing simultaneity, which is compared to alternatives in Griliches and Mairesse (1998). Ackerberg and Caves (2003) discusses this issue and compares treatments proposed by Olley and Pakes (1996) and Levinsohn and Petrin (2003). While many papers have estimated production or cost functions for electric generating plants, including Knittel (2002), Kleit and Terrell (2001), Christensen and Greene (1976), we are not aware of explicit discussions or treatments of either simultaneity or selection problems in this context.

address this concern. We choose to use an instrumental variables approach, instrumenting for input levels with measures of state-level electricity demand. This is highly correlated with the intensity with which inputs are used to generate electricity at the plant, but are uncorrelated with, for instance, how efficiently an individual plant's feedwater pumps are working. This approach is likely to be particularly effective for the energy equation, given the responsiveness of energy input choices to demand fluctuations in real time. It may be less powerful in identifying variation in ex ante labor and maintenance choices, depending *inter alia* on the anticipation of the state demand and the ability of our instruments to separately identify the coefficients on labor and maintenance.

The potential selection issue is more difficult to address. The plants in our sample seem more stable than those studied in many other contexts (especially see Olley and Pakes, 1996), suggesting that the selection problem may be somewhat less severe for electric generation. However, plant exit increases in restructuring regimes, not because the plant is retired but because divestitures remove the plants from the reporting database. To the extent that the divestitures are mandated by restructuring, this should not create a selection problems. But without better information on what determines discretionary divestitures, we have no direct way to assess their impact on the results. One indirect way to assess the significance of potential selection effects is to compare results for the unbalanced panel we use in most of our work to those for a panel of plants that continue to operate through the end of our sample period, for which potential selection effects are likely to be most severe. Substantial differences across those results may suggest the need to more carefully treat potential selection biases.

Taking logs and substituting in variable names, equations (PF1) and (PF2) become:

$$\text{(PF1b)}\quad \ln(MWh_{\text{irst}}) = \beta_1^{E}\ln(BTU\ FUEL_{\text{irst}}) + \beta_2^{E} AGE_{\text{irst}} + \beta_3^{E} FGD_{\text{irst}} + \gamma_{\text{IOU}}\ IOU{*}RESTRUCTURED_{\text{rst}} + \gamma_{\text{MUNI}}\ MUNI{*}RESTRUCTURED_{\text{rst}} + \alpha_{\text{i}} + \delta_{\text{t}} + \eta_{\text{irst}}^{E}$$

and

$$\text{(PF2b)}\quad \ln(MWh_{\text{irst}}) = \beta_1^{A}\ln(EMPLOYEES_{\text{irst}}) + \beta_2^{A}\ln(NON\text{-}FUEL\ EXPENSES_{\text{irst}}) + \beta_3^{A} AGE_{\text{irst}} + \beta_4^{A} FGD_{\text{irst}} + \gamma_{\text{IOU}}\ IOU{*}RESTRUCTURED_{\text{rst}} + \gamma_{\text{MUNI}}\ MUNI{*}RESTRUCTURED_{\text{rst}} + \alpha_{\text{i}} + \delta_{\text{t}} + \eta_{\text{irst}}^{A}$$

which we estimate using instrumental variables and, for comparison, ordinary least squares.[30, 31]

Stochastic production function models (see Kumbhakar and Lovell, 2000) start with a similar specification:

$$\ln y_{it} = \ln f(x_{it};B) + v_{it} - u_i$$

where v_i captures random noise and u_i is the technical inefficiency parameter modeled to be bounded below at zero. Typically, $v_i \sim N(0, \sigma^2_v)$ and u_i is assumed to have some distribution over the non-negative numbers (*e.g.* truncated normal or half normal), and v_i and u_i are independently distributed. We take advantage of our panel data set to model u_i as a function of both the plant fixed effects (α_i) and the restructuring variables. The more years of data we have for a given plant, the more likely it is that the expectation of v_i for that plant is zero over the time period, and the less likely it is that u_i, including the restructuring variables, will pick up random shocks at a plant.[32] No stochastic frontier models of which we are aware have addressed the potential simultaneity or selection issues.

Results from estimating the fuel equation and the labor and materials equation are presented in Tables 9 and 10, respectively. In both tables, we restrict our attention to the set of plants that are classified as baseload, on the assumption that the production technology at a baseload plant, designed to run continuously, is more likely to be common across plants, up to our plant-specific efficiency parameters. Not only is this technology likely to be different from that for peaking plants, which runs only occasionally during high demand periods, but the technologies across peaking plants seem likely to be much more heterogeneous. In Table 9, Column (1) presents the

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[30] We impose equality on equation PF2b, allowing the error to capture the effect of deviations between actual output, used as the dependent variable, and the planned available output, hypothesized in the original production function description. To the extent that actual output deviates from planned output in a systematic way, the error will not be mean zero. If this deviation changes with restructuring (as, for example, if actual output becomes less predictable), the change in the mean error may confound the estimated restructuring effect. We thank Aviv Nevo for pointing this out.

[31] Nonfuel expenses are a dollar, rather than quantity measure, and should be deflated with the appropriate price deflator before including in the production function. Unfortunately, there is no reasonable deflator available. By using expenses to proxy for material inputs, we are implicitly assuming that material input prices did not change over time other than as picked up by our year-effects, and that relative prices across plants or regions are constant over time. Neither assumption is particularly satisfying. We present some alternative specifications below, and are currently exploring alternative possibilities for a deflator.

[32] We have also estimated versions of the production function models presented below that impose the truncated normal distribution on the inefficiency term, albeit without using instrumental variables.

OLS results for fuel while Columns (2) and (3) present results where we instrument for fuel inputs with the state-level electricity demand (*STATE SALES*) and the square of that variable.[33] The specifications in Columns (1) and (2) include all of the baseload plants, Column (3) includes the set of plants that were still in our data set as of 1999. Column (4) uses the same set of plants as Columns (1) and (2) and includes the richer set of restructuring dummies.

The qualitative results in all four columns are very similar—fuel use is very highly correlated with the megawatt-hours a plant produces. Comparing Columns (1) and (2), we see that instrumenting for fuel inputs raises the coefficient slightly, although the difference in the coefficients is trivial (the coefficient increases from 1.021 to 1.028) and statistically insignificant. If we had a simultaneity problem and lower output were correlated with lower fuel efficiency, we would expect the coefficient to fall when we use instrumental variables, contrary to what we observe.[34] In all four specifications, the coefficient on fuel is slightly greater than one, although a test that it is equal to one cannot be rejected for the specification in Column (2) or (4). This suggests slight increasing returns to scale with respect to fuel, consistent with the fact, which is well understood by power systems engineers, that plants use fuel more efficiently at higher levels of output.

Column 3 provides some insight into concerns over the attrition of plants due both to retirements and sales that eliminated data reporting. Sales are particularly an issue in retail access states, as exempt wholesale generators (EWGs) purchased plants that incumbents were required to divest during restructuring. Since EWGs are not regulated by FERC in the traditional sense, these companies are not required to report operating data on their plants, and hence drop out of the database. If the plants dropping out of the sample were systematically increasing or decreasing in efficiency relative to surviving plants, selection bias could contaminate the restructuring estimates. One could construct plausible stories that plants selected for purchase were very efficient and thus good acquisition targets, or that inefficient plants left the database due to retirements or sales that offered the new owners the opportunity for substantial gain if efficiency could be improved. The correlation coefficient of the last year of data on the plant with the efficiency measures used in the regression is negative (-0.17 for employees per MW, -0.05 for

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Coefficient estimates from these specifications are very similar to the OLS results presented, albeit without using instrumental variables are not dependent on the functional form of the error term.

[33] The annual state sales measures the total sales to ultimate customers for that year (measured in megawatt-hours) including sales made from imports into the state. The F-statistic from the test that both *STATE SALES* and *STATE SALES SQUARED* are zero in the first stage for Column (2) is F(2,6196)=50.05.

non-fuel expenses per MW), suggesting that less efficient plants tend to drop out of the database.[35] To investigate the likely impact of selection on the results, we have restricted the sample in column (3) to plants that did not exit by 1999. The results for this sample are very similar to the results in column (2), suggesting that selection is not biasing our results. This may not be completely unexpected, given that many of the exits from our data set were driven by sales to unregulated companies (who were no longer required to report data) rather than plant closures, and in a number of cases, these sales were not discretionary.

In all four specifications, the coefficient estimates for *IOU*RESTRUCTURED* are small and statistically indistinguishable from zero, suggesting that restructuring has not caused utilities to become substantially more efficient at converting fuel to electricity. This suggests little medium-run benefit from restructuring in fuel efficiency, though a caveat is in order. While variations on the order of even 0.5%-1% in fuel productivity are economically significant, it may be difficult to measure these sufficiently precisely with our aggregated data. Because fuel efficiency at a plant is heavily influenced by factors such as the allocation of output across units at a plant, the number of times its units are stopped and started, and for how long the units were running below their capacity, our inability to measure or control for possible changes in these operational characteristics makes it difficult to capture precisely potential efficiency changes.

Table 10 presents results from the labor and material side of the production function. Column (1) presents the OLS results while Columns (2) and (3) present results where we instrument for ln(*EMPLOYEES)* and ln(*NONFUEL EXPENSES)* with the state-level electricity demand, the square of that variable and state-level unemployment rates.[36] The coefficient estimate on ln(*NONFUEL EXPENSES)* increases dramatically when we instrument, from 0.029 to 1.039. We believe that for electricity generating plants, this result is consistent with the presence of negative productivity shocks that are likely to be plant outages requiring more than the usual material inputs.

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[34] Instrumenting also alleviates possible measurement error in the fuel variable, which would tend to increase the fuel coefficient, all else equal. We cannot assess which explanation is most reasonable.

[35] This correlation coefficient is confounded by the fact that inefficient plants might also drop from the sample if they are shut down.

[36] The F-statistic from the test that *STATE SALES*, *STATE SALES SQUARED* and *STATEUNEMP* are zero in the first stage for Column (2) is F(3,6195)=17.64 for ln(*NONFUEL EXPENSES*) and F(3,6195)=35.95 for ln(*EMPLOYEES*). *STATEUNEMP* is negative in the ln(*NONFUEL EXPENSES*) and positive, though not statistically significant, in the ln(*EMPLOYEES*) specification. We are in the process of developing additional instruments for ln(*EMPLOYEES*).

While the coefficient on ln(*EMPLOYEES)* also increases in magnitude, it is statistically indistinguishable from its previous level or from zero due to the substantial increase in the imprecision of the estimated coefficient. This could reflect two problems. First, we do not have instruments with sufficient power to identify independent variation in labor and material inputs. Second, *NONFUEL EXPENSES* includes payroll costs (not separately identified), so both this and *EMPLOYEES* will reflect changes in staffing.[37] One way to explore the impact of this is to estimate the production function with a single input. We do this in column (3) for ln(*EMPLOYEES*) and in column (4) for ln(*NONFUEL EXPENSES*). When we only include ln(*EMPLOYEES*), it is significantly correlated with output, although the size of the coefficient is smaller than the coefficient on *ln(NONFUEL EXPENSES*), which has roughly the same size whether or not we include ln(*EMPLOYEES*). In addition, we have estimated specifications similar to those in columns (2) and (4) that allow the coefficient on ln(*NONFUEL EXPENSES*) to vary with restructuring. This would capture effects due to non-neutral changes in material efficiency, as well as to changes in the prices of maintenance inputs that are systematically correlated with restructuring. The interaction term is not statistically different from zero, suggesting either that these are insignificant effects, or roughly offsetting.

Consider the coefficient on *IOU*RESTRUCTURED*. In Column (1) where we use OLS, it is negative and economically and statistically significant. The sum of coefficients on the input variables are much smaller than in the IV columns, so to the extent plants in restructuring states reduced inputs facing lower output, the effect is loaded onto the *IOU*RESTRUCTURED* variable. There are two reasons the OLS coefficient on the inputs are likely to be understated. First, they are likely to reflect measurement error, or at least variation that is uncorrelated with output. If most plants were padding their labor force with extra employees and spending more than the optimal level on operations and maintenance, we might be unable to pick up the true marginal productivity of these variables given the variation in our data set. Movements in these variables would be driven not by unconstrained profit-maximizing firms re-optimizing their input decisions, but by firms adjusting to new political and regulatory environments. Second, they may be low if negative shocks to productivity are mostly plant outages that require more than the usual labor or material inputs. In columns (2) and (4)-(6), the restructuring variables are positive and suggest that plants are moving closer towards the production frontier in the face of competition. The specifications in Columns (1)-(4) include all of the baseload plants. Column

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[37] The elasticity of *NONFUEL EXPENSES* with respect to *EMPLOYEES* is about .5 in our data, broadly consistent with our back of the envelope calculations suggesting that labor costs are roughly half of the total nonfuel operating budget.

(5) includes the set of plants that were still in our data set as of 1999. Again, the results are comparable to those in Column (2), suggesting that selection is not biasing our results.

6. Conclusion

This research is the first analysis of the impact of electricity generation sector restructuring in the United States on plant-level efficiency, and the results are encouraging. The results suggest that firms may reduce some operating expenses, particularly in their nonfuel operating budget, in anticipation of increased competition in electricity generation resulting from regulatory reform and restructuring. Production function estimates provide evidence of potential efficiency gains associated with restructuring activity, though these are sensitive to identification of the input productivity parameters. There is little evidence of increases in fuel efficiency relative to plants in non-restructuring regimes, though there may be some gain relative to government and cooperatively-owned plants within states that restructured. These plant-level reductions are consistent with evidence of efficiency gains following restructuring in other industries, as well as predictions based on incentives and property rights.

Any gains identified in this work reflect short- or medium-run effects. It is possible that even with operating efficiency gains in the short-run, the benefits of restructuring may not be substantial, if, for example, there are reductions in knowledge-sharing that affect productivity growth over time, or the benefits are offset by costs associated with restructuring. It is possible, however, that longer run effects will be more striking as firms respond to the new incentives created by restructuring with investments in both human and physical capital that further enhance efficiency. If California's crisis does not induce reversals of the restructuring movement, and regulators do not shut down data reporting and researcher access to detailed plant-level data, time may enable us to distinguish among these possibilities.

Data Appendix – Table A1: Summary of Variables

Variable	Definition	Source
Output and Input Variables		
LN_NET MWH	Log of the net MWh generation of the plant.	UDI
LN_NONFUEL EXPENSE	Log of the annual non fuel production expenses ($)	UDI
LN_EMPLOYEES	Log of the average number of employees at the plant.	UDI
LN_BTU	“og of the total btus of fuel burned by the plant. Calculated as (tons of coal * 2000 lbs/ton* btu/lb) + (barrels of oil*42 gal/barrell*btu/gal) + (Mcf gas*1000 cf /mcf*btu/cf). The values of the btu content of each fuel are provided in the UDI data for each plant each year.	UDI
LN_FUELMWH	Log of the annual fuel cost of all fuels at the plant ($) divided by the net mwhs of electricity produced.	UDI
LN_FUELEXP_BTU	Log of the total fuel expenses divided by the total btus burned (see below for calculation of total btus).	UDI
Restructuring Variables		
IOU	Dummy equal to 1 for plants classified as IOU, holding, or private companies.	1997 UDI Utility Datapak Book
MUNI	Dummy equal to 1 for plants owned by utilities classified as government or cooperative utilities.	1997 UDI Utility Datapak Book
*IOU*RESTRUCTURED*	Dummy equal to one for IOU plants in states that restructured in years following the advent of formal hearings.	Restructuring information compiled from: EIA "Status of State Electric Industry Restructuring Activity" Timeline as of July 2002, EIA "The Changing Structure of the Electric Power Industry: An
*MUNI*RESTRUCTURED*	Dummy equal to one for MUNI plants in states that restructured in years following the advent of formal hearings	
*IOU*LAW PASSED*	Dummy equal to one for IOU plants in states that restructured, beginning with year that legislation was enacted	

*MUNI*LAW PASSED*	Dummy equal to one for MUNI plants in states that restructured, beginning with year that legislation was enacted	Update, 12/96," EEI "Electric Competition in the States" February, 2001, EIA "The Changing Structure of the Electric Power Industry: 2000 An Update," NARUC "Utility Regulatory Policy in the United States and Canada, Compilation" 1994 - 1995 and 1995 – 96, "Restructuring the Electricity Industry," The Council of State Governments, 1999, and State PUC websites, relevant legislation and reports.
*IOU*HEARINGS*	Dummy equal to one for IOU plants in states that did not restructure in years following the advent of formal hearings.	
*MUNI*HEARINGS*	Dummy equal to one for MUNI plants in states that did not restructure in years following the advent of formal hearings.	
*IOU*RETAIL ACCESS*	Dummy equal to one for IOU plants in states that restructured in years following the advent of retail access.	
*MUNI*RETAIL ACCESS*	Dummy equal to one for MUNI plants in states that restructured in years following the advent of retail access.	
*IOU*RESTRUCTURED_YEARS*	Counter variable beginning with 1 in year of formal hearings for IOU plants in states that restructured.	
*MUNI*RESTRUCTURED_YEARS*	Counter variable beginning with 1 in year of formal hearings for MUNI plants in states that did restructure.	
INDEPENDENT / OTHER VARIABLES		
LN_MW	Log of the gross MW nameplate capacity of the plant, rounded to the nearest MW.	UDI
AGE	Number of years since the oldest unit at the plant came on line.	UDI
FGD	Dummy equal to 1 indicating the operation of a FGD scrubber at the plant.	UDI
CAPACITY FACTOR	Capacity factor of the plant, calculated as (*NET MWH*) / (*GROSS MW* * hours in year)	UDI
CAPACITY FACTOR, LAG	Capacity factor lagged one year (missing if the plant does not have data for the preceding year).	UDI
STATE SALES	State-level utility sales in gigawatthours, not including non-utility sales..	Sales: Sales to Ultimate Customers from EIA's "Electric

		Sales and Revenue" Table 6 and EIA's "Electric Power Annual" Tables 117 and 90.
PLANT CATEGORIZATION VARIABLES		
LOAD TYPE	Based on the load type reported in FERC Form 1 through 1992. We assign plants to the last load type reported if they change load type no more than twice, otherwise we do not assign load types to missing data years. We use this cutoff to include plants had a "stray" change--one peak, cycle or shutdown type in the middle of a string of "base" types, for example.	UDI
FUEL TYPE	Based on the primary fuel burned at the plant	UDI
ECONOMIC AND WEATHER VARIABLES		
ANNUAL_UNEMPLOYMENT	Annual average unemployment in the state.	Bureau of Labor Statistics
ANNUAL_HDDAYS	Population weighted heating degree days for each state-year. (use MD for DC)	U.S. Dept. of Commerce National Oceanic and Atmospheric Administration Historical Climatology Series, “Monthly State, Regional, and National Heating Degree Days Weighted By Population”
ANNUAL_CDDAYS	Population weighted cooling degree days for each state-year. (use MD for DC)	

Note: UDI stands for the Utility Data Institute O&M Production Cost Database. All data in the UDI production cost data bases are extracted from the FERC Form 1 (filed by investor-owned utilities), EIA Form 412 (filed by municipal and other government utilities), and RUS Form 7 & 12 (filed by electric cooperatives). These are annual reports.

Data Appendix - Table A2: Summary Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
LN_NET MWH	10670	14.063	1.779	4.860	16.905
LN_NONFUELEXP	10670	15.875	1.144	9.674	18.694
LN_EMPLOYEES	10670	4.556	1.115	0.000	7.099
LN_BTU	10670	30.278	1.723	15.571	33.067
LN_MW	10670	6.282	0.871	4.605	8.286
AGE	10670	27.887	12.950	0.000	76.000
FGD	10670	0.124	0.330	0.000	1.000
CAPACITY FACTOR, LAG	10015	0.402	0.232	0.000	0.976
IOU	10670	0.804	0.397	0.000	1.000
MUNI	10670	0.196	0.397	0.000	1.000
*IOU*RESTRUCTURED*	10670	0.107	0.309	0.000	1.000
*MUNI*RESTRUCTURED*	10670	0.013	0.113	0.000	1.000
*IOU*LAW PASSED*	10670	0.043	0.204	0.000	1.000
*MUNI*LAW PASSED*	10670	0.005	0.072	0.000	1.000
*IOU*HEARING*	10670	0.080	0.272	0.000	1.000
*MUNI*HEARING*	10670	0.023	0.149	0.000	1.000
*IOU*RETAIL ACCESS*	10670	0.007	0.085	0.000	1.000
*MUNI*RETAIL ACCESS*	10670	0.002	0.044	0.000	1.000
*IOU*RESTRUCTURED*YEARS*	10670	0.311	1.025	0.000	7.000
MUNI RESTRUCTURED*YEARS*	10670	0.037	0.377	0.000	7.000
LN_STATE SALES	10670	11.168	0.851	8.125	12.627
ANNUAL_UNEMP	10670	0.064	0.021	0.022	0.180
ANNUAL_CDDAYS	10632	4382.386	2144.606	414	10758
ANNUAL_HDDAYS	10632	1439.386	931.737	81	3879

Table 1: Number of Plants Affected by Restructuring in Each Year

Year	Total Plants	*HEARINGS*	*RESTRUCTURED*	*RETAIL ACCESS*
1981	465	0	0	0
1982	490	0	0	0
1983	511	0	0	0
1984	527	0	0	0
1985	546	0	0	0
1986	572	0	0	0
1987	582	0	0	0
1988	588	0	0	0
1989	592	0	0	0
1990	597	0	0	0
1991	601	0	0	0
1992	591	0	0	0
1993	602	0	28	0
1994	598	29	113	0
1995	608	72	189	0
1996	589	163	212	0
1997	569	262	268	0
1998	556	295	261	57
1999	486	279	207	41
TOTAL	10,670	1,100	1,278	98

Note: *HEARINGS* identifies plants in states that have started formal hearings but did not pass legislation, *RESTRUCTURED* indicated those that have started formal hearings that eventually go on to pass legislation, and *RETAIL ACCESS* indicates plants in states that have started retail access.

Table 2a: Summary of Data for Plants Larger Than 100 MW, 1981 - 1999

Variable	Units	Mean	Std. Dev	Min	Max	#Obs
EMPLOYEES / MW	Employees/MW	.233	.162	.004	2.470	10670
NONFUEL EXPENSE/ MW	$/MW	18388	11777	73	164773	10670
FUEL EXPENSE/MWH	$/MWh	26.28	27.69	2.30	1688.86	10670
CAPACITY FACTOR	0-1	.403	.233	.00012	.9762	10670
HEAT RATE	(mmBtu/mwh)	11.59	10.26	.00046	938.99	10670
*(BTU EXPENSE)*10*^{6}	($/Btu) * 10^6	19.297	678.654	.107	58958.33	10670
MW	MW	764.51	654.05	100	3969.12	10670
AGE	Years	27.89	12.95	0	76	10670
FGD	0/1	.124	.330	0	1	10670
% COAL	%	59.87%	.490	0	1	10670
% GAS	%	29.20%	.455	0	1	10670

Table 2b: Summary of Data for Plants Larger Than 100 MW, 1990

Variable	*RESTRUCTURED*		*NON-RESTRUCTURED*		Difference in Means	T-statistic for Difference
	Mean	Std. Dev.	Mean	Std. Dev.		
EMPLOYEES / MW	.255	.219	.235	.146	.020	1.31
NONFUEL EXPENSE/ MW	21089	13950	17456	10016	3633	3.65**
FUEL EXPENSE/MWH	26.83	14.56	26.06	31.50	.77	0.39
CAPACITY FACTOR	.376	.233	.403	.240	-.027	-1.39
HEAT RATE	11.31	1.97	12.08	7.22	-.77	-1.79
*(BTU EXPENSE)*10*^{6}	2.32	.92	1.96	1.13	.35	4.18**
MW	744	642	754	676	-10.28	-0.19
AGE	28.79	12.21	25.82	12.37	2.97	2.95**
FGD	.079	.271	.166	.373	-.087	-3.25**
% COAL	44.70%	.498	71.86%	.450	-27.16%	-6.98**
% GAS	42.05%	.495	17.29%	.379	24.76%	6.86**

Note: N for NON-*RESTRUCTURED*= 295, N for *RESTRUCTURED*= 302
** Significant at .05 level or better

Table 3a: Percentage Change in Costs From 1990 to 1996

Difference of Means Tests
Companies in Non-Restructuring Versus Restructuring States

	N	Distribution	Transmission	Generation
Restructuring Mean	74	12.3%	22.7%	-17.0%
Non-Restructuring Mean	50	18.0%	33.1%	3.8%
Difference		-5.6%	-10.3%	-20.8%
t stat		-1.14	-1.26	-3.61**

*significant at 5% level **significant at 1% level
All measures are in nominal dollars.

Table 3b: Percentage Change in Costs Per MWh[#] From 1990 to 1996

Difference of Means Tests
Companies in Non-Restructuring Versus Restructuring States

	N	Distribution	Transmission	Generation
Restructuring Mean	72	1.5%	13.1%	-13.5%
Non-Restructuring Mean	48	-1.6%	12.6%	-5.12%
Difference		3.1%	0.4%	-8.34%
t stat		0.70	0.06	-1.87

*significant at 5% level **significant at 1% level
All measures are in nominal dollars.

[#] Transmission and Distribution costs per MWh are costs per MWh sales to ultimate customers, while Generation costs per MWh are costs per MWhs generated at company plants.

Note: Four observations dropped due to lack of MWh data.

Figure 1
Average Employees per MW in Restructuring and Non-Restructuring States

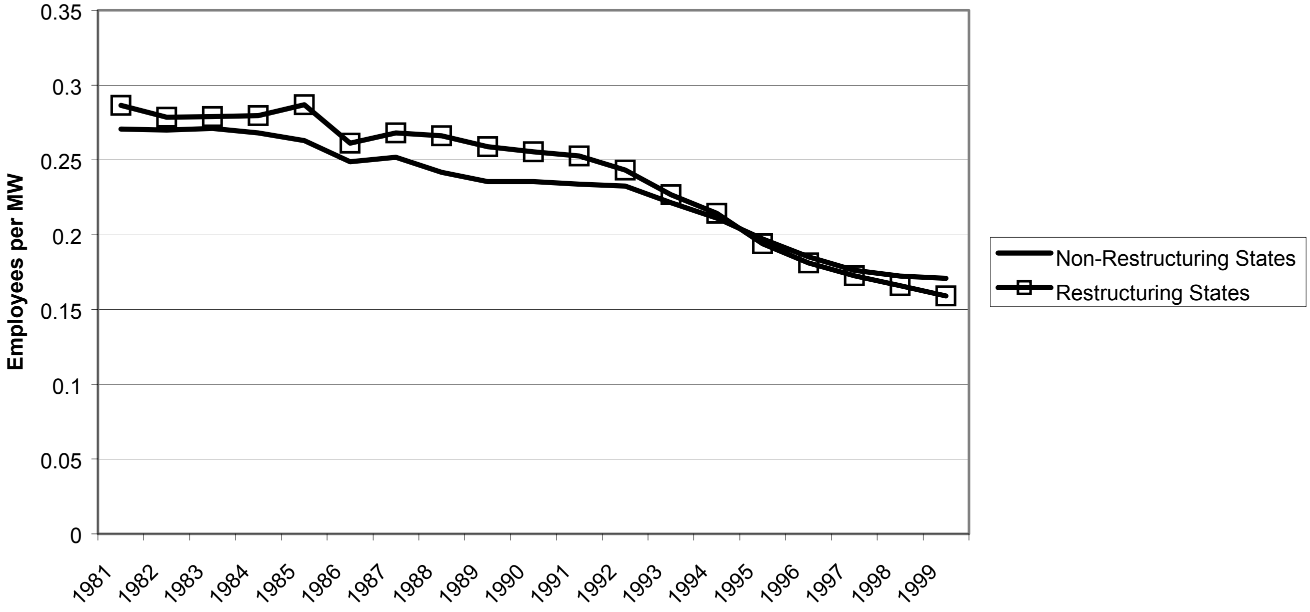

Figure 2
Average Non-Fuel Expenses per MW in Restructuring and Non-Restructuring States

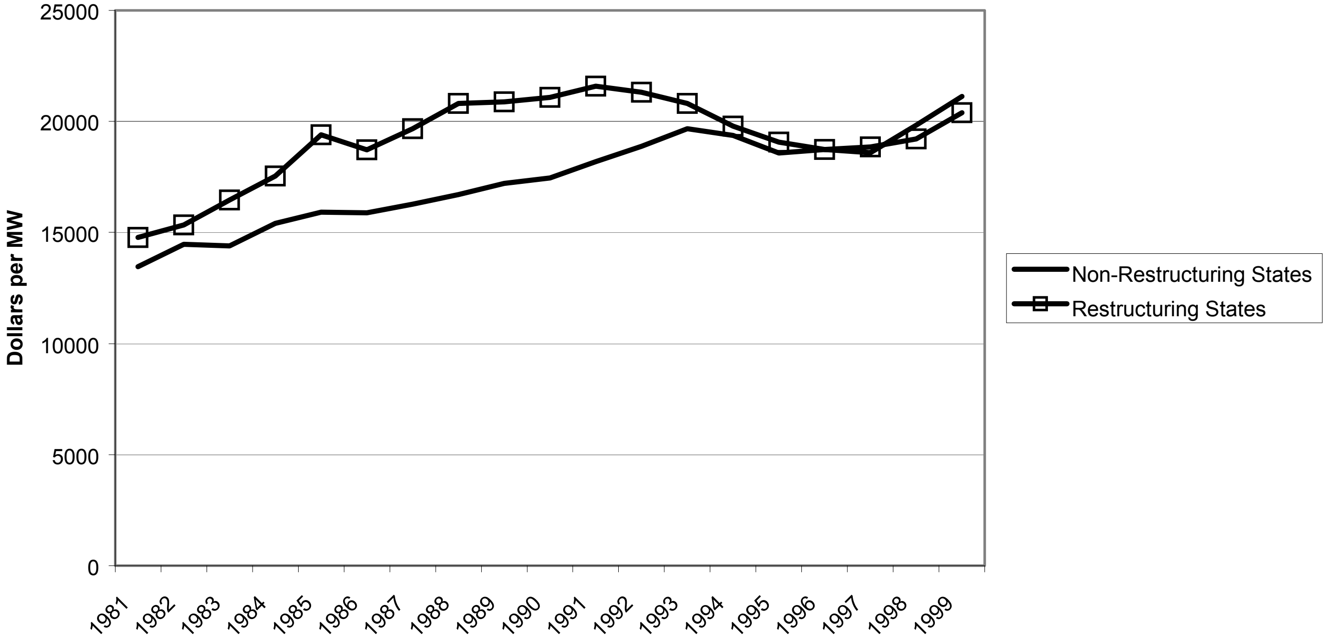

Figure 3
Average Fuel Expenses per MWh for Restructuring and Non-Restructuring States

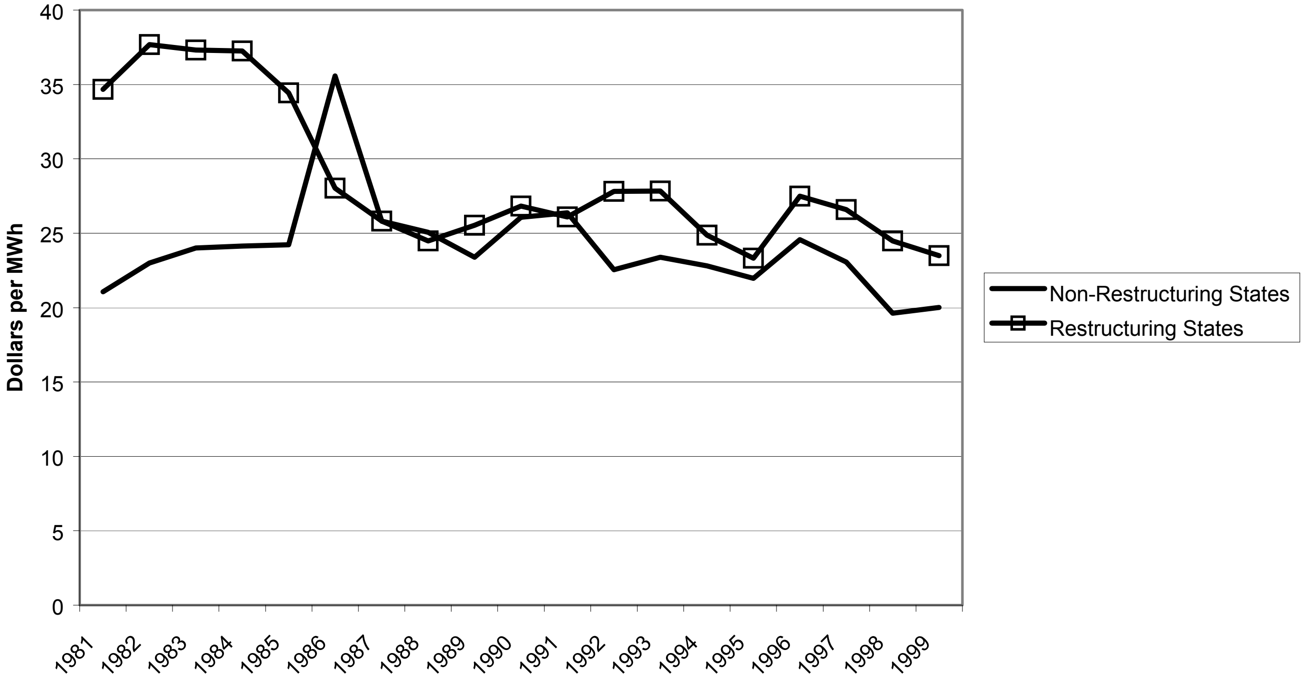

Table 4: ln(*EMPLOYEES*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS No MWh	**OLS**	**OLS Law**	**IV**	**IV Law**	**IV All Dates**	**IV All Dates**	**IV**
IOU*HEARINGS						0.003	-0.011	0.002
						(0.013)	(0.013)	(0.014)
IOU*RESTRUCTURED	-0.078***	-0.060***		-0.023*		0.001		0.014
	(0.019)	(0.019)		(0.012)		(0.014)		(0.017)
IOU*LAW PASSED			-0.076***		-0.033**		-0.029**	
			(0.020)		(0.014)		(0.014)	
IOU*RESTRUCTURED* YEARS								-0.005
								(0.005)
IOU*RETAIL ACCESS						0.136***	0.133***	0.150***
						(0.048)	(0.044)	(0.049)
MUNI*HEARING						0.096***	0.082***	0.095***
						(0.019)	(0.018)	(0.019)
MUNI*RESTRUCTURED	0.081**	0.099***		0.136***		0.157***		0.065
	(0.038)	(0.038)		(0.022)		(0.025)		(0.043)
MUNI*LAW PASSED			0.098***		0.134***		0.138***	
			(0.031)		(0.031)		(0.035)	
MUNI*RESTRUCTURED *YEARS								0.036**
								(0.014)
MUNI*RETAIL ACCESS						0.086	0.049	-0.025
						(0.063)	(0.066)	(0.075)
ln(NET MWH)		0.080***	0.080***	0.246***	0.256***	0.311***	0.298***	0.314***
		(0.009)	(0.009)	(0.036)	(0.034)	(0.047)	(0.042)	(0.047)
AGE	0.004*	0.003	0.003	0.003	0.003	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
FGD	0.060	0.076	0.081	0.109	0.113	0.123	0.121	0.123
	(0.053)	(0.048)	(0.052)	(0.081)	(0.082)	(0.087)	-0.011	(0.087)

N = 10632; 953 Plant-epoch and 19 year effects included.

Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Instruments for *MWh*: ln(*STATESALES*) and [ln(*STATESALES*)]^2

Table 5: ln(*NONFUEL EXPENSES*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS No MWh	OLS	OLS Law	IV	IV Law	IV All Dates	IV All Dates	IV
IOU*HEARINGS						-0.045**	-0.012	-0.071***
						(0.019)	(0.020)	(0.020)
IOU*RESTRUCTURED	-0.167***	-0.134***		-0.065***		-0.077***		-0.014
	(0.021)	(0.021)		(0.019)		(0.020)		(0.024)
IOU*LAW PASSED			-0.124***		-0.040*		-0.022	
			(0.025)		(0.023)		(0.021)	
IOU*RESTRUCTURED* YEARS								-0.031***
								(0.007)
IOU*RETAIL ACCESS						-0.219***	-0.171***	-0.158**
						(0.068)	(0.065)	(0.069)
MUNI*HEARING						0.131***	0.166***	0.104***
						(0.026)	(0.027)	(0.027)
MUNI*RESTRUCTURED	-0.010	0.022		0.092***		0.076**		-0.025
	(0.050)	(0.046)		(0.035)		(0.036)		(0.060)
MUNI*LAW PASSED			0.100		0.170***		0.200***	
			(0.074)		(0.050)		(0.053)	
MUNI*RESTRUCTURED* YEARS								0.032
								(0.020)
MUNI*RETAIL ACCESS						-0.047	-0.112	-0.169
						(0.089)	(0.098)	(0.106)
ln(NET MWH)		0.145***	0.148***	0.456***	0.497***	0.401***	0.447***	0.396***
		(0.013)	(0.013)	(0.057)	(0.055)	(0.066)	(0.063)	(0.066)
AGE	-0.001	-0.001	-0.001	-0.002	-0.003	-0.003	-0.003	-0.003
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
FGD	0.171***	0.200***	0.210***	0.262**	0.274**	0.251**	0.264**	0.252**
	(0.032)	(0.032)	(0.028)	(0.129)	(0.133)	(0.124)	(0.128)	(0.124)

N = 10632; 953 Plant-epoch and 19 year effects included.

Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Instruments for *MWh*: ln(*STATESALES*) and [ln(*STATESALES*)]^2.

Table 6: Non-Utility Generators (NUG) Results, IV Estimates

	(1)	(2)	(3)	(4)
	IV ***ln(NON-FUEL EXPENSES)***	**IV** ***ln(NON-FUEL EXPENSES)***	**IV** ***ln(EMPLOYEES)***	**IV** ***ln(EMPLOYEES)***
IOU*HIGH NUGS	-0.017	0.003	-0.051**	-0.053**
	(0.017)	(0.019)	(0.010)	(0.010)
MUNI*HIGH NUGS	0.097**	0.088**	0.061**	0.028
	(0.028)	(0.031)	(0.015)	(0.017)
IOU*BOTH		-0.042		0.006
		(0.022)		(0.012)
MUNI*BOTH		0.036		0.120**
		(0.054)		(0.030)
ln(NET MWH)	0.548**	0.548**	0.160**	0.163**
	(0.045)	(0.046)	(0.025)	(0.025)
AGE	-0.003	-0.003	0.003	0.003
	(0.004)	(0.004)	(0.002)	(0.002)
FGD	0.282*	0.283*	0.095	0.096
	(0.138)	(0.138)	(0.076)	(0.076)

N = 10632; 953 Plant-epoch and 19 year effects included.
Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%
Instruments for *MWh*: ln(*STATESALES*) and $[\ln(\mathit{STATESALES})]^2$.

Table 7: Results by Fuel-Type, Baseload Plants, IV Estimates

	ln(*NONFUEL EXPENSES)*		*ln(EMPLOYEES)*	
	COAL	**GAS**	**COAL**	**GAS**
IOU*RESTRUCTURED	-0.082**	0.008	-0.008	0.058**
	(0.034)	(0.046)	(0.024)	(0.026)
MUNI*RESTRUCTURED	0.104*	0.155	0.109***	0.149
	(0.056)	(0.165)	(0.040)	(0.093)
ln(NET MWH)	1.110***	0.674***	0.916***	0.353***
	(0.315)	(0.147)	(0.223)	(0.083)
AGE	-0.016**	0.016	-0.003	0.025*
	(0.007)	(0.027)	(0.005)	(0.015)
FGD	0.344***	----	0.229**	----
	(0.131)		(0.093)	
Observations	5459	1027	5459	1027
Number of Plant Epochs	498	141	498	141

Plant-epoch and year fixed effects included.

Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Instruments for *MWh*: ln(*STATESALES*) and $[\ln(STATESALES)]^2$

Table 8 Test for Mean Reversion Effect, IV Estimates

	ln(EMPLOYEES)	*ln(NON-FUEL EXPENSES)*
***IOU*RESTRUCTURED*_cheap**	0.004	-0.043**
	(0.014)	(0.021)
***IOU*RESTRUCTURED*_expen**	-0.053***	-0.081***
	(0.013)	(0.022)
***MUNI*RESTRUCTURED*_cheap**	0.221***	0.181***
	(0.036)	(0.058)
***MUNI*RESTRUCTURED*_expen**	0.089***	0.050
	(0.027)	(0.042)
ln(NET MWH)	0.251***	0.463***
	(0.036)	(0.057)
AGE	0.003	-0.002
	(0.002)	(0.003)
FGD	0.099	0.256**
	(0.082)	(0.129)

N = 10569; 933 Plant-epoch and 19 year fixed effects included.

Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Instruments for *MWh*: ln(*STATESALES*) and [ln(*STATESALES*)]^2

Table 9: Leontief Production Function— Baseload Plants, ln(*NET MWH*) as a function of Fuel

	(1) OLS	(2) IV	(3) IV, 1999 Plants	(4) IV
IOU*HEARINGS				0.004
				(0.003)
IOU*RESTRUCTURED	0.001	0.002	0.005	0.006
	(0.002)	(0.003)	(0.003)	(0.004)
IOU*RETAIL ACCESS				-0.003
				(0.009)
MUNI*HEARINGS				0.018***
				(0.004)
MUNI*RESTRUCTURED	-0.009	-0.009	-0.007	-0.004
	(0.006)	(0.006)	(0.006)	(0.006)
MUNI*RETAIL ACCESS				-0.025
				(0.038)
ln(*BTU FUEL)*	1.021**	1.028***	1.049***	1.024***
	(0.004)	(0.018)	(0.022)	(0.021)
AGE	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.001)	(0.001)	(0.001)
FGD	-0.003	-0.002	-0.000	-0.003
	(0.007)	(0.016)	(0.016)	(0.016)
Observations	6885	6885	6024	6885
Number of Plant Epochs	665	665	570	665

Plant-epoch and year fixed effects included.
Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%
Instruments for ln(*BTU FUEL)*: ln(*STATESALES*), [ln(*STATESALES*)]^2.

Table 10: Production Function—
Baseload Plants, ln(*NET MWH*) as a function of Labor & Materials

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	**IV**	**IV, Employees as only input**	**IV, Non-Fuel as only input**	**IV, 1999 Plants**	**IV**
IOU*HEARINGS						0.057
						(0.038)
IOU*RESTRUCTURED	-0.117**	0.100**	-0.056***	0.101**	0.123**	0.154**
	(0.013)	(0.042)	(0.018)	(0.043)	(0.049)	(0.067)
IOU*RETAIL ACCESS						0.377**
						(0.175)
MUNI*HEARINGS						-0.140**
						(0.061)
MUNI*RESTRUCTURED	-0.115**	-0.123**	-0.152***	-0.121**	-0.117*	-0.112
	(0.034)	(0.059)	(0.038)	(0.059)	(0.063)	(0.075)
MUNI*RETAIL ACCESS						0.099
						(0.469)
ln(EMPLOYEES)	0.171**	0.070	1.096***		-0.091	-0.057
	(0.024)	(0.339)	(0.172)		(0.426)	(0.428)
ln(NON-FUEL EXPENSES)	0.029	1.445***		1.484***	1.553***	1.867***
	(0.021)	(0.297)		(0.236)	(0.364)	(0.491)
AGE	0.004	0.017**	0.001	0.018**	0.019**	0.022**
	(0.002)	(0.008)	(0.005)	(0.008)	(0.009)	(0.011)
FGD	-0.196**	-0.445***	-0.270***	-0.446***	-0.446***	-0.511**
	(0.071)	(0.162)	(0.103)	(0.164)	(0.168)	(0.201)
Observations	6885	6885	6885	6885	6024	6885
Number of Plant Epochs	665	665	665	665	570	665

Plant-epoch and year fixed effects included.

Standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Instruments for ln(*EMPLOYEES)* and ln(*NONFUEL EXPENSES*): ln(*STATESALES*), [ln(*STATESALES*)]^2, and *STATEUNEMP*.

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