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Does Incentive Regulation Provide the Correct Incentives?: Stochastic Frontier Evidence from the US Electricity Industry

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Does Incentive Regulation Provide the Correct Incentives?: Stochastic Frontier Evidence from the US Electricity Industry

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Abstract

Many policy-makers are currently weighing the advantages of deregulating electricity markets over more traditional regulatory methods. However, within this traditional regulatory environment many options exist. In particular, the use of incentive regulation programs in US electricity markets has grown during the past two decades. These programs differ in both their goals and how they attempt to meet these goals. In this paper, I discuss the wide array of programs that have been utilized, and investigate the impact of individual programs on the technical efficiency of a large set of coal and natural gas generator units. Within a stochastic frontier framework, I allow the distribution of inefficient production to be a function of the regulatory environment the plant operates under. The results suggest that while certain incentive regulations increase observed technical efficiency, others have either no effect or even lead to a reduction in efficiency.

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1 Introduction

The method of regulating investor-owned electricity utilities (IOUs) has undergone a tremendous amount of change in recent years. While many states are now moving toward a system centered around a competitive market for electricity generation, the vast majority of IOUs still operate under a traditional regulatory environment. Furthermore, more traditional methods of regulation are likely to continue for a number of reasons. For one, given the potential for market power during peak time periods in a deregulated market, the success in markets that have undergone deregulation has been mixed. Secondly, given the limited transmission networks in many markets, without extensive expansion in existing transmission networks the potential for market power is likely to be too great for deregulating some markets.[1]

Therefore, many regulators are faced with designing effective regulatory methods within the confines of traditional regulatory oversight structures. In recent years, there have been an increase in the number of options available within the traditional regulatory framework. Specifically, the use of "incentive regulation" programs in US electricity markets has grown during the past two decades. Incentive regulation programs seek to alter the incentives of firms in order to achieve certain goals, such as demand reductions or increases in the efficiency of generators.

While much of the current research has focused on the inefficiency created by restructuring electricity markets through the existence of market power, as state regulators choose between sustaining traditional regulatory practices or deregulating electricity generation, the ability of incentive regulation programs to achieve their goals is of great importance.[2] In addition, given the wide array of programs that have been used to achieve similar goals, state regulators are also be faced with the decision as to which type of program is most effective.

In this paper, I summarize the types of programs that have been utilized. Next, I analyze the impact of these programs on technical efficiency at the plant level and firm level. I build on existing stochastic frontier techniques by specifying the distribution of inefficiency to be a function of the regulatory environment that the plant operates under. The results suggest that while certain incentive regulations increase observed technical efficiency, many have either no effect or lead to a *reduction* in efficiency. The estimates from this analysis provide regulators with a benchmark as

[1] See Borenstein, Bushnell, and Knittel (1999) for a discussion of the issues that will likely drive the success of deregulation.

[2] For studies focusing on the existence of market power in electricity markets see Borenstein and Bushnell (1997), Borenstein, Bushnell, and Knittel (1997), Borenstein, Bushnell, and Knittel (1999), and Borenstein, Bushnell, and Wolak (1999) for the California market, and Wolak and Patrick (1996) and Wolfram (1999) for a discussion of market power conditions in the UK.

to how these programs have altered the incentives of the IOUs and quantify the benefits of these programs.

The remainder of the paper is organized as follows. Section 2 provides a brief discussion of the variety of programs that have been utilized. Section 3 discusses the data used in the study and the econometric methodology. The results of the base case specifications are presented in section 4. Section 5 expands on these specifications, while section 6 concludes the paper.

2 Incentive Regulation Use

In their most basic sense, incentive regulation programs can be categorized into one of two general categories: (1) programs that address demand reduction/shifting, and (2) those that address generator efficiency. Within these two categories a variety of different programs have been used. In this section, I provide a review of these programs, while discussing the rationale behind their use and discuss the indirect incentives these programs may create in other facets of IOU behavior that regulators seek to control.

2.1 Demand Reduction/Shifting Programs

Demand based incentive regulation programs are the most commonly used incentive regulation programs. The types of demand based programs used fall into two categories, referred to as (a) demand side management (DSM) and (b) load management. The first of these attempts to reduce the sum of demand, while the second attempts to shift demand across time periods.

2.1.1 Demand Side Management Programs

Rebate Programs With the onset of the energy crisis during the 1970s, state regulators sought to reduce the demand for electricity. The most common method for accomplishing this goal was to provide incentives for consumers, in the way of rebates, to replace older model appliances with those of newer, more efficient, models. Likely because the regulatory relationship between IOUs and regulators was already in place, the state public utility commissions (PUCs) chose the IOUs to carry out this task. Under such programs the IOUs would provide a rebate for the purchase of new appliances and subsequently be reimbursed, by the PUC, for these rebates.

It is unclear why the IOU is the best agent to provide this service. A by-product of demand reduction is a loss in revenues for the firm. If these revenues exceed the costs of providing the

electricity, then the program implies a loss in profits for the IOU. Therefore, there is a natural tendency for the firm to resist such programs, or make the rebate program less attractive to the consumer. State PUCs addressed this by not only reimbursing the IOUs for the amount spent on the rebate programs, but often reimbursing the IOUs for the lost profits from such programs. A second method PUCs used to address the disincentive of firms to seek demand reduction are "revenue decoupling programs."

Revenue Decoupling Programs Under revenue decoupling programs, after some level of sales, the IOU must rebate the difference between the marginal price and the marginal cost to the consumers – thus reducing the incentive for firms to sell the marginal unit of electricity. One drawback of this program is that because the firm must rebate the difference between price and costs, the firm no longer has an incentive to minimize costs. As long as the firm keeps the marginal costs below the marginal price, the firm does not benefit from producing efficiently.

2.1.2 Load Management Programs

During off-peak demand hours, utilities have a surplus of generation units available. Due to start-up costs (implying a cost non-convexity), it may actually be more costly *not* to run these plants, since the added future start up costs may outweigh the current variable costs of operating the plant. Therefore, it is possible that during off-peak time periods, the marginal cost of electricity production may be zero, if not negative.[3] In contrast, during peak-load periods IOUs are often forced to run high cost units in order to meet demand. Therefore, total costs of providing electricity would often be greatly reduced if demand was more constant across time periods. Load management programs address this by providing incentives for the consumer, e.g. off-peak price discounts, to shift demand across time periods.

2.2 Generator Efficiency Programs

In addition to demand side incentive regulation programs, a variety of programs that seek to increase the productive efficiency of generation units have been utilized. These programs fall into roughly two categories – those that seek to directly reward efficiency gains and those that seek to provide the firm with incentives to produce efficiently by allowing the firm to profit from reductions in costs.

[3] Do to the physical properties of electricity, generated electricity cannot simply be "waisted". Therefore, negative marginal costs are possible.

2.2.1 Direct Reward Programs

Thermal Efficiency Programs Thermal efficiency programs provide the firm with an incentive to reduce the heat rate of generation facilities.[4] Often these programs set price as a function of a base heat rate level. Therefore, if the firm operates at a lower heat rate (implying it operates more efficiently than the guideline) the firm retains the benefits from the heightened efficiency level. Therefore, given a fixed price the firm has the incentive to operate at the highest attainable efficiency level. Similar programs have also been used for nuclear units focusing on the capacity factor.

Equivalent Availability Programs Availability programs focus on increasing the percentage of the time a plant is available to produce electricity, whether or not it is called upon to actually do so. These programs provide a disincentive for firms to keep plants off-line, thereby reducing total generation costs if low cost generators would have been held off-line, as well as potentially increasing the reliability of the network.

2.2.2 Indirect Reward Programs

Price Cap Programs Beginning with Averch and Johnson (1962) a number of critiques have been waged against rate-of-return regulation. Averch and Johnson illustrate that because the firm's profit rate is tied to the amount of capital it employs, the firm has an incentive to utilize too much capital in the production process, thus producing inefficiently. Firms regulated via price cap regulation do not have this incentive. Because the firm is able to profit from increases in efficiency, the firm has the incentive to utilize the efficient level of capital. Although price cap regulation has been utilized much less in the electricity industry than other regulated industries in the US (e.g. telecommunications), some PUCs have adopted price cap regulation and their use is increasing.[5]

Rate-of-Return Range Programs Again, one of the drawbacks from rate-of-return regulation is that if the firm reduces costs, the effect is to increase the rate-of-return the firm is currently

[4] The heat rate refers to the amount of energy wasted, in the form of heat, in the production process. Therefore, the lower the heat rate, the more efficient the plant is.

[5] Illinios has also adopted benchmark regulation that produces much the same incentives as price cap regulation. Under benchmark regulation, the firms price is set as an average of the prices charged by of firms in neighboring states. Therefore, if you are a firm in Illinois your capital expenditures do not impact the price and you have the incentive to produce efficiently. However, the incentives are less clear when the rates of the firms that impact your price are also dependent on your price. See Shliefer (1985) for a discussion of the theoretical issues.

earning. If the rate-of-return constraint is always binding cost reductions cause regulators to initiate a rate hearing, the end result of the cost reduction might be a lower rate-of-return for the firm. Therefore, the firm may have less of an incentive to seek reductions in costs. While price cap regulation corrects this disincentive, if the firm's profit level becomes too high, the regulator may face pressure to reduce the price cap from consumer groups.[6] Rate-of-return range programs address this by allowing the firm's rate-of-return to fluctuate inside some band before a rate hearing is initiated. Therefore, as long as the firm remains within this band, the firm has an incentive to undergo efficiency increases.

In a dynamic setting, it is less clear how such a program will impact efficiency. When the actual rate-of-return falls to this lower bound, rates are altered so that the firm rate-of-return is increased to some intermediate level between the lower and upper bounds. Therefore, the firm may have less of an incentive to produce efficiently, since the penalty from producing inefficiently is reduced. Also, the firm may choose to lower efficiency in order to reach this lower bound, and then, once rates are increased, increase efficiency so as to earn a higher rate-of-return.

2.3 Fuel Cost Pass-Through Programs

Fuel cost pass-through programs do not fit into either of the above categories, but have been used extensively in the regulation of generation units. Their appeal comes from the savings associated with fewer rate hearings. Absent pass-through programs fluctuating fuel costs imply that the firm's rate-of-return will have a high degree of variance between rate hearings – since prices are held constant between rate hearings. Therefore, fluctuating fuel costs are likely to cause an increase in the number of rate hearings, and an increase in the costs associated with regulation.[7] To control for this, many PUCs have adopted automatic fuel cost pass-through programs where some, if not all, of the changes in fuel costs are directly passed on to the consumer without the need of a rate hearing. While such programs are likely to reduce the need for rate hearings, they may also reduce the incentive for firms to minimize fuel costs, since the burden of increases in costs are passed through to consumers.[8]

[6] For price cap regulation to be effective in correcting this disincentive, it must be credible in the sense that the regulator must be able to commit to either low or high profit draws.

[7] See Joskow (1974) for a discussion of these programs and their political implications.

[8] This study is not the first to make this point, Brown, Einhorn, and Vogelsang (1991), among others, also note this.

3 Empirical Investigation

The use of such a wide-array of incentive regulation programs brings up a number of economic questions as to their impact on firm behavior. The most obvious question is whether programs designed to increase generator efficiency meet this goal. However, it may also be of interest to policy-makers whether incentive regulation programs designed to meet one goal have unintended effects on other facets of firm behavior. In this section, I discuss and estimate an econometric model that addresses these questions. In particular, I estimate a stochastic frontier model that allows for the distribution of efficiency to depend on the generator's regulatory environment.

3.1 Econometric Framework

To estimate the impact of incentive regulation programs on efficiency levels requires the estimation of a production frontier. Econometric estimation of production frontiers that allow for the existence of inefficiency began with Aigner, Lovell and Schmidt (1977), Meeusen and van den Broeck (1977), and Battese and Corra (1977). The technique is based on the assumption that there exists some deterministic production frontier, for which firms must produce on or below. However, because of the stochastic nature of variables such as weather, other acts of god, and the presence of unobserved variables, at times a firm may be able to produce in excess of this production frontier, implying the observed frontier is stochastic.

Unlike simpler methods such as ordinary least squares, stochastic frontier analysis explicitly models the possibility that given this production frontier, firms may produce inefficiently. In particular, stochastic frontier analysis assumes that to the econometrician there are two unknown random variables associated with the error term. The first characterizes the randomness in the production process, while the second characterizes the possibility that the plant is operating inefficiently. To account for these two unknowns, stochastic frontier techniques model the stochastic nature of the production function as a composite error term. One portion of the error term is a classic stochastic term, allowed to be both positive and negative, another term takes on only non-positive values – accounting for the effects of inefficiency. A typical specification is as follows:

$$\ln f_i = \ln f\left(\mathbf{x}_i\right) + \eta_i + v_i \tag{1}$$

where $f\left(\mathbf{x}_i\right)$ is the deterministic production function, $\mathbf{x}_i$ the vector of inputs, η_i a non-positive random variable reflecting inefficiency, and v_i a mean zero error term.

To estimate the model, parametric assumptions must be made regarding the distributions of η_i and v_i, as well as the assumed function form of $\ln f\left(\mathbf{x}_i\right)$. The most common parametric specifications

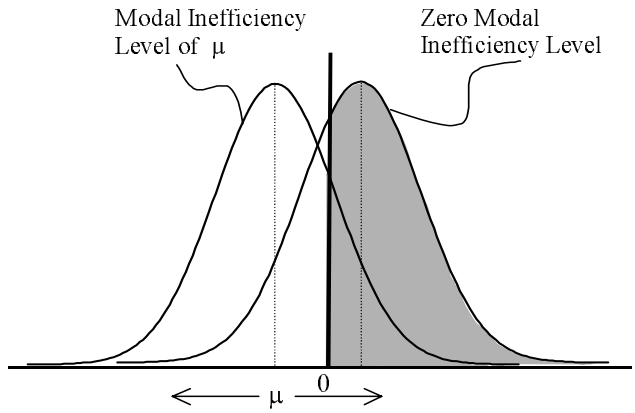

Figure 1: Varying Modal Value

for the error terms are to assume v_i as normally distributed with mean zero and variance σ_v^2, and η_i as a truncated (at zero) normally distributed random variable where the non-truncated distribution is $N(\mu, \sigma_\eta)$.[9] For the problem at hand, however, we are interested in how incentive regulation programs impact the efficiency of generators. This implies that we are testing whether the distribution of inefficiency varies with the regulatory environment the generator operates under.

The previous literature has dealt with this issue by taking the estimated value of $\eta_i + v_i$ and calculating the $E[\eta_i|\eta_i + v_i]$ and then treating this value as the dependent variable in a second regression. However, it is widely known that the parameter estimates from such a two–step estimator are inefficiently estimated. Recently, the literature has noted these shortcomings and instead treated μ as dependent on covariates when deriving the likelihood function.[10,11] It is this approach I employ here, allowing μ to shift depending on the regulatory environment the plant operates under (see Figure 1).

I model μ as containing both a deterministic component and a component that depends on the regulatory environment the firm operates under. Specifically, I test whether certain incentive regulation programs have an impact on the level of inefficiency. I analyze six different incentive regulation programs (see Table 1 for their descriptions), focusing on programs that are likely to have an impact on efficiency.[12] Formally, μ is modeled as:

[9] A number of different specifications for the composite error term have been used in the literature. Due to its convenience the half normal distribution is often used. However, other specifications such as the truncated normal (Stevenson (1980)) and the two-parameter Gamma distribution have been used (Greene (1990)).

[10] Kumbhakar, Gosh, and McGuckin (1991) also employ this method in analyzing US dairy farms.

[11] See Appendix B for the derivation of the likelihood function.

[12] Demand-side management programs, such as rebates or load smoothing, are not likely to impact plant level efficiency, since these programs do not change the incentives of the firm with respect to the operation of generating

Variable	Description
D_{eaf}	Equal to one if the plant operated under an incentive regulation program that rewards for plant availability levels.
D_{hr}	Equal to one if the plant operated under an incentive regulation program that rewards for lower heat rate levels.
D_{ror}	Equal to one if the firm owning the plant operated under an incentive regulation program that allows the rate-of-return of the IOU to fluctuate inside given range.
D_{cap}	Equal to one if the firm owning the plant is regulated via either price caps or benchmark regulation.
D_{fuel}	Equal to one if the firm owning the plant operated under an incentive regulation program that allows for pass-through of some level of fuel costs.
D_{revdec}	Equal to one if the firm owning the plant operated under an incentive regulation program that, after some level of sales, decouples revenues.

Table 1: Performance Based Regulation Programs Analyzed

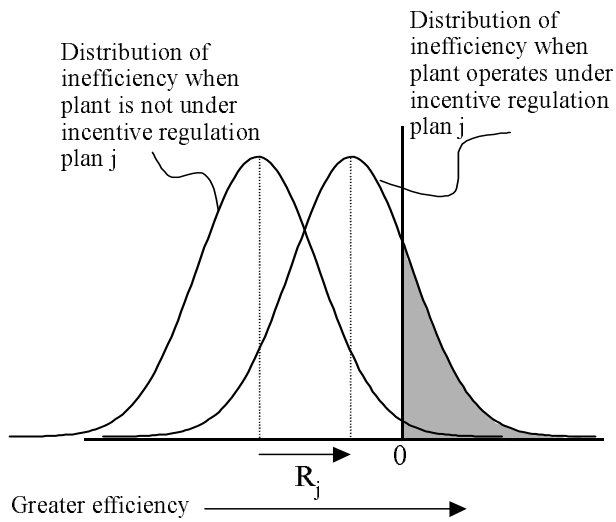

Figure 2: The Impact of Incentive Regulation Programs on the Distribution of Inefficiency

$$\mu = \mu_o + R_{eaf} D_{eaf} + R_{hr} D_{hr} + R_{ror} D_{ror} + R_{cap} D_{cap} + R_{fuel} D_{fuel} + R_{revdec} D_{revdec} \qquad (2)$$

where μ_o represents that mean of the *un*truncated distribution for plants that do not operate under any of the modeled incentive regulation programs. For $\mu_o < 0$, μ_o represents the modal value of inefficiency for plants that do not operate under any of the modeled incentive regulation programs. However as Figure 1 illustrates, because μ_o represents the mean of the untruncated distribution, a value of $\mu_o \geq 0$, implies the modal value of inefficiency for such firms is zero.

The variables D_j are indicator variables equal to one if the plant operates under the incentive regulation program j and R_j is the parameter associated with the incentive regulation program j. In particular, R_j measures the impact the incentive regulation program j has on the modal value of inefficiency for a given plant. For example, as illustrated in Figure 2, if $\hat{R}_j > 0$ then the estimates imply that the modal value of *in*efficiency is reduced, since on average, the plants operating under the incentive regulation program j produce more output given an equal amount of inputs.

Finally, I assume that $f(\mathbf{x}_i)$ takes the form of a modified Cobb-Douglas production function. In their study on US coal plants Joskow and Schmalensee (1987) found that the plant's vintage significantly impact thermal efficiency and reliability, both of which would impact the production function of plants. Therefore, I augment the Cobb-Douglas production function to control for the

units. Therefore, these programs are not included.

vintage of the plant, including $g(Vintage)$ defined as

$$\ln(Vintage)\,\gamma_1 = \ln Vintage + \gamma_2 (\ln Vintage)^2$$

where $Vintage$ is the year the plant was built minus 1943 (the year of the earliest plant in the data set).

The Cobb-Douglas production function for coal plants implies that output is governed by the following:

$$y_i = \beta K_i^{\alpha_K} L_i^{\alpha_L} Coal_i^{\alpha_C} Oil_i^{\alpha_O} g(Vintage, \gamma)\, e^{\eta_i + v_i} \tag{3}$$

where, K_i is the level of capital employed, L_i the level of labor, $Coal_i$ the quantity of coal utilized and Oil_i the quantity of oil used.

By taking the logarithm of both sides, this implies:

$$\begin{aligned} \ln y_i &= \ln\beta + \alpha_K \ln K_i + \alpha_L \ln L_i + \alpha_C \ln Coal_i + \alpha_O \ln Oil_i \\ &\quad + \gamma_1 \ln Vintage + \gamma_2 (\ln Vintage)^2 + \eta_i + v_i \end{aligned} \tag{4}$$

A similar specification for natural gas plants is also made.

3.2 The Data

To estimate the impact of the regulatory environment on productive efficiency, I employ an unbalanced panel data set of generator specific outputs and inputs taken at yearly intervals. The data are from the years 1981 to 1996 for a large subset of IOU generators and were collected as part of the Federal Energy Regulatory Commissions (FERC) Form 1 data requirements. The data track yearly total production of the generators, the quantity of inputs used in the production process, as well as a variety of plant level characteristics.

The measurement of output used is the net megawatt hours produced by the plant in a given year.[13] Labor is the number of full-time equivalent employees. Two fuels are used in the operation of both coal and gas plants. For coal plants, I include the total tonnage of coal used during the year, as well as the number of barrels of oil used in the generation process. For gas plants,

[13] Net megawatts is defined as the amount of electricity consumed, which differs from the amount of electricity generated because of "losses" sustained when the electricity travels through transmission lines.

Fuel Type	Variable	Mean	Standard Deviation	Min	Max
Coal	Megawatt Hours (1000s)	3660	3834	.221	21883
	Employees (full-time)	187	151.0	10	1211
	Capacity (MWs)	774.2	703.2	11	3953
	Coal (1000 Tons)	1780	1969	.190	35063
	Oil (1000 Barrels)	57.01	3317	0	8245
Regulatory	ROR Range Program	.0152	—	0	1
	EAF Program	.0832	—	0	1
	Heat Rate Program	.0515	—	0	1
	Price Cap/Benchmark	.0145	—	0	1
	Fuel Cost Pass-Through	.0411	—	0	1
	Revenue Decoupling	.0592	—	0	1
Gas	Megawatt Hours (1000s)	1750	1805	11.17	11417
	Employees (full-time)	82.84	64.04	10	819
	Capacity (MWs)	641.0	535.0	8	2295
	Gas (10000 MCF)	1859	1819	24.73	10600
	Oil (1000 Barrels)	216.0	602.1	0	8336
Regulatory	ROR Range Program	.0057	—	0	1
	EAF Program	.1032	—	0	1
	Heat Rate Program	.0172	—	0	1
	Price Cap/Benchmark	.0079	—	0	1
	Fuel Cost Pass-Through	.1656	—	0	1
	Revenue Decoupling	.0789	—	0	1

Table 2: Summary Statistics

both the quantity of gas, measured in million cubic feet and the number of barrels of oil used are included.[14,15]

To obtain a suitable measurement of capital is not as straight forward. Because the data are taken at an annual interval, measurements of inefficiency can manifest themselves in two ways. For one, an inefficient plant may utilize more inputs to product the same amount of output than that of an efficient plant. Second, an inefficient plant may operate less often than an efficient plant. In addition, the nature of electricity generation implies that during certain time periods efficient production calls for higher marginal cost units to not operate. If we were to ignore this these "peaking" plants would appear to be inefficient. To control for this, I focus attention on base-load plants, those plants that are designed to continuously generate electricity. By focusing on base-load plants, the capacity of the plant, measured in the maximum sustainable output of electricity, is an accurate measurement of the capital input. Therefore, the parameter estimates measure the impact of performance based regulation on inefficiency that takes the form of excess input usage and excess generator outages.[16]

Table 2 lists the summary statistics of the variables used in the study, while the data sources are described in Appendix A.[17]

4 Results

4.1 Coal Plants

The results for the coal plants are listed in Table 3. The estimates imply that there exists economies of scale in coal generation, as the sum of the α's is 1.081, and the sum is statistically different from 1.[18] The parameter estimates with respect to plant vintage suggest that more recently built plants are capable of generating a greater amount of electricity given input levels, likely because they are

[14] The FERC Form 1 data do no report quantity of gas used in the production process, but instead the cost of the fuel. To obtain a quantity measurement, I used the average price of natural gas paid by IOUs for each state to obtain an estimate of the volume of fuel used.

[15] For coal and natural gas generation units, oil is sometimes used as a startup fuel, i.e. for heating up the plants boilers from a cooled state. Therefore, for some units the value for the oil variable is zero. In order to allow for the taking of a logarithm of this variable, one is added to the quanity of oil used for each observation.

[16] After these restrictions, the number of observations for coal units is 4030, while the number of observations for gas plants is 1889.

[17] To control for outliers, plants were only chosen if they produced a positive amount of electricity, employed greater than ten employees, and used a positive amount of either coal or gas.

[18] The t-statistics associated with testing the null hypothesis that the sum of the coefficients equals one is 16.41.

Maximum Likelihood Estimates			
Parameter	**Estimates**	**Standard Error**	**P–value**
$\ln \beta$	3.145	.0861	.000
α_K	.3697	.0156	.000
α_L	.0103	.0147	.482
α_C	.6774	.0013	.000
α_O	.0051	.0012	.000
$\ln Vintage$	.4959	.1015	.000
$(\ln Vintage)^2$	–.1065	.0161	.000
μ_o	–.0228	.0069	.000
R_{eaf}	.1535	.0170	.000
R_{hr}	.0715	.0293	.015
R_{ror}	–.1406	.3050	.562
R_{cap}	–.0242	.0411	.556
R_{fuel}	–.0596	.0053	.000
R_{revdec}	.2807	.1417	.048
σ_v	.2289	.0111	.000
σ_η	.0253	.0118	.000
$N = 4030$. Asymptotic standard errors reported.			

Table 3: Base Case Coal Plant Results

capable of utilizing fuel inputs more efficiently. The estimates with respect to the square of vintage suggests that this effect is becoming less strong.[19]

The parameter estimate of μ_o suggests that $\mu_o < 0$, implying that the modal plant that do not operate under any performance based regulation produces inefficiently. The estimate with respect to the variance of the inefficiency distribution suggest that the majority of such plants operate inefficiently. To get a sense of this Figure 3 plots the distribution of inefficiency for plants that do not operate under any performance based regulation program implied by the parameter estimates of μ_o and σ_η, as well as the distribution associated with the 95% upper confidence interval for σ_η. The results suggest that a vast majority of firms that do not operate under performance based regulation produce inefficiently. The point estimates of μ_o and σ_η imply that 87 percent of such firms produce inefficiently, while evaluating the distribution at the 95% upper confidence value of σ_η implies 74 percent of the firms produce inefficiently.

The results with respect to the specific performance based regulation programs suggest that EAF, heat rate, and revenue decoupling programs are associated with an increase in efficiency. Specifically, the results suggest that plants that operate under EAF programs product 15.35 percent more electricity, *ceteris paribus*, than firms that do not operating under such programs. Firms that operate under heat rate programs are associated with a 7.15 percent increase in output, while revenue decoupling programs are associated with a 28 percent increase in output.

However, the results with respect to fuel pass-through programs imply that certain "incentive" regulation programs may provide the wrong incentives with respect to generator efficiency. The results imply that plants operating under fuel pass-through programs have lower efficiency levels. Therefore, while fuel pass-through programs may reduce the need for costly rate hearings, they may also create an indifference to efficient use of inputs for the firm. Plants that operate under fuel pass-through programs are associated with 2.78 percent *less* output for a given amount of inputs.

To get a sense for the distribution of inefficiency for firms that operate in these environments, Figure 4 plots the implied distributions of efficiency under these programs. The distributions suggest that virtually all firms that operate under fuel pass-through program produce inefficiently, while all firms that operate under EAF and revenue decoupling programs produce efficiently. Furthermore, the vast majority of firms that operate under a heat rate program produce efficiently.

Finally, the results also suggest that price-cap/benchmark, rate-of-return range and revenue decoupling programs do not have not a statistically significant impact on plant level efficiency.

[19] The point estimates would imply that the vintage effect would be zero in the year 2045, well outside the time span of the data.

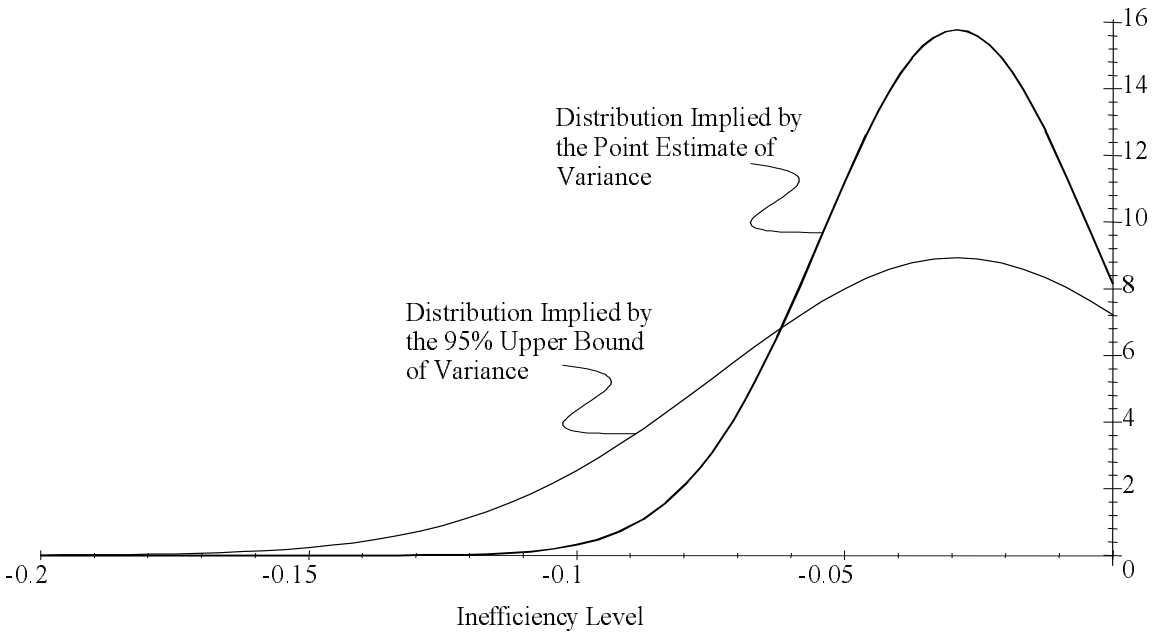

Figure 3: Variance Bounds for the Distribution of Coal Plant Inefficiency

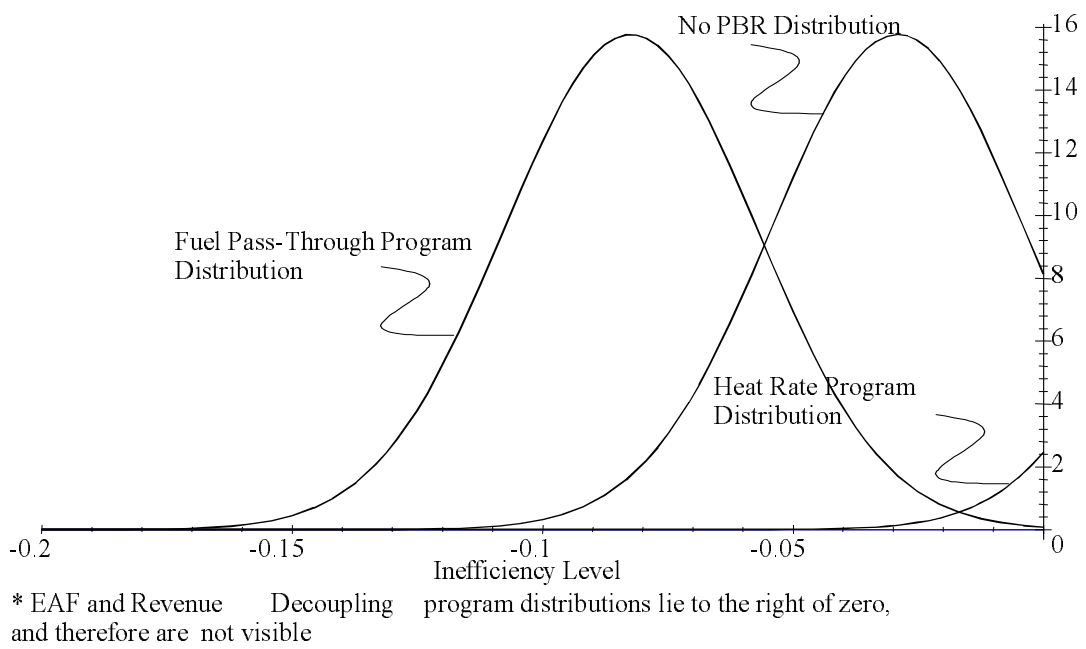

Figure 4: Implied Distributions of Inefficiency for Coal Plants

4.2 Gas Plants

The results for the natural gas plants are listed in Table 4. The estimates are similar in nature to those of the coal plants. Once again, the estimates imply that there exists economies of scale in natural gas generators, as the sum of the α's is 1.097, and is statistically different from 1.[20] Interestingly, the results suggest that the plant's vintage does not have as an important impact on the production frontier. The coefficient associated with the log of the vintage is only marginally significant, while the squared term is not significant. The results with respect to inefficiency suggest that the modal inefficiency level is zero, since the parameter estimates of μ_o cannot reject the null hypothesis that $\mu_o = 0$.

As with the coal plant specification, the results suggest that while certain programs provide a heightened incentive to produce efficiently, others may reduce this incentive. The parameter estimates associated with two programs are statistically significant at conventional levels. Specifically, the results suggest that plants operating under a heat rate incentive regulation program are statistically significantly more efficient than those that do not, producing 15.54 percent more output. In contrast, plants operating under rate-of-return range programs produce 2.17 percent *less* output.

Like the coal specification, the parameter estimate associated with fuel pass-through programs is negative. However, the p-value associated with fuel pass-through programs is .113, implying caution should be taken when deriving policy implications. Also similar to the coal specification, the parameter estimate associated with EAF programs is positive, but unlike the coal specification not statistically significant.

Figure 5 plots the implied distributions of inefficiency for the incentive regulation programs that are statistically significantly different (or nearly so) from the no incentive regulation distribution. Because μ_o is no statistically different from zero, I treat it as zero in the figure.

5 Alternative Specifications

5.1 Firm Level Results

The base case specification makes the assumption that each plant level observation is an independent observation. However, it is likely that plants operated by the same firm have similar efficiency levels. In addition, because performance based regulation programs are adopted at the plant level, there impact on plants of the same firm are likely to be strongly correlated. This correlation would suggest

[20] The t-statistics associated with testing the null hypothesis that the sum of the coefficients equals one is 3.56.

Maximum Likelihood Estimates			
Parameter	**Estimates**	**Standard Error**	**P−value**
$\ln \beta$	−.5128	.3374	.129
α_K	.2770	.0328	.000
α_L	.0543	.0337	.107
α_G	.7756	.0293	.000
α_O	−.0098	.0035	.005
$\ln Vintage$	.8476	.5159	.100
$(\ln Vintage)^2$	−.1196	.0837	.153
μ_o	.2310	.2386	.333
R_{eaf}	.2072	.1338	.122
R_{hr}	.1554	.0701	.027
R_{ror}	−.0217	.0109	.046
R_{cap}	−.0262	.0954	.784
R_{fuel}	−.0471	.0297	.113
R_{revdec}	−.0051	.0417	.903
σ_v	.3129	.0023	.000
σ_η	.0311	.0055	.000

$N = 1889$. Asymptotic standard errors reported.
P-vlaues listed are for two-tailed tests.

Table 4: Base Case Gas Plant Results

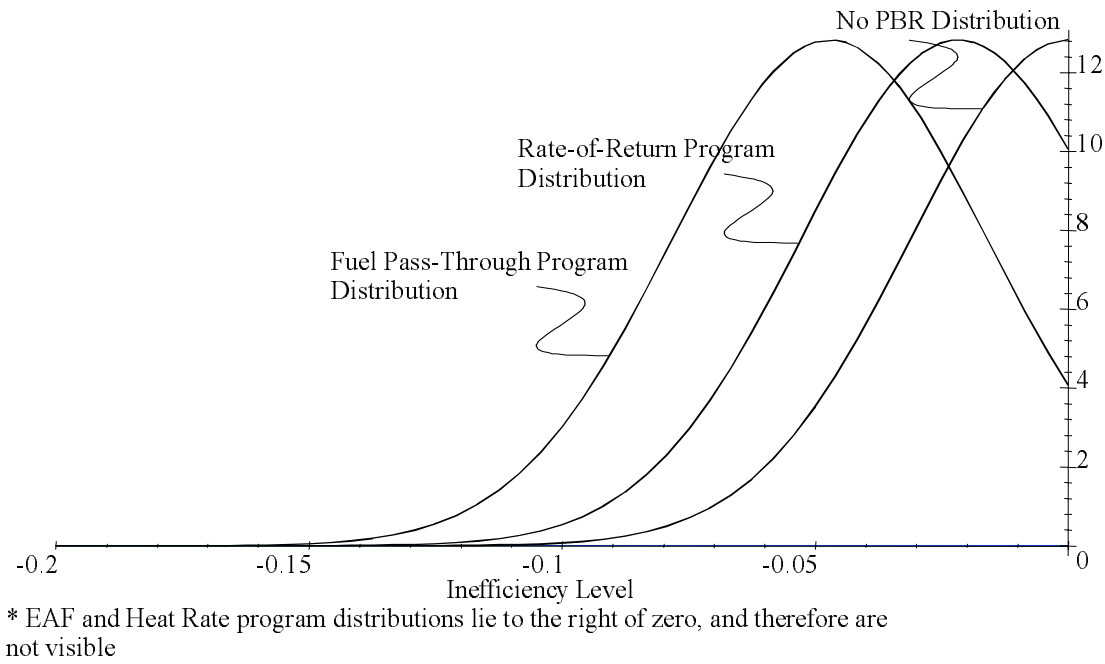

Figure 5: Implied Distributions of Inefficiency for Gas Plants

that estimating efficiency at the plant level and treating each observation as independent would tend to understate the standard errors. To control for this, I also estimated the above specification by summing the plant level observation across firms, for a given year, generating a firm and year specific observation.[21]

The estimates for the coal plants are reported in Table 5, while the estimates for the natural gas plants are reported in Table 6. The conclusions from above are robust to the firm-level specification.

5.2 Dynamic Impact of Regimes

The previous specifications established a correlation between performance based regulation and plant and firm level efficiency. However, often, if not always, performance based regulation is adopted in order to alter the behavior of the firm, for example, to provide the incentives for inefficient firms to increase their efficiency. If this is the case, then we would expect performance based regulation more frequently used with firms that operate inefficiently. This would imply that the above results might be biased against finding that performance based regulation improves

[21] An additional way to control for this would be to include fixed firm effects. Unfortunately convergence could not be achieved under this assumption.

Maximum Likelihood Estimates			
Parameter	**Estimates**	**Standard Error**	**P−value**
$\ln \beta$	3.137	.1203	.000
α_K	.3766	.0204	.000
α_L	.0521	.0182	.004
α_C	.6333	.0151	.000
α_O	.0041	.0016	.000
μ_o	-.0357	.0059	.000
R_{eaf}	.1655	.0267	.000
R_{hr}	.1001	.0418	.017
R_{ror}	−.0317	.0775	.682
R_{cap}	−.0031	.0974	.975
R_{fuel}	−.0250	.0324	.000
R_{revdec}	.0470	.0870	.588
σ_v	.2723	.0283	.000
σ_η	.0323	.0151	.033
$N = 1772$. Asymptotic standard errors reported.			

Table 5: Firm Level Coal Plant Results

Maximum Likelihood Estimates			
Parameter	**Estimates**	**Standard Error**	**P−value**
$\ln \beta'$	−.7357	.2303	.001
α'_K	.3648	.0255	.000
α'_L	−.1624	.0830	.107
α'_G	.8071	.0217	.000
α'_O	−.0097	.0028	.726
μ_o	.0127	.0118	.280
R_{eaf}	.0380	.0381	.318
R_{hr}	.1950	.0573	.001
R_{ror}	−.0218	.0099	.028
R_{cap}	−.0196	.06417	.760
R_{fuel}	−.0907	.1097	.408
R_{revdec}	.1039	.3887	.789
σ_v	.1934	.0042	.000
σ_η	.0422	.0142	.001

$N = 402$. Asymptotic standard errors reported.

P-vlaues listed are for two-tailed tests.

Table 6: Firm Level Gas Plant Results

efficiency.[22] In particular, this may explain the positive correlation between *in*efficiency and fuel pass-through programs.

If incentive regulation is passed as a response to inefficient production, then one can still ask how incentive regulation impacts *changes* in efficiency without the same endogeneity issues, since the efficiency level has been "differenced" out. In this section I estimates how the regulatory impacts changes in efficiency.

As above, let the production function for coal plants be (and the analogous production function for gas plants):

$$\ln y_t = \ln \beta + \alpha_K \ln K_t + \alpha_L \ln L_t + \alpha_C \ln Coal_t + \alpha_O \ln Oil_t + \eta_t + v_t \tag{5}$$

This implies that the change in the output from one year to the next is governed by:

$$\Delta \ln y_t = \alpha_K \Delta \ln K_t + \alpha_L \Delta \ln L_t + \alpha_C \Delta \ln Coal_t + \alpha_O \Delta \ln Oil_t + \Delta\eta_t + \Delta v_t \tag{6}$$

As above, I assume that v_t are iid normally distributed with mean zero and standard deviation, σ_v, implying that Δv_t is mean zero with standard deviation $\sigma_{\Delta v}$. We are interested in whether $\Delta\eta_t$ is dependent on the regulatory environment the plant operates under. Unlike previous specification, however, $\Delta\eta_t$ is no longer constrained to be nonpositive, since a firm's *change* in efficiency may be positive or negative. Therefore, I specify $\Delta\eta_t$ as being independent of v_t, with mean $\rho_t D_t$, where D_t is the matrix of performance based regulation variables described above and ρ is the associated vector of parameters, and standard deviation, $\sigma_{\Delta\eta}$.[23,24]

Tables 7 and 8 report the results from the dynamic specification. The parameter estimates with respect to the production function are similar to those obtained from the previous specifications. Not surprisingly, the coefficient associated with the respective fuel source are larger in the dynamic specification since the majority of output fluctuations are due to changes in fuel quantities.

The parameter estimates associated with the performance based regulation variables are largely consistent with the previous specifications. With respect to the coal plants, the estimates with

[22] If the decision to operate efficiently was a short-term one then there would not be a biased present. If this were the case current regulatory status would not be correlated with error term. However, if there exists frictions to becoming more efficient then the error term would be serially correlated and since past efficiency levels would likely have an influence on current regulatory status the *current* error term would be correlated with the *current* regulatory status, thereby biasing the coefficients.

[23] Note that we are interested in how the current regulatory structure impacts efficiency, i.e. D_{it}, and not the change in the regulatory structure, ΔD_{it}.

[24] One additional advantage to this specfication is that if the error term v_{it} contains a fixed firm effect, it will be differenced out.

respect to m_o, the yearly change in efficiency for firms not operating under performance based regulation, suggests that these firms are decreasing their efficiency levels over time. However, this parameter estimate is marginally statistically significant and rather small. The estimate of m_o in the gas plant specification suggests that the level of efficiency for plants not operating under performance based regulation is increasing. For both coal and gas plants, the estimate of $\hat{\rho}_{eaf}$ suggest that firms regulated under EAF programs are associated with improvement in efficiency, however for the gas plant specification the estimates is positive, but not statistically significant (as was the case in the levels specification). For the coal plant specification, the estimates suggest that plant operating under EAF programs increase their efficiency by 1.39 percent per year. This result is consistent with the previous results with respect to coal plants.

For both the coal and natural gas specifications, the estimate with respect to heat rate programs ($\hat{\rho}_{hr}$) suggests that heat rate programs lead to greater efficiency levels. Specifically, the estimates suggest that coal plants operating under heat rate programs are associated with 4.8 percent yearly increase in efficiency, while natural gas plants are associated with a 4.6 percent increase in efficiency. This, too, is consistent with the previous results that plants and firms operating under heat rate programs. Also consistent with the previous results, the dynamic specification is suggestive that fuel pass-through programs lead to *lower* efficiency levels, with fuel pass-through programs leading to a yearly reduction in efficiency of 5.56 percent for coal plants and 1.5 percent for gas plants.

The estimates suggest that the previous results are robust to controlling for the potential endogeneity of regulation. As with the previous specification, the dynamic models suggest that EAF and heat rate programs tend to increase generator efficiency, while fuel pass-through programs tend to decrease efficiency. Furthermore, there is some evidence that revenue decoupling programs are associated with increases in efficiency levels, however, the estimates are rather noisy.

5.3 Summary of Results

Given the number of specifications estimated, I summarize the results in Table 9. For the program/specification observations that are statistically significant, the sign of the coefficient is presented in the table. For observations that are not statistically significant, the cell reads "none." Evident from the table is that there is strong evidence that Heat Rate programs increase the efficiency of electricity production. While, no other program is significant in each specification, Fuel Pass-through programs have a negative influence on efficiency in every coal specification. One potential explanation for this is that often, IOUs hold stakes in coal plants, given the wide-array of hold up problems that can exist. Therefore, if regulators have not taken this into account, implying the IOU can profit from over purchasing coal, the IOU has an incentive to operate inefficiently.

Ordinary Least Squares Estimates			
Parameter	**Estimates**	**Standard Error**	**P−value**
α_K	.1697	.0097	.000
α_L	.0757	.0108	.000
α_C	.9361	.0066	.000
α_O	.0024	.0010	.021
m_o	-.0075	.0040	.065
ρ_{eaf}	.0139	.0017	.000
ρ_{hr}	.0481	.0297	.109
ρ_{ror}	−.0003	.0298	.992
ρ_{cap}	.0053	.0410	.898
ρ_{fuel}	−.0556	.0235	.018
ρ_{revdec}	−.0697	.0565	.217
$N = 3885$. Asymptotic standard errors reported.			

Table 7: Dynamic Model Results for Coal Plants

Ordinary Least Squares Estimates			
Parameter	**Estimates**	**Standard Error**	**P−value**
α'_K	.1446	.0304	.000
α'_L	.0525	.0345	.032
α'_G	.9013	.0155	.000
α'_O	−.0088	.0023	.000
m_o	.0752	.0164	.000
ρ_{eaf}	.0815	.0572	.154
ρ_{hr}	.0462	.0111	.000
ρ_{ror}	−.0900	.2468	.715
ρ_{cap}	−.0938	.0978	.337
ρ_{fuel}	−.0145	.0048	.002
ρ_{revdec}	.0126	.0059	.033
$N = 1385$. Asymptotic standard errors reported.			

Table 8: Dynamic Model Results for Gas Plants

	Specification					
	Plant Level		Firm Level		Dynamic	
Program	**Coal**	**Gas**	**Coal**	**Gas**	**Coal**	**Gas**
EAF	+	none	+	none	+	none
Heat Rate	+	+	+	+	+	+
Rate-of-Return	none	−	none	−	none	none
Price Cap	none	none	none	none	none	none
Fuel Pass-through	−	none	−	none	−	−
Revenue Decoupling	+	none	none	none	none	+

Table 9: Summary of Results

Similarly, for each coal specification, EAF programs are associated with heightened efficiency.

No other program appears to have a consistent pattern, and therefore caution should be taken when forming policy implications with respect to these programs.

6 Conclusions

Despite the recent expansion of competitive markets for electricity generation, more traditional regulatory practices are likely to continue. Therefore, the issue of whether incentive regulation programs provide firms with the incentive to increase efficiency will continue to be of importance to policy-makers and market analysts. In this paper, I investigate whether a variety of incentive regulation programs impact plant level efficiency and the change in plant level efficiency. The results suggest that while a subset of incentive regulation programs are associated with heightened efficiency, others may reduce incentives for firms to produce efficiently. Therefore, regulators must be aware of the indirect incentives that "incentive" regulation create, when designing regulation. The empirical results imply that while heat rate and availability programs likely increase plant level efficiency, other incentive regulation programs, such as fuel pass-though and rate-of-return range programs may reduce efficiency.

The policy implications of this study are clear. Regulators must be aware of the indirect impacts of incentive regulation programs, and design them appropriately. As they have an obligation to their shareholders, IOUs are profit maximizing entities, and changes in the regulatory environment that are designed for specific goals will impact the incentives of IOUs in other facets.

The analysis presented here can be extended in a number of directions. For one, it would be interesting to study how the productive efficiency incentives of firms operating in deregulated mar-

kets differ from those that operate under more traditional regulation. It could be argued that firms that operate in a deregulated regime have the correct incentives to produce efficiently. Therefore, by using these firms as a benchmark, one can ask the question of how close incentive regulation programs come to reproducing market conditions. In addition, as more regulatory agencies rely on price cap regulation, we will be able to better analyze the incentives of price cap regulation.

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A Data Sources

Data on the level of output and inputs for each plant were taken from FERC Form 1 data. Output is the net megawatt hours produced from the plant during the previous year. The level of capital is the capacity rating of the plant. The level of labor is the average number of full time employees working at the plant during the given year. For coal plants, there are two types of fuel used in the production process– coal, measured as total tons of coal utilized and oil, measured as the number of barrels of oil used. Data on the status of the regulatory environment were collected from *Incentive Regulation in the Electric Utility Industry.* The data on the average price for natural gas were obtained from the Energy Information Administration's *Historical Natural Gas Annual 1930 through 1997*, and collected from their website.

B Derivation of the Likelihood Function

The derivation of the likelihood function follows that of Stevenson(1980). Let $\varepsilon = \eta + v$ where η and v are defined as above. η characterizes the distribution of inefficiency and can take only negative values. It is further assumed that the modal value of η is a function of the regulatory environment, R and has the functional form of $R\gamma$ where γ is a vector of parameters. Given this, η and v have the following distributions:

$$\begin{aligned} k(\eta) &= \frac{1}{\Phi\left(\frac{-R\gamma}{\sigma_\eta}\right)\sqrt{2\pi}\sigma_\eta} \exp\left[-\frac{1}{2}\left(\frac{\eta - R\gamma}{\sigma_\eta}\right)^2\right] \text{ for } \eta < 0 \\ &= 0 \text{ otherwise} \end{aligned} \tag{7}$$

and

$$g(v) = \frac{1}{\sqrt{2\pi}\sigma_v} \exp\left[-\frac{1}{2}\left(\frac{v}{\sigma_v}\right)^2\right] \tag{8}$$

where Φ is the cumulative standard normal distribution function.

For each observation, only an estimate of ε is obtained therefore we must solve for the partial density function of ε. To obtain the pdf of ε, we express the random variables in terms of ε and η and integrate out η:

$$\begin{aligned} f(\varepsilon) &= \int_{-\infty}^{0} \frac{1}{\Phi\left(\frac{-R\gamma}{\sigma_\eta}\right) 2\pi\sigma_v\sigma_\eta} \exp\left[-\frac{1}{2}\left(\left(\frac{\eta - R\gamma}{\sigma_\eta}\right)^2 + \left(\frac{\varepsilon - \eta}{\sigma_v}\right)^2\right)\right] d\eta \\ &= \sigma^{-1}\phi\left(\frac{\varepsilon - R\gamma}{\sigma}\right)\left[\Phi\left(\frac{-R\gamma}{\sigma\lambda} - \frac{\varepsilon\lambda}{\sigma}\right)\right]\left[\Phi\left(\frac{-R\gamma}{\sigma_\eta}\right)\right]^{-1} \end{aligned} \tag{9}$$

where ϕ is the standard normal pdf, Φ is the standard normal distribution function, and $\sigma \equiv \left(\sigma_\eta^2 + \sigma_v^2\right)^{1/2}$, $\lambda \equiv \sigma_\eta / \sigma_v$

Noting that $\sigma_\eta^2 = \sigma^2 \left(\frac{\lambda^2}{1+\lambda^2}\right)$, the likelihood function is the product over all observations of $f(\varepsilon)$:

$$\mathcal{L} = \prod_{n=1}^{N} \sigma^{-1} \phi\left(\frac{\varepsilon - R\gamma}{\sigma}\right) \left[\Phi\left(\frac{-R\gamma}{\sigma\lambda} - \frac{\varepsilon\lambda}{\sigma}\right)\right] \left[\Phi\left(\frac{-R\gamma}{\sigma}\left(\frac{1+\lambda^2}{\lambda^2}\right)^{1/2}\right)\right]^{-1} \tag{10}$$

Taking the log of $\mathcal{L}$, gives:

$$\begin{aligned} \log \mathcal{L} \quad = \quad & -\frac{N}{2}\ln\sigma^2 - \frac{N}{2}\ln 2\pi - \frac{1}{2\sigma^2}\sum_{i=1}^{N}(\varepsilon - R\gamma)^2 \\ & + \sum_{i=1}^{N}\ln\Phi\left(\frac{-R\gamma}{\sigma\lambda} - \frac{\varepsilon\lambda}{\sigma}\right) - \sum_{i=1}^{N}\ln\Phi\left(\frac{-R\gamma}{\sigma}\left(\frac{1+\lambda^2}{\lambda^2}\right)^{1/2}\right) \end{aligned} \tag{11}$$

$\log \mathcal{L}$ is maximized over the parameter space to obtain estimates of the parameters and their associated standard errors.