Incorporating Undesirable Outputs into Malmquist TFP Index: Environmental Performance Growth of Chinese Coal-Fired Power Plants

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Incorporating Undesirable Outputs into Malmquist TFP Index: Environmental Performance Growth of Chinese Coal-Fired Power Plants

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Abstract

In this article we examine the effects of undesirable outputs on the Malmquist TFP indices. Our empirical work uses an unbalanced panel which covers 796 utility and non-utility coal-fired power plants in China during 1996-2002. In order to meet the requirement of a balanced panel for calculating the Malmquist indices, an innovative fake unit approach has been introduced. Our final results show that (1) the growth of the Chinese electricity heavily depends upon an increase of resource input; and (2) huge potential remains with regards to the efficiency improvement and emissions control in Chinese coal-fired power plants.

Keywords: Malmquist indicies, total factor productivity, Chinese electricity, power plant efficiency

JEL classification: D24, L94

1. Introduction

Although it is widely acknowledged in efficiency analysis literature that analysts should consider the effects of undesirable outputs, in studies of productivity change analysis, very few published papers have taken these effects into consideration. As environmental concern increases, there is a more urgent need for us to consider such effects. Following a discussion of previous literature on the Malmquist TFP index, this paper attempts to contribute to the discussion of this concern in three ways. Firstly, it attempts to incorporate undesirable outputs into productivity change measurement by introducing a new emission-incorporated Malmquist TFP index. Secondly, this paper tries to define a pure environmental performance index based on previous studies on attribute-incorporated Malmquist indices. Thirdly, this research attempts to provide a relatively objective analysis of performance growth in Chinese coal-fired power plants. Lam and Shiu (2004) reported a 2.1% annual TFP growth of the Chinese electricity generation sector between 1995 and 2000, using a DEA benchmarking approach. However, their paper represented more of a snapshot of the Chinese electricity industry, rather than a complete investigation. This is because the number of observations made was quite small. The data used included annually aggregated figures in terms of administrative provinces, and only 30 DMUs were studied. Also, they only considered traditional inputs and outputs, leaving emissions resulting from electricity generation

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unconsidered. However, the large share of coal-fired generating capacity has caused serious economic and environmental problems in China. So the incorporation of emissions into productivity change evaluation becomes necessary.

The panel data sample used in this research covers 796 utility and non-utility coal-fired power plants, distributed throughout 12 provinces in the mainland of China between 1996 and 2002. The total generating capacity of the sample was about 104GW in 2002. Calculating the Malmquist index normally requires a balanced panel data sample. However, during the report period many new power plants were built while old power plants were shut down on an annual basis. Apparently, it is therefore very hard to meet this balanced requirement. In order to solve this problem, this research introduces an innovative 'fake' decision-making unit approach. To the authors' knowledge, no other published papers on TFP change have used this method before.

In this paper, section 2 reviews previous literature on both the traditional Malmquist TFP and the attribute-incorporated Malmquist indices. Section 3 outlines the research methodology. Both an emission-incorporated Malmquist TFP index and a pure environmental performance index are defined in this section. Section 4 describes the research data, and also summarizes techniques for introducing a fake unit into the DEA-related Malmquist model. Section 5 reports the empirical results and section 6 concludes the paper.

2. Literature Review

2.1 Traditional Productivity Change Index

Analysis using index numbers to measure the TFP change of various production processes has been conducted for many years. Nishimizu and Page (1982) proposed a method to decompose TFP change into technical change (*TECHCH*) and technical efficiency change (*EFFCH*) when examining productivity change in Yugoslavia between 1965 and 1978. *TECHCH* was defined as change in the best practice production frontier, while *EFFCH* was defined to include all other productivity change, including 'learning by doing, diffusion of new technological knowledge, improved managerial practice, and so on'. In Nishimizu and Page's decomposition, the total TFP change is the sum of *TECHCH* and *EFFCH*. Bauer (1990) extended the decomposition of TFP change by showing how changes in cost efficiency might affect TFP growth. Generally, the above explorations require the arbitrary selection of a functional form for production technology, whereas the methods used below entail a non-parametric DEA approach.

Fare et al. (1994) calculated the TFP index as the geometric mean of two Malmquist productivity indices, the latter of which was introduced by Caves et al. (1982a, 1982b). Assume that the production technology S^t at time *t* can be written as

$$S^t = \{ (x^t, y^t) : \text{inputs} \;\; x^t \;\; \text{can be used to produce} \; y^t \},$$

where $x^t \in R_+^N$ denotes input bundles and $y^t \in R^+$ refers to output bundles for time *t* (*t* = 1,…, T). Fare et al. (1994) then defined the output distance function at time *t* as

$$D_c^t(x^t, y^t) = Inf\{\theta : (x^t, y^t/\theta) \in S^t\},$$

where $D_c^t(x^t, y^t) \le 1$ if and only if $(x^t, y^t) \in S^t$ under CRS assumption. Similarly, the output distance function at time *t+1* can also be defined. To calculate the related Malmquist index, two more distance functions have to be defined with respect to two different time periods. One is to measure the distance of production (x^{t+1}, y^{t+1}) relative to technology at time *t*, and the other is that of production (x^t, y^t) relative to technology at time *t+1*.

Figure 1: Output Distance Function and the Malmquist TFP Change Index

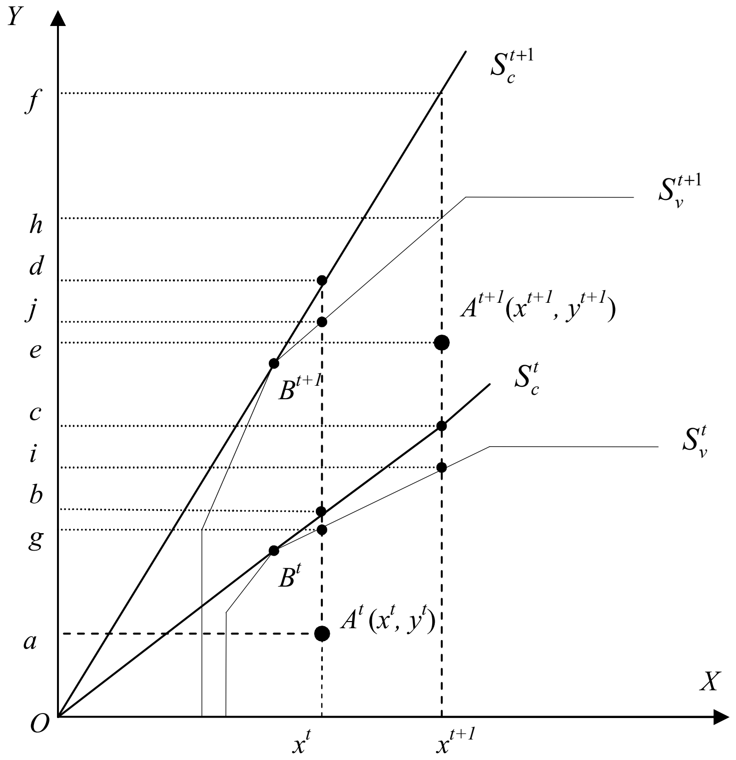

Figure 1 shows the calculation of output distance functions. In Figure 1 S_c^{t+1} and S_c^t represent CRS production frontiers, while S_v^{t+1} and S_v^t represent VRS production frontiers, at times *t+1* and *t* respectively. Under CRS, the measures of various output distance functions are:

$$D_c^t(x^t, y^t) = Inf\{\theta : (x^t, y^t/\theta) \in S^t\} = oa/ob \quad (1)$$

$$D_c^{t+1}(x^{t+1}, y^{t+1}) = Inf\{\theta : (x^{t+1}, y^{t+1}/\theta) \in S^{t+1}\} = oe/of \quad (2)$$

$$D_c^t(x^{t+1}, y^{t+1}) = Inf\{\theta : (x^{t+1}, y^{t+1}/\theta) \in S^t\} = oe/oc \quad (3)$$

and

$$D_c^{t+1}(x^t, y^t) = Inf\{\theta : (x^t, y^t/\theta) \in S^{t+1}\} = oa/od \quad (4)$$

Fare et al.'s Malmquist TFP change index $M^{Fare}(x^{t+1}, y^{t+1}, x^t, y^t)$ can then be defined as

$$\begin{aligned} M^{Fare}(x^{t+1}, y^{t+1}, x^t, y^t) &= \left[\frac{D_c^t(x^{t+1}, y^{t+1})}{D_c^t(x^t, y^t)} \times \frac{D_c^{t+1}(x^{t+1}, y^{t+1})}{D_c^{t+1}(x^t, y^t)} \right]^{1/2} \\ &= \underset{(EFFCH_c)}{\frac{D_c^{t+1}(x^{t+1}, y^{t+1})}{D_c^t(x^t, y^t)}} \times \underset{(TECHCH_c)}{\left[\frac{D_c^t(x^{t+1}, y^{t+1})}{D_c^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_c^t(x^t, y^t)}{D_c^{t+1}(x^t, y^t)} \right]^{1/2}} \\ &= \left(\frac{oe}{of}\right)\left(\frac{ob}{oa}\right)\left(\frac{of}{oc} \times \frac{od}{ob}\right)^{1/2} \end{aligned} \tag{5}$$

The ratio outside the brackets in Equation (5) is defined as technical efficiency change (*EFFCH*) and the ratio inside the brackets as technical change (*TECHCH*).

$$EFFCH_c = \frac{D_c^{t+1}(x^{t+1}, y^{t+1})}{D_c^t(x^t, y^t)} = \left(\frac{oe}{of}\right)\left(\frac{ob}{oa}\right) \tag{5a}$$

$$TECHCH_c = \left[\frac{D_c^t(x^{t+1}, y^{t+1})}{D_c^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_c^t(x^t, y^t)}{D_c^{t+1}(x^t, y^t)} \right]^{1/2} = \left(\frac{of}{oc} \times \frac{od}{ob}\right)^{1/2} \tag{5b}$$

Normally, if VRS is assumed then there is

$$D_c(x, y) = D_v(x, y) \times SE(x, y) \tag{6}$$

where SE represents the scale efficiency. Based on Equation (6), Fare et al. further decomposed the *EFFCH* term into two more components under the VRS frontier: pure technical efficiency change (*PEFFCH*) and scale efficiency change (*SCH*).

$$\frac{D_c^{t+1}(x^{t+1}, y^{t+1})}{D_c^t(x^t, y^t)} = \underset{(PEFFCH_v)}{\frac{D_v^{t+1}(x^{t+1}, y^{t+1})}{D_v^t(x^t, y^t)}} \times \underset{(SCH)}{\frac{SE^{t+1}(x^{t+1}, y^{t+1})}{SE^t(x^t, y^t)}} \tag{7}$$

In terms of Figure 1 the ratio forms of $PEFFCH_v$ and SCH can be written in the following ratio forms:

$$PEFFCH_v = \frac{D_v^{t+1}(x^{t+1}, y^{t+1})}{D_v^t(x^t, y^t)} = \left(\frac{oe}{oh}\right)\left(\frac{og}{oa}\right) \tag{7a}$$

$$SCH = \frac{SE^{t+1}(x^{t+1}, y^{t+1})}{SE^t(x^t, y^t)} = \left(\frac{oh}{of}\right)\left(\frac{ob}{og}\right) \tag{7b}$$

Finally then, Fare et al.'s Malmquist TFP change index $M^{Fare}(x^{t+1}, y^{t+1}, x^t, y^t)$ is decomposed as:

$$M^{Fare}(x^{t+1}, y^{t+1}, x^t, y^t) = PEEFCH_v \times SCH \times TECHCH_c \tag{8}$$

Ray and Desli (1997) pointed out that Fare et al.'s (1994) decomposition in Equation (8) posed a problem of internal inconsistency. They argued that Fare et al.'s measure of *TECHCH*, which is defined in Equation (5b), correctly measures technical change only when CRS is assumed. However, if this is the case under CRS then no scale inefficiency exists by definition. In other terms, if scale inefficiency does exist and leads to the VRS assumption, then Fare et al.'s measure of technical change is flawed because it does not measure the shift in the VRS frontier.

Ray and Desli's argument is very strong. They then proposed their decomposition of the Malmquist TFP index based on VRS frontiers. However, Ray and Desli's decomposition is not without problems. Firstly, as Fare et al. (1997) pointed out, although Ray and Desli provided different specifications for the *TECHCH* and *SCH* components based on VRS reference technology, their overall Malmquist TFP index was still computed in terms of a CRS benchmark. Therefore, Ray and Desli's overall measure of Malmquist TFP is in essence identical to Fare et al.'s (See Appendix). Secondly, Ray and Desli (1997) also recognized that highest average productivity could only be achieved at the tangent point of VRS and CRS frontiers. The problem then becomes whether or not we believe that the VRS frontier can represent best practice in the industry. If not, then there is no ground for us to use the shift of VRS frontier to represent technical change correspondingly. Thirdly, Grifell-Tatje and Lovell (1995) pointed out that when VRS is assumed, the Malmquist TFP index defined in Equation (5) provides an inaccurate measure of TFP change. This inaccuracy is systematic and depends on the magnitude of scale economies. All these reasons question the rationality of using the VRS frontier as a benchmarking technology for calculating the Malmquist TFP indices.

Therefore, this paper adopts the CRS frontier as a benchmarking technology. However, in recognition of Ray and Desli's inconsistency argument against Fare et al.'s decomposition, the author only decomposes the Malmquist TFP index into two components, namely technical efficiency change (*EFFCH*) and technical change (*TECHCH*), as defined in Equation (5).

2.2 Incorporating Emissions into Malmquist Indices

One of the persistent difficulties in the measurement of productivity is how to explain the effect of certain attributes of the production process. Current literature on attribute-incorporated Malmquist indices mainly focuses on the examining process and the quality features of a production. This section attempts to develop an emission-incorporated Malmquist TFP index based on the discussion of current literature.

Fixler and Ziechang (1992) showed how the Malmquist productivity index can be used to account for changes in inputs, outputs and process and quality attributes. Denote inputs by $x^t \in R^+$, outputs by $y^t \in R^+$ and attributes by $a^t \in R^+$ for time period t ($t = 1,...,T$). Then the production technology S^t at time t becomes

$$S^t = \{(x^t, y^t, a^t): \text{inputs } x^t \text{ can be used to produce } y^t \text{ and } a^t\}.$$

The distance functions with respect to different time periods can then be defined. For example, the input distance function incorporating attributes $a^t \in R^+$ at time t is defined as

$$D^t(x^t, y^t, a^t) = Sup\left\{\rho : (x^t/\rho, y^t, a^t) \in S^t\right\}$$

Fixler and Ziechang (1992) defined their attribute-incorporated, input-oriented productivity index as Equation (9), which is essentially extended from Equation (5) to include the attribute vector *a*:

$$M_a^{Fixler}(x^{t+1}, y^{t+1}, a^{t+1}, x^t, y^t, a^t) = \left[\frac{D^t(x^t, y^t, a^t)}{D^t(x^{t+1}, y^{t+1}, a^{t+1})} \times \frac{D^{t+1}(x^t, y^t, a^t)}{D^{t+1}(x^{t+1}, y^{t+1}, a^{t+1})}\right]^{1/2} \quad (9)$$

Following Fixler and Ziechang, Fare et al. (1995) proposed a new Malmquist index to incorporate the non-marketable attributes of production when measuring the service quality of Swedish pharmacies:

$$M_a^{Fare}(x^{t+1}, y^{t+1}, a^{t+1}, x^t, y^t, a^t) = \left[\frac{D^t(x^{t+1}, y^{t+1}, a^{t+1})}{D^t(x^t, y^t, a^t)} \times \frac{D^{t+1}(x^{t+1}, y^{t+1}, a^{t+1})}{D^{t+1}(x^t, y^t, a^t)}\right]^{1/2} \quad (10)$$

$$(M_a^{Fare})$$

Fare et al.'s definition is actually a reciprocal of Fixler and Ziechang's. Since Fare et al. (1995) used input distance functions to define the Malmquist productivity index, a value of less than one therefore corresponds to performance improvement, whereas a value greater than one reflects performance deterioration. This is an unhelpful representation of productivity growth, which we will return to later.

Based on the same logic as that apparent in Equation (5), Equation (10) can be decomposed into two factors. These are

$$M_a^{Fare} = \underbrace{\frac{D^{t+1}(x^{t+1}, y^{t+1}, a^{t+1})}{D^t(x^t, y^t, a^t)}}_{(EFFCH_a)} \times \underbrace{\left[\frac{D^t(x^{t+1}, y^{t+1}, a^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1}, a^{t+1})} \times \frac{D^t(x^t, y^t, a^t)}{D^{t+1}(x^t, y^t, a^t)}\right]^{1/2}}_{(TECHCH_a)} \quad (10a)$$

Fare et al. also defined a quality (or quality change) index for the technology between time *t* and *t+1*:

$$Q(x^{t+1}, y^{t+1}, a^{t+1}, x^t, y^t, a^t) = \left[\frac{D^t(x^t, y^t, a^{t+1})}{D^t(x^t, y^t, a^t)} \times \frac{D^{t+1}(x^{t+1}, y^{t+1}, a^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1}, a^t)}\right]^{1/2} \quad (11)$$

$$(Q_a^{t,t+1})$$

The above three factors, including $EFFCH_a$, $TECHCH_a$ and $Q_a^{t,t+1}$, were reported as non-separable indices in Fare et al. (1995).

From the above, Equation (10) can also be arranged as:

$$M_a^{Fare} = Q\,(x^{t+1}, y^{t+1}, a^{t+1}, x^t, y^t, a^t) \times \left[\frac{D^t(x^{t+1}, y^{t+1}, a^{t+1})}{D^t(x^t, y^t, a^{t+1})} \times \frac{D^{t+1}(x^{t+1}, y^{t+1}, a^t)}{D^{t+1}(x^t, y^t, a^t)}\right]^{1/2}, \quad (12)$$

where $Q(x^{t+1}, y^{t+1}, a^{t+1}, x^t, y^t, a^t)$ is defined as in Equation (11).

If we can assume that the distance function is multiplicatively separable in attributes and inputs/outputs[1], that is, if

$$D^t(x^{t+1}, y^{t+1}, a^{t+1}) = A^t(a^{t+1}) \times D^t(x^{t+1}, y^{t+1}), \tag{13}$$

then the second factor on the right hand side of Equation (12) becomes

$$\begin{aligned}
&\left[\frac{D^t(x^{t+1}, y^{t+1}, a^{t+1})}{D^t(x^t, y^t, a^{t+1})} \times \frac{D^{t+1}(x^{t+1}, y^{t+1}, a^t)}{D^{t+1}(x^t, y^t, a^t)}\right]^{1/2} \\
&= \left[\frac{D^t(x^{t+1}, y^{t+1}) \times A^t(a^{t+1})}{D^t(x^t, y^t) \times A^t(a^{t+1})} \times \frac{D^{t+1}(x^{t+1}, y^{t+1}) \times A^{t+1}(a^t)}{D^{t+1}(x^t, y^t) \times A^{t+1}(a^t)}\right] \\
&= \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \times \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)}\right]^{1/2} \\
&= M^{t,t+1}
\end{aligned} \quad . \tag{14}$$

If the separability assumption of Equation (13) is held, the attribute-incorporated Malmquist index M_a^{Fare} can therefore be written as

$$\begin{aligned}
M_a^{Fare} &= Q_a^{t,t+1} \times M^{t,t+1} \\
&= Q_a^{t,t+1} \times EFFCH^{t,t+1} \times TECHCH^{t,t+1}
\end{aligned} \tag{15}$$

The three factors on the right-hand side of Equation (15) are identified by Fare et al. (1995) as separable indices. The results of Fare et al. (1995) showed that quality attributes do make a difference in measured productivity change, but the separability assumption made in Equation (13) may not be appropriate.

Following Fare et al. (1995), Giannakis et al. (2005) used a similar definition of the quality-incorporated Malmquist index on a benchmarking study of electricity distribution utilities in the UK between 1991/92 and 1998/99. Compared with Fare et al. (1995), Giannakis et al.'s contributions are twofold. Firstly, differently from Fare et al. (1995), in which quality refers to attributes which require the use of more resources, Giannakis et al. (2005) used the number of minutes lost and the number of interruptions as attributes of quality. Therefore, although the term quality is still used, these attributes are actually the undesirable outputs of distribution utilities. Because undesirable outputs exist extensively in many production systems, Giannakis et al.'s extension on Fare et al.'s quality-incorporated Malmquist index can thus be used for a greater playing field.

Secondly, Giannakis et al. (2005) used the Malmquist index as described in Thanassoulis (2001), in which DEA efficiency scores, rather than distance functions, are used to define the Malmquist index. Because in CRS DEA the value of an input-oriented distance function is equal to the reciprocal of the DEA efficiency score[2], Thanassoulis' definition is actually in

[1] In reality, the quality factor $A^t(.)$ can be computed residually by taking rations of two related distance functions.

[2] The input-oriented technical efficiency is equal to the inverse of the input distance function, while output-oriented technical efficiency is equal to the output distance function. Also, under the CRS

line with Fixler and Ziechang's (1992) definition (which can be seen in Equation (9)). By this definition, a value greater than one reflects performance growth and a value less than one corresponds with performance degradation.

Giannakis et al. (2005) also reported an inconsistency between non-separable and separable Malmquist indices. However, Giannakis et al. (2005) did not notice the internal inconsistency problem of Fare et al. (1994), which was explained in the previous section. Their final decomposition of the quality-incorporated Malmquist indices still included a scale component when measuring *TECHCH* under the CRS frontier. Some of their final results may therefore be misleading.

To summarize, Fixler and Ziechang (1992) successfully showed how the Malmquist productivity indices can be used to account for changes in inputs, outputs and process and quality attributes. Fare et al. (1995) suggested that quality attributes do make a difference in measuring Malmquist productivity change. Also, their research results showed that the separability assumption is not consistent with the attribute-incorporated distance function. Giannakis et al. (2005) extended the attribute-incorporated Malmquist index to include undesirable outputs as quality attributes. This extension enlarged the playing field of the attribute-incorporated Malmquist indices. Additionally, as explained above, Fare et al.'s measurement is not in line with the daily custom of the people. Fixler and Ziechang (1992) and Giannakis et al. (2005) have escaped this problem by using a different setting for the Malmquist productivity index.

Based on the above, this paper will firstly, define an emission-incorporated Malmquist index following Fixler and Ziechang (1992) and Giannakis et al. (2005). Secondly, although inconsistent evidence for a separability assumption (for their samples) is reported in both Fare et al. (1995) and Giannakis et al. (2005), because some new features will be assigned to variables in the Malmquist indices in this paper, the authors will test the separability assumption again before formally rejecting it - so as to not make an arbitrary conclusion.

3. Methodology

It is widely acknowledged that ignoring undesirable outputs in efficiency analyses may bring misleading results. Therefore, it is necessary to examine the effects of undesirable outputs on productivity change over time.

3.1 Incorporating Emissions into the Malmquist Productivity Index

Assume that we have N (homogeneous) decision making units (DMUs), each using M inputs $x \in R_+^M$ to produce P desirable outputs $y^d \in R_+^P$ and S undesirable outputs $y^u \in R_+^S$. The production technology S^t at time t ($t = 1, 2, ..., T$) can be written as

$$S^t = \{ (x^t, y^{d,t}, y^{u,t}) : \text{inputs } x^t \text{ can be used to produce } y^{d,t} \text{ and } y^{u,t} \}.$$

Under the CRS frontier, the input distance function incorporating undesirable outputs is defined as

$$D^t(x^t, y^{d,t}, y^{u,t}) = Sup\left\{ \rho : (x^t/\rho, y^{d,t}, y^{u,t}/\rho) \in S^t \right\}$$

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frontier, the input oriented technical efficiency is equal to the output oriented technical efficiency. For details, please refer to (Coelli et al., 2005).

Similarly, distance functions with respect to different time periods can also be defined. Following Fixler and Ziechang (1992), we can then define the emissions-incorporated input-oriented Malmquist TFP index ($M_e^{t,t+1}$) as

$$M_e^{t,t+1}(x^{t+1},y^{d,t+1},y^{u,t+1},x^t,y^{d,t},y^{u,t})=\left[\frac{D^t(x^t,y^{d,t},y^{u,t})}{D^t(x^{t+1},y^{d,t+1},y^{u,t+1})}\times\frac{D^{t+1}(x^t,y^{d,t},y^{u,t})}{D^{t+1}(x^{t+1},y^{d,t+1},y^{u,t+1})}\right]^{1/2} \quad (16)$$

As mentioned above, Equation (16) is actually equal to Equation (17), which is similar to those defined in Giannakis et al. (2005).

$$M_e^{t,t+1}=\left[\frac{TE_c^t(x^{t+1},y^{d,t+1},y^{u,t+1})}{TE_c^t(x^t,y^{d,t},y^{u,t})}\times\frac{TE_c^{t+1}(x^{t+1},y^{d,t+1},y^{u,t+1})}{TE_c^{t+1}(x^t,y^{d,t},y^{u,t})}\right]^{1/2} \quad (17)$$

In Equation (17), for example, $TE_c^t(x^{t+1},y^{d,t+1},y^{u,t+1})$ represents a firm's technical efficiency score under the CRS frontier at time t, using input and output bundles at time *t+1*.

Based on the same logic as Equation (5), the emissions-incorporated input-oriented Malmquist index defined in Equation (16) can be decomposed as follows:

$$M_e^{t,t+1}=\underbrace{\frac{D^t(x^t,y^{d,t},y^{u,t})}{D^{t+1}(x^{t+1},y^{d,t+1},y^{u,t+1})}}_{(EFFCH_e^{t,t+1})}\times\underbrace{\left[\frac{D^{t+1}(x^{t+1},y^{d,t+1},y^{u,t+1})}{D^t(x^{t+1},y^{d,t+1},y^{u,t+1})}\times\frac{D^{t+1}(x^t,y^{d,t},y^{u,t})}{D^t(x^t,y^{d,t},y^{u,t})}\right]^{1/2}}_{(TECHCH_e^{t,t+1})} \quad (18)$$

Note that the above equations $M_e^{t,t+1}$, $EFFCH_e^{t,t+1}$ and $TECHCH_e^{t,t+1}$ have already incorporated undesirable outputs.

Following Fare et al. (1995), a similar pure environmental performance Malmquist index is defined as

$$Q_e^{t,t+1}=\left[\frac{D^t(x^t,y^{d,t},y^{u,t})}{D^t(x^t,y^{d,t},y^{u,t+1})}\times\frac{D^{t+1}(x^{t+1},y^{d,t+1},y^{u,t})}{D^{t+1}(x^{t+1},y^{d,t+1},y^{u,t+1})}\right]^{1/2}$$
$$\left(=\left[\frac{TE_c^t(x^t,y^{d,t},y^{u,t+1})}{TE_c^t(x^t,y^{d,t},y^{u,t})}\times\frac{TE_c^{t+1}(x^{t+1},y^{d,t+1},y^{u,t+1})}{TE_c^{t+1}(x^{t+1},y^{d,t+1},y^{u,t})}\right]^{1/2}\right) \quad (19)$$

Apparently, if we allow separability assumption in the decomposition, based on the same logic as Equation (15), the emission-incorporated Malmquist index can be decomposed as follows:

$$M_e^{t,t+1}=Q_e^{t,t+1}\times EFFCH^{t,t+1}\times TECHCH^{t,t+1} \quad (20)$$

It is worth repeating that, as explained in the previous section, in the non-separable model $Q_e^{t,t+1}$ is not a component of $M_e^{t,t+1}$. In fact, in most cases $M_e^{t,t+1}$ is not equal to the multiplication of $Q_e^{t,t+1}$, $EFFCH_e^{t,t+1}$ and $TECHCH_e^{t,t+1}$.

3.2 Computation of Distance Functions

The computation of both $M_e^{t,t+1}$ and $Q_e^{t,t+1}$ is similar to those discussed in Fare et al. (1995) and Giannakis et al. (2005). The only difference is that both of them assume that all inputs, outputs and attributes are freely disposable. This paper uses different disposability assumptions for different undesirable outputs in order to reflect the situation in terms of the pollution abatement technologies used (Yang, 2007).

Due to this similarity, only two of the distance functions which enter into the Malmquist index defined in Equation (16) are presented. These measure the distance of production $(x^t, y^{d,t}, y^{u,t})$ relative to the technology at time *t* and time *t+1* respectively.

Denote undesirable outputs with weak disposability by y_w^u, while undesirable outputs with strong disposability by y_s^u . The corresponding reference technology satisfying this assumption is then as follows:

$$S^t = \{(x^t, y^{d,t}, y_w^{u,t}, y_s^{u,t}) : y^{d,t} \le Y^{d,t}\lambda, y_w^{u,t} = Y_w^{u,t}\lambda, y_s^{u,t} \ge Y_s^{u,t}\lambda, x^t \ge X^t\lambda, \lambda \in R_+\}$$

Because in DEA the value of the input distance function is equal to the inverse of the input-oriented technical efficiency, therefore, the calculation of distance function for firm *j* at time *t* relative to the technology at time *t* is as follows:

$$\begin{aligned}
&\left[D_j^t(x^t, y^{d,t}, y_w^{u,t}, y_s^{u,t})\right]^{-1} = \min\theta \\
&s.t. \\
&y_j^{d,t} \le Y^{d,t}\lambda \\
&\theta y_{w,j}^{u,t} = Y_w^{u,t}\lambda \\
&\theta y_{s,j}^{u,t} \ge Y_s^{u,t}\lambda \\
&\theta x_j^t \ge X^t\lambda \\
&\lambda \in R_+
\end{aligned} \tag{21}$$

Similarly, the calculation of distance function for firm *j* at time *t*, relative to the technology at time *t+1* is as follows.

$$
\begin{aligned}
&\left[D_j^{t+1}(x^t, y^{d,t}, y_w^{u,t}, y_s^{u,t})\right]^{-1} = \min\theta \\
&s.t. \\
&y_j^{d,t} \le Y^{d,t+1}\lambda \\
&\theta y_{w,j}^{u,t} = Y_w^{u,t+1}\lambda \\
&\theta y_{s,j}^{u,t} \ge Y_s^{u,t+1}\lambda \\
&\theta x_j^t \ge X^{t+1}\lambda \\
&\lambda \in R_+
\end{aligned} \tag{22}
$$

For a further example of the distance functions which enter into the environmental performance Malmquist index defined in Equation (19), we list the following:

$$
\begin{aligned}
&\left[D_j^{t}(x^t, y^{d,t}, y_w^{u,t+1}, y_s^{u,t+1})\right]^{-1} = \min\theta \\
&s.t. \\
&y_j^{d,t} \le Y^{d,t}\lambda \\
&\theta y_{w,j}^{u,t+1} = Y_w^{u,t}\lambda \\
&\theta y_{s,j}^{u,t+1} \ge Y_s^{u,t}\lambda \\
&\theta x_j^t \ge X^{t}\lambda \\
&\lambda \in R_+
\end{aligned} \tag{23}
$$

3.3 Decomposition of Newly Defined Malmquist Indices

In terms of the distance functions defined in Equations (21)-(23), we then proceed to calculate $M_e^{t,t+1}$, which is defined in Equation (18) in the following modified format which distinguishes strongly and weakly disposable undesirable outputs:

$$
M_e^{t,t+1} = \underbrace{\frac{D^t(x^t, y^{d,t}, y_s^{u,t}, y_w^{u,t})}{D^{t+1}(x^{t+1}, y^{d,t+1}, y_s^{u,t+1}, y_w^{u,t+1})}}_{(EFFCH_e^{t,t+1})} \times \underbrace{\left[\frac{D^{t+1}(x^{t+1}, y^{d,t+1}, y_s^{u,t+1}, y_w^{u,t+1})}{D^t(x^{t+1}, y^{d,t+1}, y_s^{u,t+1}, y_w^{u,t+1})} \times \frac{D^{t+1}(x^t, y^{d,t}, y_s^{u,t}, y_w^{u,t})}{D^t(x^t, y^{d,t}, y_s^{u,t}, y_w^{u,t})}\right]^{1/2}}_{(TECHCH_e^{t,t+1})} \tag{24}
$$

Similarly, we calculate the pure environmental performance index $Q_e^{t,t+1}$ in Equation (25), which is modified from Equation (19):

$$
Q_e^{t,t+1} = \left[\frac{D^t(x^t, y^{d,t}, y_s^{u,t}, y_w^{u,t})}{D^t(x^t, y^{d,t}, y_s^{u,t+1}, y_w^{u,t+1})} \times \frac{D^{t+1}(x^{t+1}, y^{d,t+1}, y_s^{u,t}, y_w^{u,t})}{D^{t+1}(x^{t+1}, y^{d,t+1}, y_s^{u,t+1}, y_w^{u,t+1})}\right]^{1/2} \tag{25}
$$

The above three indices $M_e^{t,t+1}$, $EFFCH_e^{t,t+1}$ and $TECHCH_e^{t,t+1}$ are reported as non-separability indices which have incorporated undesirable outputs.

If assuming separability, $M_e^{t,t+1}$ can then be decomposed as follows:

$$M_e^{t,t+1} = Q_e^{t,t+1} \times EFFCH^{t,t+1} \times TECHCH^{t,t+1}, \quad (26)$$

where $Q_e^{t,t+1}$ is as defined in Equation (25) and $EFFCH^{t,t+1}$ and $TECHCH^{t,t+1}$ are defined as in Equation (5).

To facilitate an explanation of newly defined indices, traditional Malmquist TFP indices are also calculated for the purpose of comparison. Two kinds of comparisons can be performed in this paper based on the indices reported. The first comparison is between the traditional Malmquist productivity index ($M^{t,t+1}$), defined in Equation (5), and the new emissions-incorporated Malmquist productivity index ($M_e^{t,t+1}$). This comparison shows the rationality of the new Malmquist productivity index. The second comparison is between the separability and non-separability versions of the new Malmquist indices. A two-sample T-test is used to examine whether the result difference between the separability and non-separability indices is significant. This comparison illustrates whether or not the separability assumption in Equation (13) is reasonable.

4. Panel Data and Variables

4.1 Panel Data

The panel data used covers 796 utility and non-utility coal-fired power plants distributed throughout 12 provinces in the mainland of China, including Henan, Hubei, Hunan, Jiangxi, Heilongjiang, Jilin, Liaoning, Inner Mongolia, Beijing, Tianjin, Hebei and Shanxi, and encompassing the area circled by the thick line in Figure 2.

Figure 2: Coverage of Panel Data Sample

The majority of the sample power plants are very small low-parameter power plants with an installed capacity less than 50MW. For calculation simplicity, when the provincial aggregated data of these small inefficient power plants is available, the aggregated data is used as a large DMU in the model. Two reasons support the use of this aggregated data. Firstly, because DEA is an extreme point method, these small and inefficient power plants can never affect the position of the production frontier. So the use of aggregated data does not have any active influence on the final performance measurement. Secondly, in general the majority of small power plants have been controlled by their owners less effectively than the big power plants[3]. Using aggregated data can therefore help to eliminate some sampling errors.

Table 1 shows the ratio of sample total to total installed capacity in China during the report period, and also the number of observations made in each report year. During the report period some asset reconfigurations occurred in the sample power plants. For example, some power plants with multiple units were split up into smaller power plants and some small power plants were merged together to form larger ones. All of the data in the sample has been reconfigured to reflect the industry's structure by the end of 2002. Table 1 also shows that the large unbalanced data panel used in this paper includes 1626 real observations in total.

Table 1: Percentage of Panel Sample Total to China Total

Report year	1996	1997	1998	1999	2000	2001	2002
Sample total capacity (GW)	67.80	70.82	81.04	87.66	93.69	101.39	104.3
China total capacity (GW)	178.86	192.29	209.88	223.43	237.54	252.80	265.55
Percentage (%)	37.91	36.83	38.61	39.23	39.44	40.11	39.28
No. of observations	205	205	216	243	247	254	256

The data from each power plant, such as installed capacity, annual oil and coal consumption, annual number of employees, annual electricity generation, and quality of fuel, was mainly collected during the author's fieldwork in China between 2005 and 2006. Data on the quality of fuel is complemented by the CED (2004).

There are some merits in using plant-level panel data to analyse the productivity growth of Chinese coal-fired power plants. Firstly, it permits the analysis of productivity change for each individual plant. Secondly, because sample power plants remain the same at different points during the report period, it is statistically advantageous for us to find and eliminate sampling errors.

4.2 Selection of Variables

The traditional variables used include electricity generated, capital, labour, and fuel.

Electricity generated is used as desirable output (Y^d), and is measured by the unit *MWh*. Traditional inputs (X) include capital, labour and fuel. Capital is measured by installed capacity *(MW)*. Labour is measured by the number of employees, this being the average yearly number during the report period. Quality of labour can be very different in terms of education, training, experience, etc. However, because it is hard to measure, we simply assume in this research that there is no noticeable difference in labour quality. Fuel is measured by energy (or heat)

[3] This is because in China the majority of large coal-fired power plants are directly controlled by central government firms, and small power plants are largely controlled by local authorities.

input. Because in almost all Chinese coal-fired power plants oil-fired (sometimes gas-fired) equipment is also installed for boiler-preheating and standby purposes, given the certain load of a boiler, the more oil or gas it uses, the less coal is consumed. In order to make the final efficiency evaluation accurate and the comparison between power plants meaningful, it is therefore necessary to convert all kinds of fossil fuel consumption into the same unit in this paper, namely the terajoule (TJ).

Undesirable variables (Y^u) refer to emissions resulting from the electricity generation process. Emissions from coal combustion mainly comprise CO_2, SO_2, CH_4, N_2O, NO_x, CO, and Non-methane volatile organic compounds (NMVOC). An accurate estimate of these emissions depends on having knowledge of several interrelated factors, including combustion conditions, technology, and emission control policies, as well as fuel characteristics. In general, the identification and quantification of emissions by fuel type is essential for the performance evaluation of power plants in this research. Different methods can be used to estimate emissions. The methods used here are based on the IPCC Reference Approach[4]. In this paper, only SO_2 emissions are included as an undesirable output[5]. Following Yang and Pollitt (2007), strong disposability is assumed for SO_2 emissions.

The summary statistics of the variables selected are shown in Table 2. For clarity, only data collected in 1996 and 2002 is reported here. Variables have been grouped in order to reflect their characteristics.

Table 2: Summary Statistics of Variables Used

Year	Variables	Annual generation (MWh)	Installed capacity (MW)	No. of employees	Energy input (TJ)	SO2 Emissions (tonne)
		Y^d	X			Y^u
1996	Total	355918559	67802	229852	4151350	2405943
	Maximum	11359460	1700	5930	114616	101576
	Minimum	21690	12	156	299	46
	Standard deviation	1966789	333	1072	20634	16540
	Mean	1719413	328	1110	20055	11623
2002	Total	534344481	104299	168582	5944600	3493289
	Maximum	12323690	2400	3367	124968	132552
	Minimum	4740	24	52	81	7
	Standard deviation	2118624	407	596	22406	17894
	Mean	1950162	381	615	21695.62	12749

4 For more detail, please refer to *Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories: Reference Manual*.

5 On the basis of currently available data resources, CO_2 and NO_x emissions can also be estimated. However, because so far there isn't any CO_2 emission control in use in the coal-fired electricity generation, it is very hard to say whether there has been any technical improvement in CO_2 emissions control. A similar situation is also the case for NO_x control in Chinese coal-fired power plants.

4.3 Data Compilation

The quality of the data used could potentially have a serious effect on the final results. The quality of the data is mainly affected by two sets of factors, namely the presence of outliers in observations and the special requirements of the research. Hair et al. (1998) and Coelli et al. (2005) both provided good discussions on the reasons of the presence of outliers and the methods used for eliminating their influence. While the presence of outliers mainly results from statistical inaccuracy, the special requirements of the research being undertaken are largely decided by what we are doing.

In order to calculate the Malmquist indices defined above, the panel data used has to be balanced. That is, all DMUs must be observed across all time periods. This special requirement creates an obvious difficulty with regards to calculation. During the 7 year report period new power plants continued to be built, while old plants continued to be shut down. Since 1980 the Chinese administration has implemented its energy conservation program for the reduction of energy wastage. This implementation was particularly evident during the report period. In 1998, when the serious electricity shortage was temporarily halted, many small and wasteful generating units were shut down and replaced by larger and more technically efficient facilities (Yang, 2006). Therefore, it is very hard to balance the data panel using the real observed data, as in each report year some empty data entries always appear.

One way of dealing with the unbalanced data panel, and therefore being able to meet the balanced requirement for the Malmquist index calculation, is to find out those DMUs which are observed in all of the report years. However, two factors prevent us from using this method. Firstly, in China's case this means that we have to greatly reduce the size of the research sample. The final results will then become less comprehensive. Secondly, because all power plants which emerge or disappear within a report year cannot be considered in the model, the final results are more a measurement of the remaining sample rather than a general reflection of the whole industry. This study introduces an innovative approach in order to circumvent this problem. Essentially, a fake unit is created to fill in any empty data entry and therefore make the unbalanced data panel balance.

As a guideline, this fake unit uses a very large amount of each of the inputs to produce a very small amount of each of the desirable outputs and a very large amount of each of the undesirable outputs. In general, the fake unit exhibits the following features:

(1) Similarity - it uses the same kinds of inputs and produces and the same kinds of desirable and undesirable outputs as other real DMUs do.
(2) Inefficiency - the amount of input it uses is no less than that of any other DMU in the sample. Also, the amount of desirable output it produces is no more than, and the amount of undesirable output it produces is no less than, those of any other DMU in the sample.
(3) Being omissible - its effect on the final calculation should be easy to pinpoint and delete.

The first feature of the fake unit ensures that it can be used as a substitute in the calculation. Because the basic benchmarking technology used is DEA, which is an extreme point method, the second feature ensures that the presence of the fake unit in the calculation does not affect the position of the production frontier. The third feature ensures that because the fake unit is created for calculating purposes only, its presence should not affect the correctness of calculations for all of the real observations. Essentially, the fake unit approach introduces an unbalanced panel concept into DEA Malmquist indices.

The use of the fake unit influences the final calculation of Malmquist indices in two ways in this study. Firstly, in the case of a power plant which is shut down during a report year, because real observations have been used up to that report year, it is therefore expected that in the calculation the power plant will have a large efficiency decrease one year after. In terms of the kind of fake unit created, this decrease can be several hundred times less than a normal value. Secondly, in the case of a power plant which is newly built during a report year, because real observations are used after that report year, it is therefore expected that in the calculation the power plant will have a large efficiency increase one year after. Similarly, in terms of what kind of fake unit is created, this increase can be several hundred or even several thousand times more than a normal value. So both cases are apparently very easy to pinpoint in the final results. Calculations which are influenced by the presence of the fake unit can then be easily deleted. Therefore, the final results for all of the real observations can be reliably upheld as correctly reflecting performance.

5. Results

Results are calculated using models and equations as defined above. Although our calculations yield power plant-specific Malmquist indices, given the large number of observations, more aggregate results are provided. Results are reported below in two different ways, namely, individual DMU and differing report years. The productivity index is decomposed into two components: *EFFCH* and *TECHCH*.

5.1 Indices Calculated in Terms of Individual DMU

Table 3 displays those results calculated for the traditional, non-separability, and separability models. The values presented for individual DMUs are the geometric means of Malmquist productivity indices over the report period. Given the large number of sample power plants, only several examples and mean values for all DMUs are listed.

From Table 3, TFP growth can first be observed in all three models during the report period. The TFP growth indices in the traditional and non-separability models are slightly larger than 3%, while the TFP growth index in the separability model is only 0.8%.

Secondly, in both models which consider the effects of emissions, the value of the environmental performance index $Q^{t,t+1}$ is less than one. This indicates a decrease in the environmental performance of Chinese power plants during the report period. The above finding shows that the effect of the endeavour of Chinese authorities to improve emissions control in the electricity industry is not clear during the report period.

Thirdly, Table 3 displays the main source of TFP growth. In all three models we can see that TFP growth mainly comes from technical change (*TECHCH*). This indicates that the frontier shift contributed more to TFP growth during the report period. There is an approximate increase of 3% in the *TECHCH* indices across all three models. This result corresponds with two things which occurred in China during the report period. Above all, many new large generating units with high technical parameters were installed annually between 1996 and 2002. Table 1 reflects some of the features of this trend. For example, there was a 107 GW coal-fired generating capacity growth in China between 1996 and 2002, the majority of which came from large generating units with a scale of no less than 300 MW. This could possibly bring the technical frontier forwards. Also, when the serious electricity shortage in China was temporarily remedied in 1998, the Chinese government started a new round of electricity reform that focused on building an efficient electricity industry. Many small and inefficient coal-fired power plants were shut down. All of these efforts are expected to have some positive effects on the performance improvement of Chinese coal-fired power plants.

Table 3: Geometric Mean of the Malmquist Productivity Indices Over Report Period in Terms of Individual DMU

Power plants	Traditional			Non-separability				Separability			
	$M^{t,t+1}$	$EFFCH^{t,t+1}$	$TECHCH^{t,t+1}$	$M_e^{t,t+1}$	$EFFCH_e^{t,t+1}$	$TECHCH_e^{t,t+1}$	$Q^{t,t+1}$	$M_e^{t,t+1}$	$EFFCH^{t,t+1}$	$TECHCH^{t,t+1}$	$Q^{t,t+1}$
1	1.007	0.974	1.034	1.004	0.981	1.023	0.986	0.993	0.974	1.034	0.986
2	1.138	1.100	1.034	1.131	1.091	1.038	0.816	0.928	1.100	1.034	0.816
3	1.200	1.169	1.027	1.190	1.152	1.033	0.917	1.101	1.169	1.027	0.917
……	……			……				……			
277	0.985	0.945	1.042	0.985	0.945	1.042	0.981	0.966	0.945	1.042	0.981
278	1.007	0.980	1.028	1.007	0.980	1.028	0.993	1.001	0.980	1.028	0.993
Mean	1.034	1.001	1.033	1.033	1.001	1.032	0.974	1.008	1.001	1.033	0.974

Table 4: Geometric Mean of the Malmquist Productivity Indices in Terms of Different Report Year

Year	Traditional			Non-separability				Separability			
	$M^{t,t+1}$	$EFFCH^{t,t+1}$	$TECHCH^{t,t+1}$	$M_e^{t,t+1}$	$EFFCH_e^{t,t+1}$	$TECHCH_e^{t,t+1}$	$Q^{t,t+1}$	$M_e^{t,t+1}$	$EFFCH^{t,t+1}$	$TECHCH^{t,t+1}$	$Q^{t,t+1}$
1997	1.015	1.013	1.002	1.014	1.010	1.005	0.994	1.009	1.013	1.002	0.994
1998	1.002	0.955	1.049	1.011	0.956	1.058	0.980	0.981	0.955	1.049	0.980
1999	1.017	1.056	0.963	1.011	1.051	0.962	1.008	1.026	1.056	0.963	1.008
2000	1.021	0.971	1.052	1.015	0.983	1.033	0.975	0.996	0.971	1.052	0.975
2001	1.039	0.981	1.059	1.042	0.976	1.068	0.967	1.005	0.981	1.059	0.967
2002	1.036	0.977	1.061	1.039	0.988	1.051	0.972	1.007	0.977	1.061	0.972
Mean	1.022	0.992	1.030	1.022	0.993	1.029	0.983	1.004	0.992	1.030	0.983

Fourthly, while the efficient frontier has experienced a positive shift, the performance gap between efficient and inefficient power plants has remained largely unchanged. In all three models the *EFFCH* indices are equal to 1.001, which indicates that no apparent efficiency catch-up effect can be observed in the industry during the report period.

Last but not least, the result difference between the non-separability and separability models shows the inconsistency of the separability assumption. A two-sample T-test by STATA rejects the hypothesis that both models have equal mean values at the 0.1% significance level. Therefore, we decided not to pursue a separability version of Malmquist index decomposition any further in the study. This agrees with the findings in Fare et al. (1995) and Giannakis et al. (2005).

5.2 Indices Calculated in Terms of Different Report Years

Table 4 displays the geometric means of the Malmquist productivity indices of all the power plants observed in that report year. Similar results to those in Table 3 can be found in Table 4.

Firstly, TFP growth is once again observed in all three models. The TFP growth indices in the traditional and non-separability models are 2.2%, while in the separability model this figure is approximately 0.4%. The TFP growth indices in the traditional and non-separability models are quite similar to those reported by Lam and Shiu (2004), in which a 2.1% annual TFP growth was noted in the Chinese electricity generation sector between 1995 and 2000. Secondly, a less-than-one environmental performance index is achieved. Thirdly, the main source of TFP growth comes from technical change. Fourthly, almost no efficiency catch-up is present in the industry. This again indicates that the frontier shift contributed more to TFP growth during the report period than the catch-up effects. Finally, the inconsistency between the non-separability and separability models is observed once again. In general, the results in Table 4 confirm those in Table 3.

From Tables 3 and 4, it is first of all very clear that the results of three models have very similar change patterns. This supports our emissions-incorporated Malmquist productivity index. Secondly, it is worth noting that the TFP Malmquist indices achieved in Table 3 are slightly larger than those in Table 4. This is probably due to the fact that after the fake unit has been introduced the number of observations in the calculation of Table 3 becomes different to the number of observations in the calculation of Table 4. In Table 3 the number of observations is 278 throughout the report period. However, in Table 4 the number varies in terms of different report years. For example, the number is 205 in 1996 and 256 in 2002 (Table 1). As there were more new efficient power plants in the latter part of the report period, it is expected that they will exert more of an influence on the final geometric mean when making the calculations for Table 3.

5.3 Correlation of Malmquist Indices between Models

Table 5 exhibits the correlation coefficients of the geometric mean of the Malmquist indices between the non-separability and traditional models. Generally speaking, a high correlation coefficient between two sets of data indicates a high consistency in both sets of data.

Table 5: Correlation of Malmquist Indices

Correlation		Emissions-incorporated Malmquist				Traditional Malmquist		
		M_e	$EFFCH_e$	$TECHCH_e$	Q	M	$EFFCH$	$TECHCH$
Emissions incorporated Malmquist	M_e	1.0000						
	$EFFCH_e$	0.9780	1.0000					
	$TECHCH_e$	0.2976	0.0952	1.0000				
	Q	-0.4988	-0.4723	-0.2454	1.0000			
Traditional Malmquist	M	0.9705	--	--	-0.6339	1.0000		
	$EFFCH$	--	0.9658	--	-0.6162	0.9811	1.0000	
	$TECHCH$	--	--	0.7751	-0.2546	0.3234	0.1366	1.0000

First of all, the correlation between Malmquist indices in the emissions-incorporated model and those in traditional model is very high. This supports our definition of emissions-incorporated Malmquist TFP indices and corresponds with the results achieved in the previous section.

Secondly, in both emissions-incorporated and traditional models the overall productivity indices are more correlated to *EFFCH* indices than to *TECHCH* indices. This suggests that although the frontier shift (*TECHCH*) contributes more to an increase in productivity growth, it is less correlated with that growth than is efficiency change. A similar finding on the correlation between productivity growth, efficiency change and technical change can also be seen in Giannakis et al. (2005).

Thirdly, in both models the correlation coefficients between *EFFCH* and *TECHCH* are quite low, which implies that the change in efficiency is independent of the technical frontier shift and vice versa. That is, an observed *TECHCH* index increase does not necessarily mean an increase in the *EFFCH* index.

Finally, the environmental performance index Q has both low and negative correlation coefficients with both emissions-incorporated and traditional Malmquist productivity indices. This is inconsistent with our intuition. As the results of the traditional and non-separability models are highly correlated, this suggests to some extent that during the report period the improvement in generation performance has come at the expense of environmental performance (at least with respect to sulphur dioxide). A possible hypothesis for this inconsistency is that the environmental performance index, as defined in Equation (25) using Fare et al.'s (1995) format, is either incorrect or inappropriate on this occasion (if for example, other dimensions of environmental performance need to be included). A definitive examination of this is beyond the scope of this paper.

6. Conclusion

Numerous analyses regarding the use of the Malmquist index to measure the TFP change have been conducted. Yet to our knowledge, there are few published papers which take the undesirable outputs of DMUs into consideration when evaluating productivity change over time. Previous studies of the performance of DMUs show that the ignorance of undesirable outputs might yield misleading results (Kopp et al., 1982; Fare et al., 1989). It is therefore necessary to test the effects of undesirable outputs on the TFP change of DMUs. In this paper, previous literature regarding TFP change has been examined and summarized. The strengths of existing papers have then been combined in order to serve our attempt to define an emissions-incorporated Malmquist index.

Something worthy of note is that, firstly, this paper defines a new emissions-incorporated Malmquist TFP index to measure the overall TFP change of Chinese coal-fired power plants. This paper adopts CRS as the benchmarking technology. However, in recognition of Ray and Desli's (1997) inconsistency argument against Fare et al.'s (1994) decomposition, the author only decomposes the final calculation of Malmquist TFP index into two components, namely, technical efficiency change (*EFFCH*) and technical change (*TECHCH*). Secondly, this paper also defines a pure environmental performance index in order to measure the performance improvement of the control of emissions in Chinese coal-fired power plants. The final results support the authors' definition of emissions-incorporated Malmquist TFP indices. Thirdly, in order to meet the requirement of a balanced panel data sample for calculating the Malmquist indices, an innovative fake unit approach has been introduced in this paper. This approach makes possible the calculation of a Malmquist index with an unbalanced data panel. The methodology in the paper could easily be extended to incorporate more emissions variables, such as CO_2, as data allows.

Besides contributing to research methodology, this paper also entails policy implications. The results show that during the report period the TFP growth mainly came from technical change. This result supports the Chinese government's efforts to build a more efficient electricity industry. However, the results also indicate that the growth of Chinese coal-fired power sector today still heavily depends upon an increase of resource input. This is evident from the fact that, at best, the annual TFP growth of the sample coal-fired power plants between 1996 and 2002 only averages about 2%. Yet during the period of our study (1996-2002) the annual increase of the sample power plants was 6.81% in coal-fired capacity and 10.29% in coal-fired generation (CED, 2004). Furthermore, no apparent efficiency catch-up effects or improved environmental performance indices can be found in our results. This, coupled with results in Yang and Pollitt (2007), which shows average inefficiency after adjusting for operating conditions of around 10%, suggests that huge potential remains with regards to the improvement of efficiency and control of emissions in the Chinese coal-fired power plants. That is to say, for the Chinese authorities, the continuation of its efforts in the conservation of energy and the increasing of energy efficiency still have a very crucial role to play.

It is important to point out however that our study only examines the TFP growth at existing plants, since Malmquist indicies cannot capture the productivity growth (or indeed environmental performance improvement) resulting from the closure of old plants and their replacement with newer ones. Hence we might expect aggregate TFP growth to show faster TFP growth than what we find. Our analysis does include the positive TFP effects of ramping up new plants to full efficiency in their early years of operation. This would negate the old to new replacement effect to some extent. However given that emissions are strongly correlated with actual electrical output (rather than capacity) at a given plant the new for old effect might remain significant on environmental performance. We will investigate this further in subsequent research.

Appendix: Ray and Desli's Decomposition of Malmquist TFP Index

Following the parameterization of section 2, Ray and Desli's decomposition can be started from the measurement of output distance functions under VRS. In terms of Figure 1, VRS distance functions can be written as

$$D_v^t(x^t, y^t) = oa/og \tag{A1}$$

$$D_v^{t+1}(x^{t+1}, y^{t+1}) = oe/oh \tag{A2}$$

$$D_v^t(x^{t+1}, y^{t+1}) = oe/oi \tag{A3}$$

and

$$D_v^{t+1}(x^t, y^t) = oa/oj \tag{A4}$$

Ray and Desli then defined the TFP change index $M^{Ray}(x^{t+1}, y^{t+1}, x, y)$ as

$$\begin{aligned} M^{Ray}(x^{t+1}, y^{t+1}, x^t, y^t) = & \left[\frac{D_v^t(x^t, y^t)}{D_v^{t+1}(x^t, y^t)} \times \frac{D_v^t(x^{t+1}, y^{t+1})}{D_v^{t+1}(x^{t+1}, y^{t+1})}\right]^{1/2} \times \frac{D_v^{t+1}(x^{t+1}, y^{t+1})}{D_v^t(x^t, y^t)} \\ & \times \left[\frac{SE^t(x^{t+1}, y^{t+1})}{SE^t(x^t, y^t)} \times \frac{SE^{t+1}(x^{t+1}, y^{t+1})}{SE^{t+1}(x^t, y^t)}\right]^{1/2} \end{aligned} \tag{A5}$$

where SE represents the scale efficiency (see A5c'), and

$$TECHCH_v = \left[\frac{D_v^t(x^t, y^t)}{D_v^{t+1}(x^t, y^t)} \times \frac{D_v^t(x^{t+1}, y^{t+1})}{D_v^{t+1}(x^{t+1}, y^{t+1})}\right]^{1/2} = \left(\frac{oj}{og} \times \frac{oh}{oi}\right)^{1/2} \tag{A5a}$$

$$PEFFCH_v = \frac{D_v^{t+1}(x^{t+1}, y^{t+1})}{D_v^t(x^t, y^t)} = \left(\frac{oe}{oa}\right)\left(\frac{og}{oh}\right) \tag{A5b}$$

$$SCH_v = \left[\frac{SE^t(x^{t+1}, y^{t+1})}{SE^t(x^t, y^t)} \times \frac{SE^{t+1}(x^{t+1}, y^{t+1})}{SE^{t+1}(x^t, y^t)}\right]^{1/2} \tag{A5c}$$

Normally, if VRS is assumed the scale efficiency (SE) is the quotient of CRS efficiency over VRS efficiency. Then Equation (A5c) can be written as

$$SCH_v = \left[\frac{SE^t(x^{t+1}, y^{t+1})}{SE^t(x^t, y^t)} \times \frac{SE^{t+1}(x^{t+1}, y^{t+1})}{SE^{t+1}(x^t, y^t)}\right]^{1/2} = \left(\frac{oi}{oc} \times \frac{ob}{og} \times \frac{oh}{of} \times \frac{od}{oj}\right)^{1/2} \tag{A5c'}$$

Clearly, the only decomposition factor which is equal in both Fare et al.'s and Ray and Desli's decomposition is the factor *PEFFCH*.

If using the ratio forms of various indices as defined in Equation (A5a), (A5b) and (A5c') to replace the corresponding parts in Equation (A5), we get

$$
\begin{aligned}
M^{Ray}(x^{t+1}, y^{t+1}, x^{t}, y^{t}) &= \left(\frac{oj}{og}\times\frac{oh}{oi}\right)^{1/2}\times\left(\frac{oe}{oa}\right)\left(\frac{og}{oh}\right)\times\left(\frac{oi}{oc}\times\frac{ob}{og}\times\frac{oh}{of}\times\frac{od}{oj}\right)^{1/2} \\
&= \left(\frac{oe}{oa}\right)\left(\frac{ob}{oc}\times\frac{od}{of}\right)^{1/2} \\
&= \left(\frac{oe}{of}\right)\left(\frac{ob}{oa}\right)\left(\frac{of}{oc}\times\frac{od}{ob}\right)^{1/2}
\end{aligned}
\tag{A6}
$$

Clearly, the right-hand side of Equation (A6) is equal to that of Equation (5) in section 2. That is,

$$
M^{Ray}(x^{t+1}, y^{t+1}, x^{t}, y^{t}) = M^{Fare}(x^{t+1}, y^{t+1}, x^{t}, y^{t}) \tag{A7}
$$

This means that the overall measures of the Malmquist TFP index in Fare et al. (1994) and Ray and Desli (1997) are identical.

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