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ABSTRACT

In this paper we investigate the effect of the introduction of incentive regulation upon the total factor productivity (TFP) growth of electricity generation companies in the United States, using sample data on 61 firms observed over a 13-year period from 1986 to 1998. Empirical estimates of TFP growth are obtained using three techniques: Tornqvist index numbers, a stochastic cost frontier and a stochastic input distance function. The results obtained using the stochastic cost frontier are discarded because they are found to differ from those obtained using the other techniques, apparently as a consequence of violations of the required cost minimizing behavioral assumptions, which are not uncommon in regulated industries. Tests of hypotheses regarding the effect of regulatory reform upon TFP (using the distance function results) indicate that the introduction of incentive regulation has not had the desired positive effect upon the economic performance of the firms involved. In fact, in the case of these data, we find that performance is negatively related with the introduction of the new regulatory regimes, a result that is the opposite of the theoretical predictions.

Key words: Incentive regulation, Total Factor Productivity Growth, Cost Frontier, Input Distance Function, Törnqvist index

1. Introduction

The regulation of infrastructure industries, such as electricity, gas and water supply, has undergone substantial changes over the past few decades, with the rise in popularity of the so-called *incentive regulation* approaches. Changes have occurred in many countries around the world. In countries such as the UK and Chile, a number of infrastructure industries have been privatized, and incentive regulation regimes, such as *price-cap regulation*, have been implemented. In the USA, where investor owned utilities were more the norm, the traditional method of *rate-of-return regulation* is also being gradually replaced with alternative incentive regulation regimes (eg. see Newbery, 2000).

It is widely argued that incentive regulation methods, such as price cap regulation, are expected to provide stronger incentives for cost reduction and technological innovation (relative to rate-of-return regulation). This is because the regulated firm is permitted to keep any "extra" profits it may happen to earn, if it manages to reduce its costs of production at a rate greater than the rate of allowed (real) price changes.[1] However, given that many countries have only recently introduced these incentive regulation methods, there is limited empirical evidence available for one to assess if the benefits that are predicted by the economic theory actually eventuate in practice.

Thus the primary motivation of this study is to see if we can find empirical evidence to support the hypothesis that incentive regulation methods actually have had a positive influence upon the productivity of those US electricity supply businesses which have been exposed to these new regulatory methods. To this end, we have compiled historical data on the generation businesses of 61 US electricity supply utilities, observed over a 13-year period from 1986 to 1998. This group of 61 firms include some that have faced incentive regulation methods and some that have not. Furthermore, the year in which a particular firm first faced the change in regulatory regime differs between firms. Hence, the nature of this data allows us to control for macro-economic effects to some extent.

A secondary aim of this paper is to investigate the effect of choice of methodology upon the productivity measures obtained. Previous studies have used a variety of methods to calculate total factor productivity (TFP) growth and efficiency levels in infrastructure industries. For example, see the excellent survey of the methods used in electricity industries, provided by Jamasb and Pollitt (2002), who note the use of stochastic frontier production frontiers, cost functions, data envelopment analysis, and Tornqvist index numbers, among others. Generally,

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[1] See Parker (1996) for a good introductory discussion of these issues.

each study tends to apply only one method to the data at hand. However, as some studies have shown (eg. see the Coelli 2002 analysis of productivity growth in electricity generation in Australia) different methods can in some cases provide quite different measures, especially when perfect competition assumptions are violated – which is often the case in regulated industries. In this study, we utilise three often used methods – Tornqvist index numbers, stochastic cost frontiers and stochastic input distance functions – to calculate our productivity measures. This empirical analysis helps highlight the relative advantages and disadvantages of these methods, and in particular allows us to demonstrate the degree to which the performance measures can change when one uses different methodologies.

The outline of this paper is as follows. In the next section we describe and discuss the three alternative performance measurement methods that we use to measure TFP growth in this study. This is followed in section 3 with a brief description of the US electricity supply industry, along with a discussion of the data set used in this study. The next section provides an assessment of the influence of regulatory regime upon firm-level productivity measures, and then conclusions follow in the final section.

2. Methodology

The methods that are used to measure the TFP change can be roughly classified into two groups according to the types of prices employed, i.e. market price and shadow prices. Market prices are the actual prices that people pay for the goods and services, while shadow prices (internal prices to the firms) are derived from the shape of the underlying production technology. Three TFP measurement approaches that are widely applied are: the Törnqvist price-based index number, stochastic frontier analysis (SFA) and data envelopment analysis (DEA). The Törnqvist price-based index number approach uses market prices, while the SFA and the DEA involve the estimation of a production technology, and hence the use of shadow prices derived from the shape of the estimated frontier.

The Törnqvist price-based index number approach has the advantage that it can be used when limited data are available (e.g. aggregate industry-level data). The SFA and DEA frontier approaches require more data (i.e. firm-level panel data), however they have the advantage that they allow one to identify various components of the TFP growth (such as technical change, efficiency change and scale effects), which are often of particular interest to regulators. The SFA approach has an advantage over the DEA approach when analyzing data in a stochastic environment. This is because DEA typically does not attempt to take statistical noise into account (and consequently may provide inaccurate efficiency measures), while the parametric approach does attempt to accommodate statistical noise and allows performing tests of hypotheses regarding the structure of the production technology.

This study utilizes two alternative SFA approaches, i.e. cost frontier and input distance functions, in a TFP analysis of panel data on 61 U.S. electric utilities observed over the time period of 1986-1998, and compares the results with those obtained using the traditional Törnqvist price-based index number approach. The main objective is to examine the sensitivity of the estimates obtained to the choice of TFP measurement methodology, and to illustrate the implications that these choices may have in the implementation of incentive regulation. We now describe each of these three methods in some detail.

2.1. The Törnqvist Price-Based Index Number (TPIN) Approach

TFP change is generally defined as the residual growth in outputs not explained by the growth in input use. Following Caves, Christensen and Diewert (1982), a Törnqvist TFP index may be constructed as the ratio of a Törnqvist output index to a Törnqvist input index. The logarithmic form of the Törnqvist TFP change index between periods t and $t+1$ is defined as

$$\begin{aligned}\ln\left(TFP_{i,t+1}/TFP_{i,t}\right)^T &= \frac{1}{2}\sum_{m=1}^{M}\left[\left(r_{mi,t+1}+r_{mi,t}\right)\left(y_{mi,t+1}-y_{mi,t}\right)\right] \\ &\quad -\frac{1}{2}\sum_{k=1}^{K}\left[\left(s_{ki,t+1}+s_{ki,t}\right)\left(x_{ki,t+1}-x_{ki,t}\right)\right]\end{aligned} \tag{2-1}$$

where the T superscript refers to *Törnqvist*; $i=1,...,I$ indexes firms; $k=1,...,K$ indexes input variables; $m=1,...,M$ indexes output variables; $x_{ki,t}$ is the log of the k-th input quantity, $X_{ki,t}$; $y_{mi,t}$ is the log of the m-th output quantity, $Y_{mi,t}$; $r_{mi,t}$ is the observed revenue share of the m-th output; and $s_{ki,t}$ is the observed cost share of the k-th input.

For the single-output case, which is considered in the empirical part of this study, equation (2-1) is rewritten as

$$\ln\left(TFP_{i,t+1}/TFP_{i,t}\right)^T = \left(y_{i,t+1}-y_{i,t}\right)-\frac{1}{2}\sum_{k=1}^{K}\left[\left(s_{ki,t+1}+s_{ki,t}\right)\left(x_{ki,t+1}-x_{ki,t}\right)\right] \tag{2-2}$$

As noted earlier, the Törnqvist TFP index approach has the advantage that it can be used to measure the TFP change when limited data is available. However, this approach also has some shortcomings. It requires information on both quantities and prices of outputs and inputs. In addition, it cannot be used to decompose the TFP change measure into its components, such as technical change (frontier shift) and technical efficiency change (catch-up), which are of broad interest for regulators.[2] This problem can be addressed by gaining access to panel data and using a frontier technique, such as a stochastic cost frontier or a stochastic input distance function, to decompose the measured TFP growth into its components.

2.2. The Stochastic Cost Frontier Approach

Following Greene (1980), a translog stochastic cost frontier may be defined as follows.

$$\begin{aligned} c_{it} &= \beta_0 + \sum_{k=1}^{K} \beta_k w_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} w_{kit} w_{lit} + \sum_{m=1}^{M} \beta_{y_m} y_{mit} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \beta_{y_m y_n} y_{mit} y_{nit} \\ &+ \sum_{k=1}^{K}\sum_{m=1}^{M} \beta_{ky_m} w_{kit} y_{mit} + \beta_z z + \frac{1}{2}\beta_{zz} z^2 + \sum_{k=1}^{K} \beta_{kz} w_{kit} z + \sum_{m=1}^{M} \beta_{y_m z} y_{mit} z + v_{it} + u_{it} \end{aligned} \qquad (2\text{-}3)$$

where c is the log of total cost, C; w_k is the log of k-th input price, W_k; z represents a time trend variable; v is a symmetric error term (designed to capture the effects of random noise); u is an asymmetric error term (included to capture the effects of cost inefficiency); the βs are unknown parameters to be estimated, and all other notation is as previously defined.

In this study, we follow the standard practice of assuming a normal distribution for v and a half-normal distribution for u. That is, we set $v \sim N(0,\sigma_v^2)$ and $u \sim |N(0,\sigma_u^2)|$. Given these distributional assumptions, the parameters of this model can then be estimated using the method of maximum likelihood. Furthermore, note that we follow the suggestion of Battese and Corra (1977), and replace the two variance parameters with the two new parameters $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 / \sigma^2$. By doing this we can search the parameter space of γ between 0 and 1, to provide good starting values for the iterative maximization routine which is used to calculate the maximum likelihood parameter estimates.

For the single-output and three-input case, equation (2-3) is rewritten as

$$\begin{aligned} c_{it} &= \beta_0 + \sum_{k=1}^{3} \beta_k w_{kit} + \frac{1}{2}\sum_{k=1}^{3}\sum_{l=1}^{3} \beta_{kl} w_{kit} w_{lit} + \beta_y y_{it} + \frac{1}{2}\beta_{yy} y_{it}^2 + \sum_{k=1}^{3} \beta_{ky} w_{kit} y_{it} + \beta_z z \\ &+ \frac{1}{2}\beta_{zz} z^2 + \sum_{k=1}^{3} \beta_{kz} w_{kit} z + \beta_{yz} y_{it} z + v_{it} + u_{it} \end{aligned} \qquad (2\text{-}4)$$

Young's theorem requires that symmetry restrictions are imposed so that

$$\beta_{kl} = \beta_{lk} \quad \text{for all } k,l = 1,2,3 \qquad (2\text{-}4a)$$

and homogeneity of degree +1 in input prices requires imposition of the additional restrictions

[2] See Coelli et al (2003) for further discussion.

$$\sum_{k=1}^{3} \beta_k = 1, \tag{2-4b}$$

$$\sum_{k=1}^{3} \beta_{kl} = 0\,, \quad l = 1,2,3 \tag{2-4c}$$

$$\sum_{k=1}^{3} \beta_{ky} = 0\,, \tag{2-4d}$$

$$\sum_{k=1}^{3} \beta_{kz} = 0\,. \tag{2-4e}$$

These restrictions can be imposed by estimating a model where the cost variable and K-1 input price variables are normalized by the K-th input price variable. Equation (2-4) can be rewritten as

$$\begin{aligned} c_{kit}^* &= \beta_0 + \sum_{k=1}^{2} \beta_k w_{kit}^* + \frac{1}{2}\sum_{k=1}^{2}\sum_{l=1}^{2} \beta_{kl} w_{kit}^* w_{lit}^* + \beta_y y_{it} + \frac{1}{2}\beta_{yy} y_{it}^2 + \sum_{k=1}^{2} \beta_{ky} w_{kit}^* y_{it} + \beta_z z \\ &+ \frac{1}{2}\beta_{zz} z^2 + \sum_{k=1}^{2} \beta_{kz} w_{kit}^* z + \beta_{yz} y_{it} z + v_{it} + u_{it} \end{aligned} \tag{2-5}$$

where $c_{kit}^* = \left(c_{kit}/w_{Kit}\right)$, $w_{kit}^* = \left(w_{kit}/w_{Kit}\right)$ and $w_{lit}^* = \left(w_{lit}/w_{Kit}\right)$. Once the parameters of this equation have been estimated, the parameters associated with the K-th normalizing input can then be calculated using these estimated parameters and the restrictions in equation (2-4a) to (2-4e).

A measure of total factor productivity change $\left(TFPC_{it,t+1}\right)$, for each firm between any two time periods, can be calculated by using the estimates of the coefficients of the cost frontier in equation (2-5) and the firm-level sample data. The logarithmic form of the TFPC between period t and $t+1$ for the i-th firm is defined as

$$\begin{aligned} \ln\left(TFP1_{i,t+1}/TFP1_{i,t}\right) &= \ln\left(CE_{i,t}/CE_{i,t+1}\right) - \frac{1}{2}\left[\partial c_{i,t+1}/\partial t + \partial c_{i,t}/\partial t\right] \\ &+ \frac{1}{2}\left[\left(1-\partial c_{i,t+1}/\partial y\right) + \left(1-\partial c_{i,t}/\partial y\right)\right]\left(y_{i,t+1} - y_{i,t}\right) \end{aligned} \tag{2-6}$$

where the three terms on the right-hand-side of equation (2-6) represents the cost efficiency change $\left(CEC_{it,t+1}\right)$, technical change $\left(TC_{it,t+1}\right)$ and scale efficiency change $\left(SEC_{it,t+1}\right)$, respectively.

The formula in equation (2-6) has been derived by exploiting Diewert's (1976) Quadratic Identity Lemma, following a similar derivation to that outlined for the distance function case in Orea (2002). This formula is quite similar to that provided in Bauer (1990), which was alternatively derived using a differential approach. The main differences between the two sets of TFP decomposition formula is that the technical change and scale efficiency change measures in equation (2-6) are evaluated at the *t* and *t+1* data points, while the Bauer (1990) formula is only evaluated at the *t* data point. This difference will have minimal effect on the empirical measures obtained in most instances.

The cost efficiency measure, (CE_{it}), in equation (2-6) is the cost efficiency prediction of the i-th firm in the t-th time period, and is calculated from the cost frontier in equation (2-5) using the method outlined in Coelli (1996). The technical change measure, $(TC_{it,t+1})$, is the mean of the technical change measures evaluated at the period t and period $t+1$ data points. The scale efficiency change measure, $(SEC_{it,t+1})$, relates to the change in scale efficiency, which requires calculation of the output elasticity in period t, $\partial c_{i,t}/\partial y$, and period $t+1$, $\partial c_{i,t+1}/\partial y$.

When information on input *quantities* is also available, the regulator can also calculate an allocative efficiency change $(AEC_{it,t+1})$ component, which is equal to the difference between the $(TFPC_{it,t+1})$ measure obtained from the cost frontier in equation (2-6) and the Törnqvist *TFPC* index in equation (2-2). The allocative efficiency change $(AEC_{it,t+1})$ measure yields

$$AEC_{it,t+1} = \frac{1}{2}\sum_{k=1}^{3}\left[\left(\left(\partial c_{ki,t}/\partial w_k\right)-s_{ki,t}\right)+\left(\left(\partial c_{ki,t+1}/\partial w_k\right)-s_{ki,t+1}\right)\right]\left(w_{ki,t+1}-w_{ki,t}\right) \tag{2-7}$$

This $AEC_{it,t+1}$ measure will be equal to 0 when the observed cost shares, $s_{ki,t}$, are identical to the "efficient" cost shares, $\partial c_{ki,t}/\partial w_k$, or when there is no change in the input price vector.

Thus, the total factor productivity change $(TFPC_{it,t+1})$ for each firm between any two time periods can be decomposed into four components: the cost efficiency change $(CEC_{it,t+1})$, technical change $(TC_{it,t+1})$, scale efficiency change $(SEC_{it,t+1})$, and allocative efficiency change ($AEC_{it,t+1}$). In the empirical part of this paper, we report two TFPC measures, one with and one without the AEC measure included. That is,

$$TFPC1_{it,t+1} = CEC_{it,t+1} + TC_{it,t+1} + SEC_{it,t+1} \tag{2-8}$$

and

$$TFPC2_{it,t+1} = TFPC1_{it,t+1} + AEC_{it,t+1} \qquad (2\text{-}9).$$

Cost functions have been used extensively in empirical analyses of production in infrastructure industries over recent decades[3]. This has been in preference to the use of production function estimates. This is most likely because of the ready availability of cost data;

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[3] For example, see Burns and Weyman-Jones (1996) and references cited therein.

the fact that they can accommodate multiple outputs; and also because in most cases input prices are more likely to be exogenous than the input quantities. However, the cost function approach requires one to accept the behavioral assumption that the producer is cost-minimizing in production. If this assumption is incorrect, perhaps because of political intervention or a regulatory bias, the duality between the cost frontier and the production frontier will be violated, leading to incorrect measures of allocative efficiency, technical efficiency, scale efficiency, and technical change. This issue has provided a motivation for the development of the distance function techniques that are discussed in the following section.

2.3. The Stochastic Input Distance Function Approach

Following Coelli and Perelman (1999), a translog input distance function may be defined as follows.

$$\begin{aligned} d_{it} &= \beta_0 + \sum_{k=1}^{K} \beta_k x_{kit} + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} x_{kit} x_{lit} + \sum_{m=1}^{M} \beta_{y_m} y_{mit} + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M} \beta_{y_m y_n} y_{mit} y_{nit} \\ &+ \sum_{k=1}^{K}\sum_{m=1}^{M} \beta_{ky_m} x_{kit} y_{mit} + \beta_z z + \frac{1}{2}\beta_{zz} z^2 + \sum_{k=1}^{K} \beta_{kz} x_{kit} z + \sum_{m=1}^{M} \beta_{y_m z} y_{mit} z \end{aligned} \tag{2-10}$$

where d is the log of input distance, D; and all other notation is as previously defined.

For the single-output and three-input case, equation (2-10) is rewritten as

$$\begin{aligned} d_{it} &= \beta_0 + \sum_{k=1}^{3} \beta_k x_{kit} + \frac{1}{2}\sum_{k=1}^{3}\sum_{l=1}^{3} \beta_{kl} x_{kit} x_{lit} + \beta_y y_{it} + \frac{1}{2}\beta_{yy} y_{it}^2 + \sum_{k=1}^{3} \beta_{ky} x_{kit} y_{it} + \beta_z z \\ &+ \frac{1}{2}\beta_{zz} z^2 + \sum_{k=1}^{3} \beta_{kz} x_{kit} z + \beta_{yz} y_{it} z + v_{it} \end{aligned} \tag{2-11}$$

Young's theorem requires that symmetry restrictions are imposed so that

$$\beta_{kl} = \beta_{lk} \quad \text{for all } k,l = 1,2,3 \tag{2-11a}$$

and homogeneity of degree +1 in input requires imposition of the additional restrictions

$$\sum_{k=1}^{3} \beta_k = 1, \tag{2-11b}$$

$$\sum_{k=1}^{3} \beta_{kl} = 0, \quad l = 1,2,3 \tag{2-11c}$$

$$\sum_{k=1}^{3} \beta_{ky} = 0, \tag{2-11d}$$

$$\sum_{k=1}^{3} \beta_{kz} = 0. \tag{2-11e}$$

Imposing these restrictions upon equation (2-11) yields the estimating form of the input distance function, in which the distance term, d, can be viewed as an error term as follows

$$\begin{aligned} -x_{Kit} &= \beta_0 + \sum_{k=1}^{2}\beta_k x_{kit}^* + \frac{1}{2}\sum_{k=1}^{2}\sum_{l=1}^{2}\beta_{kl}x_{kit}^* x_{kit}^* + \beta_y y_{it} + \frac{1}{2}\beta_{yy}y_{it}^2 \\ &+ \sum_{k=1}^{2}\beta_{ky}x_{kit}^* y_{it} + \beta_z z + \frac{1}{2}\beta_{zz}z^2 + \sum_{k=1}^{2}\beta_{kz}x_{kit}^* z + \beta_{yz}y_{it}z - d_{it} \end{aligned} \tag{2-12}$$

where $x_{kit}^* = (x_{kit}/x_{Kit})$. By replacing the distance term, $-d_{it}$, with a composed error term, $v_{it} - u_{it}$, equation (2-12) can be estimated as a standard stochastic frontier function.

The total factor productivity change $(TFPC_{it,t+1})$ for each firm between any two time periods can be calculated by using the estimates of the coefficients of the input distance frontier in equation (2-12). The logarithmic form of the TFPC between period t and $t+1$ for the i-th firm is defined as

$$\begin{aligned} \ln\left(TFP1_{i,t+1}/TFP1_{i,t}\right) &= \ln\left(TE_{i,t+1}/TE_{i,t}\right) + \frac{1}{2}\left[\partial d_{i,t+1}/\partial t + \partial d_{i,t}/\partial t\right] \\ &+ \frac{1}{2}\left[\left(1+\partial d_{i,t+1}/\partial y\right) + \left(1+\partial d_{i,t}/\partial y\right)\right]\left(y_{i,t+1} - y_{i,t}\right) \end{aligned} \tag{2-13}$$

where the three terms on the right-hand-side of equation (2-13) represents the technical efficiency change $(TEC_{it,t+1})$, technical change $(TC_{it,t+1})$ and scale efficiency change $(SEC_{it,t+1})$, respectively.

The formula in equation (2-13) has been derived by exploiting Diewert's (1976) Quadratic Identity Lemma, following a similar derivation to that outlined for the *output* distance function case in Orea (2002).

The technical efficiency measure, (TE_{it}), in equation (2-13) is the technical efficiency prediction of the i-th firm in the t-th time period, which is calculated using the method outlined in Battese and Coelli (1988). The technical change measure, $(TC_{it,t+1})$, is the mean of the technical change measures evaluated at the period t and period $t+1$ data points. The scale efficiency change measure, $(SEC_{it,t+1})$, calculates the change in scale efficiency, which requires calculation of the production elasticity at the period t, $\partial d_{i,t}/\partial y$, and period $t+1$, $\partial d_{i,t+1}/\partial y$.

When information on input prices is available, the one can also calculate an allocative efficiency change $(AEC_{it,t+1})$ component, which is equal to the difference between the $(TFPC_{it,t+1})$ measure obtained from the input distance frontier in equation (2-12) and a Törnqvist *TFPC* index in equation (2-2). The allocative efficiency change $(AEC_{it,t+1})$ measure yields

$$AEC_{it,t+1} = \frac{1}{2}\sum_{k=1}^{3}\left[\left[\left(\left(\partial d_{ki,t}/\partial x_k\right) - s_{ki,t}\right) + \left(\left(\partial d_{ki,t+1}/\partial x_k\right) - s_{ki,t+1}\right)\right]\left(x_{ki,t+1} - x_{ki,t}\right)\right]. \tag{2-14}$$

This $AEC_{it,t+1}$ measure will be equal to 0 when the market input shares, $s_{ki,t}$, equal to the shadow input shares, $\partial d_{ki,t}/\partial x_k$, or when there is no change in the input quantity vector.

Thus, the total factor productivity change $(TFPC_{it,t+1})$ for each firm between any two time periods can be decomposed into four components: the technical efficiency change $(TEC_{it,t+1})$, technical change $(TC_{it,t+1})$, scale efficiency change $(SEC_{it,t+1})$, and allocative efficiency change $(AEC_{it,t+1})$. In the empirical part of this paper, we report two TFPC measures, one with and one without the AEC measure included. That is,

$$TFPC2_{it,t+1} = TEC_{it,t+1} + TC_{it,t+1} + SEC_{it,t+1} + AEC_{it,t+1} \tag{2-15}$$

$$TFPC2_{it,t+1} = TFPC1_{it,t+1} + AEC_{it,t+1} \tag{2-16}$$

This input distance function approach can be viewed as a multiple output version of a production frontier. It considers the amount by which the input set of each firm may be proportionally contracted with the output set held fixed. The advantages of this approach are that it avoids the problems associated with the cost function approach when cost minimization is violated and it is much less complicated than the shadow cost function approach. In addition, it allows one to specify multiple outputs in a primal setting and avoids the endogenous regressors criticism that is sometimes leveled at the production frontier approach [Coelli, (2000)]. There are increasing numbers of the studies applying this approach in analyses of infrastructure industries [e.g. Coelli and Perelman (1999, 2000), Carrington, Coelli, and Groom (2002), and Atkinson and Primont (2002)].

3. The U.S. Electricity Supply Industry

3.1. Overview of the industry

For a number of decades, the U.S. electricity supply industry has been predominantly comprised of investor-owned utilities (IOUs). These IOUs traditionally have been vertically integrated utilities – generating, transmitting, and distributing the electricity that they sell to customers living in their territories, where regulations provide them with exclusive rights to supply electricity in their specified territory. Traditionally, an electricity customer has paid one regulated price for electricity to a single vertically integrated utility responsible for generation, transmission, distribution, and marketing. Under this form of regulation, electric utilities have the potential to exert their market power and they will receive a guaranteed profit for the generation of electricity. This led to strong incentives to over invest in capital as well as operating at an inefficient level of production, which is of broad interest for regulators [e.g., Averch and Johnson (1962), Atkinson and Halvorson (1980), Rungsuriyawiboon and Stefanou (2003)]. This lack of efficiency incentives contributed to various legislative changes and to the recent adoption of more incentive compatible regulatory structures in some parts of the U.S.

The U.S. electricity supply industry has changed significantly in the past two decades. This has been partly driven by a number of legislative changes. The first of note was when Congress passed the Public Utility Regulatory Policies Act of 1978 (PURPA), which allowed independent generators to sell their electricity to utilities at regulated rates. Then the 1992 Energy Policy Act, followed by the Federal Energy Regulatory Commission's (FERC's) Orders 888 and 889 in 1996, expanded the PURPA initiative by forcing utilities with transmission networks to deliver power to third parties at nondiscriminatory cost-based rates. These policy initiatives recognize that while electricity transmission and distribution remain natural monopolies, competition in generation is possible with open access to transportation networks. Policies to open markets led to new competitors in generation and marketing, with a restructuring of the industry away from the regulated, single-provider model.[4]

During this period of legislative changes, a movement towards incentive regulation methods also began to gather pace. There were relatively few applications of incentive regulation in U.S. electric utilities in the 1980s. However, incentive regulation began to make substantial inroads in this industry in the early 1990s. By the end of the decade there were 28 electric utilities with some form of incentive regulation in 16 states [Sappington et al (2001)].

3.2. Electricity industry data

The empirical analysis in this study focuses on steam electric power generation using a fossil fuel as the primary fuel for major investor-owned utilities in the United States. This generation source is the dominant part of the electricity industry[5]. Panel data on 61 electric

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[4] These changes have not all been implemented at the same pace in all parts of the U.S. In some States the reforms have moved quite slowly.

[5] About 61.1 percent of all the electricity supplied by the U.S. electric power industry comes from steam turbines fired by fossil fuel. Recent figure indicate that coal-fired generation accounts for 84 percent, natural gas accounts for 12.7 percent, and petroleum comprises 3.3 percent. Investor-Owned Utilities own 71 percent of the U.S. generating

utilities over the time period of 1986-1998 are used in the empirical analysis. A list of the electric utilities included in this study is available from the authors on request.

The primary sources of data are obtained from the Energy Information Administration (EIA), the Federal Energy Regulatory Commission (FERC), the Bureau of Labor Statistics (BLS), and the Federal Reserve Board (FRB). The data set used to obtain the TFP measures contains measurements of firm output quantities, input quantities, input prices and costs for steam electric power production. The definitions of these variables are summarized below.

Output

The output variable, Y_{it}, is represented by net steam electric power generation in megawatt-hours, which is defined as the amount of power produced using fossil-fuel fired boilers to produce steam for turbine generators during a given period of time.

Price and Quantity of Fuel Input

The price of fuel aggregate, W_{1it}, is a Tornqvist price index of fuels (i.e. coal, oil, gas) which is calculated as a weighted geometric average of the price relatives with weights given by the simple average of the value shares in period *t* and $t+1$.

$$\left(\frac{W_{1it+1}}{W_{1it}}\right) = \prod_{f=1}^{3}\left(\frac{P_{fit+1}}{P_{fit}}\right)^{\left(\frac{a_{fit}+a_{fit+1}}{2}\right)} \tag{3-1}$$

where $a_{fit} = \frac{P_{fit}Q_{fit}}{\sum_{f=1}^{3} P_{fit}Q_{fit}}$, P_{fit} is the price of the f-th fuel (i.e. coal, oil, gas), and Q_{fit} is the consumption of the same fuel. The Törnqvist price index of fuel aggregate is converted into multilateral Törnqvist price index to confirm the transitivity property using the EKS method discussed in Coelli, Rao and Battese (1998, Ch 4).

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capacity owned by both utilities and nonutility generators and are responsible for 74 percent of all retail sales of electricity (EIA 2000).

The quantity of fuel, X_{1it} , is calculated as the steam power production fuel costs divided by the multilateral Tornqvist price index for fuels.

Price and Quantity of Aggregate Labor and Maintenance Input

The price of labor and maintenance aggregate, W_{2it}, is a cost share-weighted Tornqvist price index for labor and maintenance. The price of labor is a firm-level average wage rate. The price of maintenance and other supplies is an industry-level price index of electrical supplies. The Törnqvist price index of labor and maintenance aggregate is also converted into multilateral Törnqvist price index using the EKS method.

The quantity of labor and maintenance, X_{2it}, is measured as the aggregate costs of labor and maintenance divided by the multilateral Tornqvist price index for labor and maintenance. Data on labor and maintenance costs are calculated by subtracting fuel expenses from total steam power production expenses.[6]

Price and Quantity of Capital Input

The price of capital, W_{3it}, is the yield of the firm's latest issue of long term debt adjusted for appreciation and depreciation of the capital good using the Christensen and Jorgenson (1970) cost of capital formula.

$$W_{3it} = p_{kt}\left[i_{dit} + s_{it}\left(r_{eit} - i_{dit}\right) + d - f_t\right] \qquad (3\text{-}2)$$

where p_{kt} is a price index for electrical generating plant and equipment; i_{dit} is the adjusted corporate bond rate by firm based upon its bond ratings by Moody's Investor Service; s_{it} is the equity share of total capital defined as total proprietary capital (TPC) divided by the sum of total proprietary capital and total long-term debt (TOTB); r_{eit} is the equity rate of return defined as the ratio of net income to total proprietary capital; d is a depreciation rate assuming 30 years straight line depreciation; and f_t the inflation rate.

The values of capital stocks are calculated by the valuation of base and peak load capacity at replacement cost to estimate capital stocks in a base year and then updating it in the subsequent years based upon the value of additions and retirements to steam power plant as

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[6] These costs were not separated into labor and non-labor costs because the wide spread use of outsourcing has made such distinctions rather arbitrary.

discussed in Considine (2000). The base year capacity is calculated by multiplying the price of new generation capacity in dollars per megawatt and the base year nameplate capacity in megawatts.

$$X_{3it} = P_{cit} C_{it}\,, \quad t = 1986 \tag{3-3}$$

where P_{cit} is the price of new generation capacity in dollars per megawatt, and C_{it} is the nameplate capacity in megawatts.

For the subsequent years, the values of capital stocks are calculated by

$$X_{3it} = \frac{(1-\upsilon)(X_{3it-1})p_{kit}}{p_{kit-1}} + A_{it} - R_{it}\,, \qquad t = 1987,...,1998 \tag{3-4}$$

where υ denotes the depreciation rate;[7] X_{3it} is equal to the nominal stock divided by the price index for electrical generating plant and equipment, p_{kit} ; A_{it} and R_{it} denote additions and retirements to steam power plant.

Cost

The total cost for steam electric power generation, C_{it}, is defined as the sum of the product of input prices and quantities for aggregate fuel, aggregate labor and maintenance and capital.

$$C_{it} = \sum_{k=1}^{3} W_{kit} X_{kit}\,, \tag{3-5}$$

The final data set is a balanced panel of 61 electric utilities for the years 1986 to 1998 with a total of 793 observations. Table 1 represents a summary of the data used in this study[8]. The average expenses of aggregate fuels, aggregate labor and maintenance, and capital are calculated to be 258.79, 66.66, and 97.43 million dollars, respectively. The mean cost shares of fuel, labor and maintenance, and capital account for 59, 18, and 23 percent, respectively.

4. Empirical results

4.1 Discussion of parameter estimates

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[7] A depreciation rate of 0.033 is used.

[8] All price indices used in this study are obtained and calculated relative to the base period 1993.

The data described in the previous section were used in the calculation of Tornqvist TFP indices and also in the estimation of the cost and input distance functions described in section 2. The maximum likelihood parameter estimates for these two functions (obtained using the computer program described in Coelli, 1996) are listed in Table 2. The data variables used in the model estimation were each transformed by division by their respective geometric means. This transformation does not alter the performance measures obtained, but does allow one to interpret the estimated first-order parameters as elasticities, evaluated at the sample means.

If we first focus on the estimates of the input elasticities in Table 2, we observe that the distance function estimates of 0.574, 0.136 and 0.290 (for fuel, labor and maintenance, and capital, respectively) differ significantly from the cost frontier estimates of 0.449, 0.361 and 0.190. These elasticities can also be interpreted as shadow shares, and hence indicate that when TFP measures are calculated using these estimates, the two TFP measures are likely to differ for the average firm, if the input quantities change at different rates through time. Given that substantial labor shedding has occurred during this period, it is likely that this issue will be important. Furthermore, we observe that the average *observed* shares in this data set are 0.59, 0.18 and 0.23, respectively. These shares are fairly similar to (but not identical to) the distance function shares, but clearly differ from the cost frontier shares. Given this observation, we expect that the TFP growth estimates obtained using the Tornqvist index (which uses observed shares) is likely to more closely approximate the distance function TFP measures, relative to the cost frontier TFP measures.

The reasons for the large differences that we observe between the cost frontier shares and the other two sets of shares warrant further discussion. One possible cause of these differences could be some type of systematic measurement error in either the input quantities or prices. For example, in the way in which capital price is measured. This possibility cannot be discounted, but as indicated in the previous section, we have taken great care in this regard. A second possible culprit is that the distance function estimates suffer from some type of simultaneous equations bias, due to an endogenous regressors problem, as discussed in Atkinson, Cornwell and Honerkamp (2003). However, given the arguments outlined in Coelli (2000) regarding the absence of an endogeneity problem in input distance functions (when firms are shadow cost-minimisers), and given the fact that the distance function shares and shadow shares are fairly similar, we do not believe that this is likely to be an issue.

We then come to the third and most likely culprit, that of the violation of the cost minimization assumption. In infrastructure industries such as this, this assumption is unlikely to be appropriate, due to factors such as political and regulatory interventions. Therefore, when cost minimization is no longer applicable, duality theory will no longer apply, and hence the cost elasticities cannot be assumed to equal the input shares. Thus, any TFP calculations (and decompositions) based upon cost frontier estimates in this situation need to be treated with a large amount of caution.[9]

An issue closely related to this, is the Averch-Johnston (AJ) effect, which predicts that the use of rate of return regulation (which is applied to most businesses in this data sample) tends to cause the shadow price of capital to decrease and hence encourages over capitalization. From our distance function shadow cost share of capital (0.290), we note that it closely approximates the observed capital share (0.23), suggesting that this is not an issue in this industry. Alternatively, when we look at the (most likely biased) cost frontier shadow cost share of capital (0.190), we appear to obtain evidence of this AJ effect. However, given the above discussion, one is inclined to put more weight on the distance function results, relative to these cost frontier results.

The estimated parameters in Table 2 also provide information on scale economies and technical change. Using the first order coefficient of the output variable, we can calculate the elasticities of scale relative to the cost and input distance functions as

$$RTS = \left(\partial c/\partial y\right)^{-1} = -\left(\partial d/\partial y\right)^{-1},$$

where a value of RTS greater than one imply increasing returns to scale, while values less than one imply decreasing returns to scale, and values equal to one indicate constant returns to scale. From the Table 2 parameter estimates, we find RTS measures very close to one in value, indicating that the technology exhibits constant returns to scale, at the sample mean. This result is not surprising given the results reported in past studies (e.g. see Christensen and Greene, 1976).

The first order coefficients of the time trend variable in Table 2 provide estimates of the average annual rate in technical change. The cost frontier estimates suggest that the technology

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9 Another possible reason for the differences in the estimates could be the result of violations of regularity conditions. Economic theory indicates that these economic functions should satisfy certain monotonicity and curvature conditions. A cost function should be non-decreasing and concave in input prices and non-decreasing in output quantities, while an input distance function should be non-decreasing and concave in input quantities and non increasing in output quantities. Tests of these conditions indicate that the concavity condition is satisfied at approximately two thirds of observations in the distance function, while it is violated in all observations in the cost function. This result adds further weight to our concerns about the reliability of the cost function estimates. With regard to the monotonicity conditions, we note that these are 15 violations in the cost frontier case and six in the distance function case. This rate of violation is quite low, indicating that this condition is satisfied at the vast majority of observations.

is improving at a rate of 2.2% per year, while the distance function estimates suggest a more modest 0.8% per year. The latter measure is likely to be more reliable, given the above discussion. In addition, we note that it also more closely approximates the technical change measures reported in other studies of the US electricity supply industry (e.g. see Atkinson et al, 2003).

4.2 Discussion of performance measures

Some summary measures of the TFP growth measures (and components) described in section 2 are listed in Table 3. The mean value reported for the Tornqvist index (TPIN) is 1.518, indicating that the average annual change in this TFP measure over this period is 1.518 percent per year. This is quite similar to the value of 1.496 reported for the distance function case, but differs significantly from the value of 3.545 reported for the cost function case. The fact that the cost function measure differs from the others is not surprising given the previous discussion. In the following discussion we will focus most attention on the distance function measures, since they are expected to be the more reliable ones.

In looking at which components contribute most to TFP change in the distance function section of Table 3, we observe that the major contribution is from TC (0.826%),[10] followed by TEC (0.318%), AEC (0.315) and lastly SEC (0.038%). The large contribution from TC conforms with most past studies of this industry (e.g. Atkinson and Primont, 2002). The near zero contribution of SEC is not surprising, given that the estimated technology exhibits constant returns to scale (at the sample mean).

In Table 4 we produce weighted averages of our results, where the firm-level results have been weighted by the output of each firm. These weighted average results are likely to give a more accurate picture of the industry-level changes over time. We note that the weighted mean TFP growth measure is quite similar to the unweighted mean, in the case of the Tornqvist and distance function results. However, it is interesting to observe that the weighted TC measure is almost 40% larger than the unweighted measure, indicating that larger firms have been pushing out the frontier at a faster rate. This is perhaps due to them having greater resources devoted to research and development, or maybe due to these larger firms having higher growth rates and

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[10] It is reassuring to note that these TC measures, formed by averaging firm-level measures, are similar to those obtained earlier, which were derived by evaluating the time derivative at the sample means.

hence more opportunities to benefit from embodied technical change in new investments. However, further research is required confirm these hypotheses.

Tables 3 and 4 also contain year-by-year averages. These annual measures indicate the degree of volatility in the TFP growth measures. For example, in the final column of Table 4, we see that TFP growth varies from a high of 5.598% in 1986/87 to a low of negative 1.202% in 1989/90, and from the associated TEC column, we see that most of this TFP volatility is due to TEC. These measures illustrate the degree to which exogenous factors, such as the business cycle and climatic conditions, can affect efficiency measures. Given this, it would clearly be prudent for an analyst to not base TFP growth measures upon only a handful of years of data, where the danger that an unusual event could significantly affect the measures obtained.

Annual averages of the firm-level measures are reported in Table 5. There is a wealth of information in this table. Of particular note is the degree to which TFP performance varies from firm to firm, from an annual average decrease of 3.858% for firm 43 to an increase of 10.758% for firm number 2. The distribution of TFP scores is further illustrated using the frequency distributions reported in Table 6 and Figure 1. This variability in performance is of particular interest to us in this study. In particular, to what extent can this variation be explained by different regulatory regimes?

4.3 The influence of regulation

In this section we test a number of hypotheses regarding the degree to which the regulatory regime has influenced firm-level productivity performance. Firstly, as noted in Sappington et al (2001), by the end of the 1990's, 28 electric utilities in 16 different States faced some form of incentive regulation. Of the 61 utilities included in the data set used in the present study, 11 faced some form of incentive regulation for some part of the sample period. Details of these schemes are summarised in Table 7. As can be seen in this table, incentive regulation was introduced in different States in different years.

The first hypothesis we consider is whether there was a significant difference in performance of firms when they faced incentive regulation versus those under more traditional forms of regulation. The means of TE, TFP1 and TFP2 for these two groups are reported under hypothesis (1) in Table 8. The null hypothesis that the means of the two groups are equal is rejected for all three pairs of means at the 5% level of significance. In fact, for all pairs of means reported in Table 8 this null hypothesis was rejected at he 5% level in all cases.

What is of interest is to note that those firms facing incentive regulation have lower mean TE levels and lower mean TFP growth. This is contrary to what the theory predicts should happen. One possible reason for this finding is that we have perhaps not accounted for particular macro economic effects that may be making the earlier part of the 1986-1998 data period look good and hence given that adoption of incentive regulation methods occurred in the latter half of the period, our measures may be affected. To attempt to remove the effect of this possibility we excluded the 1986-1990 data (which is the period prior to 1991, the date on which the first firm in the sample faced incentive regulation) and then re-ran the t-tests. The results, which are reported as hypothesis (2) in Table 8, come to the same set of conclusions as the first set. Hence the macro effects issue does not appear to be crucial.

Another possible explanation of our unexpected results is that of "endogenous selection", in that those State regulators who decided to implement incentive regulation methods did so because they knew that the firms in their State were not performing well and hence needed some encouragement. To test this hypothesis we took the 1986-1990 results and dived the firms into those that would subsequently adopt incentive regulation and those that would not. The results reported in Table 8 under hypothesis (3) confirm our suspicions. Those firms that subsequently face incentive regulation do have lower performance during this period. This means that we cannot have much faith in the reliability of the results of hypothesis (1).

Hence we consider one final hypothesis test. In this test we focus only upon those firms that actually do face incentive regulation and we look at the period of three years immediately prior to the regulatory change for that firm and compare it to the following first three years of the regulatory regime for that firm. Given that we are no longer comparing adopters and non-adopters the endogenity issue is removed. Furthermore, given that we focus on a short time period, macro effects should also be minimised. The results of hypothesis (4) in Table 8 indicate that performance declines following the introduction of incentive regulation, which confirms the conclusion of hypothesis (1). Thus, in this instance, the empirical evidence suggests that incentive regulation has not achieved the desired result.

5. Conclusions

In this paper we have sought to make a number of contributions. First, we have provided up to date information on productivity growth in fossil-fuel steam electricity generation in the United States. Using sample data on 61 firms observed over a 13-year period from 1986 to 1998, we found that productivity has improved at the rate of approximately 1.5 percent per year over this period. We have also calculated productivity growth for each firm in the sample, finding that they range from a four percent annual decline for one firm to an 11 percent annual increase for the best performing firm.

Second, we have compared and contrasted three different methods of productivity measurement. Namely, Tornqvist index numbers, stochastic cost frontiers and input distance functions. We argue that the latter method is to be preferred because of its ability to deal with violations of cost minimizing behavior (which are common in regulated industries) and because it allows one to decompose productivity growth into various components that are of interest to regulators (such as technical change and efficiency change).

Finally, we have used our empirical results to test various hypotheses regarding the effect of regulatory reform upon productivity. From the results of this analysis, we conclude that the introduction of incentive regulation has not had the desired positive effect upon the economic performance of the firms involved. In fact, in the case of these data, we find that performance is negatively related with the introduction of the new regulatory regimes. Whether this is a result of the failure of these regulatory methods, or a failure to properly implement the methods is an issue that warrants further attention.

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Table 1: Data summary for 61 electric utilities over the periods of 1986-98

Variable	Units	Mean	S. D.	Minimum	Maximum
Output, Y	($\times 10^6$ *MWhr*)	13.709	12.561	0.499	79.723
Fuel, X_1	($\times 10^6$ *dollars*)	300.568	351.842	12.823	2,522.324
Labor and Maintenance, X_2	($\times 10^6$ *dollars*)	61.776	53.366	1.810	444.453
Capital, X_3	($\times 10^6$ *dollars*)	955.225	877.403	9.070	3,878.295
Price Index of Fuel, W_1		0.861	0.208	0.306	1.338
Price Index of Labor and Maintenance, W_2		1.079	0.255	0.443	1.928
User Costs of Capital, W_3		0.102	0.019	0.009	0.203
Total Cost, C	($\times 10^6$ *dollars*)	410.643	376.033	25.668	2,233.418

Note: The observed shares are 58.6% by fuel, 17.9% by labor and maintenance, and 23.5% by capital

Table 2: Parameter estimates for the cost frontier and input distance function

Model	Cost Frontier			Input Distance Function		
Parameter	**Estimates**	**S.D.**	**t-ratio**	**Estimates**	**S.D.**	**t-ratio**
β_0	-0.270	0.012	-22.055	0.256	0.010	24.495
β_1	0.449	0.022	19.998	0.574	0.017	34.655
β_2	0.361	0.030	11.983	0.136	0.018	7.671
β_3	0.190			0.290		
β_{11}	0.267	0.128	2.095	-0.118	0.047	-2.516
β_{12}	-0.360	0.110	-3.287	0.127	0.042	3.041
β_{13}	0.093			-0.009		
β_{22}	0.525	0.169	3.111	-0.011	0.041	-0.266
β_{23}	-0.164			-0.116		
β_{33}	0.071			0.125		
β_y	0.966	0.006	155.078	-0.976	0.008	-128.787
β_{yy}	0.028	0.012	2.400	-0.023	0.014	-1.676
β_{1y}	-0.059	0.025	-2.337	-0.056	0.018	-3.034
β_{2y}	-0.011	0.031	-0.343	-0.004	0.017	-0.252
β_{3y}	0.069			0.060		
β_z	-0.022	0.002	-10.455	0.008	0.002	5.015
β_{zz}	0.002	0.001	1.458	0.001	0.001	1.456
β_{1z}	0.038	0.008	4.756	0.006	0.005	1.346
β_{2z}	-0.048	0.011	-4.453	0.007	0.004	1.466
β_{3z}	0.010			-0.013		
β_{yz}	-0.005	0.002	-2.297	0.006	0.002	3.195
σ^2	0.113	0.007	16.177	0.110	0.007	15.175
γ	0.974	0.008	122.552	0.979	0.009	112.813
Log likelihood function			200.651			220.574
LR test of the one-sided error			207.896			190.514

Table 3: Annual average TFP change measures (unweighted)*

Year	TPIN	Cost Frontier Model						Input Distance Model					
		CEC	TC	SEC	AEC	TFPC1	TFPC2	TEC	TC	SEC	AEC	TFPC1	TFPC2
86-87	6.631	6.455	1.652	0.146	2.001	8.253	10.255	6.550	0.083	-0.078	-0.281	6.555	6.274
87-88	1.575	1.962	1.888	0.042	2.615	3.892	6.507	0.083	0.270	0.199	1.068	0.552	1.620
88-89	4.003	2.748	2.073	0.250	1.477	5.071	6.548	2.574	0.469	0.063	0.569	3.106	3.675
89-90	-2.570	-4.401	2.062	-0.165	-0.371	-2.504	-2.874	-3.294	0.598	-0.049	0.454	-2.745	-2.291
90-91	-2.287	-2.052	2.109	-0.062	1.971	-0.006	1.966	-3.550	0.695	0.012	0.764	-2.843	-2.079
91-92	0.999	0.096	2.208	-0.069	1.222	2.235	3.457	0.443	0.792	-0.006	-0.265	1.228	0.963
92-93	0.109	-0.922	2.273	-0.282	1.156	1.069	2.225	0.131	0.880	-0.243	-0.725	0.768	0.043
93-94	1.767	0.012	2.361	0.114	0.421	2.486	2.907	0.387	0.977	0.070	0.530	1.434	1.964
94-95	0.428	-0.817	2.467	-0.032	1.008	1.617	2.626	-1.006	1.076	-0.059	0.279	0.010	0.290
95-96	2.377	0.089	2.514	-0.120	0.362	2.483	2.845	1.223	1.170	-0.127	0.129	2.266	2.396
96-97	3.488	0.702	2.451	0.498	0.516	3.651	4.167	0.956	1.325	0.501	0.372	2.782	3.154
97-98	1.696	-0.961	2.500	0.244	0.128	1.783	1.912	-0.686	1.572	0.171	0.890	1.057	1.947
Mean	**1.518**	**0.243**	**2.213**	**0.047**	**1.042**	**2.503**	**3.545**	**0.318**	**0.826**	**0.038**	**0.315**	**1.181**	**1.496**

* All measures are in percentage terms.

Table 4: Weighted annual average TFP change measures

Year	TPIN	Cost Frontier Model						Input Distance Model					
		CEC	TC	SEC	AEC	TFPC1	TFPC2	TEC	TC	SEC	AEC	TFPC1	TFPC2
86-87	5.867	5.641	2.099	-0.049	2.169	7.692	9.861	5.516	0.539	-0.126	-0.330	5.929	5.598
87-88	1.465	1.378	2.367	0.023	2.567	3.768	6.335	0.316	0.673	0.020	0.447	1.010	1.457
88-89	2.108	0.452	2.532	0.055	1.104	3.038	4.142	1.043	0.830	-0.023	0.076	1.849	1.926
89-90	-1.416	-3.662	2.541	-0.040	-0.059	-1.161	-1.220	-2.662	0.948	0.016	0.496	-1.698	-1.202
90-91	-1.133	-1.497	2.605	-0.002	2.028	1.105	3.133	-2.543	1.023	0.033	0.547	-1.486	-0.939
91-92	1.227	1.431	2.702	0.007	2.886	4.139	7.025	0.186	1.089	0.048	-0.199	1.322	1.123
92-93	1.557	-1.723	2.752	-0.020	-0.344	1.009	0.665	0.528	1.213	-0.017	-0.376	1.724	1.348
93-94	1.040	-0.027	2.835	0.019	1.538	2.827	4.365	-0.192	1.325	0.006	0.169	1.139	1.308
94-95	0.864	-0.805	2.982	0.029	1.273	2.206	3.479	-0.814	1.406	0.006	0.360	0.598	0.958
95-96	3.371	0.475	3.090	0.012	0.613	3.577	4.189	1.760	1.523	0.020	-0.217	3.303	3.086
96-97	2.156	-0.699	3.105	0.121	0.812	2.527	3.339	0.583	1.662	0.168	-0.864	2.414	1.550
97-98	1.624	-0.852	3.116	0.125	0.373	2.390	2.762	-0.242	1.896	0.095	0.224	1.749	1.973
Mean	**1.561**	**0.009**	**2.727**	**0.023**	**1.246**	**2.760**	**4.006**	**0.290**	**1.177**	**0.021**	**0.028**	**1.488**	**1.516**

Table 5: Average TFPC Decomposition by Firm (in Percentage)

Firm	TPIN TFPC	Cost Frontier Model						Input Distance Model					
		CEC	TC	SEC	AEC	TFPC1	TFPC2	TEC	TC	SEC	AEC	TFPC1	TFPC2
1	0.683	-0.328	2.247	0.050	1.227	1.969	3.196	-1.052	0.789	0.068	1.002	-0.195	0.807
2	11.175	8.650	0.756	0.663	1.153	10.068	11.221	8.322	0.769	-0.095	1.762	8.996	10.758
3	-0.047	-2.192	2.892	-0.045	0.578	0.655	1.232	-1.496	1.282	-0.118	0.323	-0.332	-0.009
4	2.877	1.652	1.319	-0.023	0.117	2.948	3.064	0.480	1.280	-0.005	1.111	1.755	2.867
5	0.285	0.530	1.281	-0.243	1.307	1.568	2.875	0.143	-0.215	-0.168	0.521	-0.239	0.281
6	1.758	1.533	2.649	-0.089	2.413	4.093	6.505	0.711	0.693	-0.080	0.419	1.324	1.743
7	0.098	-0.333	1.065	0.086	0.624	0.818	1.443	-0.440	0.634	0.043	0.000	0.237	0.237
8	0.827	-0.203	1.996	0.029	0.984	1.823	2.807	-0.315	0.957	0.034	0.157	0.677	0.834
9	0.337	-0.615	1.882	0.020	0.736	1.287	2.024	-0.508	1.110	0.031	-0.119	0.633	0.514
10	-0.152	-1.079	0.710	0.058	-0.447	-0.311	-0.759	-1.091	0.552	0.130	0.570	-0.409	0.161
11	1.971	1.238	0.979	-0.078	0.253	2.139	2.393	0.235	1.117	-0.058	0.643	1.293	1.936
12	1.934	-0.232	3.493	0.018	1.338	3.279	4.617	1.635	1.091	0.007	-0.834	2.733	1.899
13	1.615	0.758	1.424	0.028	0.615	2.210	2.825	0.610	0.885	0.029	0.077	1.525	1.602
14	-0.960	-2.175	0.847	-0.175	-0.605	-1.502	-2.107	-2.943	1.411	0.029	0.606	-1.503	-0.897
15	0.569	-0.578	3.209	-0.023	2.022	2.608	4.630	-0.385	1.593	-0.029	-0.602	1.179	0.577
16	1.854	0.084	3.172	0.015	1.458	3.271	4.729	0.417	1.001	0.067	0.247	1.485	1.732
17	2.529	1.252	1.659	0.056	1.001	2.967	3.968	1.013	0.892	0.075	-0.074	1.979	1.905
18	1.907	0.325	2.064	0.073	0.550	2.462	3.012	-0.190	0.663	0.159	1.280	0.632	1.911
19	2.601	1.033	3.026	0.203	1.690	4.263	5.952	0.972	1.118	0.063	0.427	2.153	2.580
20	9.341	5.622	3.032	0.288	-0.341	8.942	8.600	2.740	-0.072	0.815	5.795	3.484	9.279
21	1.121	0.212	2.905	0.014	2.123	3.130	5.253	0.013	1.188	0.006	-0.089	1.206	1.117
22	3.318	1.704	2.491	-0.098	0.811	4.098	4.909	2.033	0.154	-0.179	1.266	2.008	3.274
23	2.017	1.806	0.636	0.373	0.862	2.815	3.677	1.375	0.798	0.108	-0.294	2.282	1.988
24	0.593	1.026	-0.562	0.182	0.094	0.646	0.740	0.161	0.139	0.280	0.009	0.580	0.590
25	2.447	0.549	3.042	-0.254	0.907	3.337	4.244	1.210	1.145	-0.292	0.359	2.062	2.421
26	-0.337	-0.866	1.023	-0.012	0.461	0.145	0.606	-1.406	1.327	-0.051	-0.176	-0.130	-0.306
27	1.475	-1.366	4.921	0.018	2.056	3.573	5.630	-0.250	2.343	0.015	-0.628	2.108	1.480
28	2.848	0.909	2.568	0.045	0.702	3.522	4.225	0.608	1.096	0.052	1.074	1.755	2.829
29	3.222	1.211	3.376	-0.037	1.371	4.550	5.920	1.839	1.037	0.045	0.262	2.921	3.183
30	0.906	-0.146	2.443	0.066	1.419	2.363	3.782	0.240	0.851	0.030	-0.244	1.121	0.877
31	2.017	0.001	2.813	0.109	0.875	2.923	3.798	0.254	0.667	0.147	0.943	1.068	2.011
32	0.784	0.294	1.082	0.060	0.697	1.437	2.133	-0.227	1.102	0.049	-0.032	0.924	0.892
33	2.415	1.959	0.953	0.006	0.537	2.918	3.456	1.865	-0.098	0.052	0.556	1.819	2.375
34	-0.392	-0.556	1.169	0.047	1.041	0.660	1.701	-0.253	-0.393	-0.048	0.308	-0.694	-0.386
35	0.861	-1.402	3.106	-0.080	0.724	1.624	2.348	-0.598	1.039	-0.099	0.532	0.342	0.874
36	1.627	0.278	1.685	0.106	0.972	2.069	3.041	0.111	1.031	0.115	0.007	1.257	1.264
37	0.147	0.710	2.359	0.329	3.167	3.398	6.565	0.249	-0.048	0.275	-0.335	0.476	0.141
38	-0.826	-1.146	1.911	0.005	1.468	0.769	2.238	-0.672	-0.188	0.009	0.094	-0.850	-0.757
39	-0.532	-2.680	3.683	0.051	1.541	1.054	2.595	-0.591	1.140	-0.001	-1.068	0.548	-0.520
40	0.918	0.588	0.500	0.115	0.374	1.204	1.578	0.394	0.514	0.051	-0.081	0.959	0.878
41	2.023	-0.719	4.718	-0.007	1.930	3.991	5.921	0.676	1.047	0.009	0.277	1.731	2.009
42	1.727	-0.806	4.174	0.106	1.740	3.474	5.215	-0.603	2.443	-0.182	0.082	1.658	1.739
43	-3.943	-3.891	2.891	-0.833	2.041	-1.834	0.207	-3.982	0.814	-0.739	0.048	-3.906	-3.858
44	2.556	1.526	1.142	0.336	1.078	3.004	4.082	1.053	0.284	0.221	0.643	1.558	2.201
45	1.674	0.559	2.234	0.015	1.184	2.808	3.991	0.649	1.178	-0.034	-0.145	1.793	1.648
46	2.915	-1.245	4.742	-0.072	0.479	3.425	3.904	-0.285	2.104	-0.095	1.197	1.724	2.921
47	-0.580	-1.569	1.568	0.084	0.530	0.084	0.614	-1.627	0.830	0.087	0.692	-0.710	-0.018
48	1.433	0.580	2.788	-0.012	1.935	3.356	5.291	1.263	0.985	0.006	-0.848	2.255	1.406
49	2.191	1.608	0.297	0.199	-0.046	2.103	2.057	1.716	-0.143	0.164	0.417	1.737	2.154
50	3.498	0.582	4.079	0.171	1.657	4.832	6.489	2.726	0.286	0.153	0.068	3.164	3.232
51	1.679	0.446	1.246	0.010	0.031	1.702	1.733	0.067	1.046	0.046	0.519	1.159	1.678
52	1.521	-0.787	3.509	0.018	0.871	2.739	3.610	0.080	1.257	0.019	0.162	1.356	1.518
53	2.079	0.135	2.626	-0.032	0.875	2.729	3.604	0.628	1.131	0.027	0.216	1.786	2.002
54	4.422	3.449	1.881	0.082	1.162	5.412	6.574	3.723	-0.517	0.190	0.762	3.396	4.158
55	0.785	-0.067	-0.152	0.103	-0.904	-0.115	-1.019	-0.140	0.810	0.120	-0.001	0.790	0.789
56	-1.966	-2.953	2.268	-0.121	1.077	-0.805	0.272	-1.553	1.097	-0.054	-1.421	-0.510	-1.931
57	0.102	-0.049	1.641	0.333	1.776	1.925	3.701	0.382	-1.138	0.410	0.370	-0.346	0.023
58	2.115	0.200	4.284	-0.037	2.340	4.447	6.787	0.598	1.808	-0.058	-0.249	2.347	2.098
59	0.418	-0.755	3.620	-0.012	2.289	2.852	5.141	-0.790	1.155	0.050	0.029	0.415	0.444
60	0.582	-0.072	1.488	0.478	1.307	1.895	3.202	-0.736	0.386	0.360	0.588	0.010	0.598
61	1.539	0.596	2.149	0.102	1.351	2.848	4.199	0.321	1.104	0.039	0.055	1.463	1.518
Mean	**1.518**	**0.243**	**2.213**	**0.047**	**1.042**	**2.503**	**3.545**	**0.318**	**0.826**	**0.038**	**0.315**	**1.181**	**1.496**

Table 6: Distribution of Average Total Factor Productivity Change

Total Factor Productivity Change (%)	TPIN Approach Number of Firms	TFPC1		TFPC2	
		Cost Frontier Approach Number of Firms	Input Distance Approach Number of Firms	Cost Frontier Approach Number of Firms	Input Distance Approach Number of Firms
< -2.0	1	0	1	1	1
-2.0-0.0	9	5	11	2	8
0.0-2.0	31	18	36	10	34
2.0-4.0	19	29	12	25	15
4.0-6.0	1	7	0	16	1
6.0-8.0	0	0	0	5	0
8.0-10.0	1	1	1	1	1
> 10.0	1	1	0	1	1

Table 7: Incentive Regulation of U.S. Electric Utilities in the Sample Data

No	Name	State	Period	Type of Plans
6	Niagara Mohawk Power	NY	1991-1995	Revenue cap
			1998-2002	Rate freeze
7	Central Illinois Light	IL	1998-2002	Price cap
8	Central Illinois Public Service	IL	1998-2003	Price cap
25	Southern California Edison	CA	1997-2001	Price cap
26	Tampa Electric	FL	1995-1999	Rate freeze
34	Central Maine Power	ME	1991-1993	Revenue-per-customer cap
			1995-2000	Price cap
35	Consolidated Edison -NY	NY	1995-1997	Revenue-per-customer cap
			1997-2000	Rate case moratorium
46	Montana Power	MT	1997-1998	Price cap
52	Public Service of Colorado	CO	1997-2001	Rate case moratorium
54	Rochester Gas & Electric	NY	1993-1996	Revenue cap
			1996-2002	Rate case moratorium
59	Union Electric	MO	1995-2001	Rate freeze

Table 8: Tests of hypotheses regarding the effects of regulatory regime*

Period	Incentive Regulation	TE	TFP1	TFP2
(1) H_0 = means between adopters and non-adopters during 1986-98 are equivalent				
1986-1998	no	0.842	1.205	1.539
	yes	0.715	1.103	1.380
(2) H_0 = means between adopters and non-adopters during 1991-98 are equivalent				
1991-1998	no	0.841	1.200	1.531
	yes	0.715	1.103	1.380
(3) H_0 = means between adopters and non-adopters during 1986-90 are equivalent				
1986-1990	no	0.854	1.296	1.588
	yes	0.793	1.154	1.415
(4) H_0 = means between 3 year before and after adoption for all IR adopters are equivalent				
various	before	0.805	1.301	1.431
	after	0.759	1.126	1.398

* All differences were found to be significant at the 5% level.

Figure 1: Distribution of Average Total Factor Productivity Change