

Productivity Growth and Efficiency under Leontief Technology: An Application to US Steam-Electric Power Generation Utilities

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Abstract – A theoretical framework is developed for decomposing partial factor productivity and measuring technical inefficiency when the underlying technology is characterized by factor non-substitution. With Farrell's (1957) radial index of technical inefficiency being inappropriate in this case, Russell's (1985; 1987) non-radial indices are adapted to measure technical inefficiency in a Leontief model. A system of factor demand equations with a regime specific technical inefficiency term is proposed and estimated allowing for dependence across inputs using a copula approach. Then the paper presents a complete decomposition of partial factor productivity changes using a dataset of U.S. steam-power electric generation utilities.

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1. Introduction

The decomposition of productivity growth has been explored and measured extensively to include efficiency changes over time in addition to scale effect and technical change components (see Fried et al (2008) for a recent overview). This partitioning of the different contributions is important as it implies different incentives or remedies to influence different components. For example, expansionary investment involves impacting the scale effect of the growth decomposition, while replacement investment acts on the technical change effect. Decisions and incentives to learn how to extract the full potential of implemented technologies are acting on the efficiency change component of promoting growth.

The core theoretical concept for building these measures is the production technology, where one can define formally the notions of technical efficiency (operating on the boundary of the feasible technology set), technical progress (shifting the boundaries of this set) and scale effects (moving along the boundary of an existing set). The abundant economic literature on the estimation of stochastic production frontier functions and the subsequent measurement of technical inefficiency has assumed, in general, that the underlying production technology displays some degree of substitutability between factors of production. This is not unusual as a production technology with zero input elasticity of substitution would imply that the cost-minimizing

inputs are independent of their prices, which is a restrictive assumption in many real world applications.¹

Although this is true for the agricultural sector, certain types of production activities may exhibit a zero elasticity of substitution among inputs. Some examples are given by Komiya (1962) who investigated the technological progress in the US steam power industry, Lau and Tamura (1972) who propose the use of a non-homothetic Leontief production function to analyze the Japanese petrochemical industry², Nakamura (1990) who utilized a non-homothetic generalized Leontief technological structure for empirically analyzing the Japanese iron and steel industry, Buccola and Sil (1996) who measured productivity in the agricultural marketing sector, Holvad *et al.*, (2004) who maintain that the transport industry might be characterized by Leontief-type technologies when analyzing cost efficiency in the Norwegian bus industry. Furthermore, a stream of literature in agricultural economics in modeling crop response to different fertilizer's nutrients levels, has maintained zero substitution among crop nutrients using a linear plateau specification motivated by the von Liebig farm technology.³

¹ Indeed, Bravo-Ureta *et al.* (2007) in their meta-regression analysis reviewing 167 empirical studies for measuring productive efficiency in agricultural applications, in both developed and developing countries, found that the vast majority of those hinge either on a Cobb-Douglas or a translog functional specification to approximate the underlying production technology allowing for substitution possibilities among factors of production.

² Haldi and Whitcomb (1967) and Ozaki (1970) used a similar approach based on a homothetic Leontief production function on their analysis of economies of scale in US and Japanese industry, respectively.

³ Paris (1992) presents an excellent overview of the historical literature and an econometric estimation approach, and Holloway and Paris (2002) address productive efficiency in the context of the von Liebig specification. Guan *et al.* (2006) introduce an alternative modeling framework when encountering limited substitution grounded in an agronomic model of nutrient exchange.

Sorting out the components of productivity growth initially involves identifying the relationship between the input combination and the boundary of the production set. Measuring technical inefficiency in the case of Leontief type technologies is of interest in itself given Farrell's (1957) radial measures are the basis for most applied work on the measurement of efficiency. However, the radial measures can be inadequate in that they may classify inefficient input combinations as being efficient, while input- and output-oriented measures might not coincide even under constant returns-to-scale.⁴ Once the technology is governed by a Leontief-type structure, it is plausible to have inefficiency displayed by none, all or a subset of the inputs, rendering radial measures unsatisfactory. In addition, output-oriented measures may fail to recognize inefficiencies when they affect a subset of the inputs only. If we accept that some specific production activities exhibit a zero elasticity of substitution among factors of production, then alternative ways are needed to define and empirically measure technical efficiency and to analyze factor productivity growth.

The purpose of this paper is to develop a framework for modeling productivity growth under factor non-substitution that accounts for technical inefficiency and technical progress. The econometric modeling framework accommodates the absence of substitution possibilities among inputs where inefficiency between factors can be correlated. Our theoretical model is based on the non-homothetic Leontief production function suggested by Lau and Tamura (1972) which is the most general function with

⁴ Färe and Lovell (1978) proved that if a regular production technology is linear homogeneous then input technical efficiency coincides with output technical efficiency. However, this is not true in factor limitation production technologies as once the plateau is reached firms may be identified as being output technical efficient, but certainly they are not efficient under an input conserving approach.

zero elasticities of substitution between all pairs of inputs allowing at the same time differential returns-to-scale and technical progress (regress) to inputs. This Leontief frontier model adapts the copula approach to modeling the joint distributions between the one-sided error terms that capture factor-specific technical inefficiencies. Factor-specific technical efficiencies are specified and measured using Kopp's (1981) orthogonal indices of technical efficiency, combined into an overall technical efficiency measure using Russell's (1985; 1987) non-radial index of productive efficiency. Then, we proceed to the developing a tractable approach for the analysis of partial factor productivity growth.

The model is applied to a panel data set of 72 fossil-fuel fired steam electric power generation utilities in the US observed during the 1986-96 period. When analyzing the economies of scale and technical progress in the generation of steam-electric power also in the US, Komiya (1962) found that the Leontief factor limitation model provided a better representation of the data compared with the traditional Cobb-Douglas unitary substitution model. Hence, in this study we maintain *a priori* that the US steam electric power utilities offer a good case for applying the suggested theoretical framework for measuring technical efficiency and decomposing partial factor productivity in factor limitation models. Further, we assume that errors associated with factor demands and factor-specific technical inefficiencies can be correlated across factors.

The next section develops the theoretical framework for measuring technical efficiency in production structures that exhibit zero elasticity of substitution among inputs, while section 3 presents the empirical model discussing briefly the econometric methods used. Section 4 presents the estimation results of an application to US electric

utilities and finally, section 5 provides some concluding remarks and suggestions for future extensions.

2. Theoretical Framework

Assume that producers in period t utilize a vector of variable inputs $\mathbf{x} \in \mathfrak{R}_+^J$ together with a vector of quasi-fixed inputs $\mathbf{z} \in \mathfrak{R}_+^K$ to produce a single output $y \in \mathfrak{R}_+$ through a well-behaved technology described by the closed, nonempty production possibilities set $T(t) = \{(\mathbf{x}, \mathbf{z}, y) : \mathbf{x} \in \mathfrak{R}_+^J, \mathbf{z} \in \mathfrak{R}_+^K \text{ can produce } y\}$. Accordingly, for every $y \in \mathfrak{R}_+$ we can define the input correspondence set as all the input combinations capable of producing y , *i.e.*,

$$L(y, \mathbf{z}|t) = \{\mathbf{x} \in \mathfrak{R}_+^J : (\mathbf{x}, \mathbf{z}, y|t) \in T(t)\} \quad (1)$$

If we assume that the above defined production technology is characterized by *ex ante* limited substitutability between factors of production, we can define the cost function for all y such that $L(y, \mathbf{z}|t) \neq \emptyset$:

$$C(y, \mathbf{w}, \mathbf{z}, t) = \min_{\mathbf{x}} \{\mathbf{w}' \mathbf{x} : \mathbf{x} \in L(y, \mathbf{z}|t)\} \quad (2)$$

which is the minimum cost of producing output quantities y with period's t technology, when the factor prices $\mathbf{w} \in \mathfrak{R}_{++}^J$ are strictly positive. Applying Shephard's lemma in (2) we obtain the system of derived demand equations as:

$$\frac{\partial C(y, \mathbf{w}, \mathbf{z}, t)}{\partial w_j} = g_j(y, \mathbf{z}, t) = x_j. \quad (3)$$

Since the elasticity of substitution between any pair of factors of production, holding output constant, is assumed to be zero, the derived demand functions are independent of factor prices. Such a system has been utilized by Komiya (1962) who refers to this as “*plant base factor limitational production function*” and by Haldi and Whitcomb (1967), Ozaki (1970) and Lau and Tamura (1972). The function $g_j(\cdot)$ is a positive real-valued convex function defined and finite for all finite $y > 0$ with $g_j(0) = 0$.

The production function $f(\mathbf{x}, \mathbf{z}, t): \mathfrak{R}_+^J \rightarrow \mathfrak{R}_+$ corresponding to the dual cost function defined in (2) is given by

$$y = \max_y y: \mathbf{w}'\mathbf{x} \geq C(y, \mathbf{w}, \mathbf{z}, t); \quad (4)$$

which means that, for any given set of factor prices, the maximum y is obtained such that the observed cost of production is greater than or equal to the optimum factor cost. The solution of the above optimization problem requires $x_j \geq g_j(y, \mathbf{z}, t) \quad \forall j$.⁵ Assuming that $g_j(\cdot)$ is non-decreasing and lower semi-continuous in y , we may define its generalized inverse, and hence the production function may be reformulated as

$$y = \max_y \{y: x_j \geq g_j(y, \mathbf{z}, t) \quad \forall j\} = g_j^{-1}(x_j, \mathbf{z}, t). \quad (5)$$

The maximum y that satisfies the above optimization problem is then given by

$$y = f(x, z, t) = \min_{x_j} \{g_j^{-1}(x_j, \mathbf{z}, t)\}, \quad (6)$$

which is a non-homothetic Leontief production function corresponding to the dual cost function defined in (2). It is non-homothetic as the expansion path is not necessarily a

⁵ See Lau and Tamura (1972) pp. 1171-72.

ray through the origin and the elasticities of substitution are zero between any pair of factors of production. Given relation (6) the input requirement set for this non-homothetic technological structure, may be restated as

$$L(\mathbf{y}, \mathbf{z}|t) = \{x: \min_j \bar{g}_j^{-1}(x_j, \mathbf{z}, t) \geq y, \forall_j\} \quad (7)$$

where $L(\mathbf{y}, \mathbf{z}|t)$ satisfies the correspondence $\mathfrak{R}'_+ \rightarrow \mathfrak{R}$.⁶ In addition to the production function and the input correspondence set the following two subsets are important: (a) the isoquant and, (b) the technically efficient subset. In the case of the non-homothetic Leontief technology both sets are defined, respectively, as

$$Q(\mathbf{y}, \mathbf{z}|t) = \{x: x \in L(\mathbf{y}, \mathbf{z}|t), \forall_{k,j,k \neq j}; x_k \geq g_k(\mathbf{y}, \mathbf{z}, t) \wedge x_j = g_j(\mathbf{y}, \mathbf{z}, t)\} \quad (8)$$

and

$$E(\mathbf{y}, \mathbf{z}|t) = \{x: x \in L(\mathbf{y}, \mathbf{z}|t), x_j = g_j(\mathbf{y}, \mathbf{z}, t) \forall_j\} \quad (9)$$

Unlike conventional technologies where substitution possibilities among factors of production exist, the efficient subset of the input correspondence is a subset of the isoquant for each output level y .⁷ Actually, the efficient subset coincides with the right angle point of the Leontief-type technology isoquants (*i.e.*, L-shaped). In these instances, where the production technology exhibits L-shaped isoquants, technical efficiency

⁶ According to Chambers (1988) this type of production technology is a special case of what he calls *Kohli-output* nonjoint or nonlinear Leontief production technology. It is also a member of the CES family of production functions introduced by Arrow *et al.*, (1961) when the elasticity of substitution is set to be zero.

⁷ The variable elasticity of substitution (VES) and weak input disposability functions are also examples of production functions whose isoquants are not contained in their efficient subsets (Färe and Lovell, 1978).

coincides with productive efficiency as defined by Farrell (1957) since allocative efficiency is always maintained (i.e., the cost-minimized input bundle is always on the left angles of the isoquants).⁸

In the case of the non-homothetic Leontief production technology, Farrell's (1957) measure could well classify an inefficient input bundle as being efficient since it's a radial measure that constraints the input contraction to be the same across inputs. In contrast, Russell's (1985; 1987) non-radial measure of technical efficiency allowing for different inputs to display different reduction levels is suitable for technologies that exhibit non-substitution among factors of production. Figure 1 illustrates the nonsubstitution between two inputs (e.g., fuel and labor) and a production function given by (6), where the production unit is producing a given level of output (\bar{y}) using an input combination defined by point *A*, with L_1 units of labor and F_1 units of fuel. The same level of output can be produced by reducing the use of both inputs until point *B* which lies on the isoquant associated with the minimum level of inputs required to produce \bar{y} . Farrell's definition of a radial measure of input-oriented technical inefficiency is the ratio OC/OA . In this case both input contractions are the same, i.e., $OL_2/OL_1 = OF^*/OF_1$. However, point *C* is not the minimum level of inputs required to produce \bar{y} , as labor is used in excessive quantities. This point is on the isoquant \bar{y} but it does not lie in the efficient set of inputs, therefore the technical inefficiency is due to the excess use of the labor input. If we decrease its use until point *B* and leave the fuel input constant we produce the same output \bar{y} .

⁸ However, this presumes that any change in factor prices does not affect the fixed proportion in which inputs are combined in the production process.

On the other hand, Russell's (1985; 1987) non-radial index can appropriately measure technical inefficiency of that type of production technology. Using the input correspondence defined in (7), the Russell non-radial technical inefficiency index can be defined as

$$TE^R = \min_{\theta} \left\{ \prod_j [\theta_j]^{\frac{1}{\sum_j \xi_j}} : (\theta_1 x_1, \dots, \theta_j x_j) \in L(y, z|t) \wedge \theta_j \in (0, 1] \forall_j \right\} \quad (10)$$

where Π denotes the product over j , $\xi_j = 1$ if $x_j > 0$ and $\xi_j = 0$ if $x_j = 0$.⁹ The index in (10) is the ratio of two distances computed along diverging rays. The Russell measure clearly generalizes the Farrell input-oriented measure of technical efficiency, with the latter being the special case for $\theta_j = \bar{\theta} \forall j$. Figure 1 illustrates how inputs F and L are contracted by different proportions to reach the technical efficient input mix to reach the efficient point B .

In this case technical inefficiency should be measured non-radially and is defined as the distance DB/DA which is different from the Farrell (radial) measure of OC/OA . Labor needs to be reduced by OL^*/OL_1 , while fuel needs to be reduced by OF^*/OF_1 and $OL^*/OL_1 \neq OF^*/OF_1$. Given the nature of the underlying production technology, Russell's measure is actually the simple geometric average of the orthogonal non-radial factor-specific technical efficiency indices suggested by Kopp (1981).¹⁰ Formally, they are defined as

⁹ As shown by Russell (1985; 1987), the technical inefficiency index defined in (10) satisfies commensurability, indication and weak monotonicity properties but not that of homogeneity.

¹⁰ Instead of the simple average, Russell's technical efficiency measure can be obtained using an unweighted geometric mean.

$$TE_j^{KP} = \min_{\theta_j} \{ \theta_j : \theta_j > 0, \min_j g_j^{-1}(\theta_j x_j, \mathbf{z}, t) \} \quad (11)$$

or using (3) under technical inefficiency as

$$TE_j^{KP} = \frac{g_j(y, \mathbf{z}, t)}{x_j} \quad (12)$$

where $\theta_j \in (0, 1]$ is the orthogonal factor-specific measure of technical efficiency. Factor-specific technical efficiency defined in (11) or (12) has an input-conserving interpretation, which however, cannot be converted into a cost saving measure due to its non-radial nature.¹¹ Under this assumption and using relation (12) we may redefine overall technical (or cost) efficiency as

$$TE^{KP}(\mathbf{z}, t) \equiv \prod_j \left[\frac{g_j(y, \mathbf{z}, t)}{x_j} \right]^{\frac{1}{\sum_j \xi_j}} \quad (13)$$

From the above index of factor specific technical inefficiency, we may derive a complete decomposition formula for partial factor productivity growth. The partial factor productivity growth approach is appropriate when dealing with a production system where significant capital structures are involved and this system is at long-run equilibrium.¹²

¹¹ Akridge (1989) using Kopp's (1981) findings, developed a single factor technical cost efficiency (SFTCE) index defined as the potential cost savings from adjusting a single factor to its technical efficient level, while holding all other inputs at observed levels. This measure may be important in cases where the total outlays of any factor constitute a small proportion of total cost of production.

¹² When estimating a system allowing for dynamic adjustment that is manifested as a linear accelerator, optimal net investment is defined as $\dot{z}^* = m(z^* - z)$, where z^* is the long-run optimal capital stock (that necessarily depends on arguments taken as fixed such as prices), z is the current capital stock and m is the adjustment rate. When $\dot{z}^* = m(z^* - z) = I^* - \delta z$ and $m = \delta$, then $I^* = \delta z$.

Following Reifschneider and Stevenson (1991) and Battese and Coelli (1995) inefficiency effects model, we may assume that factor-specific technical inefficiency defined above, is affected by the utilization of the available capacity by individual firms as well as by time (i.e., autonomous changes due to learning-by-doing effects). Then, taking logarithms and totally differentiating with respect to time relation (12) we obtain¹³

$$\begin{aligned} \widehat{TE}_j^{KP}(z, t) + \sum_k \frac{\partial \ln TE_j^{KP}}{\partial \ln z_k} \hat{z}_k \\ = \frac{\partial \ln g_j(y, z, t)}{\partial \ln z_k} \hat{z}_k + \frac{\partial \ln g_j(y, z, t)}{\partial \ln y} \hat{y} + \frac{\partial \ln g_j(y, z, t)}{\partial t} - \hat{x}_j \end{aligned} \quad (14)$$

where a “ $\hat{\cdot}$ ” over a function or variable indicates its time rate of change. Substituting into (14) the conventional *Divisia* index of partial factor productivity growth, i.e., $P\dot{F}P_j = \dot{y} - \dot{x}_j$ we obtain

$$\widehat{P\dot{F}P}_j = \widehat{TE}_j^{KP}(z, t) + \sum_k \frac{\partial \ln TE_j^{KP}(z, t)}{\partial \ln z_k} \hat{z}_k - \frac{\partial \ln g_j(y, z, t)}{\partial \ln z_k} \hat{z}_k - T_j^t + [1 - \varepsilon_j^{Cy}] \hat{y} \quad (15)$$

where the first two terms constitute the technical efficiency changes, which contributes positively (negatively) to *PF*P growth as long as efficiency changes are associated with movements towards (away from) the production frontier. These changes may be due to

¹³ This formulation implicitly assumes a deterministic frontier. We have adopted this formulation in order for our results to be directly comparable with those of Bauer (1990) and Lovell (1996). However, in implementing the proposed model empirically, it is necessary to take into account the stochastic nature of output and to make additional distributional assumptions to obtain estimates of $TE_j^{KP}(z, t)$. Without loss of generality, these elements are added into the model in the next sections, where specific functional forms for $g(\cdot)$ as well as the mean of $TE_j^{KP}(z, t)$ are imposed.

two factors: (a) the passage of time, i.e., autonomous changes ($\widehat{TE}_j^{KP}(z, t)$, the first term) and, (b) changes in the quantity of quasi-fixed input ($\sum_k \frac{\partial \ln TE_j^{KP}}{\partial \ln z_k} \hat{z}_k$, the second term). If the passage of time does not affect technical efficiency levels or if the level of quasi-fixed input remains constant both terms equal to zero. The third term, $\frac{\partial \ln g_j(y, z, t)}{\partial \ln z_k} \hat{z}_k$, incorporates the sub-equilibrium effects associated with the existence of quasi-fixed inputs (Luh and Stefanou, 1991; Morrison, 1992). If the market price of quasi-fixed inputs coincides with their shadow price then the third term vanishes. In any other case it is positive under capacity over- (under-) utilization as long as the stock of capital increases (decreases) over time. The fourth term, T_j^t , is the factor specific technical change effect which is positive (negative) under progressive (regressive) technical change.¹⁴ The final term, $[1 - \varepsilon_j^{C_y}] \hat{y}$, is the scale effect where the sign depends on both the magnitude of the scale elasticity and the changes of the aggregate output over time. In the context of the non-homothetic Leontief production function adopted in our study, the degree of returns-to-scale can be different for each variable factor of production.¹⁵ It is positive (negative) under increasing (decreasing) returns to scale as long as output produced increases. This term vanishes when either the technology is characterized by constant returns to scale or the aggregate output quantity remains unchanged over time.

¹⁴ One of the properties of the non-homothetic Leontief production function refers that the optimal relative factor intensities may vary across firms if the output levels differ even in the case of Hicks-neutral technical change and in the absence of price changes.

¹⁵ The degree of returns-to-scale could be further vary even for the same input depending on the choice of $g(\cdot)$.

3. Econometric Model

Following previous section, we may rewrite relation (12) by taking logarithms and rearranging terms as

$$\ln x_j = \ln g_j(y, \mathbf{z}, t) - \ln TE_j^{KP}(\mathbf{z}, t) \quad \forall j \quad (16)$$

Substituting $TE_j^{KP}(\mathbf{z}, t)$ with θ_j and assuming an additive two-sided error term in each equation, v_j , capturing unobserved random factors affecting input demands (e.g., exogenous shocks, measurement errors), the econometric model is given by

$$\ln x_j = \ln g_j(y, \mathbf{z}, t) + v_j - \ln \theta_j \quad \forall j \quad (17)$$

where $\varepsilon_j = v_j - \ln \theta_j$ is the familiar composite error term presented in the stochastic frontier literature.

An important issue in the above system is whether dependencies exist between the composite error terms of the different equations. Conceptually, dependence could arise because at a given time, inefficiency in one input for firm i could be correlated with inefficiency in another input for the same firm or because contemporaneous random shocks to different inputs for firm i are correlated or dependent.¹⁶ This study does not distinguish between these two cases, allowing for dependence between the overall composite error terms.

Allowing for dependencies requires the specification of a joint distribution and it is not obvious which joint distribution one should specify given the structure of the composite error term. While researchers estimating stochastic frontier models are keen on imposing different distributional assumptions for the efficiency term, while assuming

¹⁶ Our model can be extended in a straightforward manner to allow for different types of dependencies between the composite error terms.

normality for the two-sided error term, it would be difficult to find and justify any given joint distribution for the composite error terms.

A useful direction to address this issue is the *copula* approach to modeling joint distributions.¹⁷ Broadly speaking a copula is a multivariate distribution with uniform marginals. When a copula uses some given marginal distribution functions as its arguments it will produce a joint distribution whose marginals will coincide with the above and with a given dependence structure. Indeed, in a situation where the marginal distributions, F_j of the J variates x_j are known to the researcher, Sklar's theorem (Sklar, 1959) establishes: if $C:[0,1]^J \longrightarrow [0,1]$ is a copula function then the function $H(x_1, \dots, x_j) = C(F_1(x_1), \dots, F_j(x_j); \rho)$ is a well defined joint distribution function with margins given by F_j .

The advantage of copulas is that they allow the modeling of the marginal distributions separately from that of the dependence structure, making them especially useful in situations where a researcher has some knowledge about the marginal distributions but needs to specify their joint distribution, as in the case posed by the system of derived demand equations above.

4. The Case of U.S. Electric Utility Firms

¹⁷ *Copulas* have been applied especially in the field of finance, where normality could be an untenable assumption when modelling asset returns and asymmetries in the dependence structure of different returns or markets exclude the application of a multivariate normal distribution. For an excellent survey on *copulas* and their applications the reader is referred to Trivedi and Zimmer (2007) while a mathematical treatment of *copulas* can be found in Nelsen (1999).

The application is to a panel of electric utility power generating firms in the United States over the period 1986-1996. The production technology is represented by one output and three inputs, i.e. fuels, the aggregate of labor and maintenance, and capital stocks. Fuels and the aggregate of labor and maintenance are considered as variable inputs whereas the capital stocks are treated as a quasi-fixed input in the production. Variables used in the estimation consist of output, prices and quantities of fuels, the aggregate of labor and maintenance, and capital stocks.

4.1. Model specification

We assume that the derived factor demand equations have the following general form under factor-specific technical inefficiency (Lau and Tamura, 1972)¹⁸

$$\begin{aligned} \ln x_{it}^f &= \beta_0^f + \beta_y^f \ln y_{it} + \beta_d^f D^t + \beta_{dd}^f D^{t^2} + \beta_z^f \ln z_{it} - \ln \theta_{it}^f + v_{it}^f \\ \ln x_{it}^l &= \beta_0^l + \beta_y^l \ln y_{it} + \beta_d^l D^t + \beta_{dd}^l D^{t^2} + \beta_z^l \ln z_{it} - \ln \theta_{it}^l + v_{it}^l \end{aligned} \quad (18)$$

where subscripts $i=1, \dots, N$ and $t=1, \dots, T$ correspond to firms and time, respectively; superscripts f, l are the input indices for fuel and labor; y is the volume of output produced; z is the quasi-fixed input; D^t is a simple time index capturing technical change; x^f and x^l are the levels of fuel and labor use; $u^j = -\ln(\theta^j)$, $j=f, l$ are the one-sided error terms capturing factor-specific technical inefficiency; and, v 's are the two-sided error terms. Given the above specification, factor-specific returns-to-scale are determined by the magnitude of the parameter β_y^j . Specifically, if $\beta_y^j > 1$ input j exhibits

¹⁸ Note that in the case of the non-homothetic Leontief production technology the functional specification of the derived demand equations in (19) may differ across factor of production. For simplicity we keep the same functional specification herein.

decreasing returns to scale; if $\beta_y^j = 1$ constant returns to scale and; if $\beta_y^j < 1$ increasing returns to scale.

Concerning the error terms we make the following assumptions: (a) for each $j = f, l$ v_{it}^j is assumed to be independently and identically distributed according to a normal distribution with mean zero and unknown variance σ_{vj}^2 ; (b) for the technical inefficiency terms $\theta_{it}^j = \exp(-u_{it}^j)$, it is assumed that u_{it}^j are independently distributed according to a normal distribution with mean μ_{it}^j and unknown variance σ_{uj}^2 truncated at zero so that u_{it}^j is non-negative; (c) u_{it}^j is independent from $v_{it'}^{j'}$, as it is traditionally done in the stochastic frontier literature, $\forall j, j' = 1, \dots, J$, $\forall i, i' = 1, \dots, N$, and $\forall t, t' = 1, \dots, T$. The above structure of the inefficiency random term is related to that suggested by Reifschneider and Stevenson (1991) and Battese and Coelli (1995). The composed error term for each equation is given by $\varepsilon_{it}^j = u_{it}^j + v_{it}^j$ and its density function can be derived in a straightforward manner from Battese and Coelli (1995) taking care of the fact that here u_{it}^j enters additively in our case.

In order to fully specify the log-likelihood function, the functional form of the pre-truncation mean of the efficiency terms and that of the copula functions need to be specified. Specifically, we allow the pre-truncation mean of each efficiency term to be time varying through the use of a second degree polynomial in time,¹⁹ to depend on the level of the quasi-fixed factor, capital, and on a dummy indicating deregulation

$$\mu_{it}^j = \delta_0^j + \delta_d^j D^t + \delta_{dd}^j D^{t^2} + \delta_D^j DUM_i + \delta_z^j \ln z_{it} \quad (19)$$

¹⁹ As noted by Karagiannis *et al.* (2002), in this stochastic framework, the autonomous changes in inefficiency can be isolated from those of technical change.

where DUM_i is a dummy reflecting whether the utility is located in a state that has some deregulation plan.

As far as copula specification is concerned, we investigate three different copulas, namely the *Gaussian*, *Clayton* and *Gumbel* which display a disparity of dependence structures. The *Gaussian* copula is defined by $C^G(u, v) = \Phi_2(\Phi^{-1}(u), \Phi^{-1}(v); \rho)$, where Φ_2 is the standard bivariate normal, Φ^{-1} is the inverse of the standard univariate normal and the parameter ρ is the correlation coefficient. This copula exhibits symmetry in its dependence and the type of dependence allowed for is linear only, therefore it will not give a good fit in cases where the type of dependence is different from correlation. The

Clayton copula is defined as: $C^C(u, v) = [u^{-\rho} + v^{-\rho} - 1]^{-\frac{1}{\rho}}$, $\rho \in (0, \infty)$ which exhibits asymmetric dependence with a clustering of values in the left tail and it would fit best data which display higher degree of dependence in the lower left quadrant than in the upper right quadrant. Finally, the *Gumbel* copula is defined as

$C^B(u, v) = \exp\left(-\left[-(\ln u)^\rho + (-\ln v)^\rho\right]^{\frac{1}{\rho}}\right)$ $\rho \in (1, \infty)$ which exhibits asymmetric

dependence with a clustering of values in the right tail and therefore displays higher dependence in the upper right quadrant than in the lower left quadrant.²⁰

Given our distributional assumptions and denoting the probability densities for the fuel and labor composite error terms as f_u^f and f_u^l , respectively, and their respective

²⁰ Note that it is the copula's functional form that dictates the type of dependence while the intensity of the dependence is governed by the parameter ρ . From the three copulas, only the *Gaussian* one allows for negative dependence.

cumulative distributions as by F_{it}^f and F_{it}^l , it is straightforward to write the log likelihood for a given copula function as²¹

$$Ln(B) = \sum_i \sum_t \ln \left[c^k \left(F_{it}^f \left(\varepsilon_{it}^f \right), F_{it}^l \left(\varepsilon_{it}^l \right) \right) \right] + \sum_i \sum_t \ln \left(f_{it}^f \left(\varepsilon_{it}^f \right) \right) + \ln \left(f_{it}^l \left(\varepsilon_{it}^l \right) \right) \quad (20)$$

where, $c^k(F_1, F_2) = \frac{\partial^2 C^k(F_1, F_2)}{\partial F_1 \partial F_2}$ and $k = G, C, B$ for the three alternative copula

specifications discussed previously.

After estimating the underlying system of derived demand equations, the dual and the primal rates of technical change are related to each other as follows²²

$$T_j^t = - \left(\beta_d^j + 2\beta_{dd}^j D^t \right) \quad (21)$$

The hypothesis of zero technical change can be tested by imposing the following restriction: $\beta_d^j = \beta_{dd}^j = 0 \forall j$. If the hypothesis of zero technical change cannot be rejected, the fourth term in (15) is zero, and technical change has no effect on productivity changes. In addition, Hicks-neutral technical change (*i.e.*, passage of time affects equally both variable inputs) can be statistically tested by imposing the restriction that $\beta_d^f = \beta_d^l \wedge \beta_{dd}^f = \beta_{dd}^l$.²³ Then, factor-specific returns to scale are given by

$$\varepsilon_j^{Cy} = \frac{\partial \ln x_{it}^j}{\partial \ln y_{it}} = \beta_y^j \quad (22)$$

²¹ Note that we assume that the dependence structure remains the same across i and t so that the copula function is not indexed by i nor by t . It is possible to model the dependence parameters in the copula function in such a way that they show variation across time and firms but we will assume that they are constant.

²² According to Førsund (1996) and Atkinson and Cornwell (1998), the rate of technical change should be evaluated at the frontier and therefore the marginal effect of time in the one-sided error term is not included in (21).

²³ Conventional LR-test can be used to statistically examine the aforementioned hypothesis.

The hypothesis of constant returns-to-scale can be examined imposing the restriction that $\beta_y^j = 1 \forall j$. If it cannot be rejected the final term in (15) vanishes. Finally, sufficient and necessary condition for homotheticity of the production structure implies the restriction that $\beta_y^f = \beta_y^l$.

Next, given the conditional density of u_{it}^j and the conditional mean of the inefficiency terms the components of the technical efficiency changes effect in (15) are computed as

$$\frac{\partial \ln TE_{it}^j}{\partial t} = (\delta_d^j + 2\delta_{dd}^j D^t) \xi_{it}^j \quad (23)$$

and

$$\frac{\partial \ln TE_{it}^j}{\partial \ln z_{it}} = \delta_z^j \xi_{it}^j \quad (24)$$

where $\xi_{it}^j = \exp\left(-\tilde{\mu}_{it}^j + \frac{1}{2}\tilde{\sigma}^{2j}\right) \frac{1}{\Phi(\lambda_{it}^j)} \left[-\Phi(\eta_{it}^j) + \frac{1}{\tilde{\sigma}^j} \left(\varphi(\eta_{it}^j) - \Phi(\eta_{it}^j) \frac{\varphi(\lambda_{it}^j)}{\Phi(\lambda_{it}^j)}\right)\right]$ and

$\lambda_{it}^j = \frac{\tilde{\mu}_{it}^j}{\tilde{\sigma}^j}$, $\eta_{it}^j = \frac{\tilde{\mu}_{it}^j}{\tilde{\sigma}^j} - \tilde{\sigma}^j$, $\tilde{\mu}_{it}^j = \frac{\sigma_v^{2j} \mu_{it}^j + \sigma_u^{2j} \varepsilon_{it}^j}{\sigma^{2j}}$, $\tilde{\sigma}^{2j} = \frac{\sigma_u^{2j} \sigma_v^{2j}}{\sigma^{2j}} \forall j$. The hypothesis that

factor-specific technical inefficiency is time-invariant can be tested by imposing the restrictions that $\delta_d^j = \delta_{dd}^j = 0 \forall j$. Similarly the hypothesis that the autonomous rate of change in technical inefficiency is common across factors of production implies the following restrictions to the model in (19) $\delta_d^f = \delta_d^l \wedge \delta_{dd}^f = \delta_{dd}^l$.

For the calculation of the sub-equilibrium effects in (15) we need the shadow value of the quasi-fixed input. The price of z at long-run equilibrium is $\frac{C_z + c}{r + \delta}$, where

$C_z = \frac{\partial C(y, \mathbf{w}, \mathbf{z}, t)}{\partial \mathbf{z}}$, c is the user cost of capital, r is the discount rate, and δ is the

depreciation rate of z . The long-run optimal value of z is determined by the first order

condition: $\lambda(w, y, z, t) F_z(\bullet) = \frac{C_z + c}{r + \delta}$, where $\lambda(w, y, z, t)$ is the short-run marginal

product and $F_z(\bullet)$ is the marginal physical product of z . This leads to

$z^* = h\left(\frac{C_z + c}{r + \delta}, y, w, t\right)$, which suggests that the estimation of variable input factors is

linked to the determination of z^* via the components of C_z . However, in the Leontief framework, input demands are independent of input prices.

4.2. Data

The data are those employed in Rungsuriyawiboon and Stefanou (2007) and their construction are described in greater detail therein. As an overview, output variable is represented by net steam electric power generation in megawatt-hour, 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. The price of fuel aggregate 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 $t+1$. The fuel quantities can be calculated by dividing the fuel expenses by the Tornqvist price of fuel aggregate. The aggregate price of labor and maintenance is a cost-share weighted price for labor and maintenance. The price of labor is a company-wide average wage rate. The price of maintenance and other supplies is a price index of electrical supplies from the Bureau of Labor Statistics. The weight is calculated from the

labor cost share of nonfuel variable costs for those utilities with entirely steam power production. Quantities of labor and maintenance equal the aggregate costs of labor and maintenance divided by a cost-share weighted price for labor and maintenance. 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. The price of capital 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.

The final data set is a balanced panel of 72 electric utilities for the years 1986 to 1999. Among these electric utilities, there are 45 electric utilities having all plants located in states within deregulation acts and 27 electric utilities having all plants located in states without the deregulation acts.²⁴ Table 1 represents a summary of the data for all electric utilities.

4.3. Estimation Results

Although the log-likelihood was estimated under the three different copulas, only the results for the *Gumbel* are reported in the next section since it produces the best fit as measured by the *Akaike Information Criterion*. The estimation results are presented in Table 2 and show that the coefficient estimates are statistically significant for both

²⁴ Among the twenty-seven electric utilities located in states without deregulation plan, seven electric utilities, *i.e.*, Empire District Electric, Interstate Power, Kentucky Utilities, Union Electric, UtiliCorp United, Wisconsin Power and Light, and Wisconsin Public Service served states that passed deregulation acts according to the Financial Statistics of U.S. Major U.S. IOUs (1996). However, the data used for these utilities was utility data in that state without deregulation acts only.

variable input demand equations, except for the second-order term for time. The presence of the regulatory dummy leads to declining mean fuel and labor input efficiency levels. Similarly, $\gamma^j = \frac{\sigma_{uj}}{\sigma_{vj}}$ reflects importance of the one-sided error which confirms the presence of inefficiency in the use of both fuel and labor.

A set of hypotheses concerning the presence of technical inefficiency, the production structure and the characterization of technical change are evaluated in Table 3. The null hypotheses concerning overall technical efficiency, technical efficiency for fuel and then technical efficiency for labor are all rejected soundly. Further, technical efficiency is found to be non-neutral and time varying. The assumption of homothetic production is rejected as well as the presence of constant returns to scale over all inputs and for the fuel and labor inputs separately. When testing for technical change, we find that Hicks neutrality is rejected but perceptible technical change is present jointly and separately for the variable inputs. The presence of a regulation effect is not rejected and this regulation effect has a positive but differential impact on the variable inputs. When evaluating the mean percentage change in variable input use given the presence of a regulation effect, we find that fuel use increases by 15.22% while labor use increases much slower at 3.5% reflecting the relative importance of the fuel input in terms of cost share. The results are discussed in the context of two distinct periods: 1986-1991 and 1992-1996 in an attempt to pick up a deregulation anticipation effect on the part of firms to assess if their production decisions reflect this potential change.

4.4. Technical efficiency

Table 4 presents a frequency distribution of technical efficiency measures for both the Kopp (single factor) and Russell technical efficiency measures. For the last nine years of the sample period, the Russell measure is bracketed by the factor-specific measures. Figure 2 provides the trajectory of efficiency levels which shows a gradual increase in all efficiency measures over the period.

In comparison to recent studies addressing technical efficiency for panels of US electric utilities with non-Leontief specifications, Knittel (2002) finds technical efficiency for the Cobb-Douglas specification for coal- and gas-fired plants to average 80% and 94%, respectively, with Hiebert (2002), in contrast, finding fairly high average technical efficiency of 87.9% and 80.5% for coal- and gas-fired plants, respectively, using the more flexible translog specification. Atkinson and Primont (2002) employ a panel of privately-owned electric utilities engaged in steam electric generation for the period 1961-1997. Both dual and distance functions are estimated with a flexible functional form specification of the non-Leontief variety with an average technical efficiency levels of 0.7154 and 0.6675 using the cost and distance functions, respectively. The Russell aggregate TE index estimated here averages higher generally than these studies at 90.3%.

4.5. Productivity growth

Rungsuriyawiboon and Stefanou (2007) estimate efficiency under dynamic adjustment for these electric utility firms and find that the estimated capital adjustment rate is nearly equal to the depreciate rate (3%).²⁵ Since this industry is at a long-run

²⁵ Thermal conversion efficiency is used typically to measure the performance of generating plants. The report of EIA indicates that the standard deviation of an average plant efficiency of steam electric power generating plants measured by thermal conversion efficiency is very low for each plant which supports the

equilibrium position and a Leontief technology is maintained, the shadow value of capital is constant and a proxy for the optimal \hat{z} is generated by regressing gross investment against the arguments (y, z, t) .²⁶

In this setting, only partial productivity growth measures are identified.²⁷ Fuel productivity averages 0.42% with the earlier period growing marginally faster than the later period. The contribution of technical change accounts for more than a third of this growth and is fairly consistent in its contribution over the entire period which can be characterized as modest. The most significant change over the two sub-periods is attributed to the technical efficiency change effect, which accounts for nearly 45% of the fuel productivity growth over the entire period. The later period reflects the impact of efficiency gains in fuel use with the capital adjustment contribution marginally outweighing the autonomous technical efficiency change contribution. The scale effect presents an opposite pattern being a significant contributor to fuel productivity growth in the early period and then being a negative, albeit marginal, contributor in the later period. These results suggest that fuel use decisions were targeted for efficiency gains in the later period as the prospect of deregulation loomed large.

estimation results in Rungsuriyawiboon and Stefanou (2007) that these firms are technically efficient in capital.

²⁶ When testing for the presence of a Leontief technology in the use of capital using fixed effects, we cannot reject the null hypothesis that gross investment depends on (y, z, t) and this estimation is used to generate the predicted \hat{z} .

²⁷ On productivity growth coinciding with our study period of 1987-1996, Atkinson and Primont (2002) find total factor productivity growth of 3.48% and 4.45% for the cost and distance functions estimation, respectively. For their entire study period of 1961-1996, they find negligible growth of 0.27% and 0.67%, for the cost and distance functions, respectively. They report the productivity change and its components for each year and we present the simple average for 1987-1996 period here.

Labor productivity is growing nearly three times faster than fuel productivity over the entire period with most of that growth taking place in the early period. Technological regress is present for labor but quite minor. The technical efficiency change contribution is even more dramatic in this case accounting for 73% of labor productivity growth over the entire period. Contrary to the fuel productivity growth pattern over time, the labor productivity gains from technical efficiency changes in the earlier period dominate the later period gains with the capital adjustment contribution to the efficiency change being the dominating factor with a similar magnitude to that of the fuel productivity growth case. Similar to the fuel productivity growth case, the scale effect presents an opposite pattern being a significant contributor to labor productivity growth in the early period and then being a negative, albeit marginal, contributor in the later period. These results suggest that labor use decisions were targeted for efficiency gains in the earlier period and can reflect the relative importance of managing for fuel productivity gains over labor productivity gains as the prospect of deregulation loomed large.

The capital adjustment effect is nearly the same for both factors by retarding each factor productivity growth by a similar magnitude over the entire period with the earlier period presenting the stronger impact and the later period presenting the most trivial contribution to overall factor productivity growth. This suggests that these firms have made adjustments to the point that the long-run equilibrium capital stock is being maintained.

5. Concluding Comments

The measurement of productivity and technical efficiency is problematic in the presence of factor non-substitution, Leontief technology. With an application to the large, fossil fuel fired steam electric generating utility facilities in the U.S., radial measurement of efficiency are not adequate as this approach can fail to recognize inefficiencies associated with a subset of inputs. With a view toward generalizing the econometric measurement factor demands in this setting, the Leontief technology specification is merged with the copula estimation of cross equation dependences to account for technical efficiency in the estimation of fuel and labor demand. The decomposition of partial factor productivity measures is developed that allow for scale effects, technical change, efficiency change and the impact of capital utilization.

Our results indicate that labor productivity is growing nearly three times faster than fuel productivity over the entire period with most of that growth taking place in the early period. The contribution of technical efficiency improvement is more dramatic for labor productivity growth. When we partition the 1986-96 period into two sub-periods, we find that the labor productivity gains from technical efficiency changes in the earlier period dominate the later period gains with the capital adjustment contribution to the efficiency change being the dominating factor with a similar magnitude to that of the fuel productivity growth case.

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Figure 1. Farrell's and Russell's Measures of Input Technical Inefficiency under Factor Non-substitution.

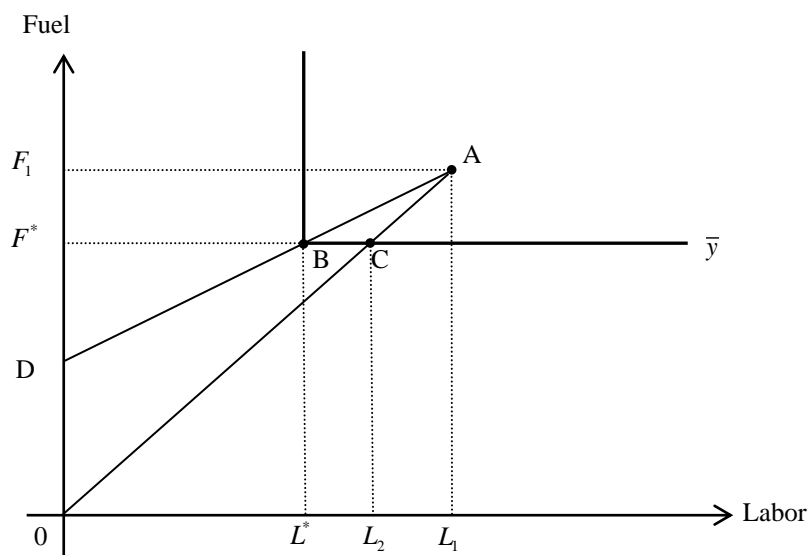


Table 1. Summary Statistics of the Data.

Variable	Mean	Min	Max	S.E.
Output (MWhr)	13,468,219	499,166	75,467,870	11,848,501
Fuel (ths BTU)	129,612	6,094	734,273	119,514
Labor (units)	3,030	80	23,305	2,701
Factor Prices (in US\$):				
Fuel	1.95	1.14	3.56	0.26
Labor	23.61	9.94	45.73	5.16
Factor Shares:				
Fuel	0.764	0.277	0.938	0.094
Labor	0.236	0.062	0.723	0.094

Table 2. Parameter Estimates of Factor Demand Equations for US Electric Utilities.

Parameter	<u>Fuel Input</u>		<u>Labor Input</u>	
	Estimate	S.E.	Estimate	S.E.
β_0	-6.6499	(0.4572)*	-6.8054	(0.4230)*
β_y	0.8036	(0.0282)*	0.5476	(0.0434)*
β_z	0.3668	(0.0436)*	0.4026	(0.0540)*
β_d	-0.0246	(0.0124)**	0.0429	(0.0216)**
β_{dd}	0.0012	(0.0019)	-0.0051	(0.0027)**
δ_0	3.7351	(0.5413)*	3.2524	(1.8432)**
δ_d	0.0082	(0.0044)**	-0.1961	(0.1043)**
δ_{dd}	-0.0020	(0.0034)	0.0104	(0.0112)
δ_D	0.2969	(0.0555)*	0.8378	(0.4102)**
δ_z	-0.2828	(0.0388)*	-0.2797	(0.1788)
σ	0.3121	(0.0184)*	0.6178	(0.1338)*
γ	0.7136	(0.2946)**	1.1098	(0.5563)**
ρ	1.0663	(0.0258)*		
$Ln(\theta)$	-412.391			

Note: Where y stands for output, z for capital, d for time and D for the regulation dummy. * (**) indicate statistical significance at the 1(5) per cent level.

Table 3. Model Specification Tests.

Hypotheses	LR-statistic	Critical Value ($\alpha=0.05$)
<i>Technical Efficiency:</i>		
Technical efficiency (<i>i.e.</i> , $\gamma^j = 0 \forall j$)	33.43	$\chi^2_{(2)} = 5.14$
Technical efficiency in fuel input (<i>i.e.</i> , $\gamma^f = 0$)	21.55	$\chi^2_{(1)} = 2.71$
Technical efficiency in labor input (<i>i.e.</i> , $\gamma^l = 0$)	19.62	$\chi^2_{(1)} = 2.71$
Time invariant inefficiency (<i>i.e.</i> , $\delta_d^j = \delta_{dd}^j = 0 \forall j$)	16.72	$\chi^2_{(4)} = 9.48$
Neutral time varying inefficiency (<i>i.e.</i> , $\delta_d^f = \delta_d^l \wedge \delta_{dd}^f = \delta_{dd}^l$)	15.68	$\chi^2_{(2)} = 5.99$
<i>Structure of Production:</i>		
Homotheticity (<i>i.e.</i> , $\beta_y^f = \beta_y^l$)	36.72	$\chi^2_{(1)} = 3.84$
CRTS (<i>i.e.</i> , $\beta_y^j = 1 \forall j$)	54.98	$\chi^2_{(2)} = 5.99$
CRTS in fuel input (<i>i.e.</i> , $\beta_y^f = 1$)	28.72	$\chi^2_{(1)} = 3.84$
CRTS in labor input (<i>i.e.</i> , $\beta_y^l = 1$)	23.54	$\chi^2_{(1)} = 3.84$
<i>Technical Change:</i>		
Hicks neutral TC (<i>i.e.</i> , $\beta_d^f = \beta_d^l \wedge \beta_{dd}^f = \beta_{dd}^l$)	15.62	$\chi^2_{(2)} = 5.99$
Zero TC (<i>i.e.</i> , $\beta_{dd}^j = \beta_{dd}^j = 0 \forall j$)	19.74	$\chi^2_{(4)} = 9.48$
Zero TC in fuel input (<i>i.e.</i> , $\beta_{dd}^f = \beta_{dd}^f = 0$)	6.02	$\chi^2_{(2)} = 5.99$
Zero TC in fuel input (<i>i.e.</i> , $\beta_{dd}^l = \beta_{dd}^l = 0$)	12.35	$\chi^2_{(2)} = 5.99$
<i>Regulation:</i>		
Absence of regulation effect (<i>i.e.</i> , $\delta_D^j = 0 \forall j$)	12.34	$\chi^2_{(2)} = 5.99$
Neutral regulation effect (<i>i.e.</i> , $\delta_D^f = \delta_D^l$)	9.41	$\chi^2_{(1)} = 3.84$

Note: When the null hypothesis involves the restriction of $\gamma=0$ (first three hypotheses) then the LR-test statistic follows a mixed chi-squared distribution, the critical values of which are obtained from Kodde and Palm (1986, table 1). These first three critical values are for the Wald statistic of the same null hypothesis, where the likelihood ratio is less than the Wald statistic. If likelihood ratio exceeds the critical value of Wald statistic, then so does the Wald test. Consequently, we still reject the null in the first three hypotheses.

Table 4. Frequency Distribution of Technical Efficiency Estimates for US Electric Utilities.

TE (%)	Kopp's Single Factor TE Indices						Russell's Aggregate		
	Fuel Input			Labor Input			TE Index		
	86-96	86-91	92-96	86-96	86-91	92-96	86-96	86-91	92-96
<30	0	0	0	0	0	0	0	0	0
30-40	1	1	2	1	1	1	0	0	0
40-50	4	3	3	0	2	1	2	1	2
50-60	10	10	10	5	6	1	4	9	5
60-70	9	9	7	6	8	6	18	17	14
70-80	20	17	21	24	24	22	20	19	19
80-90	21	24	21	34	29	36	27	26	29
>90	7	8	8	2	2	5	1	0	3
N	72	72	72	72	72	72	72	72	72
Mean	73.8	73.9	73.5	77.4	75.3	80.0	75.1	74.1	76.3
Max	92.7	93.2	92.5	91.9	91.9	91.9	90.3	89.7	90.9
Min	35.2	33.0	37.7	36.6	34.1	39.7	46.4	43.8	45.5

Figure 2. Time Development of Technical Efficiency Estimates for US Electric Utilities.

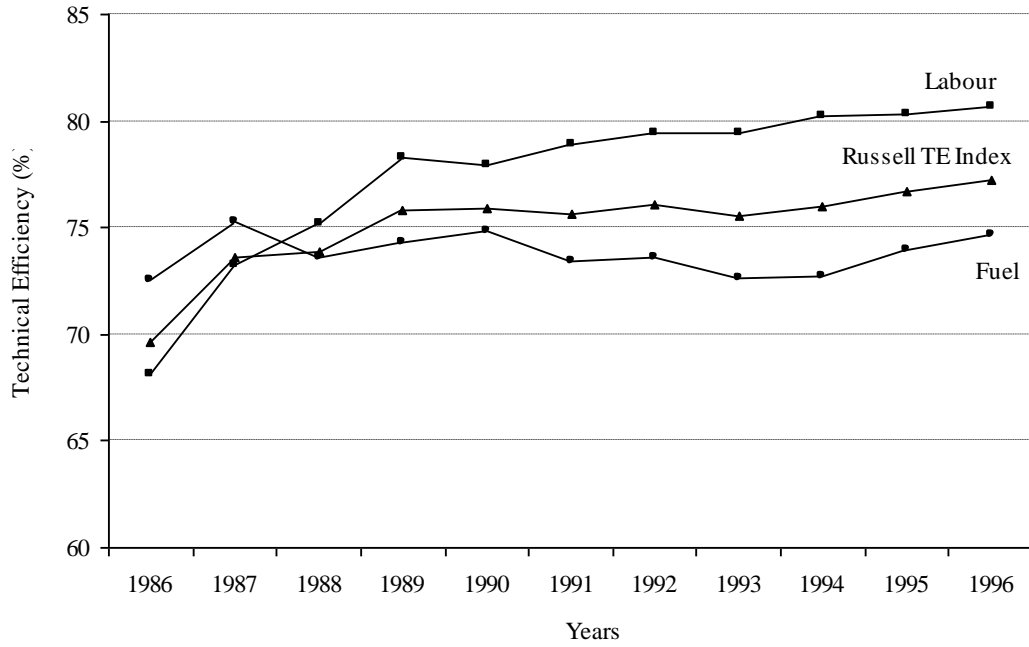


Table 5. Partial Factor Productivity Growth and Decomposition Results for US Electric Utilities (as percentages)

	1986-96	1986-91	1992-96
<hr/>			
<i>Fuel Input</i>			
PFP Growth	0.4233	0.5090	0.3376
Technical Change	0.1560	0.1625	0.1495
Scale Effect	0.2187	0.4929	-0.0555
Capacity Utilization	-0.1382	-0.1686	-0.1078
TE Change	0.1868	0.0221	0.3514
Autonomous	0.0802	-0.0009	0.1613
Capital	0.1065	0.0230	0.1901
<hr/>			
<i>Labor Input</i>			
PFP Growth	1.1115	2.1336	0.0894
Technical Change	-0.0731	-0.0735	-0.0727
Scale Effect	0.5288	1.1355	-0.0778
Capacity Utilization	-0.1517	-0.2549	-0.0485
TE Change	0.8075	1.3265	0.2884
Autonomous	0.7021	1.3233	0.0809
Capital	0.1054	0.0033	0.2075
<hr/>			