# PRODUCTIVITY AND PROFITABILITY CHANGES IN THE U.S. ELECTRIC POWER PLANTS DURING $SO_2$ TRADING REGIME

***SURENDER KUMAR****

## Abstract

We examine the productivity and profitability changes in the US electric generating plants during the $SO_2$ trading regime. Input distance function is used to compute the cumulative Malmquist productivity and Fisher productivity indexes. By exploiting the duality between cost and input distance functions, we obtain a measure of profitability, as an approximation for the Fisher productivity index. We measure productivity and profitability changes when $SO_2$ emissions are ignored in the production technology and when these emissions appear as bad output. We find that the productivity is higher when the bad outputs are modeled as weakly disposable in comparison to the situation when they are modeled as freely disposable. But we do not find any significant difference in profitability under these alternative methods of modeling of production technology concerning the disposability of bad outputs.

**JEL Classification Number**: L5, N5, Q2, Q4

**Key Words**: Electricity Generating Plants, Productivity, Profitability, $SO_2$ *Allowance* program.

----------------------

*Fellow, National Institute of Public Finance and Policy,
New Delhi 110 067, INDIA, E-mail: surender@nipfp.org.in
surenderkumarbansal@hotmail.com

## Acknowledgements

The author wishes to thank Professors Madhu Khanna and M.N. Murty, for their valuable comments on an earlier draft of this paper and encouragement. Helpful comments were provided by the anonymous referee and Dr. Kala S. Sridhar, coordinator, working papers, NIPFP.

# PRODUCTIVITY AND PROFITABILITY CHANGES IN THE U.S. ELECTRIC POWER PLANTS DURING $SO_2$ TRADING REGIME

*SURENDER KUMAR*

## Introduction

The paper aims to examine the changes in productivity and profitability of US electric utility plants during the period of the application of tradable permit system, known as $SO_2$ allowance system. We estimate the input distance function using a panel data on 67 electricity-generating plants for the period 1995-2001. Malmquist productivity and its components — technical efficiency change and technical change are measured on the basis of the estimated parameters. Fisher productivity index has an interpretation in terms of Georgescu-Roegen's (1951) notion of 'return to dollar', a measure of profitability (Althin *et al*., 1996). We also use the parameters of the distance function to measure the changes in profitability over time.

Title IV of the 1990 Clean Air Act Amendments (CAAA) establishes a market for transferable $SO_2$ emissions allowance among electric utilities. Under this system, reduction in $SO_2$ emissions are achieved by setting a cap along with allowing the trading of marketable pollution permits, popularly known as $SO_2$ *allowances*. Here each generating unit of the electricity industry is allocated a fixed number of allowances each year in proportion to emissions during the 1985-87 period and is required to hold one allowance for each ton of $SO_2$ it emits. Electricity generating firms can now transfer allowance among their own facilities, sell them to other firms, or bank them for use in future years. Thus the flexibility provided by this program enables the generating units to pursue a variety of compliance options to meet the regulation obligations, including scrubber installation, fuel switching, energy efficiency and allowance trading. Through emissions trading electricity generating firms have the incentive to find the lowest-cost means of achieving compliance and to reap financial rewards for developing those means. We examine the productivity and profitability changes of these firms during this period of trading in $SO_2$ allowances.

Previous studies have tried to examine the gains from trading in emissions in comparison to command and control alternatives such as forced scrubbing and a uniform emission rate standard (e.g., Carlson *et al*., 2000) or to judge whether there remain opportunities to reduce abatement costs through allowance trading even after plant owners have taken advantages of other cost reducing opportunities (e.g., Swinton, 2002; Coggins and Swinton, 1996). Fare *et al*. (2002) have estimated the total cost of pollution abatement of US electric plants and compared these estimates with the survey estimates of pollution abatement costs incurred by power plants. Kolstad and Turnovsky (1998) have shown that technological change has been substantially sulfur saving, which supports the case that technical progress was responsible at least in part for the drop in abatement costs of $SO_2$ emissions. This explains the differentials of observed prices of $SO_2$ allowance and the predicted abatement costs of these emissions.  But none of these studies have tried to examine the productivity and profitability changes during the period when the sulfur emissions are regulated through an environmental policy which relies on the logic of 'cap and trade' in emissions.

Although the US electric industry has received increasing attention, there are only a few empirical studies on productivity impacts of environmental regulation. To the best of our knowledge, these include Gollop and Roberts (1983) and Yaisawarng and Klien (1994). Gollop and Roberts (1983) used the cost function framework to analyze the effects of $SO_2$ restrictions on the rate of productivity growth in the electric power industry over the period of 1973-1979. They develop a firm specific measure of regulatory intensity and find that emission regulations result in significantly higher generating costs and average rate of productivity growth reduces by 0.59 percentage points per year owing to these regulations. Yaisawarng and Klien (1994) investigated the productivity performance of US power plants during 1985-1989 using a framework similar to the present study. They used the data envelopment analysis (DEA) to compute the cumulative Malmquist input-based productivity index. They account for input used to control sulfur emissions as well as emissions output. They find that productivity decreased from 1985 to each of their three target years, but grew in the last year.

The computation of profitability requires data on the prices of inputs and outputs. Price information can be had for the desired outputs and inputs, but for unwanted products price information does not exist. Like that, productivity is conventionally measured by the index numbers and the computation of index numbers is possible with the data of prices of all outputs and inputs. With regard to prices of bad outputs Repetto *et al*. (1996) suggest the need to establish market valuation for environmental damages, so that reductions in those damages can be credited to firm output. To get information on abatement expenditures, surveys have been used as principal methods but their accuracy has always been the issue of much concern. Moreover, these expenditure estimates are unlikely to be available on yearly basis. Thus, one cannot compute profitability directly, but can retrieve that information indirectly using the duality theory. In this case one can compute Malmquist productivity index using only input and output quantity data and the duality between the input distance function and the cost function provide a measure of profitability, namely Fisher productivity index.

Moreover, the conventional productivity measures, by neglecting the decrease in the $SO_2$ emissions, fail to recognize that a higher proportional increase in the production of good output was feasible with given inputs if adequate efforts had not been made to reduce $SO_2$. Thus, the conventional measures are biased because environmental compliance expenditures by the firms lead to environmental improvements, both the expenditure and improvement should be accounted for in the measurement of productivity changes. An environmentally sensitive measure, when the abatement of pollution is costly, leads to higher productivity growth estimates for a firm because this measure is sensitive to changes in pollution levels and credits the firms for pollution abatement activities while the conventional measure does not. In other words, it can be said that the environmentally sensitive measure accounts not only for the production of marketable outputs but also for producing it with a lower level of sulfur emissions. Therefore the Malmquist index measured with weak disposability of bad outputs is a better indicator of true productivity growth from the social point of view.

Our approach to measure productivity and profitability changes of US electric utility plants during the regime of $SO_2$ allowance program differs from the existing literature. Brannlund *et al*. (1995) have examined the impact on the environmental regulations on firm profits in the Swedish pulp and paper industry. They have adopted the non-parametric programming approach and measure the impact for the cross section data. Althin *et al*. (1996) have provided the theoretical framework for measuring the changes in the productivity and profitability of firms in terms of input distance function when the firm is producing only the good outputs. We apply their results when the firm is producing both good as well as bad outputs and the latter are regulated. Moreover, we take production inefficiency into account in deriving the measure of change in elasticity of scale, a component of profitability. This point contrasts markedly with Althin *et al*. since plants generally operate on different levels of efficiency; therefore taking the inherent inefficiency into account should provide a more realistic measure.

There are several studies on the measurement of productivity changes in industries, which produces good and bad outputs simultaneously during the production process. Some of these studies have treated the bad outputs as inputs,[1] while the others have treated them as a synthetic output such as pollution abatement (e.g. Gollop and Robert, 1983). Sushamamurty and Russell (2002) have pointed out that the treatment of bad outputs as inputs is not consistent with the material balance approach. The approach adopted by Gollop and Robert to treat the reduction in bad output as good output creates a different non-linear transformation of the original variable in the absence of base constrained emission rates (Atkinson and Dorfman, 2002). Pittman (1983) proposed to overcome this problem by treating good and bad outputs non-symmetrically. He was of the view of measuring the maximal radial expansion of good outputs and contraction of bad outputs. Chung *et al*. (1997) has used the directional distance function to calculate production relationships involving good and bad outputs to overcome this problem. The disadvantage of this approach in the present context is that it is difference based whereas the Malmquist productivity index and Fisher index are ratio based. Therefore, following Atkinson and Dorfman (2002) input distance function is used as an analytical tool in the present study. It provides a radial (ratio based) measure of efficiency which signals better performance for observations that are using lesser quantities of inputs for the given level of outputs. This function is less restrictive in the sense that it is not treating the bad outputs, either inputs or pollution abatement, as good output, rather it treats the bad outputs as an 'exogenous' technology shifter.

The remaining paper is organized as follows: The theoretical framework of the study is presented in section 2. Section 3 describes the empirical model. The data set employed in the paper is explained in section 4. The results of the study are discussed in section 5. The conclusions follow in section 6.

## II. Theoretical Framework

[1] Cropper and Oates (1992); Pittman (1981); Haynes *et al*. (1993, 1994), Boggs (1997); Reinhard *et al*. (1999), Murty and Kumar (2003) etc.

Conventionally a firm's performance is assessed by a measure of productivity based on the estimates of production function without considering the joint production of good output and bad outputs (pollution loads). This results in a potentially misleading comparison of productivity of firms producing significant amounts of undesirable outputs, such as water and air pollution. When firms divert resources for reducing undesirable outputs, the input/output ratios of the firm are higher and the productivity of the plant appears lower. It is understood that the constraints imposed by environmental regulation on the decisions of the firm will be subsumed within an overall measure of productivity.

Consider a firm employing a vector of inputs $\boldsymbol{x} \in \Re^{N}_{+}$ to produce a vector of outputs $\mathbf{y} \in \Re^{M}_{+}$ where $\Re^{N}_{+}$, $\Re^{M}_{+}$, are non-negative *N*- and *M*-dimensional Euclidean spaces, respectively. Let $P(\boldsymbol{x})$ be the feasible output set for the given input vector $\boldsymbol{x}$ and $L(\boldsymbol{y})$ is the input requirement set for a given output vector $\boldsymbol{y}$. Now the technology set is defined as (Fare *et al*. 1994)

$$T = \{(\boldsymbol{y}, \boldsymbol{x}) \in \Re^{M+N}_{+}, \boldsymbol{y} \in P(\boldsymbol{x}), \boldsymbol{x} \in L(\boldsymbol{y})\}. \qquad (1)$$

The assumptions about the disposability of outputs become very important in the context of a firm producing both good and bad outputs. The normal assumption of strong or free disposability about the technology implies, *if* $(y_1, y_2) \in P(\boldsymbol{x})$ and $0 \le y_1^* \le y_1$, $0 \le y_2^* \le y_2 \Rightarrow (y_1^*, y_2^*) \in P(\boldsymbol{x})$. This means, we can reduce some outputs given the other outputs or without reducing them. This assumption may exclude important production processes, such as undesirable outputs. For example, in the case of air pollution, Sulfur dioxide ($SO_2$), nitrogen oxides ($NO_x$), and carbon monoxide (CO) are regulated and the firm cannot freely dispose of them. The assumption of weak disposability is relevant to describe such production processes. The assumption of weak disposability implies, *if* $\boldsymbol{y} \in P(\boldsymbol{x})$ *and* $0 \le \theta \le 1 \Rightarrow \theta \boldsymbol{y} \in P(\boldsymbol{x})$. This means a firm can reduce the bad output only by decreasing simultaneously the good output. Hence one can characterise a world where there are non-priced outputs in production that the plant manager has an interest in controlling. The assumption of weak disposability about the production technology enables one to consider this behavior of the firm while defining the factor productivity. For the problem considered here it is convenient to decompose the plant's output vector into two sub-vectors, $\boldsymbol{y} = (\boldsymbol{g}, \boldsymbol{b})$ which represent the desirable output, $\boldsymbol{g}$, and undesirable outputs, $\boldsymbol{b}$, of the production process. The difference between these two types of outputs is captured *via* the disposability assumptions. Here it is assumed that the desirable outputs are freely disposable and the undesirable outputs may only be weakly disposable. That is, the firm may have to expand resources (or reduce 'good' output) to reduce the bad outputs.

### *II. 1. Input Distance Function*

The conventional production function defines the maximum output that can be produced from an exogenously given input vector while the cost function defines the minimum cost to produce the exogenously given output. The output and input distance functions generalize these notions to a multi-output case. The input distance function, $D_i(\mathbf{y},\mathbf{x})$ describes "how far" an input vector is from the boundary of the representative input set, given the fixed output vector.

Formally, the input distance function is defined as

$$D_i^t\left(\mathbf{y}^t,\mathbf{x}^t\right)=\min\{\, l \;:\left[\mathbf{x}^t / l ,\mathbf{y}^t\right]\in T^t\} \qquad (2)$$

Equation (2) characterizes the input possibility set by the maximum *equi*-proportional contraction of all inputs consistent with the technology set (1). These functions are defined for the technology $T^t=\{(\mathbf{x}^t,\mathbf{y}^t):\mathbf{x}^t$ can produce $\mathbf{y}^t\}$, as the 'maximal' feasible proportional contraction of the inputs. The 'mixed' periods function $D_i^0\left(\mathbf{y}^1,\mathbf{x}^1\right)$ and $D_i^1\left(\mathbf{y}^0,\mathbf{x}^0\right)$ are defined in the same manner. The input distance functions can be used to measure the Debreu-Farrell technical efficiency. The input distance function is homogeneous of degree one in inputs and dual to the cost function.[2] That is:

$$C_i([\mathbf{g},\mathbf{b}],\mathbf{w},t)=\min_x\left\{\mathbf{wx} : D([\mathbf{g},\mathbf{b}],\mathbf{x},t)\geq 1\right\} \qquad (3)$$

where $\mathbf{w}$ is a vector of input prices and C is a unit cost function if the costs are minimized. This implies that the value of input distance function would be equal to one only when the inputs are used in their cost minimizing proportions, i.e.,

$$C_i([\mathbf{g},\mathbf{b}],\mathbf{w},t)=\mathbf{wx}/D([\mathbf{g},\mathbf{b}],\mathbf{x},t) \qquad (4)$$

---

[2] For the properties of input distance function, *see* Fare and Primont (1995).

Fare and Primont (1995) show that the shadow price for each input is given by

$$\mathbf{w} = C_i([\mathbf{g},\mathbf{b}],\mathbf{w},t)\nabla_x D_i([\mathbf{g},\mathbf{b}],\mathbf{x},t) \qquad (5)$$

If one assumes that the efficiency measures over the desirable outputs and inputs are well defined and behave as expected, the bad outputs can be treated as exogenous shifters of the technology set similar to a time trend or state of technology variable. The advantage of treating the bad outputs as a shifter of technology is that it credits (penalizes) the firms for reducing (increasing) the level of bad outputs that they produce (Atkinson and Dorfman, 2002). To emphasise the point, the input distance function is now written as:

$$D_i\langle \mathbf{g},\mathbf{x},t \mid \mathbf{b}\rangle = \sup_l \left\{ l : \langle \mathbf{x}/l, \mathbf{g} \mid \mathbf{b}\rangle \in T\langle \mathbf{x},\mathbf{g},t \mid \mathbf{b}\rangle \right\} \qquad (6)$$

Assuming a single bad output, Atkinson and Dorfman have derived the appropriate monotonocity condition for bad outputs as follows. The input distance function is monotonically non-decreasing in inputs $\left(\frac{\partial D_i}{\partial x_n} \geq 0\right)$ and monotonically nonincreasing in good outputs $\left(\frac{\partial D_i}{\partial g_m} \leq 0\right)$. Now assume a single bad output and take the partial total differentiation of the input distance function equation (6) evaluated on the frontier at a fixed time [implying $D_i\langle \mathbf{g},\mathbf{x},t \mid \mathbf{b}\rangle = 1$ and $dt = 0$] to obtain

$$dD_i = \sum \frac{\partial D_i}{\partial g_m} dg_m + \sum \frac{\partial D_i}{\partial x_n} dx_n + \sum \frac{\partial D_i}{\partial b} db = 0$$

In order to keep the firm on the input distance frontier, let $dg_m = 0, \forall m$ and obtain

$$\frac{\partial D_i}{\partial b} = -\sum \frac{\partial D_i}{\partial x_n} \frac{dx_n}{db}$$

With the weak disposability assumption that the disposal of bad outputs is costly, it implies that $\frac{dx_n}{db} \le 0$ which combined with the non-negativity property for inputs $\frac{\partial D_i}{\partial x_n} \ge 0$, yields $\frac{\partial D_i}{\partial b} \ge 0$.

## II. 2. Malmquist Productivity Index

The Malmquist index is defined as the ratio of distance functions. This index requires two mixed period distance function, i.e. t-1,2. The input based Malmquist is defined as the geometric mean of two periods indexes as suggested by Caves *et al*. (1982). Formally the index is defined as:

$$M = \left\{ \frac{D_i^0(\mathbf{y}^0, \mathbf{x}^0)}{D_i^0(\mathbf{y}^1, \mathbf{x}^1)} \frac{D_i^1(\mathbf{y}^0, \mathbf{x}^0)}{D_i^1(\mathbf{y}^1, \mathbf{x}^1)} \right\}^{\frac{1}{2}} \tag{7}$$

The above equation can equivalently be written as:

$$M = \underbrace{\left[ \frac{D_i^0(\mathbf{y}^0, \mathbf{x}^0)}{D_i^1(\mathbf{y}^1, \mathbf{x}^1)} \right]}_{EfficiencyChange} \cdot \underbrace{\left[ \frac{D_i^1(\mathbf{y}^1, \mathbf{x}^1)}{D_i^0(\mathbf{y}^1, \mathbf{x}^1)} \frac{D_i^1(\mathbf{y}^0, \mathbf{x}^0)}{D_i^0(\mathbf{y}^0, \mathbf{x}^0)} \right]^{\frac{1}{2}}}_{TechnicalChange} \tag{8}$$

The first ratio measures the changes in the input-based measure of Farrell technical efficiency between years 0 and 1, i.e., efficiency changes. The geometric mean of the two ratios inside the bracket captures the shift in technology between the two periods. This term measures the technical change, i.e. shift in the production frontier of the firm over time. The value of M greater (less) than unity indicates the improvement (deterioration) over time in productivity.

### II. 3. Fisher Productivity Index and Profitability Changes

To introduce the Fisher productivity index, we need along with inputs and outputs quantity variable, the inputs and outputs price vectors namely $\mathbf{w}^t$, and $\mathbf{p}^t$ respectively also. The Fisher productivity index is defined as the ratio of the Fisher ideal output quantity index and the Fisher ideal input quantity index. Formally

$$F = \left( \frac{\mathbf{p}^1\mathbf{y}^1}{\mathbf{p}^1\mathbf{y}^0} \frac{\mathbf{p}^0\mathbf{y}^1}{\mathbf{p}^0\mathbf{y}^0} \right)^{\frac{1}{2}} \Bigg/ \left( \frac{\mathbf{w}^1\mathbf{x}^1}{\mathbf{w}^1\mathbf{x}^0} \frac{\mathbf{w}^0\mathbf{x}^1}{\mathbf{w}^0\mathbf{x}^0} \right)^{\frac{1}{2}} \tag{9}$$

or

$$F = \left\{ \frac{\mathbf{p}^1\mathbf{y}^1}{\mathbf{w}^1\mathbf{x}^1} \Big/ \frac{\mathbf{p}^0\mathbf{y}^0}{\mathbf{w}^0\mathbf{x}^0} \right\}^{\frac{1}{2}} . \left\{ \frac{\mathbf{p}^0\mathbf{y}^1}{\mathbf{w}^0\mathbf{x}^1} \Big/ \frac{\mathbf{p}^1\mathbf{y}^0}{\mathbf{w}^1\mathbf{x}^0} \right\}^{\frac{1}{2}} \tag{10}$$

Here $\frac{\mathbf{p}^0\mathbf{y}^0}{\mathbf{w}^0\mathbf{x}^0}$ is the Georgescu-Roegen's (1951) notion of 'return to dollar'. The first part of equation (10) measures the current period profitability changes whereas the second part measures the mixed period profitability changes. For the interpretation of the Fisher output oriented productivity index as a measure of profitability for simplicity we assume that prices are constant, i.e., $\mathbf{w}^0 = \mathbf{w}^1$ and $\mathbf{p}^0 = \mathbf{p}^1$ then equation (10) can be written as:

$$\hat{F} = \left\{ \frac{\mathbf{p}^1\mathbf{y}^1}{\mathbf{w}^1\mathbf{x}^1} \Big/ \frac{\mathbf{p}^0\mathbf{y}^0}{\mathbf{w}^0\mathbf{x}^0} \right\} \tag{11}$$

Following the notion of 'return to the dollar', the equation (11) implies that there is an improvement in profitability of the firm if $\hat{F} > 1$, it is constant if $\hat{F} = 1$ and there is deterioration in profitability if the $\hat{F} < 1$.

In order to measure profitability of the firms, we introduce the profit maximization problem as:

$$\prod = \max_{y^t} \left\{ \mathbf{p}^t\mathbf{y}^t - C^t(\mathbf{y}^t, \mathbf{w}^t) \right\}, t = 0,1. \tag{12}$$

The first order condition for profit maximization, when the cost function is differentiable, is given by:

$$p_m^t = \frac{\partial C^t(\mathbf{y}^t, \mathbf{w}^t)}{\partial y_m^t}, m = 1,......,M. \tag{13}$$

From this equation, we get

$$\mathbf{p}^t\mathbf{y}^t = C^t(\mathbf{y}^t, \mathbf{w}^t) e_c(\mathbf{y}^t, \mathbf{w}^t) \tag{14}$$

since $e_c(\mathbf{y}^t, \mathbf{w}^t)$ is the cost elasticity of scale (*see*, Fare and Primont, 1995), i.e.,

$$e_c(\mathbf{y}^t,\mathbf{w}^t)=\sum_{m=1}^{M}\frac{\partial C^t(\mathbf{y}^t,\mathbf{w}^t)}{\partial y_m^t}\frac{y_m^t}{C^t(\mathbf{y}^t,\mathbf{w}^t)} \qquad (15)$$

Thus the 'return to dollar' is equal to the cost elasticity (from equation (14), namely

$$e_c(\mathbf{y}^t,\mathbf{w}^t)=\frac{\mathbf{p}^t\mathbf{y}^t}{C^t(\mathbf{y}^t,\mathbf{w}^t)},t=0,1. \qquad (16)$$

Moreover, the first part of equation (10), that is the simplified measure of change in profitability, using equations (4) and (16), can be written as[3]

$$\bar{F}=\left\{\frac{D_i^0(\mathbf{x}^0,\mathbf{y}^0)}{D_i^1(\mathbf{x}^1,\mathbf{y}^1)}\frac{e_c^1(\mathbf{y}^1,\mathbf{w}^1)}{e_c^0(\mathbf{y}^0,\mathbf{w}^0)}\right\}^{\frac{1}{2}} \qquad (17)$$

This measure requires information on prices of inputs and outputs, and in the context of bad outputs the price information is either absent or not reliable, therefore we need a measure of scale of elasticity based on input and output quantity only. Therefore, we use the primal input-based measure of elasticity of scale, i.e. (*see*, Fare and Primont, 1995)

$$e_{Di}(\mathbf{x},\mathbf{y})=-\sum_{m=1}^{M}\frac{\partial D_i(\mathbf{x},\mathbf{y})}{\partial y_m}\frac{y_m}{D_i(\mathbf{x},\mathbf{y})} \qquad (18)$$

This is also known that $e_{Di}(\mathbf{x},\mathbf{y})=1/e_c(\mathbf{y},\mathbf{w})$, when $D_i(\mathbf{x},\mathbf{y})=1$ (*see,* Fare and Primont, 1995, p.53), therefore, equation (17) can be expressed as:

$$\bar{F}=\left\{\frac{D_i^0(\mathbf{x}^0,\mathbf{y}^0)}{D_i^1(\mathbf{x}^1,\mathbf{y}^1)}\frac{e_{Di}^1(\mathbf{x}^1,\mathbf{y}^1)}{e_{Di}^0(\mathbf{x}^0,\mathbf{y}^0)}\right\}^{\frac{1}{2}} \qquad (19)$$

This equation shows that the change in 'return to dollar' can be expressed as the square root of the product of change in efficiency and scale elasticity. The equation (19) is true when the firms are operating at the frontier, but in practice the value of input distance function is generally observed greater than one, i.e. $D_i(\mathbf{x},\mathbf{y})>1$. Therefore, $D_i(\mathbf{x},\mathbf{y})e_{Di}(\mathbf{x},\mathbf{y})=-e_c(\mathbf{y},\mathbf{w})$, and $\bar{F}$ can be expressed as

[3] $\bar{F}$ and F will not in general be equal since $\bar{F}$ omit mixed period terms.

$$\bar{F} = \left\{ \frac{e_{Di}^{1}(\mathbf{x}^1, \mathbf{y}^1)}{e_{Di}^{0}(\mathbf{x}^0, \mathbf{y}^0)} \right\}^{\frac{1}{2}} \tag{20}$$

Thus the change in return to dollar is the square root of the ratio of scale elasticities over time.

## III. Empirical Model

The computation of Malmquist productivity index and thereby the change in profitability index for US Electric Utilities requires the computation of distance functions. The distance functions can be computed either non-parametrically using the Data Envelope Analysis (DEA) or parametrically. Here we adopt the parametric approach for the computation of distance functions, the advantage of this approach is that it is differentiable. We employ the translog form of input distance function that is twice differentiable and flexible. The form is given by

$$\ln D_i^t(\mathbf{x}^t, \mathbf{y}^t, t) = a_0 + \sum_{n=1}^{N} a_n \ln \mathbf{x}_n^t + \sum_{m=1}^{M} b_m \ln \mathbf{y}_m^t + \frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N} a_{nn'} \ln \mathbf{x}_n^t \ln \mathbf{x}_{n'}^t$$
$$+ \frac{1}{2}\sum_{m=1}^{M}\sum_{m'=1}^{M} b_{mm'} \ln \mathbf{y}_m^t \ln \mathbf{y}_{m'}^t + \sum_{n=1}^{N}\sum_{m=1}^{M} g_{nm} \ln \mathbf{y}_m^t \ln \mathbf{x}_n^t + d_0 t + \frac{1}{2} d_{00} t^2$$
$$+ \sum_{n=1}^{N} g_{nt} t \ln \mathbf{x}_n^t + \sum_{m=1}^{M} g_{mt} t \ln \mathbf{y}_m^t, (21)$$

to compute the parameters of equation (21), we use the linear programming approach developed by Aigner and Chu (1968), that is

minimize $\sum_{k=1}^{K} \{\ln D_i^t(\mathbf{x}^t, \mathbf{y}^t, t) - \ln 1\}, k = 1,2,.....K.$ (22)

subject to

(i) $\ln D_i^t(\mathbf{x}^t, \mathbf{y}^t, t) \geq 0$

(ii) $\dfrac{\partial \ln D_i^t(\mathbf{x}^t, \mathbf{y}^t, t)}{\partial \ln y_m^t} \leq 0, m = 1,.......,i.$

(iii) $\dfrac{\partial \ln D_i^t(\mathbf{x}^t, \mathbf{y}^t, t)}{\partial \ln y_m^t} \geq 0, m = i+1,.......,M.$

(iv) $\dfrac{\partial \ln D_i^t(\mathbf{x}^t, \mathbf{y}^t, t)}{\partial \ln x_n^t} \geq 0, n = 1, \ldots\ldots., N.$

(v) $\sum_{n=1}^{N} a_n = 1, \sum_{n'=1}^{N} a_{nn'} = \sum_{n=1}^{N} g_{nm} = 0, n, n' = 1, \ldots\ldots., N$

(vi) $a_{nn'} = a_{n'n}, b_{mm'} = b_{m'm}, n, n' = 1, \ldots\ldots., N, m, m' = 1, \ldots\ldots, M$

Where K denotes the number of observations. The restrictions in (i) ensures that the value of input distance function is greater than or equal to one as the logarithm of this function are restricted to be greater than or equal to zero. Restriction in (ii) enforces the monotonocity condition of non-increasing of input distance function in good outputs, whereas the restriction in (iii) and (iv) enforces that the input distance function is non-decreasing in bad outputs and inputs respectively. Restriction (v) and (vi) impose the homogeneity and symmetry conditions respectively as required by the theory.

The Malmquist index includes total factor productivity changes due to technical change and technical efficiency changes, to the exclusion of production scale effects (Orea, 2002). The calculation of the growth rate in the Malmquist index in equation (8) was carried out as follows:

$$\ln M = \left[\ln D_i^0(\mathbf{x}^0, \mathbf{y}^0) - \ln D_i^1(\mathbf{x}^1, \mathbf{y}^1)\right] - \frac{1}{2}\left[\frac{\partial \ln D_i^1(\mathbf{x}^1, \mathbf{y}^1)}{\partial t} + \frac{\partial \ln D_i^0(\mathbf{x}^0, \mathbf{y}^0)}{\partial t}\right] \quad (23)$$

This equation provides a meaningful decomposition of $\ln M$ into changes in technical efficiency and technical changes. The negative sign of the second term transforms technical progress (regress) into positive (negative) value. This decomposition has the same structure as the traditional input-oriented Malmquist productivity index introduced by Caves *et al*. (1982).

## IV. Data

Since we are interested in the productivity and profitability effects of controlling $SO_2$ emissions under the *Allowance* program since 1995 to 2001, we restricted our attention to electricity generating plants for which each generating unit had a minimum installed nameplate generating capacity of 25 megawatts.[4] We exclude from our sample plants, which have missing data or reporting errors in a specific year. The deterministic linear programming is sensitive to outliers, to minimize the effects of outliers; we first examined the ratios of each of output to each input and compared their descriptive statistics across periods. If we observed any abnormality for any plant for a specific year, we excluded that plant from our data set. Thus our balanced panel data consist of 67 electric generating plants for the years 1995-2001.

The process of fossil-fueled electricity generation typically uses three conventional inputs; namely, fuel, labour, and capital to produce electricity and emissions of sulfur dioxide. The data come primarily from two government agencies — the Federal Energy Regulatory Commission (FERC) and the US Environmental Protection Agency (EPA). These agencies have over the years provided the public with access to data concerning regulated utilities and pollution. The FERC maintains an online database of FERC Form 1 for the years 1994 to the present. The Form 1 provides annual information of electricity production activities at the plant level. The EPA maintains an emissions database for all major US pollution sources. Its Aerometric Information Retrieval System (AIRS) database is the source of $SO_2$ data for the years 1995 to the present. The 1990 CAAA required all affected power plants to install continuous emission monitoring system (CEMS) by 1995. Consequently, all $SO_2$ data from 1995 on are CEMS stack readings.

In summary, our data set consists of a balanced panel of 67 steam electric utility plants operating during 1995-2001. Variables in the dataset include net generation, fuel input, labour and capital. We employ total net generation in million kilowatt-hours (kWh), fuel in $10^{12}$ British thermal units (BTUs) of heat content to neutralize the heterogeneous nature of coal as well as to allow for different type of fuel inputs. Labour is measured as the annual average number of employees. Capital is measured in 1996 million dollars. We use this measure of capital rather than the installed nameplate capacity because we are interested not only in the generating capacity of a plant, but also the extent to which the plants have invested in equipment to reduce $SO_2$ emissions. The descriptive statistics are provided in Table 1.

---

[4] Since only the units whose nameplate generating capacity is greater than 25 megawatts are covered under the *Allowance* program.

## V. Results

The input distance function in (21) is estimated with and without pollutant outputs. This allows us to examine the importance of the inclusion of environmental effects of production activities in our analysis of productivity and profitability changes. In Table 2 the estimated parameters for a deterministic distance function following the approach described in section 3 are presented. Both models, when $SO_2$ is considered (model1) and when $SO_2$ is ignored (model2) yield first order coefficients on inputs that have signs consistent with economic theory. That is the positive signs of inputs with respect to the input distance function indicate that the value of the function is non-decreasing with respect to inputs, i.e., as inputs are used more efficiently, a firm becomes closer to the frontier. The distance functions satisfy the regulatory conditions on good outputs and convexity on inputs and bad outputs for average values of the explanatory variables.

As described earlier the input distance function serves as an input-based measure of technical efficiency, the yearly average value of this function in both the models are presented in Table 3. We observe that the efficiency scores when $SO_2$ emissions are ignored are lower in comparison to the situation when this pollutant is considered. It reveals that the potential to increase the production of electricity with the given bundle of input decreases as the power plants are not allowed to freely dispose off the emissions of sulfur dioxide. On average the performance of these electricity producing firms ranges from 0.695 to 0.813, revealing that 19 to 30.5 percent of the current conventional inputs can be saved by improving managerial style and reorganization to the best observed practice. It is also observed that under both the situations, the average efficiency scores are decreasing continuously. The difference in technical efficiency under these two alternative formulations of production technology remains constant up to 1999 and it starts to increase after that.

Tables 4 and 5 present the average Malmquist productivity and Fisher productivity indexes. In these tables we present also the components of Malmquist productivity indices, viz., technical efficiency changes and technological changes. (Results by plants are available from the author). Here it should be noted that Malmquist index represent an aggregate measure of ‘true’ productivity changes over time rather than a theoretical change, as it takes into account changes in technical efficiency over time also. Our methods of computing the productivity changes and its components as well as profitability changes reflected by the Fisher productivity look at marginal changes between adjunct periods. Recall that index values greater (less) than one denote improvements (deterioration) in the relevant performance. Here we have calculated all the indices for both cases: when $SO_2$ is ignored and when $SO_2$ is considered as bad output in the production process.

When the technology is modeled assuming that power plants can dispose off the emissions of sulfur dioxide without incurring extra costs for the given level of electricity, as is conventionally done, the Fisher index shows profitability declines through 1996 to 2001 (Table 5). The Malmquist productivity index has value less than unity for all the study years in comparison to the adjunct years. The decomposition of the Malmquist index reveals that technical efficiency change index has value less than one in all the years, except 2000, when it is almost equal to one. Which implies that technical efficiency is declining over the study period. The technological change index has value less than one through out the study period. The changes in the technical efficiency change index and technological change index explain the variation in the Malmquist productivity index.

When the $SO_2$ emissions are considered in the production technology, we observe that the movements in the Malmquist productivity index and its components are in the same direction as they are when the production technology assumes that pollution can be thrown away without incurring any cost. Unlike Malmquist index, the Fisher index has lower values for all the study years when the disposal of $SO_2$ is costly in comparison to the situation when the disposal of sulfur dioxide emissions is free and in both the situations its value is less than one and declining over time. The comparison of technical efficiency change and technological change under alternative production technologies reveals that when the pollution is modeled as bad output in the production process the electricity generating plants observe high technical efficiency change and technical change in comparison to the production process when $SO_2$ is assumed to be freely disposable in the production process.[5]

Managi *et al*. (2002) takes the ratio of productivity index measures under weak and strong disposability of bad outputs as a measure of productivity index of environmental outputs. We extend this

---

[5] As pointed out by the reviewer, if the information on the actual trade in $SO_2$ permits are available, it is possible to use the magnitude of this trade and the prices of the traded permits (as a proxy for the price of the bad output), and work out productivity and profitability indexes. This could be compared with the distance function based measures. Unfortunately, this information is not available at the plant level.

concept to the measures of profitability also. The ratio of profitability under weak and strong disposability of bad outputs measures the change in profitability owing to changes in the environmental outputs. Table 6 presents the ratios of Malmquist productivity and Fisher productivity index under these alternative production technologies concerning the disposability of bad outputs. This table shows that the index of environmental productivity is greater than one through out the study period, crediting the firms for the efforts taken on pollution abatement. But the environmental profitability figure is less than one in the first two years and it becomes greater than one for the next three years and again it becomes less than one in the last year, i.e. we are not observing a consistent trend in environmental profitability. To measure whether the environmental productivity and environmental profitability figures are different from one, we apply the various non-parametric tests (Table 7). From these non-parametric tests it is clear that the environmental productivity figures are statistically different from one, but the figures of environmental profitability are not different from one for the whole sample. But when these tests are applied for yearly figures, it was found that environmental productivity statistically differs from one during 1998-2001 and environmental profitability statistically differs from one only in 1999-2000.

At the annual mean level, we observe that the difference in productivity and profitability under alternative production technologies concerning the disposability of bad output is very low. This low level of difference under weak and strong disposability conditions in productivity and profitability can be explained by the fact that the US electricity industry is under regulation since decades and making environmental compliance efforts by investing in abatement technologies. Therefore, the modeling of these firms under the assumption of free disposability of bad outputs may be biased and it reduces the difference in productivity and profitability under alternative production technologies (Fare *et al*., 2002).

## VI. Conclusion

In this paper, we have developed and illustrated an analytical framework for calculating plant specific productivity and profitability measures. A distinguishing feature of this framework is that it provides two-piece information simultaneously. It describes the structure of production technology, and it provides measures of productivity and profitability for each producer. The major advantage of this framework is that it does not require price information for measuring productivity and profitability of producer.

We estimated productivity and profitability changes for a sample of 67 electricity-generating plants during the years 1995 to 2001, the period of $SO_2$ allowance system. We have done this by employing the input distance function, and then computing Malmquist and Fisher indexes in the conventional way ignoring the production of $SO_2$ emissions and considering them as bad output in the production process. We have found that during this era of market-based regulation, productivity and profitability is declining under both the production technology situations. It is observed that when the emissions of sulfur are included, the productivity of the electricity-producing firms is slightly higher in comparison to the situation when it is measured in conventional way, crediting the firms for their abatement efforts. Moreover, it is observed that gap in profitability owing to environmental regulations does not manifest symmetry of any form.

## References


Aigner, D. J. and S. F. Chu (1968), “Estimating the industry production function”, *American Economic Review* 58, Pp.826-39.

Althin, R., R. Fare and S. Grosskopf (1996), “Profitability and productivity change: an application to Swedish pharmacies”, *Annals of Operations Research*, 66, Pp. 219-230.

Atkinson,S.E. and R.H. Dorfman (2002), "Bayesian measurement of productivity and efficiency in the presence of undesirable outputs: crediting electric utilities for reducing air pollution", Department of Economics, University of Georgia, Athens.

Boggs, R.L. (1997), *Hazardous Waste Treatment Facilities: Modeling Production with Pollution as Both an Input and an Output*. Unpublished Ph.D. dissertation, University of North Carolina, Chapel Hill.

Brannlund, R., R. Fare and S. Grosskopf (1995), “Environmental Regulation and Profitability: An Application to Swedish Pulp and Paper Mills”, *Environmental and Resource Economics,* 6, Pp. 23-36.

Carlson, C., D. Burtraw, M. Cropper, and K. L.Palmer (2000), “Sulfur Dioxide Control by Electric Utilities: What Are the Gains from Trade?”, *Journal of Political Economy,* 108(6), Pp. 1292–1326.

Caves, D.W., L.R. Christensen and W.E. Diewert (1982), “The economic theory of index numbers and the measurement of input, output, and productivity”, *Econometrica,* 50, Pp. 1993-40.

Chung, Y., R. Fare and S. Grosskopf (1997), "Productivity and undesirable outputs: a directional distance function approach", *Journal of Environmental Management,* 51, Pp. 229-240.

Coggins, J.S. and J.R. Swinton (1996), “The price of pollution: a dual approach to valuing $SO_2$ allowances”, *Journal of Environmental Economics and Management,* 30, Pp. 58-72.

Cropper, M.L. and W.E. Oates (1992), “Environmental Economics: A Survey”, *Journal of Economic Literature,* XXX:2 (June), Pp. 675-740.

Fare, R. and S. Grosskopf and C.A.K. Lovell (1994), *Production Frontiers*, Cambridge: Cambridge University Press.

Fare, R.; S. Grosskopf and C. Pasuraka (2002), “Estimating pollution abatement costs: a comparison of ‘stated’ and ‘revealed’ approaches”, Paper presented at the Second World Congress of the Association of Environmental and Resource Economists held at Monterey, CA, during June 23-27.

Fare, R. and D. Primont (1995), *Multi-Output Production and Duality: Theory and Applications.* The Netherlands: Kluwer Academic Publishers.

Georgescu-Roegen, N. (1951), “The aggregate linear production function and its applications to von Neumann’s economic model” in Koopmans, T. (*ed*). *Activity Analysis of Production and Allocation*. New York: Wiley. Pp. 98-115.

Gollop, Frank M., and Mark J. Roberts (1983), “Environmental regulations and productivity growth: the case of fossil-fueled electric power generation”. *Journal of Political Economy* 91, Pp. 654–74.

Haynes, K.E., S. Ratick, W.M. Bowen and J. Cummings-Saxton (1993), “Environmental Decision Models: U.S. Experience and a New Approach to Pollution Management”, *Environment International* 19, Pp. 261-75.

Haynes, K.E., S. Ratick and J. Cummings-Saxton (1994), “Toward a Pollution Abatement Monitoring Policy: Measurements, Model Mechanics, and Data Requirements”, *The Environmental Professional,* 16, Pp. 292-303.

Kolstad, Charles D., and Michelle H. L. Turnovsky (1998), “Cost functions and nonlinear prices: estimating a technology with quality-differentiated inputs”, *Review of Economics and Statistic,* 80, Pp. 444–53.

Managi, S., J.J. Opaluch, D. Jin. And T.A. Grigalunas (2002), "Environmental regulations and technological change in the offshore oil and gas industry: rethinking the Porter hypothesis", Department of Environmental and Natural Resource Economics, University of Rhode Island, Kingston, Rhode Island, (Working paper).

Murty, M.N. and Surender Kumar (2003), *Environmental and Economic Accounting for Indian Industry*, New Delhi: Oxford University Press (forthcoming).

Orea, L. (2002), “Parametric decomposition of a generalized Malmquist productivity index”, *Journal of Productivity Analysis,* 18, Pp. 5-22.

Pittman, R.W. (1981), “Issues in Pollution Control: Interplant Cost Differences and Economies of Scale”, *Land Economics,* 57:1 (February), Pp. 1-17.

Pittman, R.W. (1983), "Multilateral productivity comparisons with undesirable outputs", *The Economic Journal,* 93, Pp. 883-891.

Reinhard, S., C.A.K. Lovell and G. Thijssen (1999), “Econometric Estimation of Technical and Environmental Efficiency: An Application to

Dutch Dairy Farms", *American Journal of Agricultural Economics,* 81:1 (February), Pp. 44-60.

Repetto, R., *et al* (1996), "Has Environmental Protection Really Reduced Productivity Growth", World Resource Institute, Washington DC.

Sushamamurty, M. and R. Russell (2002), "On modeling pollution generating technologies", University of California, Riverside.

Swinton, J.R. (2002), "The Potential for Cost Savings in the Sulfur Dioxide Allowance Market: Empirical Evidence from Florida", *Land Economics,* 78(3), Pp. 390-404.

Yaisawarng, S, and D.J. Klein (1994), "The effects of sulphur dioxide controls on productivity change in the U.S. electric power industry", *Review of Economics and Statistics,* 96, Pp. 447-60.

**Table 1:** Descriptive Statistics of the Variables Used in the Study

| | Electricity ($10^6$ kWh) | $SO_2$ (tons) | Labour | Capital (Million $) | Heat ($10^{12}$ BTU) |
|---|---|---|---|---|---|
| 1995 | | | | | |
| Mean | 2946.31 | 24481.61 | 138.5 | 230.34 | 38.5 |
| Maximum | 13595.7 | 145577 | 419 | 1598.47 | 233 |
| Minimum | 117.5 | 309 | 31 | 17.23 | 1.74 |
| Std. Dev. | 2822.60 | 31933.65 | 97 | 257.59 | 39.17 |

| | | | | | |
|---|---|---|---|---|---|
| 1996 | | | | | |
| Mean | 3489.75 | 26322.32 | 136.75 | 216.87 | 40.27 |
| Maximum | 26631.2 | 180590.8 | 405 | 1570 | 212 |
| Minimum | 165.3 | 335.4 | 29 | 17.2 | 2.42 |
| Std. Dev. | 4178.76 | 35979.34 | 97.48 | 231.68 | 38.81 |
| 1997 | | | | | |
| Mean | 3230.74 | 28330.03 | 127.55 | 304.27 | 42.89 |
| Maximum | 16009.8 | 183797 | 392 | 3218.24 | 218 |
| Minimum | 145.5 | 107 | 29 | 17.07 | 2.18 |
| Std. Dev. | 3090.25 | 37988.25 | 88.29 | 555.58 | 40.66 |
| 1998 | | | | | |
| Mean | 3154.08 | 30193.88 | 138.51 | 216.95 | 47.16 |
| Maximum | 10904.3 | 167623.5 | 746 | 1520.93 | 217 |
| Minimum | 171.8 | 786.9 | 29 | 16.86 | 3.99 |
| Std. Dev. | 2727.40 | 35155.93 | 131.59 | 234.42 | 40.77 |
| 1999 | | | | | |
| Mean | 3085.06 | 26221.09 | 131.16 | 206.86 | 44.27 |
| Maximum | 11275.6 | 119655.6 | 717 | 1502.59 | 231 |
| Minimum | 7.09 | 185.2 | 31 | 17.10 | 3.99 |
| Std. Dev. | 2548.49 | 30323.26 | 111.68 | 220.48 | 39.68 |
| 2000 | | | | | |
| Mean | 3554.68 | 24498.22 | 121.64 | 220.55 | 44.74 |
| Maximum | 14516.1 | 156037 | 384 | 1467.02 | 231 |
| Minimum | 310.8 | 503 | 31 | 18.06 | 4.41 |
| Std. Dev. | 2947.51 | 30460.54 | 84.41 | 232.23 | 39.94 |
| 2001 | | | | | |
| Mean | 3245.73 | 24410.58 | 131.66 | 206.14 | 44.49 |
| Maximum | 10595.03 | 135934.9 | 532 | 1443.16 | 201 |
| Minimum | 250.4 | 783.1 | 31 | 19.28 | 3.28 |
| Std. Dev. | 2598.45 | 28471.66 | 103.96 | 213.85 | 38.68 |

**Table 2:** Translog Input Distance Function Coefficients

| Variable | Model1 | Model2 | Variable | Model1 | Model2 |
|---|---|---|---|---|---|
| Electricity (y1) | -0.523 | -0.508 | x1*x3 | 0.010 | 0.019 |
| $SO_2$ (y2) | -0.056 | . | x2*x3 | -0.014 | -0.012 |
| Labor (x1) | 0.560 | 0.477 | y1*x1 | -0.009 | -0.011 |
| Capital (x2) | 0.091 | 0.101 | y1*x2 | 0.004 | 0.003 |
| Heat Input (x3) | 0.349 | 0.423 | y1*x3 | 0.005 | 0.008 |

| | | | | | |
|---|---|---|---|---|---|
| Time (t) | -0.075 | -0.096 | y2*x1 | -0.013 | . |
| $Y1^2$ | 0.032 | 0.028 | y2*x2 | 0.008 | . |
| $Y2^2$ | -0.003 | . | y2*x3 | 0.005 | . |
| $X1^2$ | 0.085 | 0.073 | y1*t | 0.022 | 0.021 |
| $X2^2$ | -0.016 | -0.011 | y2*t | 0.0004 | . |
| $X3^2$ | -0.052 | -0.066 | x1*t | 0.003 | 0.0003 |
| $t^2$ | -0.009 | -0.008 | x2*t | -0.001 | -0.0003 |
| Y1*y2 | -0.005 | . | x3*t | -0.002 | 0.00001 |
| X1*x2 | -0.013 | -0.004 | Intercept | 3.240 | 2.927 |

**Note**: Model1: $SO_2$ is considered.
Model1: $SO_2$ is ignored.

**Table 3:** Values of Input Distance Function**.**

| Year | $D_i(\mathbf{x}, \mathbf{y})*$ | $D_i(\mathbf{x}, \mathbf{y})**$ |
|---|---|---|
| 1995 | 1.231 | 1.232 |
| 1996 | 1.285 | 1.287 |
| 1997 | 1.338 | 1.343 |
| 1998 | 1.411 | 1.414 |
| 1999 | 1.438 | 1.460 |
| 2000 | 1.420 | 1.453 |
| 2001 | 1.440 | 1.486 |

**Note**: $D_i(\mathbf{x}, \mathbf{y})$ *: $SO_2$ is considered, $D_i(\mathbf{x}, \mathbf{y})$ **: $SO_2$ is ignored.

**Table 4:** Values of Productivity and Profitability Index Numbers when $SO_2$ is considered.

| Year | Efficiency Change | Technical Changes | Malmquist Index | Fisher Index |
|---|---|---|---|---|
| 1996 | 0.958 | 0.954 | 0.914 | 0.855 |
| 1997 | 0.960 | 0.961 | 0.923 | 0.834 |

| | | | | |
|---|---|---|---|---|
| 1998 | 0.948 | 0.970 | 0.920 | 0.851 |
| 1999 | 0.981 | 0.979 | 0.961 | 0.815 |
| 2000 | 1.013 | 0.986 | 0.999 | 0.814 |
| 2001 | 0.985 | 0.994 | 0.979 | 0.763 |

**Table 5:** Values of Productivity and Profitability Index Numbers when $SO_2$ is ignored.

| Year | Efficiency Change | Technical Change | Malmquist Index | Fisher Index |
|---|---|---|---|---|
| 1996 | 0.956 | 0.952 | 0.910 | 0.867 |
| 1997 | 0.958 | 0.958 | 0.918 | 0.851 |
| 1998 | 0.950 | 0.965 | 0.917 | 0.846 |
| 1999 | 0.968 | 0.973 | 0.943 | 0.815 |
| 2000 | 1.005 | 0.979 | 0.984 | 0.748 |
| 2001 | 0.976 | 0.986 | 0.962 | 0.783 |

**Table 6 :** Environmental Productivity and Profitability Changes.

| Year | Environmental Productivity | Environmental Profitability |
|---|---|---|
| 1996 | 1.005 | 0.986 |
| 1997 | 1.006 | 0.980 |

| | | |
|---|---|---|
| 1998 | 1.003 | 1.006 |
| 1999 | 1.019 | 1.000 |
| 2000 | 1.015 | 1.088 |
| 2001 | 1.017 | 0.974 |

**Table 7 :** Values of Various Non-Parametric Tests**.**

| Non-Parametric Test | Environmental Productivity | Environmental Profitability |
|---|---|---|
| **Mean** | | |
| t-test | 3.54(0.0004) | 0.583(0.56) |
| Anova F-test | 12.52(0.0004) | 0.340(0.56) |
| **Median** | | |
| Wilcoxon/Mann-Whitney | 3.35(0.0008) | 0.996(0.32) |
| Med. chi-square | 7.84(0.005) | 0.000(1.00) |
| Adj. Med. Chi-square | 7.46(0.006) | 0.005(0.94) |
| Kruskal-Wallis | 11.21(0.0008) | 0.994(0.32) |
| Van der Waerden | 12.73(0.0004) | 1.020(0.31) |

**Note:** Values in parentheses are the probabilities.