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ANALYSIS

Environmentally sensitive productivity growth: A global analysis using Malmquist–Luenberger index

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Abstract

We examine conventional and environmentally sensitive total factor productivity (TFP) in 41 developed and developing countries over the period of 1971 to 1992. Due to the non-availability of reliable input and CO_2 emissions price data, the study uses directional distance function to derive Malmquist–Luenberger (ML) productivity index. The index allows us to decompose the TFP into measures of technical and efficiency changes. DEA is used to compute the directional distance functions. We find that TFP index value is not different when we account for the CO_2 emissions relative to the situation when they are freely disposable. But for the components of TFP change: technical and efficiency changes, the null hypothesis of whether the indexes are the same under two different scenarios cannot be accepted. Issues of catch-up and convergence, or in some cases possible divergence, in productivity are examined within a global framework. The paper also studies the impact of openness on conventional and environmentally sensitive measures of productivity.

Keywords: Total factor productivity; Malmquist–Luenberger index; Environmentally sensitive productivity; DEA; Convergence hypothesis; Openness

JEL classification: D24; O47; C61; Q25; Q43

1. Introduction

Concerns about the impact of climate policy on 'productivity' or 'economic growth' have made countries hesitant about reducing CO_2 emissions. Climate policy has different dimensions: economic, technological and ecological. The economic dimension offers solutions in terms of price signals and the technological dimension sees solutions in terms of appropriate technological development and adoption. The ecological dimension adopts a more holistic view of man–nature relationship and calls for 'green accounting' or 'sustainable development'. This paper tries to present an extension of economic approach that includes aspects of technological development and adoption as well as green accounting.

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Productivity has acted as a significant engine of growth, allowing living standards in the world to advance rapidly throughout the twentieth century. However, its traditional measures do not account for production of harmful by-products such as CO_2, which may lead to environmental damage. It is conventionally measured using index numbers, which require data on prices of all outputs and inputs and the price information for bad outputs does not exist. The distance function approach can help overcome such problems as it requires data only on quantities of inputs, outputs and pollutants. Unlike this study, others estimating productivity using the distance function approach have focused on desirable outputs only (e.g., Färe et al., 1994b; Lall et al., 2002). There are also cases that have used micro-economic in contrast to macro-economic data used by the present study while estimating the total factor productivity (TFP) in the presence of bad outputs (e.g., Yaisawarng and Klein, 1994; Ball et al., 1994; Chung et al., 1997; Hailu and Veeman, 2000).

A method of measuring TFP using distance function that is growing in popularity is the use of Malmquist indexes. However, incorporation of bad outputs into the Malmquist indexes can be problematic. As the Malmquist indexes are based on Shepherd distance functions, which are radial in nature, firms cannot be credited with the reduction of bad outputs. This does not allow for changes in technology reducing the amount of pollution generated while increasing production of good outputs. It does not capture any "de-coupling" of the production of good outputs with bad outputs. If there has been a de-coupling of pollution and production, then there may be computational problems using the Shepherd distance function (Chapple and Harris, 2003).

There are several studies on the measurement of productivity changes in industries, which produce 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 these as synthetic output such as pollution abatement (e.g. Gollop and Roberts, 1983). Murty and Russell (2002) have pointed out that the treatment of bad outputs as inputs is not consistent with the materials 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). To overcome this problem, Pittman (1983) proposed that good and bad outputs should be treated non-symmetrically. He suggested the maximal radial expansion of good outputs and contraction of bad outputs. Chung et al. (1997) have used the directional distance function to calculate production relationships involving good and bad outputs that treats good and bad outputs asymmetrically. This study follows Chung et al. (1997) and uses directional distance function to measure Malmquist–Luenberger (ML) productivity index and its components.

The components of productivity index—technical and efficiency changes are analogous to the notions of technological innovation and adoption, respectively. The ML index credits producers for simultaneously increasing good outputs and reducing the production of bad outputs such as CO_2. It also offers an alternative way of assigning weightage on the relative importance of the bad outputs which can be interpreted as if consumers have preferences for reducing bad outputs regardless of the actual damage resulting from these products (Färe et al., 2001). Although the ML index does not directly relate to changes in welfare level, it does provide a complete picture of productivity growth under environmental regulations of emissions that are of concern to society.

The measures of productivity are often obtained under alternative assumptions about the disposability of CO_2. That is, it could be either strongly or weakly disposable. While, strong disposability implies that a country can reduce CO_2 emissions without incurring any abatement costs, weak disposability assumes diversion of resources from the production of good outputs. Thus the ML index encompasses green accounting while accounting for undesirable outputs.[2]

[1] Cropper and Oates (1992), Pittman (1981), Haynes et al. (1993, 1994), Boggs (1997), Kopp (1998), Reinhard et al. (1999), Murty and Kumar (2004), etc.

[2] Hailu and Veeman (2000) termed the measurement of productivity under weak disposability of pollutants as environmentally sensitive productivity.

This paper uses non-parametric linear programming method to estimate directional distance function. Thus for each year the same 'meta' best practice frontier is constructed based on the data for 41 countries for the period 1971–1992. Each country is then compared to this best practice frontier to provide the performance scores.

Productivity analysis helps to understand the level of economic prosperity, standard of living and the degree of competitiveness of a country, although it is not the only determinant of economic growth and welfare. Therefore, it is important to find which factors determine productivity growth in the countries in the presence of reduction in carbon emissions. Though there are various theories that explain productivity growth in countries, two are of particular interest.[3] One, the convergence theory states that in low-income countries productivity tends to converge towards those of high income countries, (Baumol, 1986; Baumol et al., 1989). The rationale behind the convergence hypothesis is the concept of diminishing returns to capital. In the developed countries the capital–labor ratio is found to be high in comparison to developing countries and therefore the marginal productivity of capital in them should be low.

Two, the endogenous growth theory advocates that the difference in productivity between developed and developing countries remains constant or even diverges over time (Arrow, 1962). The foundation of endogenous growth theories lies in the concept of increasing returns to scale, that are generated from externalities associated with the acquisition of technical knowledge. However, there are institutions and policies that determine the development process of a country (Olson, 1996). This paper tries to extend this literature by empirically examining the causes of productivity changes while accounting for carbon emissions.

The remainder of the paper is structured as follows: In Section 2, we discuss the theoretical approach of the paper. Section 3 discusses the data used in the study and its results. The data set is richer than the past examinations of efficiency and productivity analyses in that it includes energy as input. The addition allows for a more thorough assessment of the production processes that generate carbon emissions from the use of energy. The paper closes in Section 4 with some concluding remarks.

2. Theoretical approach

Suppose that a country employs a vector of inputs $x \in \Re_+^N$ to produce a vector of good outputs $y \in \Re_+^M$, and bad outputs $b \in \Re_+^I$. Let $P(x)$ be the feasible output set for the given input vector x and $L(y, b)$ is the input requirement set for a given output vector (y, b). Now the technology set is defined as:

$$P(x) = \{(y,b) : x \text{ can produce } (y,b)\},\ x \in \Re_+^N \tag{1}$$

We assume that the good and bad outputs are null-joint; a country cannot produce good output in the absence of bad outputs, i.e. if $(y, b) \in P(x)$ and $b=0$ then $y=0$. The output is strongly or freely disposable if

$$(y,b) \in P(x) \text{ and } \acute{y} \leq y \text{ imply } (\acute{y},b) \in P(x) \tag{2}$$

This implies that if an observed output vector is feasible, then any output vector smaller than that is also feasible. It excludes production processes that generate undesirable outputs that are costlier to dispose. In contrast concerns about CO_2 and other greenhouse gases imply that these should not be considered to be freely disposable. In such cases bad outputs are considered as being weakly disposable and

$$(y,b) \in P(x) \text{ and } 0 \leq \theta \leq 1 \text{ imply } (\theta y, \theta b) \in P(x) \tag{3}$$

This implies that pollution is costly to dispose and abatement activities would typically divert resources away from the production of desirable outputs and thus lead to lower good output with given inputs.

[3] For a brief summary of growth theories, see Lall et al. (2002).

Following Färe et al. (1994a) a DEA model can be constructed which satisfies the above conditions. Let there be for each time period $t=1, \ldots, T$ there are $k=1, \ldots, K$ observations for of inputs and outputs ($x^{k,t}$, $y^{k,t}$, $b^{k,t}$). Using this data in a DEA framework an output set can be constructed that satisfies the above conditions:

$$P^t(x^t) = \left\{ (y^t, b^t) : \begin{array}{ll} \sum_{k=1}^{K} z_k^t y_{km}^t \geq y_m^t & m = 1, \ldots, M \\ \sum_{k=1}^{K} z_k^t b_{ki}^t = b_i^t & i = 1, \ldots, I \\ \sum_{k=1}^{K} z_k^t x_{kn}^t \leq x_n^t & n = 1, \ldots, N \\ z_k^t \geq 0 & k = 1, \ldots, K \end{array} \right\} \tag{4}$$

where z_k^t are the intensity variables or weights, assigned to each observation in constructing the production possibility frontier. Non-negativity of the intensity variable has the effect of imposing constant returns to scale.

Furthermore, to incorporate the null-jointness of outputs, the following conditions are imposed on the DEA model:

$$\sum_{k=1}^{K} b_{ki}^t > 0 \quad k = 1, \ldots, K \tag{5}$$

$$\sum_{i=1}^{I} b_{ki}^t > 0 \quad i = 1, \ldots, I \tag{6}$$

These state that every bad output is produced by some country, k, and that every country, k, produces at least one bad output (in multiple bad output situations).

2.1. Directional distance functions

As stated earlier, the directional distance function seeks to increase the good outputs while simultaneously reducing the bad outputs. Formally it is defined as:

$$\vec{D}_o(x, y, b; g) = \sup\{\beta : (y, b) + \beta g \in P(x)\} \tag{7}$$

where g is the vector of directions in which outputs can be scaled. Following Chung et al. (1997), the direction taken is $g=(y,-b)$, such that as the good outputs are increased and the bad outputs are decreased. The difference between the output distance function and the directional distance function is illustrated in Fig. 1. In contrast to the output distance function, which places output vector A on the boundary at point C, expanding both good and bad outputs simultaneously, the directional distance function starts at A and scales in the direction of increase in good outputs and decrease in bad outputs to point B on the boundary. At point B, the output vector is $\left(y^t + \beta^* g_y, b^t - \beta^* g_b\right)$ where $, \beta^* = \vec{D}_o^t\left(x^t, y^t; g_y, -g_b\right)$ with $\beta^* g_y$ has been added to the good output and $\beta^* g_b$ has been subtracted from the bad output.

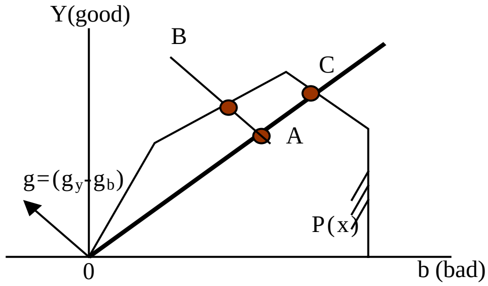

Fig. 1. Shephard output and directional distance functions.

2.2. Malmquist–Luenberger productivity index

Using directional distance functions, we define the ML productivity index. The ML index is very much based on the traditional Malmquist indexes—the main difference being that they are constructed from directional distance functions rather than Shepherd distance functions. The ML index requires a definition of the directional distance function with respect to two different periods, i.e.

$$\vec{D}_o^{t+1}(x^t, y^t, b^t; g) = \sup\{\beta : (y^t, b^t) + \beta g \in P^{t+1}(x^t)\} \tag{8}$$

This version of the directional distance function measures observations at time t based on the technology at time $t+1$. Chung et al. (1997) define the ML index of productivity between period t and $t+1$ as:

$$\mathrm{ML}_t^{t+1} = \left[\frac{\left(1+\vec{D}_o^{t+1}(x^t, y^t, b^t; y^t, -b^t)\right)}{\left(1+\vec{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})\right)} \frac{\left(1+\vec{D}_o^{t}(x^t, y^t, b^t; y^t, -b^t)\right)}{\left(1+\vec{D}_o^{t}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})\right)}\right]^{\frac{1}{2}} \tag{9}$$

The index can be decomposed into two component measures of productivity change:

$$\mathrm{ML}_t^{t+1} = \underbrace{\left[\frac{1+\vec{D}_o^{t}(x^t, y^t, b^t; y^t, -b^t)}{1+\vec{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})}\right]}_{\mathrm{MLEFFCH}_t^{t+1}} \times \underbrace{\left[\frac{\left(1+\vec{D}_o^{t+1}(x^t, y^t, b^t; y^t, -b^t)\right)}{\left(1+\vec{D}_o^{t}(x^t, y^t, b^t; y^t, -b^t)\right)} \frac{\left(1+\vec{D}_o^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})\right)}{\left(1+\vec{D}_o^{t}(x^{t+1}, y^{t+1}, b^{t+1}; y^{t+1}, -b^{t+1})\right)}\right]^{\frac{1}{2}}}_{\mathrm{MLTECH}_t^{t+1}} \tag{10}$$

The first term, MLEFFCH represents the efficiency change component, a movement towards the best practice frontier while the second, MLTECH, the technical change, i.e. a shift. If there have been no changes in inputs and outputs over two time periods, then $\mathrm{ML}_t^{t+1}=1$. If there has been an increase in productivity then $\mathrm{ML}_t^{t+1}>1$, and finally, a decrease when $\mathrm{ML}_t^{t+1}1<1$. Changes in efficiency are captured by $\mathrm{MLEFFCH}_{\mathrm{t}}^{t+1}$, which gives a ratio of the distances the countries are to their respective frontiers, in time periods t, and $t+1$. If $\mathrm{MLEFFCH}_t^{t+1}>1$, then there has been a movement towards the frontier in period $t+1$. If $\mathrm{MLEFFCH}_t^{t+1}<1$, then it indicates that the country is further away from the frontier in $t+1$, and hence has become less efficient. If technical change enables more production of good and less production of bad outputs, then $MLTECH_t^{t+1} > 1$. Whereas if $MLTECH_t^{t+1} < 1$, there has been a shift of the frontier in the direction of fewer good outputs and more bad outputs (Färe et al., 2001).

2.3. Computation of directional distance function

The technique of linear programming is used to compute the directional distance functions. Four programs need to be solved for each observation. Two use observations and technology for time period t, or $t+1$, and two use mixed period using, for example, technology calculated from period t with the observation $t+1$. The directional distance function for observation k' in period t, using period t technology can be calculated by solving the following LP problem.

$$
\begin{aligned}
&\vec{D}^{t}_{o}(x^t, y^t, b^t; y^t, -b^t) = \max\beta \\
&\text{s.t.} \\
&\sum_{k=1}^{K} z_k^t y_{km}^t \geq (1+\beta) y_{k'm}^t, m = 1, \ldots, M \\
&\sum_{k=1}^{K} z_k^t b_{ki}^t = (1-\beta) b_{k'i}^t, i = 1, \ldots, I \\
&\sum_{k=1}^{K} z_k^t x_{kn}^t \leq x_{k'n}^t, n = 1, \ldots, N \\
&z_k^t \geq 0, k = 1, \ldots, K
\end{aligned}
\tag{11}
$$

The mixed period problems can cause difficulties in calculation, whereby the observed data in period $t+1$ is not feasible in period t. For example, the observation $(y^{t+1,k'}, b^{t+1,k'})$ may not belong to the output set $P^t(x^{t+1})$. To minimise this problem, we follow Färe et al. (2001), whereby multiple year "windows" of data are the reference technology. All frontiers are constructed from three years of data—hence the frontier for 1973, for example, would be constructed from data in 1973, 1972 and 1971 which reduces the likelihood of ‘non-solutions’.

3. Data and results

We obtain the data on five variables namely, GDP, CO_2, labor force, capital stock and commercial energy consumption for 41 countries,[4] a mix of developed and developing countries for the period 1971–1992.[5] Out of these five variables the first two, GDP and CO_2 are considered as proxies of good and bad outputs respectively and the remaining three are taken as inputs. Data on the GDP, labor force and energy consumption is collected from the World Development Indicators (WDI, World Bank), whereas on CO_2 is taken from the website of World Resources. Capital stock[6] data is obtained from the Penn World Tables (Mark 5.6). GDP and capital stock are measured in 1985 US dollars, whereas CO_2 and energy consump-

[4] We have grouped all the countries in two categories—Annex-I and Non-Annex-I countries. We have 21 Annex-I countries (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Greece, Iceland, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, United Kingdom and United States) and 20 Non-Annex-I countries (Bolivia, Chile, Colombia, Ecuador, Guatemala, Honduras, Hong Kong, India, Israel, Kenya, Mexico, Morocco, Nigeria, Peru, Philippines, Syrian Arab Republic, Thailand, Venezuela, Zambia and Zimbabwe). The Annex-I parties to the United Nations Framework Convention on Climate Change are those developed countries, or regional organizations (the EU), that are listed in the Annex-I of the Climate Convention.

[5] The choice of period and countries is based on the availability of data particularly on capital stock. The Penn World Tables provide capital stock data up to 1992 especially for developing countries.

[6] Capital stock does not include residential construction but does include gross domestic investment in producers’ durables, as well as nonresidential construction. These are the cumulated and depreciated sums of past investment.

Table 1
Descriptive statistics of the variables used in the study (1971–1992)

Variable	Mean	Standard deviation	Minimum	Maximum
Annex-1 countries				
GDP growth rate	2.662	0.750	1.398	3.900
CO_2 growth rate	0.414	1.700	−2.934	4.148
Labor growth rate	1.184	0.602	0.464	2.409
Capital growth rate	4.142	1.164	2.476	6.941
Energy consumption growth rate	1.293	2.164	−6.405	3.855
Capital per labor (US$)	29227.530	11088.051	9721.000	76733.000
GDP per capita (US$)	20755.585	7628.875	8039.286	45951.950
Energy/GDP (metric tons/million US$)	0.285	0.141	0.006	0.761
Openness (export+import as % GDP)	65.601	40.745	11.239	233.537
Non-Annex-I countries				
GDP growth rate	3.708	1.870	0.820	7.880
CO_2 growth rate	3.911	2.920	−2.755	9.143
Labor growth rate	3.030	0.483	2.052	4.033
Capital growth rate	4.312	2.252	−1.218	8.245
Energy consumption growth rate	3.884	1.811	0.682	8.698
Capital per labor (US$)	7352.907	5988.130	349.000	22307.000
GDP per capita (US$)	2775.676	3813.108	205.645	20963.160
Energy/GDP (metric tons/million US$)	0.972	0.882	0.127	4.57
Openness (export+import as % GDP)	56.278	38.467	8.365	274.955

tion is measured in thousand metric tons. The labor force data is in millions of workers.

The descriptive statistics of all the variables used in the study for both of the groups, i.e., Annex-I and Non-Annex-I countries are presented in Table 1, which bring into focus the contrast between these two groups.

The highest growth rate with respect to CO_2 was observed in the Syrian Arab Republic (9.14%). A newly industrialized country Hong Kong registered the highest growth rate of GDP (7.9%) during the period studied and also had a high growth rate for CO_2 emissions (6.5%). Thailand had the second highest growth rate of GDP (7.3%) but a more rapid rate of growth in the production of CO_2, (8.3%). An examination of the overall growth rates reveal that developing countries witnessed higher growth in GDP, CO_2 and commercial energy consumption in comparison to the developed countries. Sweden, Luxembourg, France, Belgium, United Kingdom and Denmark registered negative CO_2 growth rates of 2.93%, 1.96%, 1.71%, 1.57%, 0.66% and 0.32% respectively. Thus we observe that in Non-Annex-I countries not only growth rates of the income and emissions were higher, but also there was a higher degree of variability within the group. The emission intensity of output measured as a ratio of CO_2 emission to GDP was quite high in developing countries in comparison to developed countries. However, it should be noted that the per capita GDP, capital, CO_2 emissions and commercial energy consumption were substantially higher in developed countries in comparison to the developing economies.

The approach outlined in Section 2 constructs a best-practice frontier from the data.[7] Table 2 sums up the main results, which describe the average[8] annual performance of each country and each group.[9] Recall that index values greater (less) than one denote

[7] In the computation of ML index although we followed multiple year "windows" of data as the reference technology to minimize the problem of infeasible solutions, even then there exists the problem for some countries, i.e. Hong Kong (2), Luxembourg (8), and Netherlands (13) observed infeasible linear programming for at least one of the mixed period when the carbon emissions are included as bad outputs (the values in the parentheses indicate the number of years for each country).

[8] Since the total factor productivity index is multiplicative, these averages are also multiplicative (i.e., geometric means) and the average is simply the geometric mean from those years for which the index could be computed.

[9] Disaggregated results for each country are available from the author on request.

Table 2
Decomposition of average annual changes, 1973–1992

Country	Environmentally sensitive measure			Conventional measure		
	ML	MLEFFCH	MLTECH	M	MLEFFCH	MTECH
Bolivia	0.9977	0.9955	1.0022	0.9866	0.9965	0.9900
Chile	1.0031	1.0045	0.9986	1.0072	1.0129	0.9943
Colombia	1.0008	0.9986	1.0022	1.0234	1.0237	0.9997
Ecuador	0.9939	0.9922	1.0018	0.9992	1.0112	0.9881
Guatemala	0.9941	0.9975	0.9966	1.0049	1.0038	1.0011
Honduras	0.9996	0.9973	1.0023	1.0044	0.9995	1.0049
Hong Kong	1.0138	1.0077	1.0062	1.0238	1.0375	0.9868
India	0.9987	0.9978	1.0009	0.9892	0.9943	0.9949
Israel	0.9996	1.0001	0.9995	1.0505	1.0000	1.0505
Kenya	1.0044	1.0028	1.0016	1.0158	1.0161	0.9998
Mexico	0.9981	0.9964	1.0017	0.9836	0.9894	0.9941
Morocco	0.9981	0.9982	0.9999	0.9984	1.0037	0.9947
Nigeria	0.9963	0.9970	0.9994	1.0004	0.9981	1.0023
Peru	1.0001	0.9980	1.0021	0.9974	1.0038	0.9937
Philippines	1.0012	0.9987	1.0024	0.9947	1.0041	0.9907
Syrian A.R.	0.9977	0.9968	1.0009	1.0109	1.0285	0.9829
Thailand	0.9982	0.9959	1.0023	1.0303	1.0371	1.0062
Venezuela, RB	0.9993	0.9981	1.0012	0.9923	0.9991	0.9932
Zambia	1.0058	1.0048	1.0010	0.9965	0.9940	1.0025
Zimbabwe	0.9997	0.9988	1.0009	0.9767	0.9841	0.9925
Australia	0.9983	1.0000	0.9982	1.0008	0.9968	1.0040
Austria	1.0035	1.0028	1.0008	1.0023	0.9979	1.0044
Belgium	1.0034	1.0001	1.0033	1.0059	1.0017	1.0042
Canada	0.9983	0.9995	0.9988	0.9937	1.0037	0.9900
Denmark	0.9968	0.9954	1.0015	0.9812	0.9901	0.9910
Finland	0.9996	1.0026	0.9971	1.0048	1.0207	0.9844
France	1.0091	1.0081	1.0010	1.0092	1.0123	0.9969
Greece	0.9930	0.9950	0.9980	1.0029	0.9976	1.0053
Iceland	0.9915	0.9938	0.9977	1.0132	1.0071	1.0060
Ireland	1.0088	1.0079	1.0009	1.0142	1.0178	0.9965
Italy	1.0010	1.0024	0.9986	0.9830	0.9802	1.0029
Japan	1.0072	0.9995	1.0077	0.9681	0.9811	0.9868
Luxembourg	0.9787	1.0000	0.9820	1.0052	1.0014	1.0038
Netherlands	1.0132	1.0000	1.0143	0.9788	0.9892	0.9894
New Zealand	0.9906	0.9939	0.9967	0.9956	0.9899	1.0057
Norway	1.0088	1.0095	0.9993	0.9944	0.9991	0.9926
Spain	0.9932	0.9937	0.9994	1.0022	0.9987	1.0035
Sweden	1.0055	1.0070	0.9985	0.9825	0.9879	0.9946
Switzerland	1.0054	0.9994	1.0059	0.9833	0.9851	0.9981
U.K.	1.0047	1.0022	1.0025	0.9913	0.9857	1.0057
U.S.	0.9985	0.9984	1.0000	0.9962	1.0015	0.9947
Non-Annex-I	1.0000	0.9988	1.0012	1.0042	1.0068	0.9981
Annex-I	1.0004	1.0005	1.0001	0.9956	0.9973	0.9981
All	1.0002	0.9997	1.0006	0.9998	1.0019	0.9981

ML: Malmquist–Luenberger Index; MLEFFCH: Malmquist–Luenberger Efficiency Change; MLTECH: Malmquist–Luenberger Technical Change; M: Malmquist Index; MEFFCH: Malmquist Efficiency Change; and MTECH: Malmquist Technical Change.

improvements (deterioration) in the relevant performance. Here we have calculated the ML index and its components for both cases: weak and strong disposability of CO_2 emissions.

To examine the relationship between productivity and its determinants, the study considers variables such as GDP per capita, technical inefficiency in the previous year, capital per labor and energy intensity of output measured by the use of commercial energy per unit of GDP. We included openness index also as a determinant of productivity. The openness index could be a proxy for institutional and policy framework of a country. The source of data on openness index is the WDI.

If one could establish a positive relationship between (i) GDP per capita and level of productivity and (ii) productivity and capital–labor ratio, the findings go in favor of endogenous growth theories. Higher productivity growth in lower capital–labor ratio countries would favor convergence theory because marginal product of capital would be low in high-income countries those exhibits a high capital–labor ratio.[10] Moreover, the convergence theory could be restated in the relationship between productivity and lagged technical inefficiency. This relationship would state those countries that were near the production frontier would see a lower level of productivity growth than those were farther away. Therefore, the positive relationship between productivity level and lagged technical inefficiency level would indicate the presence of convergence hypothesis (Lall et al., 2002).

A number of factors affect the pattern of CO_2 emissions, including technical change, economic growth and changes in the composition of GDP. Technical progress can yield reductions in CO_2 emissions by increasing the ratio of good output to bad output. A change in the composition of GDP of a country can also affect the level of CO_2 emissions. For example, presumably a shift away from energy intensive sector would yield a decline in CO_2 emissions. Therefore in the determinants of the productivity we have included the energy intensity of production.

The relationship with the openness variable will determine the impact of international trade on the productivity growth. The openness variable can show both positive and negative effects of increased volume of trade on the environmentally sensitive measure of productivity growth (ML index). On the negative side it captures the environmentally deteriorating effects that stem from the increased volume of trade. On the positive side it captures the environmentally beneficial effects that arise due to harmonization of environmental policies. The sign and significance of the openness variable helps one to select among the competing hypotheses on environment and international trade (Etkins et al., 1994; Taskin and Zaim, 2001).

3.1. Conventional measurement of productivity

The average Malmquist index value of 0.9998 indicates that the annual productivity decline for the sample countries was 0.002%. On average, this decline was due to technical change; the World witnessed an average technical regression of 0.02% over the study period. This progress in TFP is 0.42% per annum for Non-Annex-I countries whereas in Annex-I countries it declined by 0.44% per year. From these overall average figures of stagnation in TFP changes in countries it may be argued that effectively all GDP growth in the post-1970 period was due to high rates of input accumulation.

Zimbabwe experienced the highest decline (2.33% per year) in TFP among the sample developing countries (Table 2). Israel experienced the highest growth in TFP followed by Thailand and Hong Kong in Non-Annex-I countries. In the Annex-I countries, Japan experienced the highest decline in TFP growth followed by Netherlands. Ireland experienced the highest growth rate in TFP of the amount of 1.42% per annum.

Let the Malmquist index, M_{it} represent the conventional measure of productivity of country i in year t, the equation below specifies a possible form of relation between the conventional measure of productivity and its determinants.

$$M_{it} = \beta_{1i} + \beta_2 \mathrm{GDPPC}_{it} + \beta_3 \overrightarrow{D}_{it-1} + \beta_4 \mathrm{CAPLAB}_{it} + \beta_5 \mathrm{ENGDP}_{it} + \beta_6 \mathrm{OPEN} + \beta_7 \mathrm{ANNEX}_{it} + \varepsilon_{it}$$

where i is country index; t is time index; ε is the disturbance term such that $\varepsilon \sim N(0,\sigma_\varepsilon)$; GDPPC is the

[10] Here it is important to differentiate between σ- and β-convergences. When the dispersion of income across a group of economies falls over time, there is σ-convergence and the negative partial correlation between growth in income over time and its initial level favors β-convergence. Young et al. (2003) show that β-convergence is necessary for σ-convergence. They show that "σ_t^2 can be rising even if β-convergence is the rule. Intuitively, economies can be β-converging towards one another while, at the same time, random shocks are pushing them apart" (page 5). The present analysis relates to later category.

GDP per capita; $\vec{D}_{it-1}$ is the value of technical inefficiency in the lagged period (when the emissions of carbon are strongly disposable); CAPLAB is capital per labor; ENGDP is use of commercial energy per unit of GDP; OPEN, openness index defined as the ratio of total exports and imports to GDP; and ANNEX is the dummy variable for the group of countries, its value is equal to one if the country belongs to Annex-I countries and zero otherwise.

Table 3 (last column) provides the estimated parameters of the regressions for the M_{it} index under alternative specifications. A LM test performed on the alternative specifications of the fixed effect model rejects the null hypothesis of a common intercept in favor of one with country specific intercept terms. The choice between the fixed effect and random effect models can be made using the Hausman test. We find in the present study the fixed effect model to be the appropriate specification.

In fixed effect model, the positive relationship between the lagged technical inefficiency and productivity index favors the existence of convergence hypothesis. We also find that the sign of capital per labor is negative, while statistically significant at 15% level, again favoring the convergence hypothesis. These findings concur with Lall et al. (2002), which finds the existence of convergence hypothesis for a sample of 30 countries in the Western Hemisphere for the period 1978–1994 using the Malmquist index. Moreover, we find that the openness of a country contributes positively to productivity growth. The coefficient of the dummy variable that represents the group of countries is positive and statistically significant. It implies that the growth rate of productivity was higher in Annex-I countries in comparison to Non-Annex-I countries. The other variables included in the study are not statistically significant.

Table 3
Determinants of productivity change

Variable	Environmentally sensitive measure	Conventional measure
	Random effect model	Fixed effect model
GDPPC	6.34e−06 (2.883)*	1.33e−06 (0.408)
$\vec{D}_o^{t-1}$	1.90e−01 (2.473)**	2.46e−02 (2.263)**
LN(CAPLAB)	−4.17e−02 (−2.154)**	−5−35e−02 (−1.493)$^+$
ENGDP	−4.35e−02 (−2.06)**	−1.22e−02 (−0.313)
OPEN	7.00e−04 (2.714)*	2.10e−03 (4.904)*
ANNEX	6.79e−04 (0.023)	1.35e−01 (1.96)**
Constant	1.0219 (68.26)*	
Adjusted R^2	0.07	0.14
LM test (P-value)		0.00
Hausman test (P-value)	0.118	
N	751	776

Values in parentheses represent 't-statistics'. *, **, *** and $^+$ show the level of significance at 1%, 5%, 10% and 15% respectively. GDPPC: GDP per capita; $\vec{D}_o^{t-1}$: Lagged period value of directional distance function; LN(CAPLAB): natural log of capital–labor ratio; ENGDP: Energy Consumption to GDP ratio; OPEN: Openness Index; and ANNEX: Dummy variable 1 if the country belong to Annex-I countries and 0 otherwise.

3.2. Environmentally sensitive measurement of productivity

The average change in the ML productivity index, when CO_2 was weakly disposable, was 0.02%. This average TFP measure was the product of a positive change in innovation of 0.06% and a negative efficiency change of 0.03%. In Non-Annex-I countries Hong Kong experienced the highest growth in TFP when CO_2 was considered an undesirable output and Ecuador experienced the highest decline in the index. But in Annex-I countries, Netherlands had the highest growth and Luxembourg experienced the highest decline in ML index. However, it was technological changes that governed the change in overall productivity index in most of the countries.

The ML index had a higher value in comparison to the standard Malmquist index for India, Mexico, Peru, Philippines, Venezuela, Zambia and Zimbabwe in Non-Annex-I countries. In Annex-I countries Austria, Canada, Denmark, Italy, Japan, Netherlands, Norway, Sweden, Switzerland, U.K. and U.S. experienced the higher average value of TFP index when we account for CO_2 emissions in comparison to the situation when these emissions are freely disposable. On average in Non-Annex-I countries, the value of standard Malmquist is higher in comparison to ML index, but the reverse is the situation in Annex-I countries. This shows that Non-

Annex-I countries had lower productivity growth when carbon emissions were weakly disposable. This finding confirms that of Kopp (1998). Kopp finds that developed countries experienced technical progress in a way that economizes on CO_2 emissions but that developing countries did not during 1970 to 1990.

We run a basic '*t* test' to test the null hypothesis that whether the two productivity measures and their components were the same. It was found that the TFP index value does not change in either scenario and null hypothesis is not rejected. But for the technical and efficiency changes the null hypothesis can not be accepted for either of the groups of countries (Table 4). The relative growth rates of the conventional productivity measure and the productivity measure adjusted for the inclusion of carbon emissions depend on the relative growth rates of the desirable and undesirable outputs.[11]

It should be noted that the technical change index for any one particular country between two adjacent years is merely an index of the shift in the production frontier. A value of this factor greater than unity does not necessarily imply that the country under consideration did actually push the overall frontier outward. Therefore, in order to determine which countries were shifting the frontier or were 'innovators', the following three conditions are required for a given country (see Färe et al., 2001, p. 400):

$$\text{MLTECH}_t^{t+1}>1; \tag{a}$$

$$\vec{D}_o^{t}\left(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1}\right)<0; \tag{b}$$

$$\vec{D}_o^{t+1}\left(x^{t+1},y^{t+1},b^{t+1};y^{t+1},-b^{t+1}\right)=0. \tag{c}$$

Condition (a) indicates that the production possibility frontier shifts in the more good and fewer bad outputs direction. With a given input vector, in period $t+1$ it is possible to increase GDP and reduce CO_2 emissions relative to period t. This measures the shift in the relevant portions of the frontier between periods t and $t+1$ for a given country when the good and bad outputs are treated asymmetrically. Condition (b) indicates the production in period $t+1$ occurs outside the production possibilities frontier of period t (i.e., technical change has occurred). It implies that the technology of period t is incapable of producing the output vector of period $t+1$ with the input vector of period $t+1$. Hence the value of directional distance function relative to the reference technology of period t is less than zero. Condition (c) specifies that the country must be on the production frontier in period $t+1$.

Table 4
Hypothesis testing using basic '*t*' test (paired *t* test on average)

Null hypothesis	*P*-value	Result
All countries		
ML=M	0.8563	Accepted
MLEFFCH=MEFFCH	0.0916	Rejected
MLTECH=MTECH	0.0252	Rejected
Non-Annex-I countries		
ML=M	0.9826	Accepted
MLEFFCH=MEFFCH	0.0068	Rejected
MLTECH=MTECH	0.0000	Rejected
Annex-I countries		
ML=M	0.7960	Accepted
MLEFFCH=MEFFCH	0.3054	Accepted
MLTECH=MTECH	0.1100	Accepted

ML: Malmquist–Luenberger Index; MLEFFCH: Malmquist–Luenberger Efficiency Change; MLTECH: Malmquist–Luenberger Technical Change; M: Malmquist Index; MEFFCH: Malmquist Efficiency Change; and MTECH: Malmquist Technical Change.

Table 5 lists the innovator countries. Out of 19 two-year periods, Netherlands shifted the frontier 15 times when carbon emissions were freely disposable and three times when these emissions are accounted for in the measurement of productivity. Japan seemed to be innovators for 15 times when carbon emissions were taken into consideration and 14 times when these emissions were strongly disposable. Japan shifted the frontier after 1976–1977. A newly industrialised country, Hong Kong was innovator during 1983–1984 to 1991–1992 under both scenarios. Out of 41 countries six were innovators and all were high-income countries. None of the developing country in any 2-year period was shifting the frontier under either scenario.

Let ML_{it} represent the environmentally sensitive measure of productivity of country i in year t. The equation below specifies a possible form relation

[11] For a rigorous explanation of this relationship see appendix E in Färe et al. (2001).

Table 5
Innovative countries

Years	Environmentally sensitive measure	Conventional measure
1973–1974	Netherlands, Switzerland	Netherlands, Switzerland
1974–1975	–	Netherlands
1975–1976	–	–
1976–1977	Iceland, Japan	Iceland, Japan, Netherlands
1977–1978	Iceland, Japan, Luxembourg	Iceland, Japan, Netherlands
1978–1979	Iceland, Japan, Switzerland	Iceland, Japan, Netherlands, Switzerland
1979–1980	Iceland, Japan, Switzerland	Iceland, Japan, Switzerland
1980–1981	Iceland, Japan, Netherlands, Switzerland	Iceland, Japan, Netherlands, Switzerland
1981–1982	Iceland, Japan, Netherlands, Switzerland	Japan
1982–1983	Japan	–
1983–1984	Hong Kong, Japan	Hong Kong, Japan, Netherlands
1984–1985	Japan, Switzerland	Japan, Netherlands, Switzerland
1985–1986	Japan, Switzerland	Hong Kong, Iceland, Japan, Netherlands
1986–1987	Iceland, Japan, Luxembourg, Switzerland	Hong Kong, Iceland, Japan, Netherlands
1987–1988	Hong Kong, Japan, Switzerland	Hong Kong, Japan, Luxembourg, Netherlands, Switzerland
1988–1989	Japan, Switzerland	Japan, Luxembourg, Netherlands, Switzerland
1989–1990	Hong Kong, Japan, Switzerland	Hong Kong, Japan, Luxembourg, Netherlands, Switzerland
1990–1991	Hong Kong, Japan	Hong Kong, Japan, Luxembourg, Netherlands
1991–1992	Hong Kong	Hong Kong, Luxembourg, Netherlands

between the environmentally sensitive measure of productivity and its determinants.

$$\mathrm{ML}_{it} = \beta_{1i} + \beta_2 \mathrm{GDPPC}_{it} + \beta_3 \overrightarrow{D}_{it-1} + \beta_4 \mathrm{CAPLAB}_{it} + \beta_5 \mathrm{ENGDP}_{it} + \beta_6 \mathrm{OPEN} + \beta_7 \mathrm{ANNEX}_{it} + \varepsilon_{it}$$

where i is country index; t is time index; ε is the disturbance term such that $\varepsilon \sim N(0,\sigma_\varepsilon)$; GDPPC is the GDP per capita; $\overrightarrow{D}_{it-1}$ is the value of technical inefficiency in the lagged period; CAPLAB is capital per labor; ENGDP is use of commercial energy per unit of GDP; OPEN, openness index defined as the ratio of total exports and imports to GDP; and ANNEX is the dummy variable for the group of countries, its value is equal to one if the country belong to Annex-I countries and zero otherwise.

Table 3 (second column) provides the estimated parameters of the regressions for the ML index under alternative specifications. A LM test performed on the alternative specifications of the fixed effect model rejects the null hypothesis of a common intercept in favor of the one with country specific intercept terms. Furthermore the choice between fixed effect and the random effect models can be made using the Hausman test. We reject the null hypothesis and find the random effect model as the appropriate specification.

We find that all coefficients, except that of ANNEX, are statistically significant. It is found that the environmentally sensitive measure of productivity is higher in those countries, which are having the higher GDP per capita. The positive relationship between the technical inefficiency and productivity index when the disposal of carbon emissions is costly favors the existence of convergence hypothesis. We also find a negative relationship between the productivity index and capital labor ratio that again accepts the convergence hypothesis in these countries. It is found that energy intensity of production contribute negatively to environmentally sensitive measure of productivity.

Similar to the standard measures of productivity which is positively related to the openness of a country, the openness of a country contributes positively to the environmentally sensitive measure of productivity also. This finding is similar in spirit to the findings of Hettige et al. (1992) who point out that '…outward oriented, high-growth LDCs have slow growing or even declining toxic intensity of manufacturing…'. An OECD report explains this phenomenon by the ability of dynamic and fast growing developing countries with the higher turnover rates of the manufacturing capital stock to invest more in new processes based on cleaner techniques.

4. Conclusions

Bad outputs are ignored by the traditional measures of productivity and hence have limited use with regards to policy evaluation. However there are environmental regulations and resources are diverted from traditional productive activities to pollution abatement. As a result, these traditional measures of productivity found that environmental regulations have an adverse effect on productivity. These findings ignore the key feature of environmental regulations that diverting the resources in abatement activities leads to reduction in environmental bad outputs. The traditional measures of productivity ignore the reduction in bad outputs due to abatement activities since typically no prices are available for the undesirable outputs such as CO_2 emissions, except for the situations when tradable permits are used to restrict the emissions.

This study presents an extended view of TFP growth measured through ML index using directional distance function. The index throws insight into the sources of productivity growth to estimate an adjusted rate of TFP growth while accounting for CO_2 emissions minimization activities. Through an asymmetrical treatment of good and bad outputs, the TFP index is decomposed into efficiency and technical changes. This index provides a common dialog of different perspective of climate change debate by expanding the basic economic concept of productivity to identify the combined role of technological innovation and adoption, and green accounting.

The ML index is calculated using the non-parametric directional distance function for a group of 41 countries consisting of 21 Annex-I countries and 20 Non-Annex-I countries during the 1971 to 1992 period. On average for either of the group of countries, the value of standard Malmquist is not different from ML index. But for the components of TFP, technical and technical efficiency changes the null hypothesis of whether the different indexes are same when emissions are ignored and when they are accounted for cannot be accepted for either of the groups of countries. Out of 41 countries only six, Iceland, Hong Kong, Japan, Luxembourg and Netherlands, Switzerland were innovators. None of the developing country was shifting the frontier under either scenario.

Subsequent regression analyses find that the environmentally sensitive measure of productivity is higher in those countries, which are having the higher GDP per capita. The value of ML index is negatively associated with technical efficiency and capital labor ratio, implying presence of convergence hypothesis. Moreover, it also finds that the energy intensity of production is negatively related to the environmentally sensitive measure of productivity. However, the conventional measure of productivity remains unaffected by the composition of output growth. The openness of a country increases its TFP whether it is measured by the standard Malmquist index or ML index.

Beyond measuring of environmentally sensitive productivity growth, the present analysis demonstrates the richness of the technique that allows for investigation of important research questions on the underlying processes that influence productivity growth. Notwithstanding the striking feature of the techniques used here, data limitations involved in estimation remain an important factor. It is, therefore, necessary to be cautious while applying these results to policy formulation.

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