Driving forces of different productivity models

Halkos, George and Bampatsou, Christina

Department of Economics, University of Thessaly, Greek Public Power Corporation S.A.

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Christina Bampatsou[1] & **George Halkos**[2]

[1] *Public Power Corporation S.A.*

[2] *Laboratory of Operations Research,*

Department of Economics, University of Thessaly

c.bampatsou@gmail.com, halkos@econ.uth.gr

Abstract

In the present study, Data Envelopment Analysis (DEA) is used for the period spanning from 1980 to 2012 and for a total of 32 countries which are classified into four groups, according to their level of development (Developing, BRICS, Developed, G7). DEA allows us to measure technical efficiency under constant (CRS) and variable (VRS) returns to scale and also the Malmquist index and its components (TECHCH, EFFCH, PECH, SECH). Furthermore, we develop an order-α approach for the determination of partial frontiers. An output oriented model is applied. Labor and capital are used as inputs while the GDP index is used as output. Subsequently, energy is incorporated in the model as an additional input variable and CO_2 emissions as undesirable output. A comparison of productivity indices as derived from the analysis, allows us to highlight the different levels of productivity before and after the integration of energy and CO_2 emissions as additional variables, for each group of countries and therefore their sustainability gaps.

Keywords: Data Envelopment Analysis; Malmquist Index; Order-α approach; Energy; CO_2 emissions.

JEL Codes: O11; O57; Q01; Q43; R15.

1. Introduction

The consequences of climate change are various and quite serious. Coastal flooding from the sea level rise, severe storms and floods together with extreme weather conditions, lower and reduced agricultural production jointly with scarce water reservoirs are a few of them (Halkos, 2013). Thus climate change is related not only to the environmental problem but also to a variety of social and economic effects like decline in productivity and population migration (Halkos and Tsilika 2014, 2016). To a greater extent countries are involved in CO_2 emissions mitigation through increased efficiency and productivity of their economic sectors and the required energy consumption reductions in an efficient way.

In these lines Data Envelopment Analysis (hereafter DEA), as a nonparametric approach, can easily incorporate undesirable factors based on directional distance function (DDF) with specific direction. Based on DDF, DEA can be used to measure inefficiencies taking undesirable factors into account and then constructing the Malmquist Luenberger (ML) productivity index to measure productivity over different periods.

There are many applications of DEA and of the Malmquist Productivity Index to calculate the performance of different DMUs over time in the presence of undesirable outputs (Kortelainen, 2008; Halkos and Tzeremnes, 2009; Mahlberg *et al.*, 2011; Apergis *et al.*, 2015; Long *et al.*, 2015; Halkos and Polemis, 2016). Wang *et al.* (2016) utilize the Luenberger productivity index, which is also applied to estimate the change in productivity and its components, to analyze the main specific energy inputs that contribute to environmental productivity changes in China.

In this study, we assume that decision making units (DMUs) aim at accomplishing higher economic outputs (desirable output like GDP), using less resources (especially energy inputs), and producing less pollution in the form of emissions or environmental degradation. In this context we study the differences in productivity, among the four groups of countries with deferent levels of development (Developing, BRICS, Developed and G7), before and after the integration of energy and CO_2 emissions as additional variables in the initial model of one output (GDP) and two inputs (labor and capital). The contribution of this work, lies in the combinatorial study of full and partial productivity, with the total factor productivity index and its components. Through the total factor productivity decomposition procedure, we have clear evidence regarding the causes of change in productivity.

Therefore we manage to highlight those factors that contribute to sustainable economic development and can be used as a guide for policy making to investigate the gradual process of the diffusion and adoption of new technologies in order to achieve the highest productivity levels. Furthermore, by developing an order-α approach, we show that the determination of partial frontiers can improve estimates of productivity in a production frontier that is usually biased upwards.

2. Methodology

In order to determine the productivity levels of economic systems, we apply DEA by simultaneously estimating the longitudinal (from 1980 to 2012) and the cross-sectional aspects of panel data **(Developing:** Korea, Mexico, Turkey **BRICS:** Brazil, China, India, South Africa **Developed:** Austria, Belgium, Denmark, Spain, Finland, Greece, Ireland, Luxembourg, Netherlands, Portugal, Sweden, Hungary, Poland, Switzerland, Iceland, Norway, Australia, New Zealand **G7:** Canada, Germany, France, United Kingdom, Italy, Japan, United States**)**.

In the following sections, we present two output oriented models. In the first model (Malmquist), labor and capital are used as inputs while GDP is used as output. In the second model (Malmquist-Luenberger), labor, capital and energy are used as inputs while GDP and CO_2 emissions are used as desirable and undesirable outputs respectively. Such models allow us to determine full frontiers for constant and variable returns to scale and also to estimate the total factor productivity index (TFPCH) and its components (TECHCH, EFFCH, PECH, SECH).

To determine the main sources of changes, the TFPCH index can be broken down into the components of Technical Change (TECHCH) and Efficiency Change (EFFCH). The TECHCH index is associated with the changes in production technology, through innovations in resource saving production methods, while the EFFCH index, shows the deviation of the performance of the DMU under consideration from the best practice DMUs and is usually associated with managerial capabilities.

On a second level the EFFCH index can be decomposed into the index of Pure Efficiency Change (PECH) and the index of Scale Efficiency (SECH). These indices indicate the main source of changes in the technical efficiency index. The PECH index is associated with the changes in resource management and thus to the achievement of optimal allocation of resources in the production process. An improvement of the PECH index through a more efficient use of inputs and the investigation of the possibility of one DMU to optimize its internal organization, can reduce inefficiency. On the other hand the SECH index, illustrates the extent to which one DMU can improve its productivity by exploiting scale economies through the reduction of long run average cost as production increases. Furthermore, it gives us useful information to select the production scale that will achieve the required production level. Unsuitable size of a DMU may be the cause of technical inefficiency.

In the second part of our empirical analysis, we introduce the order-α approach to determine partial frontiers that are more robust to extreme values than the traditional full frontiers.

2.1 The model for the determination of total factor productivity index

In this study the total factor productivity index is used to measure the growth of the productivity and is defined as the ratio of total output produced to total input employed in the production process (Fischer *et al.*, 2009; Kitcher *et al.*, 2013). The idea of the Total Factor Productivity index was at first suggested by Malmquist (1953) and its expansion can be measured using the Malmquist index. The Malmquist total factor productivity index was pioneered by Caves *et al.* (1982) and further developed by Fare *et al.* (1994). It measures the change in total factor productivity among two data points by estimating the ratio of the distances of each data point in relation to a specific common technology.

Following Coelli *et al.* (2005) the output oriented Malmquist productivity index is defined as follows:

$$M_o(y_{t+1}, x_{t+1}, y_t, x_t) = \left[\frac{d_{o,t}(y_{t+1}, x_{t+1})}{d_{o,t}(y_t, x_t)} \times \frac{d_{o,t+1}(y_{t+1}, x_{t+1})}{d_{o,t+1}(y_t, x_t)} \right]^{1/2} \qquad (1)$$

where o indicates an output-orientation, y denotes output, x denotes input, M is the productivity of the most recent production point relative to the earlier production point, and d denotes the output distance function.

The first ratio inside the brackets represents the Malmquist index for period t. It indicates the previous production point (x_t, y_t), using period t technology. It calculates productivity change from period t to period $t+1$ using the technology level at period t as a benchmark. In this case, where the output Malmquist Productivity Index relies on the technology of period t, the result is:

$$M_{o,t}(x_t, y_t, x_{t+1}, y_{t+1}) = \frac{d_{o,t}(x_{t+1}, y_{t+1})}{d_{o,t}(x_t, y_t)} \qquad (2)$$

The second ratio inside the brackets represents the Malmquist index for period $t+1$. It indicates the most recent production point (x_{t+1}, y_{t+1}) using period $t+1$ technology. It measures the productivity change from period *t* to period *t+1* using the technology level at period *t+1* as a benchmark. In this case, where the output Malmquist Productivity Index is based on the technology of period *t+1*, the result will be:

$$M_{o,t+1}(x_t, y_t, x_{t+1}, y_{t+1}) = \frac{d_{o,t+1}(x_{t+1}, y_{t+1})}{d_{o,t+1}(x_t, y_t)} \tag{3}$$

The Malmquist Productivity Index can even be presented in an equivalent form as shown next:

$$M_o(y_{t+1}, x_{t+1}, y_t, x_t) = \underbrace{\frac{d_{o,t+1}(y_{t+1}, x_{t+1})}{d_{o,t}(y_t, x_t)}}_{\textbf{EFFC}} \underbrace{\left[\frac{d_{o,t}(y_{t+1}, x_{t+1})}{d_{o,t+1}(y_{t+1}, x_{t+1})} \times \frac{d_{o,t}(y_t, x_t)}{d_{o,t+1}(y_t, x_t)} \right]^{1/2}}_{\textbf{TECHC}} \tag{4}$$

In equation (4), the Malmquist total factor productivity index is the product of an efficiency change (EFFCH) in the same period and a measure of technical progress (TECHCH) as calculated by reallocations in the frontier measured at periods *t + 1* and *t*.

The values of the Malmquist Index and its components can be greater, equal or smaller than 1. An assessment of M_o less than one points to a total factor productivity decline from period t to period t+1 while an assessment greater than one specifies a productivity improvement. If the Malmquist Productivity Index is equal to 1 then productivity remains unchanged.

Furthermore the index of Efficiency Change (EFFCH) is decomposed into Pure Efficiency Change (PECH) and Scale Efficiency Change (SECH) and therefore it follows that:

$$\text{EFFCH} = \text{PECH} \times \text{SECH} \tag{5}$$

If the SECH index is greater than 1, then the changes that have occurred in the inputs between the periods *t* and *t + 1* improve the efficiency scale. If the PECH index is greater than 1, then the improvements in resource management enhance efficiency.

2.2 The model for the determination of Malmquist-Luenberger productivity index

We now turn to the Malmquist-Luenberger (ML) productivity index, which allows us to internalize pollution (CO_2 emissions). Furthermore, energy is incorporated in the model as an additional input variable. The Malmquist-Luenberger productivity index is used to calculate the growth in productivity when undesirable output production is incorporated into the production model for instantaneously decreasing the undesirable output production and increasing the desirable output production. Following Chung et al. (1997) the output-oriented Malmquist-Luenberger productivity index with undesirable output is defined as:

$$ML_{t,t+1} = \left\{ \frac{[1+\vec{D}_{o,t+1}(x_t, y_t, b_t; y_t, -b_t)]}{[1+\vec{D}_{o,t+1}(x_{t+1}, y_{t+1}, b_{t+1}; y_{t+1}, -b_{t+1})]} \times \frac{[1+\vec{D}_{o,t}(x_t, y_t, b_t; y_t, -b_t)]}{[1+\vec{D}_{o,t}(x_{t+1}, y_{t+1}, b_{t+1}; y_{t+1}, -b_{t+1})]} \right\}^{\frac{1}{2}} \quad (6)$$

The ML index may be decomposed into efficiency (MLEFFCH) and technical changes (MLTECHCH). This can expressed as:

$$MLEFFCH_{t,t+1} = \left[\frac{[1+\vec{D}_{o,t}(x_t, y_t, b_t; y_t, -b_t)]}{[1+\vec{D}_{o,t+1}(x_{t+1}, y_{t+1}, b_{t+1}; y_{t+1}, -b_{t+1})]} \right] \quad (7)$$

$$MLTECHCH_{t,t+1} = \left\{ \frac{[1+\vec{D}_{o,t+1}(x_t, y_t, b_t; y_t, -b_t)]}{[1+\vec{D}_{o,t}(x_t, y_t, b_t; y_t, -b_t)]} \times \frac{[1+\vec{D}_{o,t+1}(x_{t+1}, y_{t+1}, b_{t+1}; y_{t+1}, -b_{t+1})]}{[1+\vec{D}_{o,t}(x_{t+1}, y_{t+1}, b_{t+1}; y_{t+1}, -b_{t+1})]} \right\}^{\frac{1}{2}} \quad (8)$$

Similar to the Malmquist index, the ML productivity index also shows productivity advances if its values are larger than one and reductions in productivity if the values are less than one.

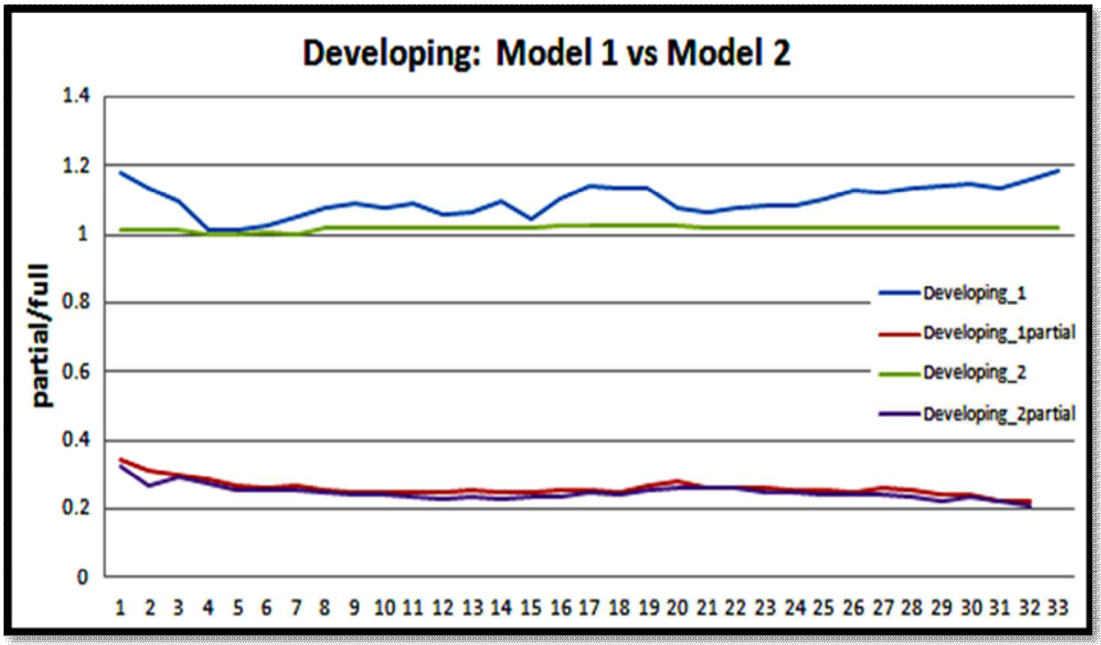
2.3 The determination of partial frontiers

In a nonparametric frontier analysis, DEA is by construction highly sensitive to outliers and measurement errors. Results may be extremely biased if we do not take them into consideration (Daraio and Simar 2007). The sensitivity to outliers is substantially reduced by partial frontier approach enveloping just a subsample of observations. In this study, we use the order-α partial frontiers[1], which are more robust to outliers as they do not enclose all the data points but just a fraction of them (Daraio and Simar, 2007). For the partial frontiers, we followed Bădin et al. (2012) and Mastromarco and Simar (2014). In place of estimating the extreme quartiles $(\alpha = 0.9, \alpha = 0.95)$ we applied a median quartile $(\alpha = 0.5)$. As Bădin et al. (2012) point out median values of α enable us to investigate the effect of the environmental variables on the distribution of efficiencies (technological catch-up).

3. Empirical Results

In this section we illustrate the productivity levels of each group of countries in the case of full and partial frontiers to both model 1 and model 2 (Figures 1, 2, 3 and 4). In particular, we compare productivity levels between model 1 and model 2 in the case of full and partial frontiers.

Figure 1: A comparison of two models for full and partial frontiers in the case of developing countries



[1] The implementation is performed in STATA.

Figure 2: A comparison of two models for full and partial frontiers in the case of BRICS

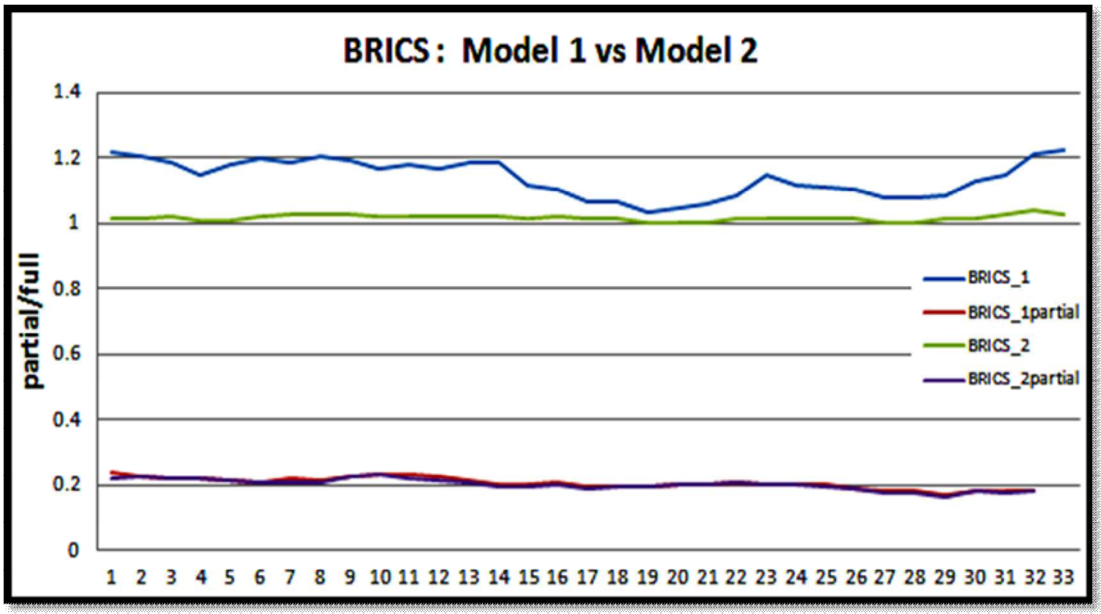


Figure 3: A comparison of two models for full and partial frontiers in the case of developed countries

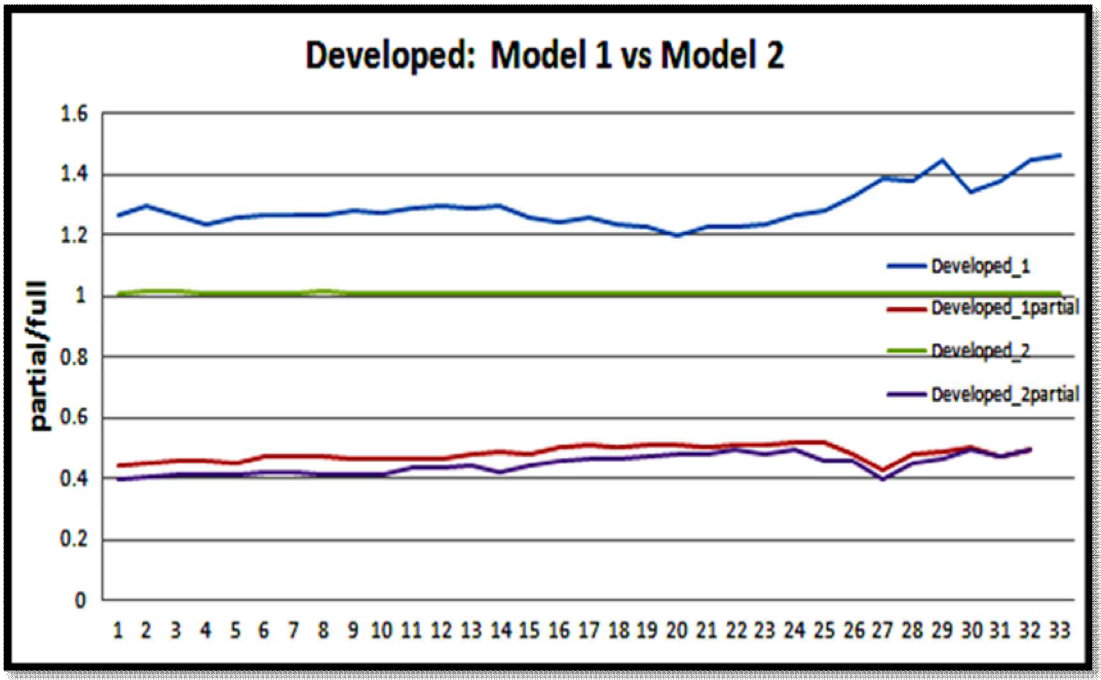
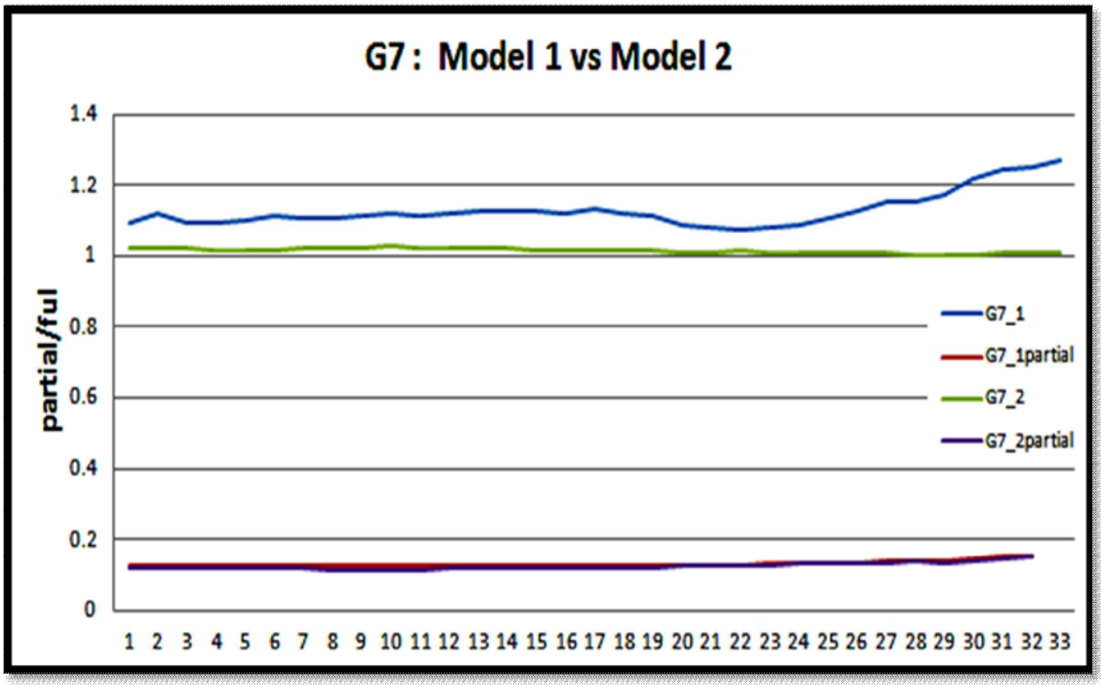


Figure 4: A comparison of two models for full and partial frontiers in the case of G7



Furthermore, subfigures 5a and 5b present diachronically the technical efficiency levels alongside with 95% confidence intervals and under the VRS assumption for full frontiers of the four categories of countries.

Figure 5a: Mean efficiency estimates and 95% confidence intervals for full frontiers in the case of model 1

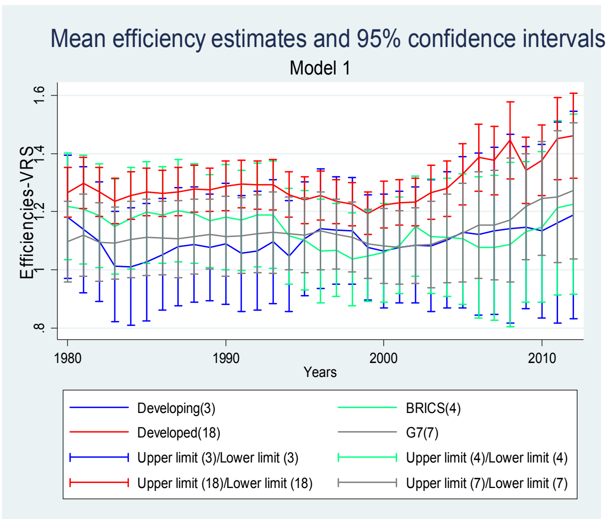


Figure 5b: Mean efficiency estimates and 95% confidence intervals for full frontiers in the case of model 2

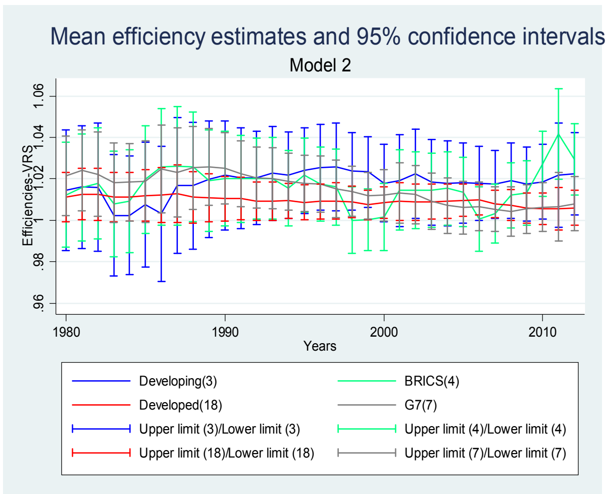


Figure 6 depicts the results of partial productivity by model and by country category allowing direct comparisons between the two models while giving a clear picture of how the four categories of countries are classified. More analytically, subfigures 6a and 6b present diachronically the technical efficiency levels alongside with 95% confidence intervals and under the partial frontiers of the four categories of countries.

Figure 6: Partial frontiers by model and by country category

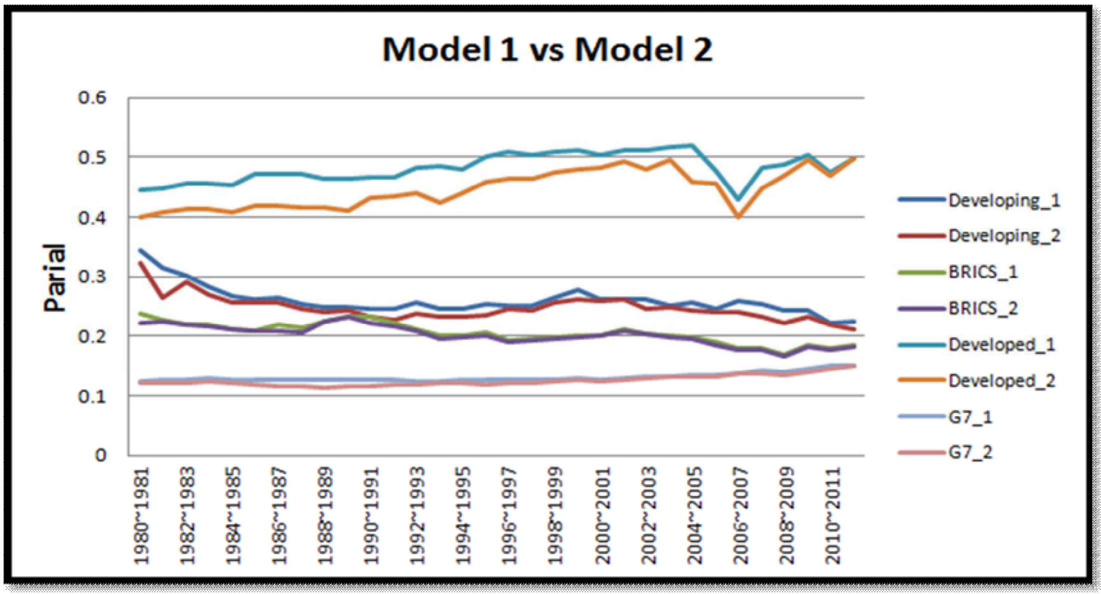


Figure 6a: Mean efficiency estimates and 95% confidence intervals for partial frontiers in the case of model 1

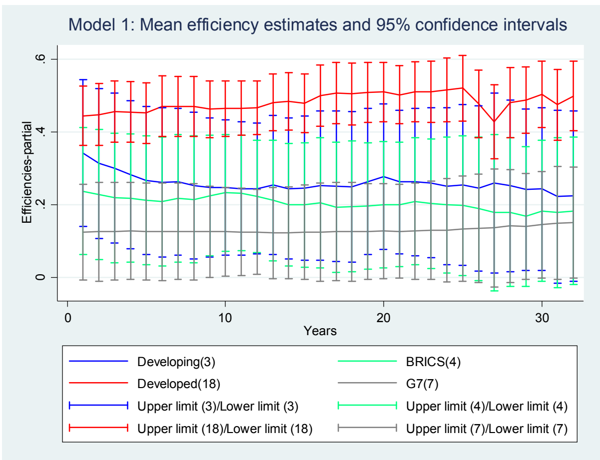
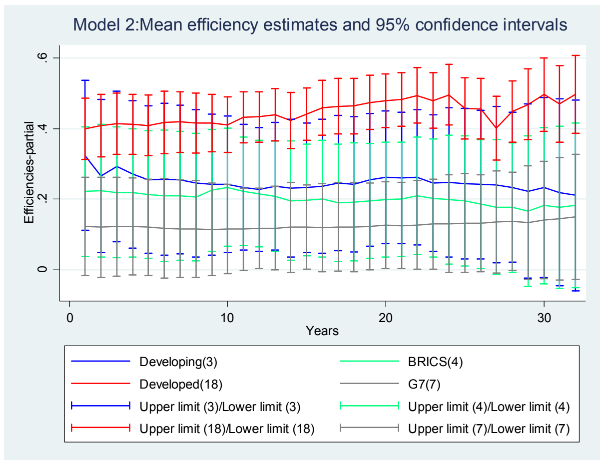


Figure 6b: Mean efficiency estimates and 95% confidence intervals for partial frontiers in the case of model 2



In Tables 1 and 2 we indicate for each category of countries the cases where the total factor productivity index and its components are greater (improvement in productivity) or smaller (productivity decline) than 1 from period t to period t+1.

Table 1: Estimation of total factor productivity index and its components in the first model

means/Model 1	Developing	BRICS	Developed	G7
TFPCH	0.991815995	0.98147	1.0015498	1.000598
EFFCH	0.994642	0.99196	0.994612	0.991085
TECHCH	0.997925	0.99162	1.007312	1.010846
PECH	0.999744	0.99945	1.000163	1.000258
SECH	0.994917	0.99237	0.994407	0.990876

Table 2: Estimation of total factor productivity index and its components in the second model

means/Model 2	Developing	BRICS	Developed	G7
TFPCH	0.992909	0.988403	1.008943	1.006511
EFFCH	0.996157	0.99431	0.997702	0.994108
TECHCH	0.997463	0.99516	1.010977	1.012471
PECH	0.999744	0.999447	1.000169	1.000392
SECH	0.996454	0.994724	0.997511	0.993736

More analytically, subfigures 7a.1, 7a.2, 7b.1, 7b.2, 7c.1, 7c.2, 7d.1, 7d.2, 7e.1 and 7e.2 present diachronically the productivity levels of TFPCH index and its components TECHCH, EFFCH, PECH and SECH alongside with 95% confidence intervals of the four categories of countries.

Figure 7a.1: Mean productivity estimates and 95% confidence intervals for TFPCH index in the case of model 1

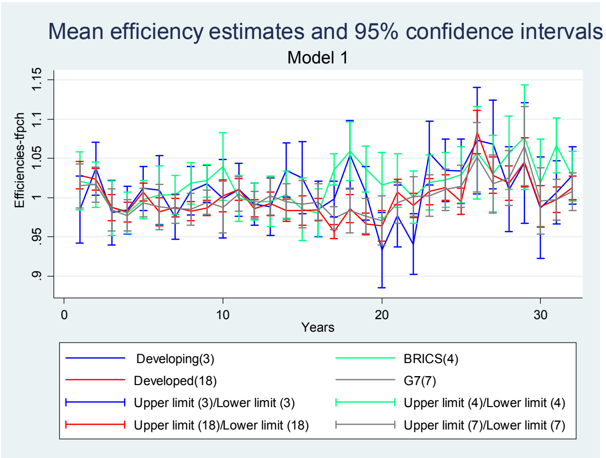


Figure 7a.2: Mean productivity estimates and 95% confidence intervals for TFPCH index in the case of model 2

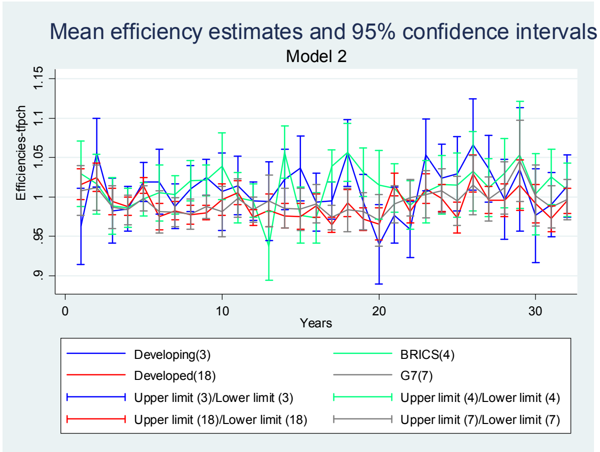


Figure 7b.1: Mean productivity estimates and 95% confidence intervals for TECHCH index in the case of model 1

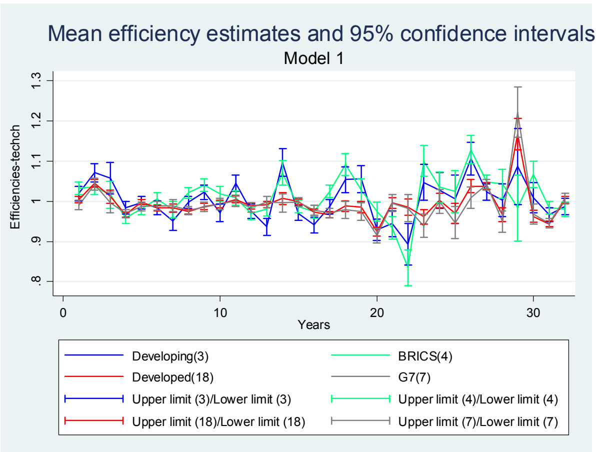


Figure 7b.2: Mean productivity estimates and 95% confidence intervals for TECHCH index in the case of model 2

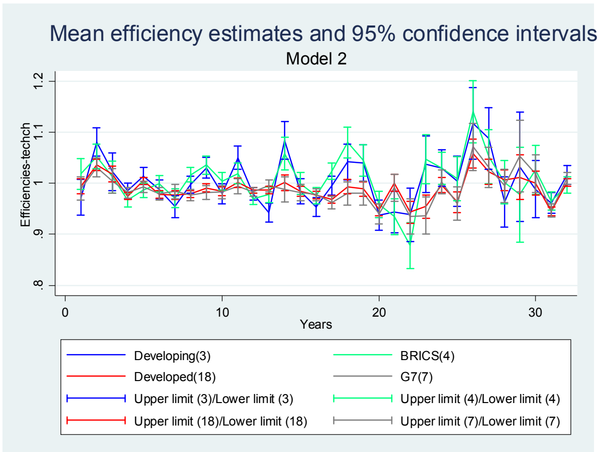


Figure 7c.1: Mean productivity estimates and 95% confidence intervals for EFFCH index in the case of model 1

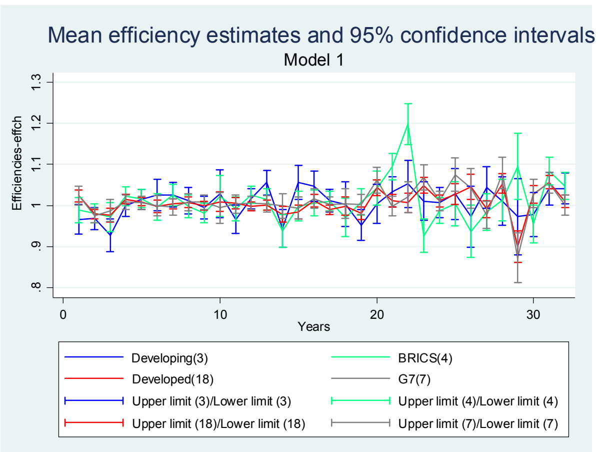


Figure 7c.2: Mean productivity estimates and 95% confidence intervals for EFFCH index in the case of model 2

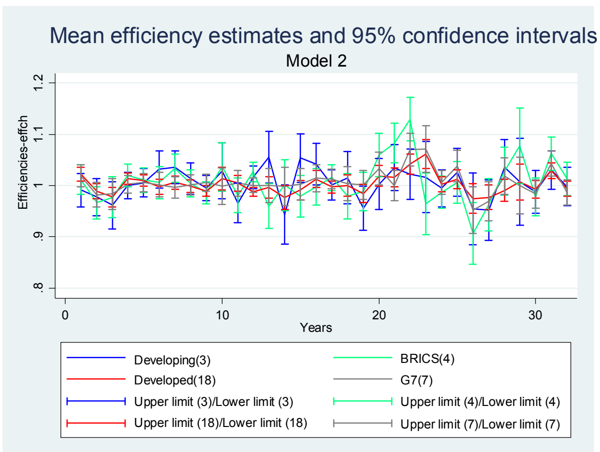


Figure 7d.1: Mean productivity estimates and 95% confidence intervals for PECH index in the case of model 1

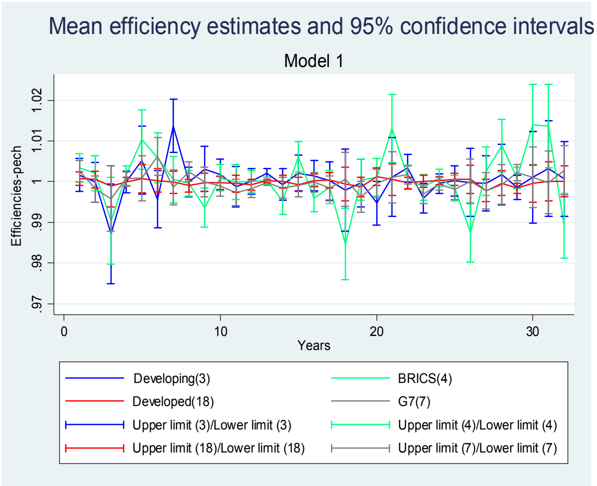


Figure 7e.1: Mean productivity estimates and 95% confidence intervals for SECH index in the case of model 1

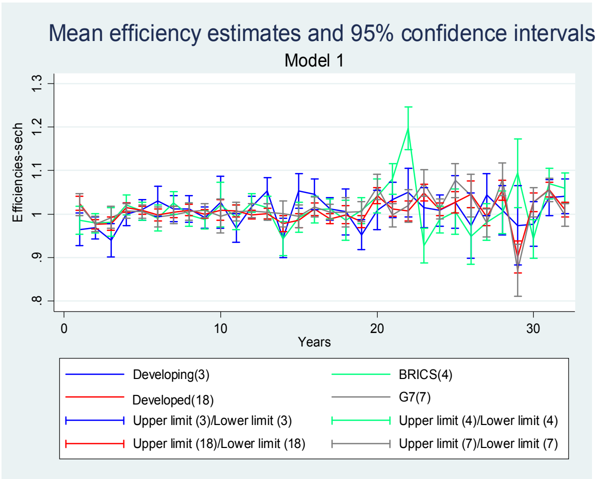


Figure 7d.2: Mean productivity estimates and 95% confidence intervals for PECH index in the case of model 2

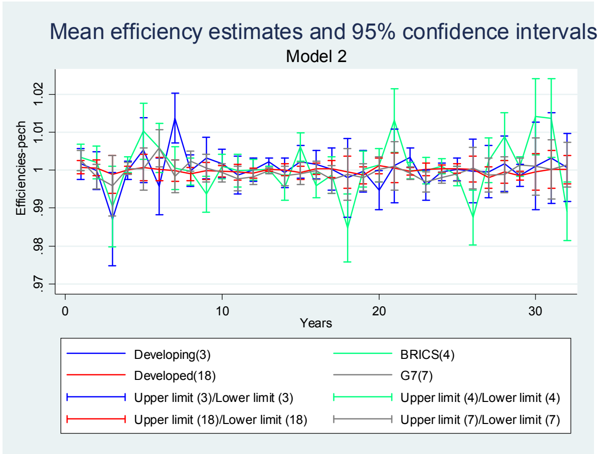
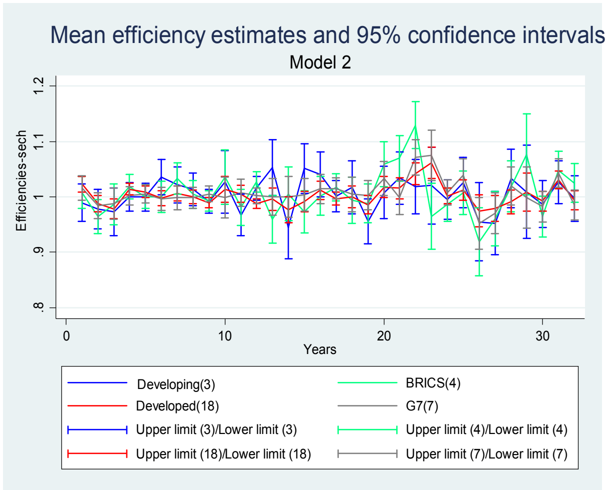


Figure 7e.2: Mean productivity estimates and 95% confidence intervals for SECH index in the case of model 2



4. Conclusions

As derived from the empirical analysis based on productivity models (Figures 1, 2, 3 and 4) full frontiers, which are sensitive to outliers, exceed partial frontiers in all four categories of countries.

Additionally, we observe that the full frontiers of the first model exceed the full frontiers of the second model in all four categories of countries (Figures 1, 2, 3 and 4). This means that when the model does not incorporate energy as an additional input variable and CO_2 emissions as undesirable output, then the productivity growth of countries is overestimated, as it does not take into account that pollution abatement activities of DMUs lower productivity growth. In contrast, partial frontiers between the first and the second model, indicate either a very large (Developing, Developed) or an absolute convergence (BRICS, G7).

In case of partial frontiers (Figure 6) the category with the highest level of productivity is the Developed, followed by Developing, BRICS and G7. From Tables 1 and 2 we observe that for both models (Model 1 and Model 2) the values of TFPCH index and its components are smaller than one in the case of Developing and BRICS. This is not the case for Developed and G7 where they manage to have the comparative advantage regarding the productivity growth of TFPCH, TECHCH and PECH with values greater than 1.

As it results, the growth in TFPCH index depends both on the production technology improvements (TECHCH) through innovations in resource saving production methods and on the achievement of optimal resource management (PECH) in the production process. These two conditions may explain the upward trend of partial frontiers in the case of Developed and G7 countries.

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