MEASURING POTENTIAL EFFICIENCY GAINS FROM DEREGULATION OF ELECTRICITY GENERATION: A BAYESIAN APPROACH

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Abstract—This paper examines the efficiency of electric power generation plants in the United States. A 1996 data set from the Utility Data Institute and county-level wage data from the Bureau of Labor statistics provide the information needed to construct measures of cost, output, and input prices for 78 steam plants using natural gas as the primary fuel. This paper uses a Bayesian stochastic frontier model that imposes concavity and monotonicity restrictions implied by microeconomic theory to measure efficiency, price elasticities, and returns to scale of these plants. Results indicate that plants on average could reduce costs by up to 13% by eliminating production inefficiency. Results also indicate that most plants operate at increasing returns to scale, suggesting further cost savings could be achieved through increasing output.

I. Introduction

ELECTRICITY restructuring and deregulation are now on the policy agenda in most states. One potentially compelling reason for deregulation is that deregulation provides important incentives for the efficient operation of electrical generators. In contrast, regulated firms receive a guaranteed profit for the generation of electricity, profit that is a function of capital investment. Thus, under regulation, firms have strong incentives to increase, rather than decrease, their costs. In contrast, deregulation should give firms the incentives to lower costs to be technologically efficient in order to maximize their profits. Although it is known that deregulation should theoretically lower production costs, little or nothing is known empirically about the magnitude of such effects. The purpose of this research will be to estimate the possible savings in production costs due to the deregulation of electrical generation across the country.

In particular, we will apply Bayesian analysis to steam electrical generators that burn natural gas as the primary fuel. The Bayesian frontier analysis supplies predictions for the frontier, plant efficiency, and returns to scale for each plant. The plant efficiency measure is the ratio of the predicted cost that would be required for an efficient firm to produce the observed output of any plant to the costs observed for that plant. For example, if a plant is 80% efficient, it could reduce costs by 20% simply by becoming more efficient. This statistic measures allocative efficiency, so it is also important to examine returns to scale. Deviations from constant returns to scale imply that a plant could reduce cost per unit by changing its level of output.

Our approach also takes the important step of applying microeconomic theory to statistical analysis. In particular, we impose concavity and montonicity upon our results. Thus, we require our estimation results to imply that the implicit demand curve for each firm for each particular input is downward sloping across all relevant ranges on that demand curve.

Section II of this paper describes the issues addressed by the project. Section III presents the data set to be used. Section IV describes the Bayesian approach to cost-frontier analysis that will be employed in the paper, as well as the restrictions implied by economic theory that we place on that analysis. Section V summarizes results, and section VI contains some concluding thoughts.

II. Cost-Frontier Analysis and the Issues Surrounding Electricity Deregulation

The production of electricity is divided into three different phases: generation, transmission, and distribution. Since the beginning of this century, it has been widely believed that all three levels of production were natural monopolies, where competition could not be counted upon to create efficient markets. To alleviate this problem, federal, state, and local governments have each regulated these three aspects of electricity production.

Unfortunately, regulation has its drawbacks. Typically, under regulation, the regulated firm receives a profit as a function of its capital expenditures. Thus, a firm may have strong incentives to overinvest in capital, such as generation facilities. This, in turn, implies that there will be too much investment in capital, and that electric plants will operate at increasing returns to scale. Of course, the price a regulated firm can charge is also constrained by political factors—how powerful both consumer interests and the relevant utility are at the relevant regulatory commission. The end result is that investment in generation may be largely a result of a political, rather than an economic, process. Given that political situations vary across states, this implies, in turn, that the efficiency of electricity generators across the country may be highly variable.

In contrast, in a competitive market situation, firms have important incentives to reduce costs. If a firm can reduce cost without reducing product quality or quantity, the firm can keep the relevant cost savings as profits. Thus, in a deregulated environment, profit-maximizing firms will seek to be as efficient as possible in order to increase the returns to their shareholders. As all the firms in a market act to lower their costs, technological efficiency, together with competition, will result in lower prices for consumers.

Over the last twenty years, important innovations have been achieved in the transmission of electrical power. The result is that the effective economic area over which elec-

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tricity can be dispatched has increased greatly. Thus, it does not seem for most locations that the generation of electrical power is a natural monopoly. Therefore, direct economic regulation of the generation of electricity may not be appropriate. Indeed, electricity generation has already been deregulated in Argentina, England, and New Zealand, and (at the time of this writing) in several U.S. states.

Thus, it now appears that it may be appropriate to deregulate the generation of electricity, while continuing to regulate the transmission and distribution of electricity. This policy issue has created a great deal of debate across the country. Here we hope to add to this debate by answering a very specific question: by how much can society expect to benefit from the increased efficiency that deregulation will create in the generation of electricity?

Deregulation, by forcing firms to face economic instead of political constraints, may have the effect of making electric generation more efficient, and thereby reducing electricity cost to consumers. Unfortunately, at this point in time, there is little information about how inefficient electrical generation currently is. The empirical work in the area is based on the data collected by Christensen and Greene (1976), which is from the early 1970s. Given the interest in this topic, recent research (Greene, 1990; Koop, Osiewalski, & Steel, 1994; Terrell & Dashti, 1998) still examines this data set. However, this data is now outdated and is also based on only a limited sample of fossil fuel electrical generators in the United States.

Bayesian cost-frontier analysis provides a very straightforward method of computing inefficiency measures for each firm based on deviations from a cost frontier that satisfies the basis tenets of economic theory. The Bayesian approach generates measures of efficiency for every electricity generator in the data set and easily provides confidence regions that are difficult to compute in classical models. We will then use this approach to calculate how much can potentially be gained in production terms from deregulation across the country. The methodology to be used will be described in detail later.

Deregulation may also bring its share of antitrust problems. It may be desirable to limit the size of firms to prevent the exercise of market power. If there are too few firms in a region, they may be able to tacitly or explicitly collude over price, raising prices to consumers, as appears to have happened in the England and Wales market.[1] On the other hand, economies of scale may allow firms to reduce average costs through expanding output. Thus, learning about available economies of scale is an important issue for a post-deregulation world, so that regulators and antitrust officials will be able to make the appropriate tradeoff between market power and economies of scale.

[1] See, for example, Green and Newbery (1992).

TABLE 1.—SUMMARY STATISTICS FOR THE DATA

Variable	Mean	S.D.
Cost (C)	50,653,645.79	51,246,491.93
Annual output (q_1)	1,537,843.24	1,741,523.54
Peak output (q_2)	649.32	548.47
Wage (P_L)	45,342.54	7,196.22
Price of fuel (P_F)	2.71	0.46
Price of capital (P_K)	1.02	0.39
Log relative wage	3.85	0.16
Log relative fuel price	1.03	0.40

III. Data

The project requires a data set measuring costs by generating plant. In particular, we must assemble a data set containing total cost, prices of fuel, capital, and labor, and two measures of output. We combined three data sources to construct these variables for 78 plants with all variables defined for the year 1996.

Our first source, the Bureau of Labor Statistics, supplies county-level data on wages by SIC code for every county in the United States. We define the wage rate (P_L) to be the average manufacturing wage for utility workers in the county where the power generating plant is located.[2] Our second data source, the Utility Data Institute Production Costs database (1998), supplies the average price of natural gas burned at each plant (P_F), the location of the plant, and total production cost (c). This data source also supplies the two measures of output that we use, output in megawatt hours (q_1) and peak output in megawatts (q_2). The use of these two measures of output allows us to account for the fact that some plants exist primarily to provide output during periods of peak demand.

As our third data source, Hilt (1996) supplies plant-level measures of the capital stock, taxes, overhead, depreciation, and operating and management expenses, all derived by allocating firm-level data to each plant. We use Hall and Jorgenson's (1971) method to calculate the price of capital (P_K) using this data.[3] We also deleted three very small generation facilities from our data set.

Table 1 contains a summary of the data. This table implies large variation in the output level across plants, which ranged from 11,406 megawatt hours (mwh) to 8,517,695 mwh in our sample. The mean cost of plants in our sample was $48,266,460. Wages, measured as the annual wages of an average manufacturing worker in the plant's county, ranged from $25,210 to $60,328. The table also shows substantial variation in the price of fuel and capital across plants.

[2] In particular, we use the average wage of SIC 49, which includes establishments engaged in the generation, transmission, and/or distribution of electricity or gas or steam.

[3] See Hazilla and Kopp (1986) for a detailed discussion of how to construct this measure for the price of capital.

IV. The Bayesian Approach to Cost-Frontier Analysis

Given data on costs, output, and prices, our goal is to estimate the efficient technology. This efficient technology is summarized by the cost frontier, which provides the amount it would cost an efficient plant facing a given set of prices (p_i) to produce a given level of outputs (q_i). We represent the cost frontier by the function $f(p_i, q_i)$, which returns the cost for an efficient plant to produce at a given output and price combination. If a plant's observed costs are higher than $f(p_i, q_i)$, that deviation is attributed in part to inefficiency. Thus, deviations from the frontier are used to construct measures of plant inefficiency.

To implement the method for multiple inputs and outputs, write the total cost of the plant as

$$\ln(c_i) = f(p_i, q_i) + u_i + v_i \tag{1}$$

where $f(p_i, q_i)$ is the cost frontier. Plant i's cost deviates from the frontier due to inefficiency (v_i) and measurement error (u_i). As is common in this literature, assume $u_i \sim IIDN(0, \sigma^2)$. For the nonnegative error term, we assume v_i follows an exponential distribution with scale parameter λ.[4]

To estimate the model, we must specify a functional form for the function f. Although the underlying function f is unknown, several properties of it are known from economic theory. For example, the costs of an efficient plant should rise as the price of inputs rise. We will use the translog model for the frontier, which will allow us to impose these properties. Allowing for nonconstant returns to scale, write the full model for the translog cost frontier for three inputs as

$$\begin{aligned} f(p, q) = a_0 + \sum_{i=1}^{3} a_i \ln p_i + \frac{1}{2} \sum_{i=1}^{3} \sum_{j=1}^{3} a_{ij} \ln p_i \ln p_j \\ + \sum_{i=1}^{2} b_i \ln q_i + \sum_{i=1}^{2} \gamma_i (\ln q_i)^2. \end{aligned} \tag{2}$$

where

$a_{ij} = a_{ji}$ for all $i, j = 1, 2, 3,$
$\Sigma_{i=1}^{3} a_i = 1,\ \Sigma_{j=1}^{3} a_{ij} = 0\ (i, j = 1, 2, 3).$

For the translog cost function, these restrictions impose homogeneity of degree 1 in factor prices, and the translog fulfills Diewert's minimum flexibility requirement for flexible functional forms as a second-order approximation to an arbitrary cost function. We impose the homogeneity restrictions by expressing cost, the price of labor, and the price of fuel as relative to the price of capital in our final model. Taking the derivative of the log cost function with respect to the log price of the input supplies the share equations associated with that input:

$$s_i(p, q) = a_i + \sum_{j=1}^{n} a_{ij} \ln p_j. \tag{3}$$

Monotonicity and concavity conditions can be easily checked using restrictions derived from the translog cost function. Monotonicity in output requires that $\partial f / \partial q > 0$, which for this translog frontier is equivalent to the restriction

$$b_i + 2\gamma_i \ln q_i > 0. \tag{4}$$

For the translog, nonnegative values for all shares ensures monotonicity in input prices $(\partial f / \partial p_i > 0)$. Concavity requires that the hessian matrix $\nabla^2 f$ be negative semidefinite. Let s denote the vector of n share equations, $\hat{s}$ an $n \times n$ diagonal matrix with the shares on the main diagonal, and A the $n \times n$ symmetric matrix of a_{ij}. Diewert and Wales (1987) proved that the translog cost function satisfies concavity if and only if $A - \hat{s} + ss^T$ is a negative semidefinite matrix.

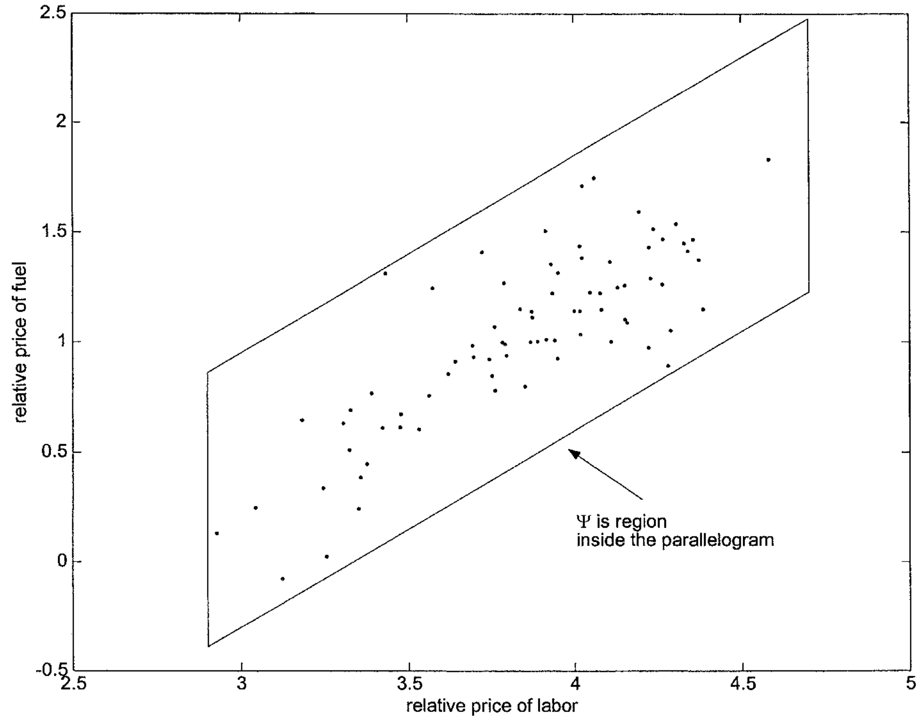
Jorgenson and Fraumeni (1981) showed that concavity can be imposed on the translog by forcing the matrix A to be negative semidefinite. Unfortunately, this restriction also causes the translog to overestimate own-price elasticities and also biases cross-price elasticities. As an alternative, Terrell (1996) suggested using a prior to impose monotonicity and concavity restrictions over a range of prices where inferences will be drawn. The results revealed little bias when the range is small (similar to those price combinations observed in his data set), but the expected biases appeared as the algorithm imposed constraints over a very wide range of prices. For this reason, we impose monotonicity and concavity only over a region Ψ. We define Ψ in terms of relative prices because concavity and monotonicity constraints depend on only relative prices. Because the relative price of labor and fuel tend to be positively correlated, we build this feature into Ψ as well. Figure 1 graphs the parallelogram Ψ where restrictions are imposed and relative prices for the actual data used in this study.

Equation (1) and (2) combine to generate a linear composed error model of the form

$$\begin{aligned} y_i &= X_i\beta + u_i + v_i \\ u_i &\sim N(0, \sigma^2) \\ v_i &\sim \text{EXP}(\lambda) \end{aligned} \tag{5}$$

[4] The methodology can easily be altered to allow for a truncated normal or gamma distribution for v, or to use a mixture of distributions as in Koop et al. (1994). We focus on the exponential distribution because van den Broeck et al. (1994) find this distribution to be more robust to prior assumptions about parameters than the other distributions. We also note that the inefficiency parameters that we will estimate measure inefficiencies relative to plants in the data set, all of which are regulated. Conceptually, deregulated plants could be far more efficient. This implies our estimates of inefficiency are biased downward.

FIGURE 1.—THE REGION Ψ VERSUS RELATIVE PRICES IN THE DATASET



where y_i denotes a log cost for plant i, X_i is a row vector of independent variables used to create the translog frontier, and β represents the coefficients of the translog. With respect to the residual terms, u_i is our "two-sided error" term reflecting measurement error, and v_i is our one-sided error capturing inefficiency of each plant. Notice that, with log cost as the dependent variable, the inefficiency error measures the percentage reduction in output due to inefficiency. For example, if the inefficiency error is 0.10, 10% of the plant's cost are attributed to inefficiency.

We complete the statistical model by specifying prior distribution functions. In the Bayesian approach, the prior distribution summarizes our knowledge of parameters in the model before analysis of the data begins. In this application, priors on the parameters of the cost frontier are used to enforce restrictions from economic theory for a relevant range of prices. For example, economic theory dictates that the efficient plant's costs will not fall when fuel prices rise. In addition, this Bayesian approach requires choosing a prior parameter to summarize our best initial guess of the efficiency of the median plant.

For our priors begin with a flat prior for β, and gamma priors for λ^{-1} and σ^2,

$$\pi(\beta) \propto 1,$$

$$\pi(\lambda^{-1}) = f_G(\lambda^{-1}|1, -\ln(r^*)), \tag{6}$$

$$\pi(\sigma^{-2}) = f_G\left(\sigma^{-2}\middle|\frac{\tau}{2}, \frac{s_p^2}{2}\right)$$

where $f_G(\cdot|\upsilon_1, \upsilon_2)$ denotes a gamma density with mean υ_1/υ_2 and variance υ_1/υ_2^2. Note that, with y_i defined as log cost, $r_i = \exp(-v_i)$ measures the efficiency of the ith firm, and r^* is simply the prior median for efficiency. Following van den Broek et al. (1994), and Koop et al. (1994), we set r^* to 0.875. With this number of observations, we do not expect the results to be sensitive to the choice of r^*.

Many applications of the Bayesian stochastic frontier model choose an uninformative prior on σ^2. Fernandez, Osiewalski, and Steel (1997) show that this leads to an improper prior in a cross-sectional application such as this one. We address this problem by choosing a gamma prior for σ^2, which ensures a proper posterior. Based on previous studies (Terrell & Dashti, 1998; Koop et al. 1994), we set τ to one and s_p^2 to 0.03, which implies a weak prior on σ^2 as well.

Following Terrell (1996), we also use the prior to impose monotonicity and concavity restrictions. Define the indicator function $h(\beta)$ set equal to one if the stochastic frontier satisfies monotonicity and concavity for all price combinations in ψ, and zero otherwise. The full prior incorporates the restrictions from theory by slicing away the portion of the density violating concavity and monotonicity using this indicator function:

$$\pi(\beta, \sigma^2, \lambda^{-1}) \propto \pi(\beta)\pi(\lambda^{-1})\pi(\sigma^{-2})h(\beta). \tag{7}$$

The prior imposes monotonicity and concavity over Ψ, the prices where inferences will be drawn. In other words, the prior sets the probability of parameter values that violate the basic tenets of microeconomic theory at relevant prices to zero.

Combining the prior and the likelihood produces the posterior density. Let $p(\theta)$ represent this posterior, where $\theta = (\beta, \sigma^2, \lambda, v)$. Note that elasticities, efficiency measures, and returns to scale are all functions of θ. The measure of efficiency for plant i is the ratio of plant i's cost to that of an efficient firm, or

$$r_i = \frac{\text{cost for an efficient firm}}{\text{cost for firm } i} = \frac{\exp(f(p_i, y_i))}{\exp(f(p_i, y_i) + v_i)} = \exp(-v_i). \quad (8)$$

Similarly, Caves, Christensen, and Swanson (1981) show that returns to scale in our two output model are

$$RTS = \left(\sum_{i=1}^{2} \frac{\partial \ln C}{\partial \ln q_i}\right)^{-1} = \frac{1}{b_1 + 2\gamma_1 \ln q_1 + b_2 + 2\gamma_2 \ln q_2}. \quad (9)$$

We generically refer to elasticities, efficiency measures, and returns to scale as functions of interest, which are combinations of parameters rather than parameters themselves in this paper. To understand how we draw inferences, let $g(\theta)$ denote an arbitrary function of interest. Obtaining the distribution and moments of $g(\theta)$ from the posterior density is conceptually straightforward. For example, the posterior mean is simply $E[g(\theta)] = \int g(\theta)p(\theta)d\theta$. Unfortunately, this integral generally cannot be computed analytically. However, if one samples n values of θ_i from the posterior, moments can be evaluated numerically. Thus, the posterior mean for a function of interest is calculated as

$$E[g(\theta)] = \frac{1}{n}\sum_{i=1}^{n} g(\theta_i).$$

Geweke (1996) summarizes several numerical advances in generating samples for posterior densities, which have made Bayesian methods applicable for many applied problems. For our model, a Gibbs sampler provides the necessary sample from the posterior. The Gibbs sampler is based on conditional densities. Koop et al. (1994) summarize the conditionals for this model and briefly describe the basic Gibbs sampler for the stochastic frontier model.

We wish to emphasize one thing about our estimates of the model parameters, efficiency scores, and returns to scale. Unlike many frequentist studies, we do not construct confidence intervals or draw inferences based on asymptotic results implying limiting normal distributions. Rather, through our Bayesian estimation, we can observe the distribution of these parameters, which may or may not resemble the classical normal distribution. This is clearly important when evaluating confidence intervals for shares and efficiency scores, statistics that have truncated asymmetric distributions. In addition, Anderson and Thursby (1986) found that the asymptotic approximations of standard errors were inaccurate in moderately sized samples, which suggests our approach also offers an advantage for drawing inference about the size of elasticities.

TABLE 2.—POSTERIOR MOMENTS FOR MODEL PARAMETERS

Parameter	Posterior Mean	Posterior S.D.	90%-Confidence Region
a_0	9.947	1.100	[8.117, 11.769]
a_1	0.614	0.349	[0.091, 1.234]
a_2	0.405	0.342	[−0.216, 0.895]
a_{11}	−0.140	0.110	[−0.327, 0.026]
a_{12}	−0.147	0.136	[−0.386, 0.064]
a_{22}	0.114	0.116	[−0.060, 0.320]
b_1	−0.442	0.195	[−0.759, −0.112]
γ_1	0.044	0.008	[0.031, 0.056]
b_2	0.845	0.260	[0.419, 1.278]
γ_2	−0.057	0.022	[−0.092, −0.021]
σ^2	0.010	0.003	[0.006, 0.014]
λ	0.132	0.022	[0.099, 0.171]

Posterior moments are computed based on 5,000 points generated from the Gibbs sampling algorithm. The endpoints of the 90%-confidence region are the 5th and 95th percentiles of the marginal densities.

TABLE 3.—SHARES AND PRICE ELASTICITIES

	Posterior Mean	Posterior S.D.	90%-Confidence Region
s_L	0.193	0.062	[0.098, 0.298]
s_F	0.691	0.067	[0.577, 0.796]
s_K	0.116	0.039	[0.055, 0.183]
ϵ_{LL}	−1.540	0.517	[−2.300, −0.648]
ϵ_{FF}	−0.529	0.246	[−0.974, −0.189]
ϵ_{KK}	−1.366	0.336	[−1.862, −0.733]
ϵ_{LF}	1.268	0.549	[0.339, 2.119]
ϵ_{LK}	0.272	0.354	[−0.220, 0.925]
ϵ_{FL}	0.363	0.215	[0.073, 0.769]
ϵ_{FK}	0.166	0.102	[0.018, 0.348]
ϵ_{KL}	0.413	0.536	[−0.429, 1.313]
ϵ_{KF}	0.953	0.453	[0.140, 1.638]

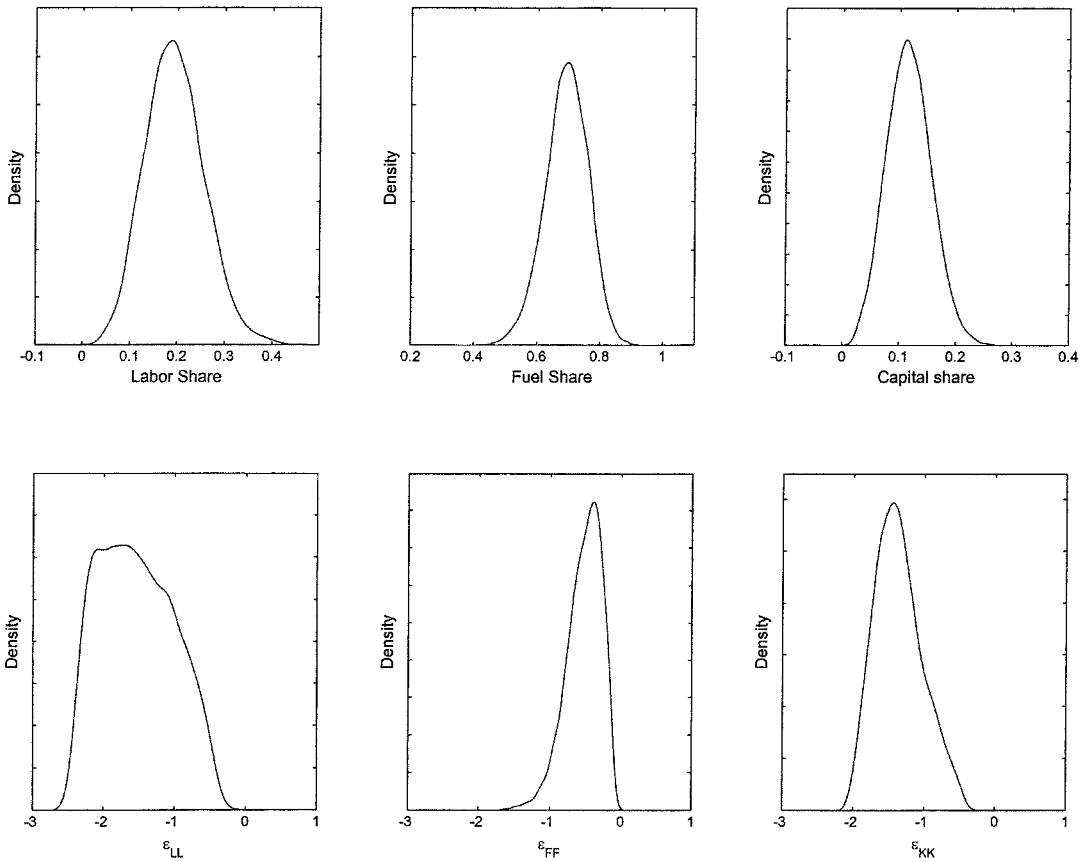
This table presents the posterior mean for shares and price elasticities calculated at the mean value of all prices and output. Posterior moments are computed based on 5,000 points generated from the Gibbs sampling algorithm. The endpoints of the 90%-confidence region are the 5th and 95th percentiles of the marginal densities.

V. Results

Table 2 presents the posterior moments for the frontier parameters λ and σ^2. The parameters of the translog frontier are difficult to interpret, so table 3 presents the posterior mean for shares and price elasticities evaluated at the mean of prices and output. Not surprisingly, the largest predicted expenditure share is that of fuel with 69.1% of total expenditures, while 19.3% of expenditures go to labor and 11.6% to capital. The own-price elasticities clearly show capital and labor usage is far more sensitive to price than fuel.[5] Many deregulated industries were able to reduce their costs,

[5] All three own-price elasticities are smaller than those reported by Terrell and Dashti (1998) for a translog frontier using 1971 electricity data. Their study also finds the same pattern in that fuel is far less sensitive to price than the other inputs.

FIGURE 2.—MARGINAL DENSITY PLOTS FOR SHARES AND ELASTICITIES



and prices, by reducing their labor costs. (See, for example, MacDonald and Cavalluzzo (1996).) The relatively small share of labor inputs may imply that the cost reduction due to potential decreases in the cost of labor supply from restructuring may be limited.

The cross-price elasticities reveal that all three inputs are substitutes in production. In particular, ϵ_{LF} and ϵ_{KF} indicate that the firm's demand for labor and capital are quite sensitive to the price of fuel, apparently attempting to use labor and capital to save fuel when faced with high fuel prices.

Figure 2 graphs the marginal densities of the shares and own-price elasticities, again evaluated at mean prices. The figure shows that the posterior density places no mass on economically implausible frontiers. The densities show a zero probability of shares less than zero or greater than one, and also rule out positive own-price elasticities. In addition, the figure shows that some densities are asymmetric, perhaps reflecting the fact that the constrained posterior density "slices away" the portion of the unconstrained density that violates monotonicity and concavity. For example, the more binding constraint on capital's share and ϵ_{FF} explain the slight skewness observed in their marginal densities. These asymmetries imply that confidence intervals and hypothesis tests based on normal densities are invalid for this model.

Returning to table 2, the results indicate a posterior mean for λ of 0.132. In other words, 1996 electric generation plants exhibited average inefficiency of roughly 13%, or were 87% efficient. Comparing our result of 87% efficiency to those of previous studies using the widely studied 1971 data set on electric utilities reveals that efficiency has fallen somewhat in the electric power generation industry. Greene's (1990) results using a double log frontier suggest firms were 90% efficient in 1971, and Terrell and Dashti (1998) find 92% efficiency for that sample based on a translog frontier.

The top panel of table 4 presents efficiency and returns to scale results for eight firms representative of the mix of firms in our sample, sorted from lowest annual output to largest. The first three columns contain posterior moments for efficiency score that summarizes how efficiently a firm produces given its current level output. For example, the posterior mean for the Edgewater (Ohio) facility suggests that it is 94.3% efficient, or, equivalently, its costs could be reduced by 5.7% by eliminating all inefficiency. For 74 of the 78 plants, the posterior means indicate more than 80% efficiency and 39 of the plants are more than 90% efficient.

The next three columns of table 4 contain returns to scale results for the eight firms in our sample. Only one plant in the entire data set of 78 exhibited decreasing returns to scale

TABLE 4.—PLANT EFFICIENCY AND RETURNS TO SCALE

	Efficiency			Returns to Scale			Output	
Plant	Posterior Mean	Posterior S.D.	Confidence Region	Posterior Mean	Posterior S.D.	Confidence Region	Total Annual	Peak
Edgewater (OH)	0.943	0.050	[0.846, 0.997]	1.439	0.113	[1.271, 1.637]	11,406	99
Greenwood (MI)	0.936	0.053	[0.831, 0.996]	1.564	0.135	[1.365, 1.799]	86,169	771
TH Wharton (TX)	0.830	0.078	[0.700, 0.963]	1.091	0.034	[1.036, 1.148]	419,983	234
Bowline Point (NY)	0.873	0.073	[0.747, 0.983]	1.251	0.070	[1.146, 1.375]	832,538	1,103
Plant X (TX)	0.932	0.052	[0.832, 0.995]	1.089	0.025	[1.050, 1.131]	905,378	418
Knox Lee (TX)	0.922	0.057	[0.814, 0.993]	1.075	0.025	[1.035, 1.117]	1,018,268	412
Stryker Creek (OH)	0.905	0.064	[0.787, 0.991]	1.061	0.032	[1.012, 1.116]	2,379,097	710
Sabine (TX)	0.922	0.058	[0.810, 0.994]	1.059	0.061	[0.967, 1.168]	8,517,695	1,834
Mississippi Plants:								
Baxter Wilson	0.897	0.066	[0.776, 0.988]	1.123	0.053	[1.042, 1.240]	2,650,786	1,206
Delta	0.930	0.053	[0.829, 0.994]	1.162	0.042	[1.096, 1.239]	175,577	194
Eaton	0.902	0.066	[0.778, 0.989]	1.120	0.077	[1.002, 1.258]	78,227	76
Rex Brown	0.916	0.058	[0.805, 0.993]	1.155	0.032	[1.105, 1.252]	283,600	271
Sweatt	0.917	0.060	[0.804, 0.994]	1.139	0.070	[1.032, 1.168]	85,363	94

Posterior moments are computed based on 5,000 points generated from the Gibbs sampling algorithm. The endpoints of the 90%-confidence region are the 5th and 95th percentiles of the marginal densities.

(0.986) and the confidence region for 16 of 78 contained returns to scale equal to one. The standard deviations and ranges for confidence regions for the mix of firms in table 4 are typical of the entire sample. Greenwood (Michigan) and Edgewater exhibited near the highest returns to scale in the sample and the average returns to scale for the entire sample was 1.14, implying most plants operated at increasing returns to scale.

The bottom panel of table 4 also illustrates the potential efficiency gains available in one state, here Mississippi. The posterior mean efficiencies for natural gas plants in that state range from 0.897 to 0.930, above the average efficiency in our sample of 0.868. This result implies that the gains to restructuring in Mississippi with respect to natural gas plants may be slightly less than the national average.

One may expect that deregulation should raise plant output and general efficiency scores. Given the highly seasonal and time-specific demand for electricity, achieving the optimal scale may be more difficult. This may be more likely to occur, however, due to lower average prices and the widespread adoption of time-of-day pricing (Train & Mehrez, 1994; Ham, Mountain, & Chan, 1997).

VI. Conclusion

The compelling argument for deregulating electricity generation is that competition increases efficiency. In the context of the current debate on deregulation, the crucial question is how large are the potential efficiency gains. By examining the current level of efficiency in the industry, this paper answers this question for natural gas generating facilities. Given the current output levels, the average plant could reduce costs by up to 13% through increased efficiency. The results also imply substantial differences in efficiency across plants. Some plants are near 100% efficient, whereas at least four plants are below 80% efficient. Our results also find natural gas generating plants typically operate at the increasing returns to scale.

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