Testing for Catching-up: Statistical Analysis of DEA Efficiency Estimates

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Abstract

We use advances in DEA techniques to examine efficiency scores and investigate the issue of convergence/divergence in a cross-country analysis. Specifically, we take use of bootstrapping techniques to examine a data set of 52 developed and developing countries. We find that when using the standard DEA model the results are sometimes less than desirable. Further, we break the sample into the two groups to examine the two-club convergence phenomenon. We find that efficiency scores are significantly different between the two groups and that there is some evidence of convergence of efficiency scores within each group.

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1 Introduction

Economic growth research has received substantial recognition in recent years. The two major strands being the cross-sectional type regressions found in Baumol (1986), which seek to determine whether there is a tendency for the world's economies to converge over time (poor catching up with the rich), and the decomposition of growth into components attributable to capital deepening and technological progress going back to Solow (1957). However, there is a third strand of research which has become increasingly popular—a method based on Malmquist Productivity Indexes (Caves, Christensen and Diewert 1982), computed via the Data Envelopment Analysis (DEA) estimator. Beginning with Färe, Grosskopf, Norris and Zhang (1994), this strand has introduced a third component into economic growth: efficiency—the ability of a given country to fully exploit available resources it has in producing total output. While much of the mainstream research suggests making adjustments to the input mix (e.g. increasing the level of physical or human capital), if the DEA approach shows that efficiencies are found to affect the growth of labor productivity, then perhaps policymakers should also address methods that would improve efficiency (e.g. establishing macroeconomic and political stability).

Conceptually, the efficiency component is nothing but the residual, somewhat like the 'Solow residual', that proxies for the aggregated effect of various factors, other than technology and standard inputs (Labor, Physical and Human Capital), on producing total output (e.g., GDP). This efficiency component can also be understood through the Liebenstein's (1966) 'X-efficiency' concept, related to internal and external motivation of an agent. In our case, X-efficiency would be related to the aggregate result of influence by local and international institutions onto each particular country. The X-efficiency is an abstract concept, which of course is unobserved, and in practice is often proxied via the Debreu (1951)-Farrell (1957) measure of technical efficiency, which is usually estimated using the DEA estimator (e.g., see Liebenstein and Maital (1992)).

The DEA method of estimating efficiency, however, has received some opposition. There are those who believe that the entire world does not exist under one production frontier. There are still others who believe that DEA has inherent flaws. Traditional (or old paradigm) DEA assumes that no measurement error exists and that the production frontier is piecewise linear. Further, some, including Koop, Osiewalski and Steel (1999), state that "the sensitivity of DEA to outliers is no doubt one of the weaknesses of the DEA approach. In particular, it is difficult to present some measure of uncertainty (e.g. confidence intervals) using DEA methods." To combat comments such as these, Simar and Wilson (1998, 2000) and others have introduced bootstrapping into the DEA framework. Their methods, based on statistically well-defined models, allow for consistent estimation of the production frontier, corresponding efficiency scores as well as standard errors and confidence intervals. Although advances were made to DEA, these have not been included in many recent papers which examine macroeconomic growth. Recently, Kumar and Russell (2002) have employed standard DEA production-frontier methods to analyze convergence by decomposing labor productivity growth into components attributable to technological change, technological catch-up (changes in efficiency) and physical capital accumulation. Their results show the main factor to be capital accumulation. Henderson and Russell (2004) extend Kumar and Russell (2002) by adding human capital accumulation into the decomposition and show that the qualitative shift from a unimodal to a bimodal distribution in labor productivity is accounted for primarily by efficiency changes (with physical capital accumulation as a secondary factor). However, both of these papers are subject to the same scrutiny as Färe, Grosskopf, Norris and Zhang (1994). If research is going to continue in this area, it needs to make notice of the advancements in DEA which address the current concerns. It must be noted that there are other useful approaches to estimating efficiency, with one of the most popular being the stochastic frontier analysis (SFA) paradigm originated by Aigner, Lovell and Schmidt (1977) and recently extended to semi and nonparametric framework by Fan, Li and Weersink (1996), Henderson (2003) and Park, Sickles and Simar (2003), to mention a few (for a comparison of various SFA and DEA estimators, see Gong and Sickles 1992 and for a survey of various methods of SFA paradigm, see Kumbhakar and Lovell 2000).

Each of the methods, whether DEA or SFA, have their own advantages and disadvantages for particular setups, and here we will focus on circumventing the drawbacks of DEA in an empirical context. Specifically, we will use the recently developed techniques in statistical analysis of DEA estimates to check for robustness of efficiency estimates for a sample of 52 developed and developing countries. We will also investigate the issue of convergence/divergence in efficiency across the developed and developing countries.

Various empirical studies on economic growth have brought convincing evidence that the world consist of at least these two groups—developed and developing countries, or 'North and South'—which are indeed distinct in their performance as well as in the key factors determining it, especially in the institutional development. Quah (1996) has theoretically justified the possibility of existence of two 'clubs' in the world, with convergence within them and divergence between them, claiming for empirical tendency for such phenomenon to be true. In our work, we will employ the notion of 'Catching-up' first discussed in the seminal paper of Abramovitz (1986). Initially envisioning this phenomenon, Abramovitz's argument was based on the discovery of the considerable reduction in the coefficient of variation of growth rates within a group of 16 industrialized countries. Later, Färe, Grosskopf, Norris and Zhang (1994) re-formalized the notion of 'Catching-up' as the decrease overtime in the distance between the actual performance of a country and its potential, according to the best-practice frontier (i.e., as the decrease in inefficiency of the countries over time). In the spirit of Färe, Grosskopf, Norris and Zhang (1994), we will consider three types of 'Catching-up' here: (i) within the entire sample, (ii) within distinct groups in the sample, and (iii) between these groups. We have two distinct groups in mind: 'developed' and 'developing' countries (we have also analyzed the groups OECD vs. non-OECD and found similar results; they can be obtained from the authors upon request).

Specifically, we first use the study of Kumar and Russell (2002) and its extension by Henderson and Russell (2004) as a stepping-stone, and compare our bootstrap bias-corrected efficiency scores with results of the latter study. Then we break the sample into two groups (developed and developing countries) to see if the efficiency scores are consistent with the two club convergence hypothesis. The remainder of this paper is organized as follows: Section 2 describes the theory of efficiency measurement as well as gives a brief description of the current advances. The third section describes the data, while the fourth section presents the results of the experiment. Finally, Section 5 concludes.

2 Methodology

In this section we discuss the backgrounds of efficiency measurement as well as the latest research advances which will help us obtain more accurate measures for our problem. Although these procedures can be used to analyze any number of (macro or micro) decision making units with multiple inputs and outputs, here we will describe the special case related to our example. For each country i $(i = 1, 2, ..., n)$ we will use the period-t input vector $x_i^t = (K_i^t, H_i^t \times L_i^t)$, where K_i^t is physical capital, and $H_i^t \times L_i^t$ is human capital augmented labor. Further, y_i^t is a single output (GDP) of country i in period t (all inputs and outputs are assumed to be positive). The technology of converting inputs into GDP for each country i, in each time period t, can be characterized by technology set

$$T_i^t \equiv \left\{ \left(x_i^t, y_i^t \right) \mid x_i^t \text{ can produce } y_i^t \right\}.$$

Equivalently, the same technology can be characterized by the output sets

$$P_i^t(x_i^t) \equiv \left\{ y_i^t \mid x_i^t \text{ can produce } y_i^t \right\}, \qquad x_i^t \in \Re_+^2.$$

Here we assume that the technology follows standard regularity assumptions, under which the Shephard (1970) output oriented distance function[1]

$$D_i^t(x_i^t, y_i^t | P_i^t(x_i^t)) = \inf \left\{ \theta \mid y_i^t/\theta \in P_i^t(x_i^t) \right\}.$$

gives a complete characterization of technology i in period t, in the sense that we always have

$$D_i^t(x_i^t, y_i^t | P_i^t(x_i^t)) \leq 1 \Leftrightarrow y_i^t \in P_i^t(x_i^t).$$

For the single output case as ours, this function is simply the ratio of actual output to the maximal (or potential) output, GDP, that can be produced from the same amount of inputs. A related concept is the Farrell output oriented technical efficiency, defined

[1] For detailed assumptions and proofs related to the distance function (and the Farrell technical efficiency meausre), see Färe and Primont (1995).

as[2]

$$\begin{aligned} TE_i^t &\equiv TE_i^t(x_i^t, y_i^t | P_i^t(x_i^t)) = \sup\left\{\theta \mid \theta y_i^t \in P_i^t(x_i^t)\right\} \\ &= 1/D_i^t(x_i^t, y_i^t | P_i^t(x_i^t)). \end{aligned}$$

When $TE_i^t = 1$, the country is considered technically efficient (on the upper boundary of $P_i^t(x_i^t)$ defined as $\partial P_i^t(x_i^t)$), whereas when $TE_i^t \geq 1$ (or ≤ 1 when the commonly used reciprocal is employed), the country is deemed technically inefficient. TE_i^t is not the only measure of technical efficiency we could employ. Besides the fact that the Debreu-Farrell measure is perhaps the most popular, it has natural interpretation in duality theory in economics and also satisfies a wide range of desirable mathematical properties and, in this sense, it is superior to many other measures (see Shephard 1970 and Russell 1990 for details).

Since the true technology and hence output sets are unknown, the individual values of technical efficiency must be estimated. One such popular tool is DEA. This procedure involves measuring given observations $XY^t = \{(x_i^t, y_i^t)\}_{i=1}^n$ against *one* "best practice" frontier (thus sub-script i can be dropped), defined as

$$\partial\widehat{P^t}(x) = \left\{y \mid y \in \widehat{P^t}(x), \lambda y \notin \widehat{P^t}(x), \lambda \in (1, \infty)\right\},$$

where $\widehat{P}(x)$ is the DEA-estimate of the output set $P(x)$, defined as

$$\widehat{P^t}(x) \equiv \left\{y \mid \sum_{i=1}^n z_i y_i^t \leq y, \sum_{i=1}^n z_i x_i^t \leq x, z_i \geq 0, i = 1, 2, ..., n, \sum_{i=1}^n z_i = 1\right\},$$

and where z_i are the intensity variables. This is a non-parametric estimator of the frontier. The last constraint in the expression above imposes variable returns to scale (VRS) assumption and its removal would instead impose constant returns to scale (CRS). Geometrically, for VRS case, the resulting estimate of the "best practice" technology represents the smallest convex free-disposable hull of the data XY^t. In the theory and measurement of economic growth, the assumption of CRS is almost always employed, and we use it for our study as well, in which case the "best practice" technology represents the smallest convex free-disposable cone of the data.

[2] Note that, in practical estimation of the technical efficinecy, our output is 'proxied' with one variable (GDP), so our 'technical' efficinecy measure also incorporates the price information. In fact, the resulting DEA estimate can be shown to be equivalent to the revenue (GDP) efficiency measure (see Färe, Grosskopf and Zelenyuk, 2004).

Further, the DEA estimate of individual technical efficiency at any fixed point (x, y), is computed relative to the estimated frontier, solving the following linear programming problem

$$\widehat{TE^t}(x, y|\widehat{P^t}(x)) = \max_{\theta, z_1, z_2, \ldots, z_n} \left\{ \theta \mid \theta y \in \widehat{P^t}(x) \right\}.^3$$

Although this procedure is relatively simple, there is a cost of using this DEA estimator. It should be obvious that, when no measurement error exists, that $\widehat{P^t}(x) \subseteq P^t(x)$. Therefore, $\partial\widehat{P^t}(x)$ is a downward biased estimator of $\partial P^t(x)$. As a result, $\widehat{TE^t}(x, y|\widehat{P^t}(x))$ is a downward biased estimate of $TE(x, y|P^t(x))$. In our case, DEA would rate countries as more efficient than they truly are $(1 \leq \widehat{TE^t}(x, y|\widehat{P^t}(x)) \leq TE(x, y|P^t(x)))$. This bias vanishes asymptotically, since the DEA estimator is consistent, with a rate of convergence given by

$$\widehat{TE^t}(x, y|\widehat{P^t}(x)) - TE^t(x, y|P^t(x)) = O_p\left(n^{-(2/M+N+1)}\right)$$

as shown by Kneip, Park and Simar (1998), under quite weak regularity assumptions on the data generating process (note that M and N are the number of outputs and inputs, respectively). In finite samples, however, the bias may be quite large, especially when the dimension of the DEA model $(M+N)$ is large relative to the sample size (since the rate of convergence depends on this dimension, as indicated by expression above).

Statistical bootstrap procedures have become a useful and popular tool to estimate bias corrected estimates. They also allow constructing confidence intervals for estimators with unknown sampling distribution—which was impossible for DEA before, and was one of the major downsides of this technique. Now we will overcome

[3] The philosophical background of the Data Generating Process for most of DEA is based on the belief that there is one unique 'best-practice' technology to which each decision making unit (country, in our case), has access to. This does not mean that each country must be on the frontier of this 'best-practice' technology. It is meant to assume 'feasibility', not necessarily efficiency. Various factors, like institutions in the country and political regimes may or may not allow each particular country to be on the frontier. Contrary to the common belief, random error is in fact allowed, but only such that the observation still belongs to the technology set. That is, the error (including measurement error) must not violate the 'feasibility' assumption. The estimation of the frontier with such errors would still be consistent, as long as the assumptions of Kneip, Park and Simar (1998) are satisfied. Such errors, however, would be picked up as part of inefficiency by the efficiency measure, and a challenge is to disentangle it from the 'true' inefficiency (see Simar and Wilson 2003 for recent attempts). In this study, we will not investigate this issue, and will treat all the deviations from the frontier as inefficiency.

this problem by using the bootstrap procedures for DEA developed by Simar and Wilson (1998), Kneip, Simar and Wilson (2003) and Simar and Zelenyuk (2003).

To briefly outline the idea of the bootstrap for individual DEA estimates, let $\mathcal{P}^t$ denote the Data Generating Process (DGP) in period t –characterized in terms of the technology set and distributions for inputs, output and inefficiency across countries in this period.[4] Neither the technology, nor any of the distributions are known. All that is observed is the random sample XY^t generated by $\mathcal{P}^t$. We also have a consistent (DEA) estimate of technical efficiency at any fixed point (x, y), which, being a function of the random sample XY^t, has some sampling distribution, which we denote with $G_n^t(\widehat{TE^t}(x, y|\widehat{P^t}(x)), \mathcal{P}^t)$. As is typical for a complicated statistic, $G_n^t(\widehat{TE^t}(x, y|\widehat{P^t}(x)), \mathcal{P}^t)$ is not known but can be estimated via a consistent bootstrap analog, $G_n^{t*}(\widehat{TE^{t*}}(x, y|\widehat{P^{t*}}(x)), \widehat{\mathcal{P}^t})$, based on $\widehat{\mathcal{P}^t}$—consistent estimate of $\mathcal{P}^t$ estimated from the original data XY^t. The DEA-estimator of output sets that uses data XY^{t*} generated from $\widehat{\mathcal{P}^t}$ would then give $\widehat{P^{t*}}(x)$—a bootstrap estimator of $\widehat{P^t}(x)$, formally defined (under CRS) as

$$\widehat{P^{t*}}(x) = \left\{ y \mid y \leq \sum_{i=1}^{n} z_i y_i^{t*}, x \geq \sum_{i=1}^{n} z_i x_i^{t*}, z_i \geq 0, i = 1, 2, ..., n \right\}$$

which from the perspective of XY^{t*}, is the true output set, and which in our original setting was an estimate of $P^t(x)$. From here, we can calculate a bootstrap estimate of technical efficiency at the same fixed point (x, y), using

$$\widehat{TE^{t*}}(x, y|\widehat{P^{t*}}(x)) = \max_{\theta, z_1, z_2, ..., z_n} \left\{ \theta \mid \theta y \in \widehat{P^{t*}}(x) \right\}.$$

Most importantly, consistency of the bootstrap ensures that

$$\left(\widehat{TE^{t*}}(x, y|\widehat{P^{t*}}(x)) - \widehat{TE^t}(x, y|\widehat{P^t}(x))\right) |\widehat{\mathcal{P}} \overset{approx}{\sim} \left(\widehat{TE^t}(x, y|\widehat{P^t}(x)) - TE^t(x, y|P^t(x))\right) |\mathcal{P}.$$

Intuitively, the unknown distribution of the difference between the true and estimated efficiency score (at (x, y)) is approximated by the distribution of the difference between the estimated and the bootstrapped efficiency score (at the same (x, y)), which, in principle, is known. This relationship allows consistent estimation of the bias and of the confidence intervals for $\widehat{TE^t}(x, y|\widehat{P^t}(x))$, at any fixed point (x, y).

[4] For formal definition of DGP, derivation of the resulting limiting distribution of DEA-estimator as well as proofs of consistency of bootstrap, see Kneip, Simar and Wilson (2003).

In practice, $G_n^{t*}(\widehat{TE}^t(x,y|\widehat{P^t}(x)),\widehat{\mathcal{P}^t})$ is approximated by generating B samples of XY_b^{t*} drawn from $\widehat{\mathcal{P}^t}$.[5] Then, the technical efficiency is re-estimated B times, yielding $\widehat{TE}_b^{t*}(x,y|\widehat{P_b^{t*}}(x))$, $b=1,2,...,B$. The bootstrap bias estimate for the DEA-estimate of efficiency score $\widehat{TE}^t(x,y|\widehat{P^t}(x))$ is then obtained from

$$\widehat{bias}_B\left(\widehat{TE}^t(x,y|\widehat{P^t}(x))\right)=\frac{1}{B}\sum_{b=1}^{B}\left(\widehat{TE}_b^{t*}(x,y|\widehat{P_b^{t*}}(x))-\widehat{TE}^t(x,y|\widehat{P^t}(x))\right),$$

which is the bootstrap approximation of the true bias defined by

$$bias\left(\widehat{TE}^t(x,y|\widehat{P^t}(x))\right)=E\left(\widehat{TE}^t(x,y|\widehat{P^t}(x))\right)-TE^t(x,y|P^t(x)).$$

The true confidence interval (of level α) for inefficiency at any point (x,y),

$$\Pr(-c_{\alpha/2}\leq\widehat{TE}^t(x,y|\widehat{P^t}(x))-TE^t(x,y|P^t(x))\leq-d_{\alpha/2}\ |\mathcal{P}^t\ )=1-\alpha$$

can also be approximated by its bootstrap analog

$$\Pr(-c^*_{\alpha/2}\leq\widehat{TE}_b^{t*}(x,y|\widehat{P_b^{t*}}(x))-\widehat{TE}^t(x,y|\widehat{P^t}(x))\leq-d^*_{\alpha/2}\ |\widehat{\mathcal{P}^t}\ )\approx1-\alpha,$$

where values of $c^*_{\alpha/2}$ and $d^*_{\alpha/2}$ are found by sorting $\left(\widehat{TE}_b^{t*}(x,y|\widehat{P_b^{t*}}(x))-\widehat{TE}^t(x,y|\widehat{P^t}(x))\right)$, then deleting $\left(\frac{\alpha}{2}\times100\%\right)$ of the elements at each end, and then setting $c^*_{\alpha/2}$ and $d^*_{\alpha/2}$ to be the endpoints (so that $c^*_{\alpha/2}\geq d^*_{\alpha/2}$) of this truncated list. As a result, we can expect that the interval

$$[\widehat{TE}^t(x,y|\widehat{P^t}(x))+d^*_{\alpha/2},\quad\widehat{TE}^t(x,y|\widehat{P^t}(x))+c^*_{\alpha/2}].$$

would cover the true but unobserved technical efficiency $TE^t(x,y|P^t(x))$ in approximately $(1-\alpha)\times100\%$ of the time.

Sometimes, as in our study, we do not simply want to look at an individual country versus the others, we may want to examine groups of countries. A naive way

[5] A critical issue here is how to obtain these bootstrap samples XY_b^{t*} so that they reliably approximate the true sampling distribution. It turns out that the most common, simple or naive bootstrap does not work here (see Simar and Wilson 2000). Two options are available: (i) smooth bootstrap (with the boundary problem taken into account) and (ii) the sub-sampling bootstrap. The asympototics and finite sample (Monte Carlo) performance of these two methods are presented in Kneip, Simar and Wilson (2003). The bottom line is that, under quite weak assumptions on the Data Generating Process, the sub-sampling bootstrap is proven to be consistent for any sub-sample size smaller than the original size and that the smooth bootstrap gives a good approximation of this consistent bootstrap.

of doing this is to compare the sample means of efficiency scores of the two groups. This ignores the relative economic weight of each country in the sample—since all efficiency scores are standardized to be between 1 and infinity (or 0 and 1). Recently, Färe and Zelenyuk (2003) have proposed aggregation of individual efficiencies into *group* efficiency, where the weights (and the aggregation function) are derived from economic optimization criterion.

To briefly outline this aggregation method, suppose we want to focus on a group within a population, call it group l $(l = 1, ..., L)$, represented by a sub-sample $i = 1, 2, ..., n_l$ $(\leq n)$ of the original sample of n countries. We will denote the input allocation among firms within group l in period t by $X^{l,t} = (x_1^{l,t}, ..., X_{n_l}^{l,t})$ and the sum of output over the countries in group l in period t with $\overline{Y}^{l,t} = \sum_i^{n_l} y_i^{l,t}$. The group technology in period t is defined by assuming a linear structure of aggregation of the output sets, i.e.,

$$\overline{P^{l,t}}(X^{l,t}) = \sum_{i=1}^{n_l} P_i^{l,t}(x_i^{l,t}), \qquad l = 1, ..., L.$$

Given this structure of aggregation, it can be shown that, for the single output case as ours, the technical efficiency of group l,

$$\overline{TE^{l,t}} = \sup\left\{\theta \mid \theta\overline{Y}^{l,t} \in \overline{P^{l,t}}(X^{l,t})\right\},$$

which disaggregates exactly into the weighted average of the individual technical efficiencies within the same group l $(l = 1, ..., L)$, where the weights are the observed output shares of each individual in the sample of the group l, i.e.,[6]

$$\overline{TE^{l,t}} = \sum_{i=1}^{n_l} TE_i^{l,t}(x_i^{l,t}, y_i^{l,t}) \times S_i^{l,t}, \qquad S_i^{l,t} = \frac{y_i^{l,t}}{\overline{Y}^{l,t}}, \qquad i = 1, ..., n_l, \quad l = 1, ..., L.$$

Specifically for our study, this formula tells us that the true efficiencies for the two groups of countries, developed and developing, in a particular period can be obtained by averaging the individual efficiency scores of each country (in this period), with weights being the observed GDP shares of each country in its group (in the same period).

[6] For multi-output case, see discussion in Fāre and Zelenyuk (2003) and Simar and Zelenyuk (2003).

Similarly, if we assume the linear structure of aggregation for the output sets over all the (non-overlapping) groups in the population, i.e.,

$$\overline{P^t}(X^{1,t}, ..., X^{l,t}, ..., X^{L,t}) = \sum_{l=1}^{L} \overline{P^{l,t}}(X^{l,t}),$$

then the technical efficiency for entire population, defined as

$$\overline{TE^t} = \sup\left\{\theta \mid \theta \sum_{l=1}^{L} \overline{Y}^{l,t} \in \overline{P^t}(X^{1,t}, ..., X^{l,t}, ..., X^{L,t})\right\},$$

would disaggregate exactly into the weighted sum of the technical efficiencies for each group l ($l = 1, ..., L$), with the weights being the output shares of each group in the population, i.e.,

$$\overline{TE^t} = \sum_{l=1}^{L} \overline{TE^{l,t}} \times S^{l,t}, \qquad S^{l,t} = \overline{Y}^{l,t} / \sum_{l=1}^{L} \overline{Y}^{l,t}, \qquad l = 1, ..., L.$$

In our case, this expression tells us that the technical efficiency of the developed and developing countries considered together under the same best-practice frontier can be obtained by averaging the group efficiencies over all groups, with weights being the shares of GDP of each group in the entire sample (all with respect to the same period).

The aggregate efficiencies outlined above are, of course, not observed, but can be estimated by replacing the true individual efficiency scores with their consistent DEA-estimates. Such DEA estimates of $\overline{TE^{l,t}}$ ($l = 1, ..., L$) and $\overline{TE^t}$ would also fall prey to the same issues as the individual efficiency estimates and a bootstrap procedure can be used to construct the corresponding confidence intervals and to correct for bias—in a similar fashion as outlined above (for detailed assumptions on the DGP and algorithm of the bootstrap, including multi-output case, see Simar and Zelenyuk 2003).

Once we have obtained aggregate efficiency scores for two or more groups, we may want to test that these aggregate scores are different from one another. Previously, when making judgement on efficiency of certain groups after using DEA, researchers often resort to using the Kruskal-Wallis test. The direct application of this test to DEA estimates does not take into account the fact that the estimates are used instead of the true efficiencies. Even more problematic is that such tests use equal weights and ignore the economic weights associated with these standardized efficiency scores. In order to sidestep this problem, we use the test provided in Simar and Zelenyuk (2003). When one wants to test that the (aggregate) efficiency of two groups (e.g., A and Z) of countries are different from one another, one can use the following null and alternative hypotheses:

$$H_o : \overline{TE^{A,t}} = \overline{TE^{Z,t}}$$

versus

$$H_a : \overline{TE^{A,t}} \neq \overline{TE^{Z,t}}.$$

We are interested in whether the relative difference ($RD_{A,Z} \equiv \overline{TE^{A,t}}/\overline{TE^{Z,t}}$) is different from unity or not. The quantity $RD_{A,Z}$ is not observed but can be estimated by replacing $\overline{TE^{A,t}}$ and $\overline{TE^{Z,t}}$ with their DEA-estimates, thus obtaining $\widehat{RD}_{A,Z}$. Further, the bootstrap confidence interval for the $RD_{A,Z}$ can be constructed in a similar fashion as discussed above (see Simar and Zelenyuk 2004 for details). The null hypothesis must then be rejected if this confidence interval does not contain unity, and fail to reject otherwise.

We can also use this for testing on non-weighted means—as estimates of first moments of the distribution of inefficiency. Finally, we will also employ a test concerning differences between the densities of the efficiencies of the two groups.

3 Data

Here we use the identical data as in Henderson and Russell (2004). For aggregate output we use real GDP per worker (RGDPCH multiplied by POP), whereas physical capital and employment are obtained through the capital per worker variable (KAPW and RGDPW) of which all are obtained from the Penn World Tables Mark 5.6 (focusing on the years 1965 and 1990, and the changes over that 25-year period). For human capital we also use the Hall and Jones (1999) construction, based on the Barro and Lee (2001) average years of education data and the Psacharopoulos (1994) survey of wage equations evaluating the returns to education. Specifically, we determine the level of human capital per country per time period, by letting e_i^t represent the average years of schooling in country i at time t, as

$$H_i^t = \exp(\phi(e_i^t)),$$

where ϕ is a piece-wise linear function, with a zero intercept and a slope of 0.134 through the fourth year of education, 0.101 through the next four years, and 0.068 for any additional years of schooling.

4 Results

4.1 Standard DEA Efficiency Measurement

Tables 1 and 2 list the efficiency levels of each of the 52 countries for the years 1965 and 1990, respectively. The first column of numbers represents whether or not a country is defined as developed or developing (a value of 1 defines a developed country). The second column of numbers are the individual efficiency scores (standard estimates) which are identical (if allowing for implosion) to the reciprocal of those found in Henderson and Russell (2004). Among the first things to note are the countries that define the world production frontier in each period. For 1965 the frontier defining countries are: Argentina, Mauritius, Netherlands, Sierra Leone, Spain and the United States (note that Mexico is very close to the frontier as well). However, in 1990, the United States has a drop in efficiency by 8.3 percentage points, Spain has decreases by almost 7 percentage points, Netherlands by about 10 percentage points, and Argentina by about 54 percentage points. The frontier in 1990 is determined solely by Hong Kong, Italy, Mauritius, and Sierra Leone.

It is worth noting the fact that some developing countries, such as Mauritius and Sierra Leone, have full (technical) efficiency and thus define portions of the frontier in both periods. At the same time, most of the developed countries were inefficient with respect to the 'best practice' frontier. This somewhat unexpected result should not necessarily be interpreted as a failure of the DEA method. On the opposite, the advantage of the DEA approach is that it allows comparing all types of countries, small and large, poor and rich, with respect to one frontier without imposing any specific parametric functional form.

This artifact that some poor countries turned out to be more efficient than many rich countries should not be misinterpreted: higher efficiency does not imply higher well-being. It only means that countries with higher efficiency scores have exploited their resources relatively better than other countries in the sample—with similar levels of inputs (e.g., Malawi, Zimbabwe and Zambia, etc). If those poor but more efficient countries were also able to increase all inputs by the same proportion, while maintaining current efficiency and constant returns to scale, then they would also have higher GDP per worker than the less efficient developed countries.

Thus, what the DEA results suggest to us is that Mauritius and Sierra Leone have exploited all the efficiency (technical and scale) they could, given their resources, and their further economic growth in GDP can come from either changes in technology or in inputs (e.g., physical or human capital accumulation). At this point, however, we would abstain from such a conclusion, until we see the results of bootstrap-based bias correction for all the DEA estimates.

Finally, Tables 1 and 2 also indicate remarkable increases in efficiency of countries like Hong Kong, South Korea and Thailand. Further, some Western European countries also have improved their efficiency considerably (Belgium, Greece, Ireland and Italy) while some others have become more inefficient relative to the 1990 'best-practice' frontier (Austria, Denmark and Norway).

4.2 Bootstrapping Individual DEA Efficiency Estimates

The results discussed above are calculated using the standard DEA efficiency scores. In order to perform the Simar and Wilson (1998) smooth homogeneous bootstrap estimation, we have to make assumption on the density of efficiency scores being independent on distributions of inputs and outputs. This assumption, however, might be inappropriate—since we have a priori knowledge of existence of two distinct groups in the population, which (while still sharing the same frontier) might have two different distributions of inefficiency. The group-wise heterogeneous DGP—that assumes homogeneity within the groups but allows for heterogeneity between them (see Simar and Zelenyuk, 2003) might be more appropriate here. If the homogeneity assumption is correct, then the smooth homogeneous bootstrap would be more efficient than the group-wise heterogeneous analog, but inconsistent if the group-wise heterogeneity assumption is correct. This is a common econometrics efficiency-consistency trade-off, and a statistical test is desirable in order to make this choice. Here, we employ the

Simar and Zelenyuk (2004) DEA-context adapted Li (1996, 1999) test for equality of densities of two random variables (estimates of efficiency scores). The results of this test are given in Table 5. The test results confirm our earlier suspicions that the distributions of efficiency scores across the groups differ with high probability, for both periods. On the other hand, quite interestingly, the distributions are very likely to have remained the same for the same group across time. This justifies the choice of group-wise heterogenous smooth bootstrap (instead of the homogenous one), which we use to obtain the results presented in the next two tables. The third column of Tables 1 and 2 list the bootstrap estimates of bias corrected DEA efficiency scores. The final columns show the estimated standard errors as well as the 95% confidence bounds.

As hypothesized, each of the countries initially considered efficient now fall below the upper boundary of the output set. The average efficiency score in both periods fell from approximately 1.6 to 1.9. Most notable of these frontier defining countries is the case of Sierra Leone. The bootstrap procedure gives a bias corrected efficiency score of 1.43 (or roughly 70% inefficient) in 1965 with similar results in 1990. This result may solidify the procedure used since many viewed Sierra Leone being on the frontier as a serious case of measurement error (the Penn World Table grades the accuracy of data of each country on an A to F scale, to which Sierra Leone received a D). The bias is corrected for all other countries on the DEA-estimated frontier, including the United States, so that no one has an efficiency score of unity (the ranks, however, are mostly preserved).

4.3 Analysis of Efficiency Distributions

It has become common to use nonparametric kernel density estimation techniques to graphically illustrate various results. This method is also useful in our context since we did not impose distributional assumptions on the efficiency scores across countries. There are, however, several complications which occur when one attempts to do this (see Simar and Zelenyuk 2004). The bottom line is that one has to take special care of at least three things. First, the random variable for which we want to estimate the density has bounded support, with many observations close to the bound. This bound must be taken into account; we do so by using the Silverman reflection method (as we also did in applying the Simar-Wilson smooth bootstrap).

Second, we do not observe the true realizations of the random variable (efficiency) whose density we want to estimate, but only their consistent estimates that are biased downward, which would most likely be reflected in biased estimation of the density. Third, some countries (at least one) are on the bound—having an efficiency score equal unity—so there is always a strictly positive probability of observing at least one country with the efficiency score of unity. This is a violation of the continuity assumption that we need to ensure consistency of density estimation. Here, we follow the suggestion of Simar and Zelenyuk (2004). We first correct for the bias with the bootstrap, as we did in the previous section, and then estimate the densities from the bias corrected efficiency scores. We estimate the densities for each group using the reflection method, with a Gaussian kernel and bandwidth selected via the Sheather and Jones (1991) method. The results are presented in Figures 1-4. Figures 1 and 2 provide convincing evidence that the two distributions are very likely to be different, as we have concluded from the test before. Figures 3 and 4 also support the test results—telling us that the distributions of efficiency scores of countries within each group, especially for developing countries, seem to have changed minimally over 25 years.

These figures, supported by Simar-Zelenyuk adapted Li-test, provide some empirical support for absence of 'Catching-up *between* the groups'—the club of the rich and club of the poor. It is useful to note that some countries have improved their efficiency (got closer to the best-practice frontier), others have worsened, but overall the distributions remain the same. As a result, there is little support for the 'Catching-up within the groups' hypothesis. This, however, may be due to the relatively low power of the Li (1996) test, especially for small samples, such as ours. In the next section, we will look for evidence when the economic importance of the standardized efficiency scores is incorporated.

4.4 Aggregate Efficiency

More interesting than the efficiency scores themselves are the conclusions that Henderson and Russell (2004) make about the impact of changes in efficiency on bimodalism. They state that, when accounting for differences in human capital across countries, efficiency changes are the primary driving force in international polarization. The idea behind this two-club or twin-peak convergence is that over the last few decades the distribution of labor productivity has been transformed from a unimodal into a bimodal distribution with a higher mean. In other words, some view the world as becoming divided into the rich and the poor. Here we are planning to look at two groups of countries: developed and developing countries. We first examine whether or not these two groups of countries differ in terms of efficiency, on average.

To incorporate our knowledge that different groups may have different distributions, we again choose the group-wise heterogeneous version of sub-sampling bootstrap (see Simar and Zelenyuk 2003 for details). The results of such a bootstrap on group or aggregate efficiencies for 1965 and 1990 are displayed in Tables 3 and 4. The eight rows in descending order are: aggregate (weighted) efficiency for the developed countries, aggregate efficiency for the developing countries, the aggregate efficiency scores for all 52 countries, the mean (non-weighted) efficiency for the developed countries, the mean efficiency for the developing countries, and the $\widehat{RD}$ statistic for both the weighted and non-weighted measures. The columns represent: the DEA-estimates, the bias corrected DEA-estimates, the estimated standard errors and the 95%-confidence lower and upper bounds for the corresponding quantities.

A common perception is that developed countries are more efficient than the developing countries. However, as we noted before, being 'rich' does not necessarily imply being efficient in the sense of full exploitation of endowed resources. In fact, it is often the case that being rich still allows some room for efficiency improvement. Nevertheless, the results of Table 3 (1965) do support that common perception: at least on average, that developed countries are more efficient than the developing countries. This is confirmed by both the weighted and non-weighted averages. Further, the $\widehat{RD}$ statistic is significantly different from unity (i.e., confidence intervals do not overlap with unity). The estimated group efficiency of the developing countries is statistically different from unity for both weighted and non-weighted aggregations, as suggested by the confidence intervals. The situation with the developed countries is different. According to the estimated confidence intervals for the weighted averages, the efficiency of the developed countries is not statistically different from unity (perfect efficiency). However, it is statistically different from unity when the non-weighted average is used. Thus, if the aggregation of efficiencies that accounts for the relative weight of each country (derived from economic optimization) is preferred, then we cannot reject the hypothesis (at the 5% level) that the group of developed countries is efficient, in the Farrell (1957) sense.

Interestingly, the estimated average inefficiency of the entire world is much higher when the non-weighted aggregation is used. This is due to the fact that the weight of the developed countries (the more efficient group) in the sample is 81.5%.

The results for 1990 are placed in Table 4 and although they are quite similar, they have slight but important differences than those of the previous table. Remarkably, the estimated weighted average inefficiency of the developed countries is now larger than it was in 1965. We now reject the null, concluding that the efficiency score for the group of developed countries is significantly different from unity. Again we find the confidence intervals of the $\widehat{RD}$ statistic not overlapping unity, indicating significant difference in efficiencies between the two groups.

It is interesting to examine the dynamics of efficiency of each group of countries. In particular, we would like to find some evidence for presence of the following phenomena:

i. 'Efficiency Catching-up/Lagging-behind *within* a group'—which we define as a situation when the average (weighted or non-weighted) efficiency for the group is increasing/decreasing.

ii. 'Efficiency Convergence/Divergence *within* a group'—when a measure of 'spread' (such as standard error, coefficient of variation, confidence intervals, etc) for weighted or non-weighted aggregates is decreasing.

iii. 'Efficiency Catching-up/Lagging-behind *between* groups'—when the average (weighted or non-weighted) efficiency of any group is getting 'closer' to that of a more efficient group.

iv. 'Efficiency Convergence/Divergence *between* groups'—when a measure of 'spread' for (weighted or non-weighted) efficiencies between groups is decreasing.

v. '*Overall* Efficiency Catching-up'—when the average (weighted or non-weighted) efficiency of the entire population is increasing.

vi. '*Overall* Efficiency Convergence/Divergence'—when a measure of 'spread' for (weighted or non-weighted) efficiencies for the entire population is decreasing/increasing.

At this point, formal statistical tests, based on DEA, for presence of most of the above listed dynamic phenomena do not exist and we are only ready to list a few interesting findings suggested by our results—in the hope to be provocative for further research.

Comparing the results of Table 3 and Table 4, we note that according to the bias corrected non-weighted means, the average efficiency of the group of developed countries virtually has not changed between the periods (1.41 vs. 1.40), while the inefficiency of the groups of developing countries has slightly increased by about 8 percentage points (2.19 vs. 2.27). This is in line with the results of density comparison across groups. However, when the economic weight of each country in its group is accounted, using the weighted aggregation, the conclusions are different. On one hand, the weighted average inefficiency of the group of developing countries has not changed over 25 years. On the other hand, the efficiency of the group of developed countries has decreased—giving us some evidence of the 'Efficiency Lagging-behind *within*' this group. Note however that, because of this decrease, the weighted average efficiency of the developing countries is closer in 1990 to that of the developed countries in 1990, relative to this difference in 1965. This is also seen from the slight increase in the value of the $\widehat{RD}$ statistic. This gives slight evidence of 'Catching-up *between* the groups', while the decrease in the range of estimated confidence intervals (and standard errors) of the $\widehat{RD}$ statistic over time gives some evidence for 'Efficiency Convergence *between* the groups' (a formal statistical test for such claims, however, is yet to be developed).

The weighted average of the two groups taken together also suggests about the decrease in efficiency in the entire sample (mainly because the group of developed countries has the majority of the economic weight when the two groups are taken together). In other words, we find evidence for further '*Overall* Efficiency Lagging behind' across all countries, on average. This is also supported by the fact that, based on the bootstrap confidence intervals, we cannot reject the hypothesis about the weighted average efficiency of the group of developed countries (and efficiency of all countries together) to be equal unity for 1965, but do reject this with high confidence for 1990 (the same hypothesis for the group of developing countries was always rejected).

Finally, one can also note that both groups possess larger inefficiency in 1990 than they had in 1965, but the range of the confidence intervals of all group efficiencies has slightly decreased for both weighted and non-weighted cases, and especially for the weighted ones. In particular, the standard errors and their ratios to the corresponding means (weighted and non-weighted) has also slightly decreased for all groups. In the manner similar to one used in Abramovitz (1986), this finding gives some support to hypothesis of 'Efficiency Convergence *within* all groups' (although not very large) meaning that relative efficiency of countries within the same group have become slightly closer. A natural extension of our work would be further development of formal statistical tests for the presence of such dynamic phenomena.

5 Conclusion

In this paper we have introduced recent advances in bootstrapping and DEA in order to analyze cross-country efficiency scores and to study the international convergence/divergence hypothesis. We describe the theory behind output based technical efficiency, methods to estimate the efficiencies of groups of countries by their economic weights, as well as methods used to correct for the small sample biases of individual and aggregate DEA estimates and construct confidence intervals. We apply these methods to the data used in Henderson and Russell (2004). We find that although many of their results are robust, that the efficiency scores of particular countries are sometimes highly misjudged, due to bias, when employing standard DEA techniques. Further, we separate the countries into those that are developed versus those which are developing. As expected, we find that there are significant differences between the two groups in each of the periods (measured with both weighted and non-weighted aggregations). Remarkably, the distributions of efficiency within these two groups have not changed significantly, according to tests of equality for densities.

As to change across time (over 25 years), our aggregate efficiency indexes suggest some evidence for 'Efficiency Lagging-behind *within*' the group of developed countries, but no change for the group of developing countries. Interestingly, we also find some evidence for slight ‘Efficiency Catching-up *between* the groups’ as well as ‘Efficiency Convergence *between* the groups’. At the same time, our indexes suggest the presence of slight ‘Efficiency Convergence *within*’ every group as well as ‘*Overall* Efficiency Lagging behind’ but ‘*Overall* Efficiency Convergence’. Finally we suggest that development of formal statistical tests for such dynamic changes in aggregate efficiency levels would be a natural extension of our present work.

References

[1] Abramovitz, M. (1986). "Catching up, forging ahead and falling behind," *Journal of Economic History*, 46, 386-406.

[2] Adams, R., A. Berger, and R. Sickles (1999). "Semiparametric Approaches to Stochastic Panel Frontiers with Applications to the Banking Industry," *Journal of Business and Economic Statistics* 17, 349-58.

[3] Aigner, D. J., C. A. K. Lovell and P. Schmidt (1977). "Formulation and Estimation of Stochastic Frontier Production Function Models," *Journal of Econometrics*, 6, 21-37.

[4] Barro, R. J. and J-W. Lee (2001). "International Data on Educational Attainment: Updates and Implications," *Oxford Economic Papers*, 53, 541-63.

[5] Baumol, W. J. (1986). "Productivity Growth, Convergence, and Welfare," *American Economic Review*, 76, 1072-85.

[6] Caves, D., L. Christensen and W. E. Diewert (1982). "The Economic Theory of Index Numbers and the Measurement of Input, Output, and Productivity," *Econometrica* 50, 1393-414.

[7] Debreu, G. (1951). "The Coefficient of Resource Utilization," *Econometrica*, 19, 273-92.

[8] Fan, Y., Q. Li and A. Weersink (1996). "Semiparametric Estimation of Stochastic Production Frontier Models," *Journal of Business and Economic Statistics*, 14, 460-8.

[9] Färe, R., S. Grosskopf, M. Norris, and Z. Zhang (1994). "Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries," *American Economic Review*, 84, 66-83.

[10] Färe, R. and V. Zelenyuk (2003). "On Aggregate Farrell Efficiency Scores," *European Journal of Operational Research*, 146, 615-20.

[11] Farrell, M. J. (1957). "The Measurement of Productive Efficiency," *Journal of the Royal Statistical Society*, Series A, 120, 253-81.

[12] Gong, B. and R. Sickles (1992). "A Comparison Between Stochastic Frontier and Data Envelopment Methods Using Panel Data," *Journal of Econometrics* 51, 259-84.

[13] Hall, R. E. and C. I. Jones (1999). "Why Do Some Countries Produce So Much More Output Per Worker Than Others?" *Quarterly Journal of Economics*, 114, 83-116.

[14] Henderson, D. J. (2003). "Nonparametric Kernel Measurement of Technical Efficiency," Working Paper 0309, State University of New York at Binghamton, U.S.A.

[15] Henderson, D. J. and R. R. Russell (2004). "Human Capital and Convergence: A Production-Frontier Approach," forthcoming, *International Economic Review*.

[16] Kneip, A., B. Park and L. Simar (1998). "A Note on the Convergence of Nonparametric DEA Estimators for Production Efficiency Scores," *Econometric Theory*, 14, 783-93.

[17] Kneip, A., L. Simar and P. Wilson (2003). "Asymptotics for DEA Estimators in Non-parametric Frontier Models," Discussion Paper, Institut de Statistique, Université Catholique de Louvain, Belgium.

[18] Koop, G., J. Osiewalski, and M. F. J. Steel (1999). "The Components of Output Growth: A Stochastic Frontier Analysis," *Oxford Bulletin of Economics and Statistics*, 61, 455-87.

[19] Kumar, S. and R. R. Russell (2002). "Technological Change, Technological Catch-up, and Capital Deepening: Relative Contributions to Growth and Convergence," *American Economic Review*, 92, 527-48.

[20] Kumbhakar S. C., and C. A. K. Lovell (2000). *Stochastic Frontier Analysis*, Cambridge, Cambridge University Press.

[21] Li, Q. (1996) "Nonparametric Testing of Closeness between Two Unknown Distributions," *Econometric Reviews*, 15, 261-74.

[22] Leibenstein, H. (1966). "Allocative Efficiency vs. 'X-Efficiency'," *American Economic Review* 56, 392-415.

[23] Leibenstein, H. and S. Maital (1966). "Empirical Estimation and Partitioning of X-Inefficiency: A Data-Envelopment Approach," *American Economic Review* 82, 428-33.

[24] Park, B., R. Sickles and L. Simar (2003). "Semiparametric Efficient Estimation of Dynamic Panel Data Models." Discussion Paper 0315, Institut de Statistique, Université Catholique de Louvain, Belgium.

[25] Psacharopoulos, G. (1994). "Returns to Investment in Education: A Global Update," *World Development*, 22, 1325-43.

[26] Quah, D. (1996). "Twin Peaks: Growth Convergence in Models of Distribution Dynamics," *Economic Journal*, 106, 1045-55.

[27] Russell, R. R. (1990), "Continuity of Measures of Technical Efficiency," *Journal of Economic Theory* 51, 255-67.

[28] Shephard, R. W. (1970). *Theory of Cost and Production Functions*, Princeton, Princeton University Press.

[29] Sheather, S. and M. Jones (1991). "A Reliable Data-Based Bandwidth Selection Method for Kernel Density Estimation," *Journal of the Royal Statistical Society*, Series B, 53, 683-90.

[30] Silverman, B. W. (1986). *Density Estimation for Statistics and Data Analysis*, Chapman and Hall, London.

[31] Simar, L. and P. Wilson (1998). "Sensitivity of Efficiency Scores : How to Bootstrap in Nonparametric Frontier Models," *Management Science* 44, 49-61.

[32] Simar, L. and P. Wilson (2000). "A General Methodology for Bootstrapping in Nonparametric Frontier Models," *Journal of Applied Statistics*, 27, 779-802.

[33] Simar, L. and V. Zelenyuk (2003). "Statistical Inference for Aggregates of Farrell-type Efficiencies," Discussion Paper 0324, Institut de Statistique, Université Catholique de Louvain, Belgium.

[34] Simar, L. and V. Zelenyuk (2004). "On Testing Equality of Two Distribution Functions of Efficiency Scores Estimated via DEA," (in progress), Institut de Statistique, Université Catholique de Louvain, Belgium.

[35] Solow, R. W. (1957). "Technical Change and the Aggregate Production Function," *The Review of Economics and Statistics*, 39, 312-20.

Table 1 - Smooth Group-Wise Heterogenous Bootstrap Results (1965)[7]

Country	D	Efficiency	Corrected	Std Error	Lower	Upper
Argentina	0	1.00	1.13	0.03	1.09	1.20
Australia	1	1.35	1.51	0.04	1.45	1.61
Austria	1	1.25	1.41	0.04	1.34	1.49
Belgium	1	1.39	1.56	0.04	1.49	1.65
Bolivia	0	1.99	2.29	0.07	2.18	2.44
Canada	1	1.18	1.33	0.04	1.27	1.41
Chile	0	1.17	1.33	0.03	1.27	1.40
Colombia	0	2.08	2.33	0.05	2.24	2.44
Denmark	1	1.37	1.53	0.04	1.47	1.61
Dominican Rep.	0	1.25	1.46	0.05	1.38	1.58
Ecuador	0	2.37	2.65	0.07	2.54	2.80
Finland	1	1.51	1.69	0.05	1.62	1.80
France	1	1.18	1.32	0.04	1.27	1.40
Germany, W.	1	1.45	1.62	0.04	1.55	1.71
Greece	1	1.81	2.04	0.06	1.94	2.16
Guatemala	0	1.04	1.20	0.03	1.13	1.27
Honduras	0	1.93	2.19	0.06	2.09	2.31
Hong Kong	0	2.17	2.45	0.07	2.33	2.59
Iceland	1	1.06	1.19	0.03	1.14	1.26
India	0	2.28	2.78	0.14	2.56	3.09
Ireland	1	1.49	1.68	0.05	1.60	1.77
Israel	1	1.63	1.82	0.04	1.75	1.92
Italy	1	1.32	1.48	0.04	1.41	1.57
Jamaica	0	1.61	1.82	0.05	1.74	1.93
Japan	1	1.83	2.08	0.06	1.98	2.20
Kenya	0	3.20	3.82	0.15	3.58	4.18
Korea, Rep.	0	2.41	2.84	0.10	2.68	3.06
Malawi	0	3.69	5.03	0.48	4.22	5.94
Mauritius	0	1.00	1.16	0.04	1.11	1.24
Mexico	0	1.00	1.12	0.03	1.08	1.18
Netherlands	1	1.00	1.12	0.03	1.07	1.19
New Zealand	1	1.20	1.35	0.04	1.29	1.43
Norway	1	1.27	1.42	0.04	1.36	1.50
Panama	0	2.17	2.44	0.07	2.33	2.59
Paraguay	0	1.02	1.35	0.12	1.16	1.59
Peru	0	1.52	1.70	0.04	1.64	1.79
Philippines	0	2.39	2.76	0.08	2.63	2.94

[7] We use 2000 bootstrap iterations, Gaussian kernel, Silverman (1986) reflection method (to account for boundary problem) and the bandwidth is selected via Sheather and Jones (1991) method.

Table 1 (Continued)

Country	D	Efficiency	Corrected	Std Error	Lower	Upper
Portugal	1	1.33	1.51	0.04	1.44	1.59
Sierra Leone	0	1.00	1.43	0.14	1.16	1.68
Spain	1	1.00	1.13	0.03	1.07	1.19
Sri Lanka	0	3.01	3.40	0.09	3.26	3.60
Sweden	1	1.20	1.34	0.04	1.28	1.42
Switzerland	1	1.04	1.16	0.03	1.11	1.23
Syria	0	1.61	1.81	0.05	1.73	1.92
Taiwan	0	1.91	2.18	0.06	2.07	2.31
Thailand	0	2.22	2.71	0.14	2.50	3.02
Turkey	1	1.77	2.02	0.06	1.91	2.14
U.K.	1	1.08	1.22	0.03	1.16	1.29
U.S.A.	1	1.00	1.13	0.03	1.08	1.19
Yugoslavia	0	1.53	1.79	0.06	1.70	1.92
Zambia	0	2.08	2.38	0.07	2.26	2.52
Zimbabwe	0	4.80	5.37	0.12	5.16	5.63
Mean	0.46	1.68	1.93	0.07	1.82	2.07

Table 2 - Smooth Group-Wise Heterogenous Bootstrap Results (1990)[8]

Country	D	Efficiency	Corrected	Std Error	Lower	Upper
Argentina	0	1.54	1.83	0.08	1.67	1.97
Australia	1	1.30	1.43	0.03	1.38	1.49
Austria	1	1.32	1.46	0.03	1.41	1.53
Belgium	1	1.16	1.28	0.03	1.24	1.35
Bolivia	0	2.29	2.75	0.10	2.58	2.95
Canada	1	1.24	1.38	0.03	1.33	1.45
Chile	0	1.54	1.82	0.07	1.68	1.96
Colombia	0	1.76	1.98	0.05	1.90	2.09
Denmark	1	1.46	1.61	0.03	1.56	1.68
Dominican Rep.	0	1.78	2.13	0.08	1.99	2.29
Ecuador	0	2.38	2.66	0.07	2.55	2.81
Finland	1	1.50	1.68	0.04	1.61	1.78
France	1	1.15	1.29	0.03	1.24	1.36
Germany, W.	1	1.35	1.51	0.04	1.45	1.60
Greece	1	1.59	1.75	0.03	1.70	1.83
Guatemala	0	1.14	1.38	0.05	1.30	1.48
Honduras	0	2.18	2.64	0.09	2.49	2.83
Hong Kong	0	1.00	1.19	0.04	1.11	1.28
Iceland	1	1.11	1.23	0.03	1.18	1.29
India	0	2.11	2.66	0.12	2.46	2.91
Ireland	1	1.17	1.30	0.03	1.25	1.37
Israel	1	1.20	1.34	0.03	1.29	1.41
Italy	1	1.00	1.13	0.03	1.08	1.19
Jamaica	0	1.83	2.25	0.08	2.12	2.42
Japan	1	1.66	1.83	0.04	1.77	1.91
Kenya	0	2.68	3.53	0.22	3.14	3.97
Korea, Rep.	0	1.67	1.91	0.05	1.82	2.03
Malawi	0	2.96	4.04	0.30	3.50	4.62
Mauritius	0	1.00	1.23	0.04	1.16	1.33
Mexico	0	1.15	1.33	0.04	1.26	1.40
Netherlands	1	1.10	1.21	0.02	1.18	1.26
New Zealand	1	1.49	1.64	0.03	1.59	1.71
Norway	1	1.54	1.73	0.05	1.65	1.83
Panama	0	2.83	3.26	0.09	3.09	3.45
Paraguay	0	1.00	1.36	0.09	1.18	1.54
Peru	0	2.41	2.86	0.12	2.63	3.07
Philippines	0	2.30	2.87	0.11	2.68	3.10

[8] We use 2000 bootstrap iterations, Gaussian kernel, Silverman (1986) reflection method (to account for boundary problem) and the bandwidth is selected via Sheather and Jones (1991) method.

Table 2 (Continued)

Country	D	Efficiency	Corrected	Std Error	Lower	Upper
Portugal	1	1.04	1.18	0.03	1.12	1.25
Sierra Leone	0	1.00	1.43	0.13	1.18	1.65
Spain	1	1.07	1.18	0.02	1.14	1.24
Sri Lanka	0	2.84	3.37	0.14	3.09	3.62
Sweden	1	1.39	1.55	0.04	1.49	1.63
Switzerland	1	1.29	1.44	0.04	1.38	1.52
Syria	0	1.20	1.34	0.03	1.29	1.40
Taiwan	0	1.58	1.74	0.03	1.69	1.81
Thailand	0	1.71	2.08	0.07	1.96	2.23
Turkey	1	1.62	1.92	0.08	1.75	2.06
U.K.	1	1.05	1.17	0.03	1.12	1.24
U.S.A.	1	1.08	1.19	0.02	1.16	1.24
Yugoslavia	0	1.73	2.06	0.08	1.92	2.21
Zambia	0	3.01	3.89	0.22	3.52	4.34
Zimbabwe	0	3.94	4.82	0.17	4.54	5.18
Mean	0.46	1.64	1.93	0.07	1.82	2.08

Table 3 - Results of Group-Wise Heterogeneous Sub-Sampling Bootstrap for Aggregate Efficiencies: Developed vs. Developing Countries (1965)[9]

	DEA Est.	Bias Corrected	Std Error	Lower	Upper
AgEf. Group A	1.19	1.22	0.13	0.90	1.37
AgEf. Group Z	1.83	2.08	0.33	1.45	2.55
AgEf. of All	1.30	1.35	0.15	0.99	1.54
MeEf Group A	1.32	1.41	0.08	1.26	1.55
MeEf Group Z	1.98	2.19	0.25	1.65	2.60
MeEf of All	1.68	1.84	0.14	1.54	2.07
$\widehat{RD}_{A,Z}$ for AgEff.	0.65	0.53	0.18	0.16	0.82
$\widehat{RD}_{A,Z}$ for MeEff.	0.67	0.62	0.11	0.41	0.82

[9] AgEf. = aggregate efficiency (weighted average), MeEf = mean efficiency (non-weighted average); Group A = 'Developed' countries, Group Z = 'Developing' countries. Confidence Intervals are all at the 0.95 level; Sub-sample size in each bootstrap replication is determined via $m_l = n_l^{\kappa}$, $\kappa = 0.7$, $l = A, Z$.

Table 4 - Results of Group-Wise Heterogeneous Sub-Sampling Bootstrap for Aggregate Efficiencies: Developed vs. Developing Countries (1990)[10]

	DEA Est.	Correction	Std Error	Lower	Upper
AgEf. Group A	1.23	1.31	0.11	1.06	1.44
AgEf. Group Z	1.78	2.08	0.22	1.63	2.49
AgEf. of All	1.34	1.47	0.12	1.20	1.64
MeEf. Group A	1.29	1.40	0.07	1.25	1.51
MeEf. Group A	1.95	2.27	0.21	1.85	2.66
MeEf. of All	1.64	1.87	0.12	1.64	2.10
$\widehat{RD}_{A,Z}$ for AgEff.	0.69	0.59	0.14	0.27	0.82
$\widehat{RD}_{A,Z}$ for MeEff.	0.66	0.59	0.10	0.36	0.76

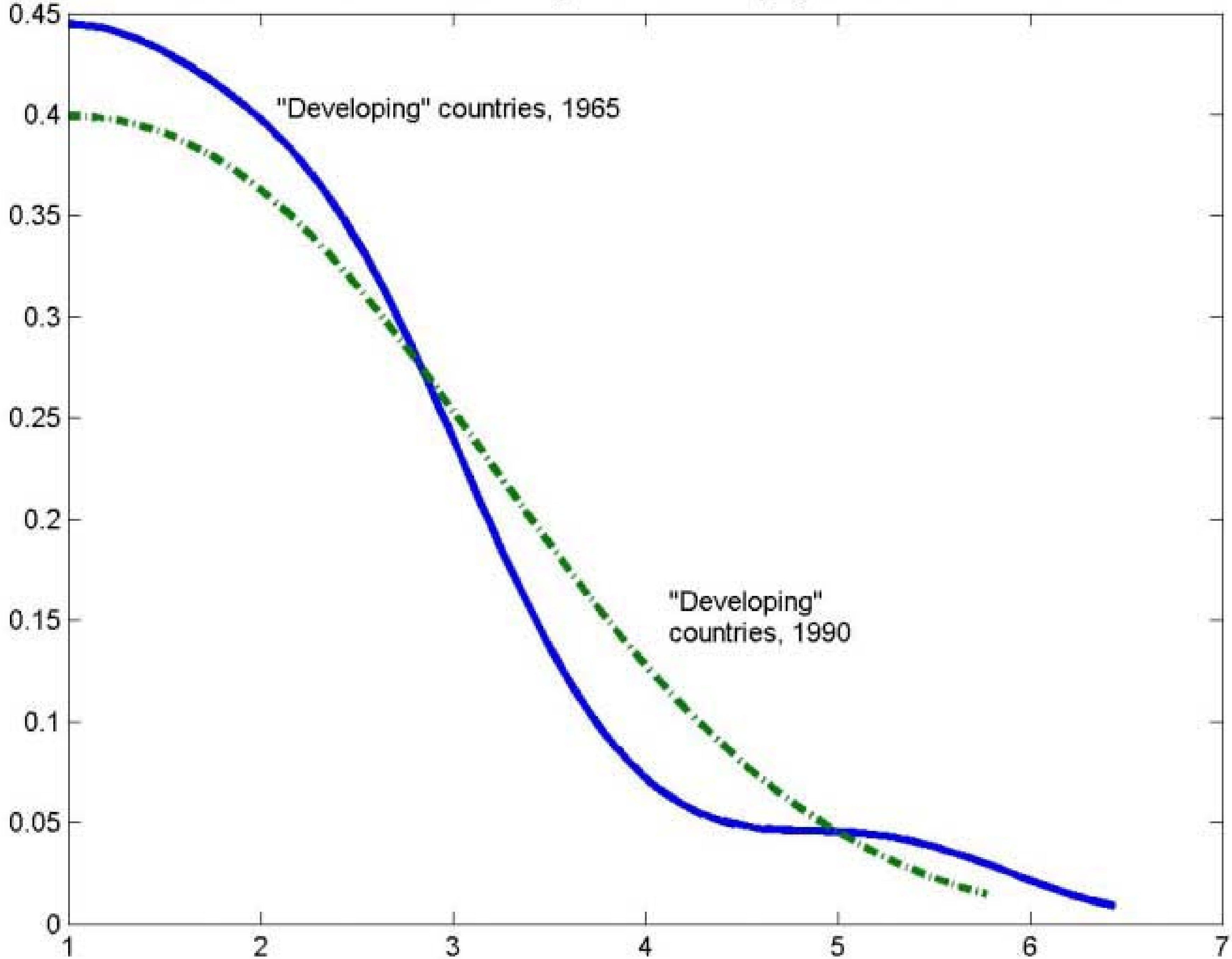
[10] AgEf. = aggregate efficiency (weighted average), MeEf = mean efficiency (non-weighted average); Group A = 'Developed' countries, Group Z = 'Developing' countries. Confidence Intervals are all at the 0.95 level; Sub-sample size in each bootstrap replication is determined via $m_l = n_l^{\kappa}$, $\kappa = 0.7$, $l = A, Z$.

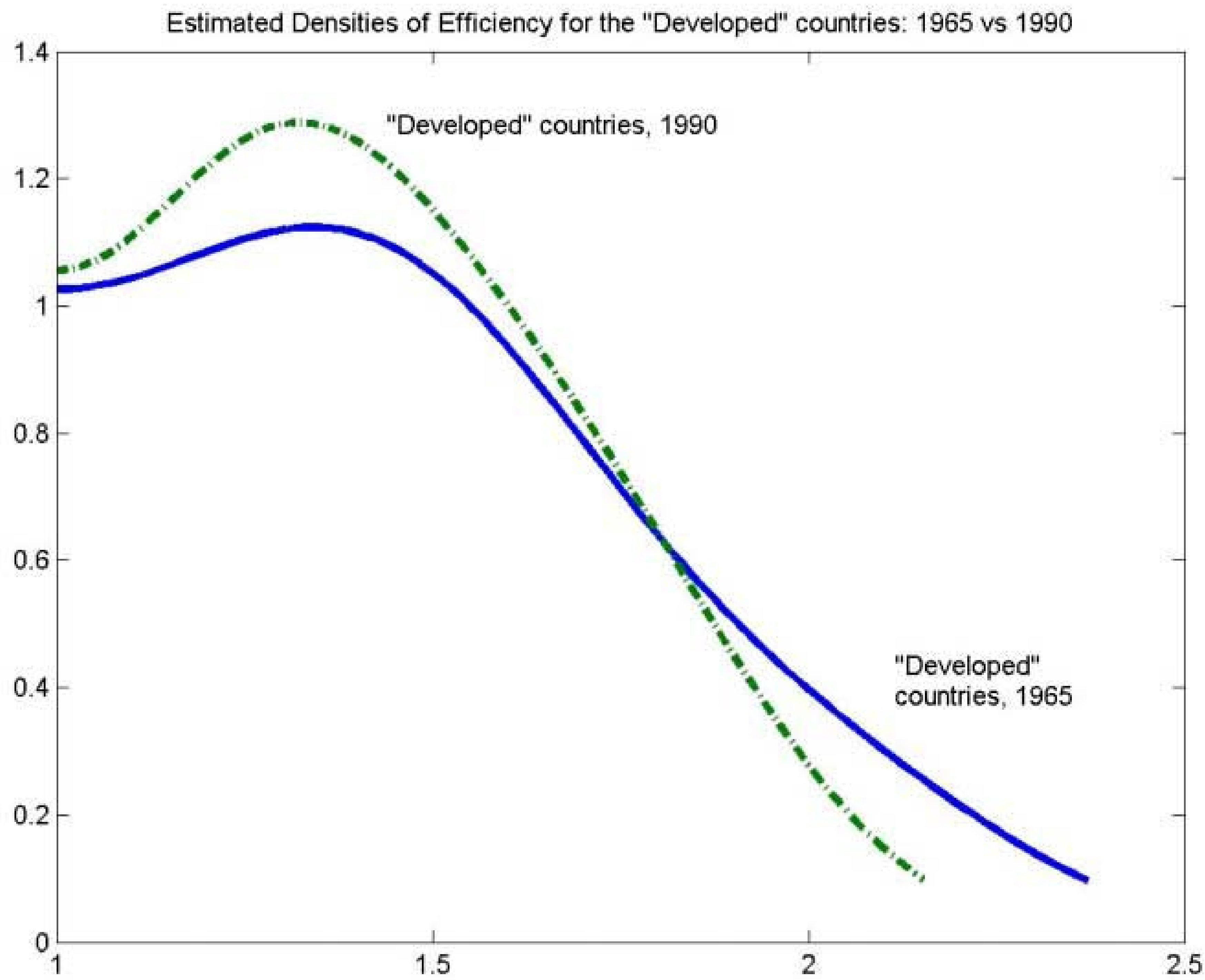
Table 5 - Results of Simar-Zelenyuk-adapted-Li Test for equality of efficiency distributions across groups (developed vs. developing countries) and across time (1965 vs. 1990) for the same groups.[11]

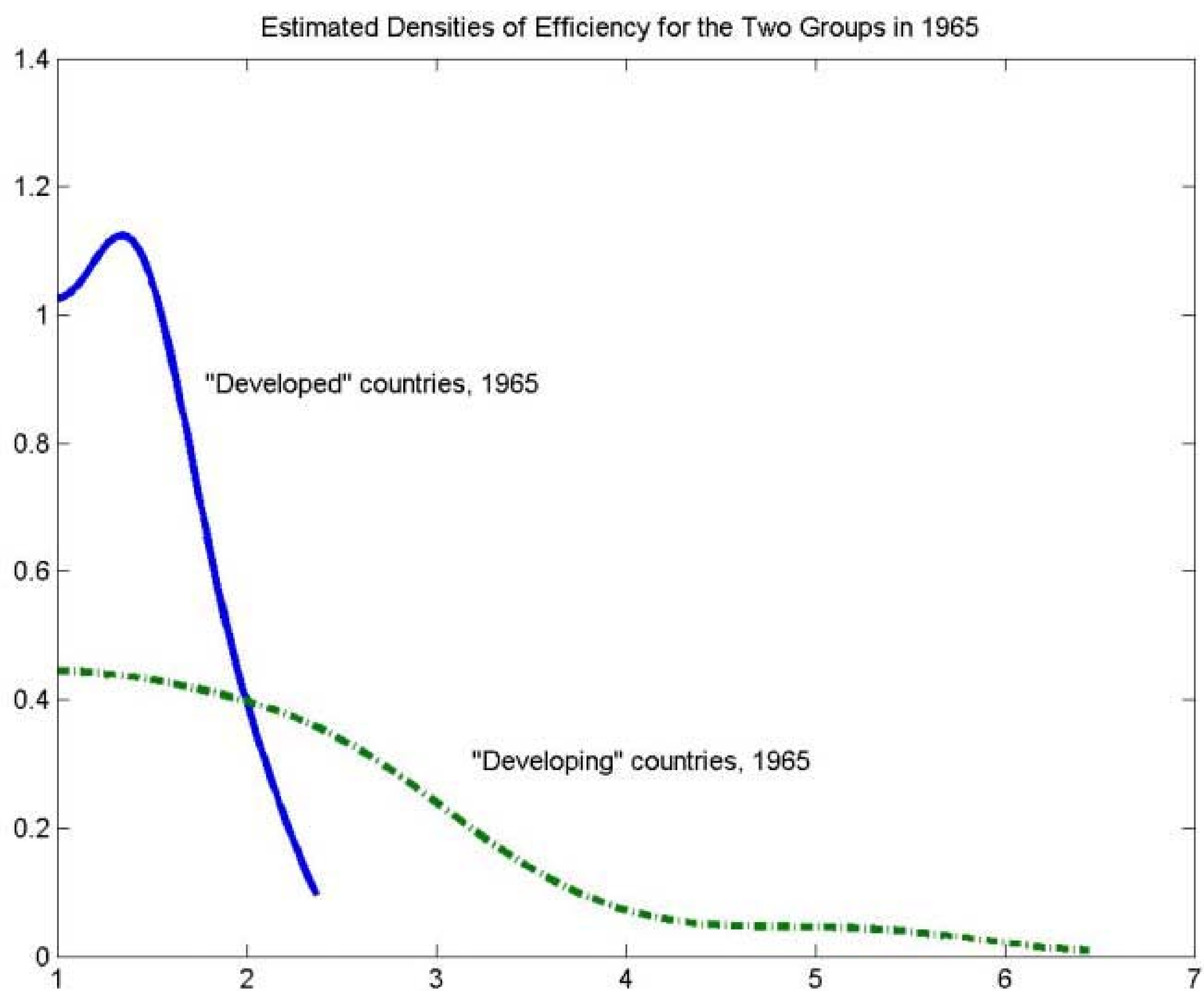
Null Hypothesis	Test Statistic	Bootstrap p-value
$f(\text{developed eff}_{65}) = f(\text{developing eff}_{65})$	5.10	0.00
$f(\text{developed eff}_{90}) = f(\text{developing eff}_{90})$	5.06	0.00
$f(\text{developed eff}_{65}) = f(\text{developed eff}_{90})$	-0.20	0.77
$f(\text{developing eff}_{65}) = f(\text{developing eff}_{90})$	-0.30	0.67

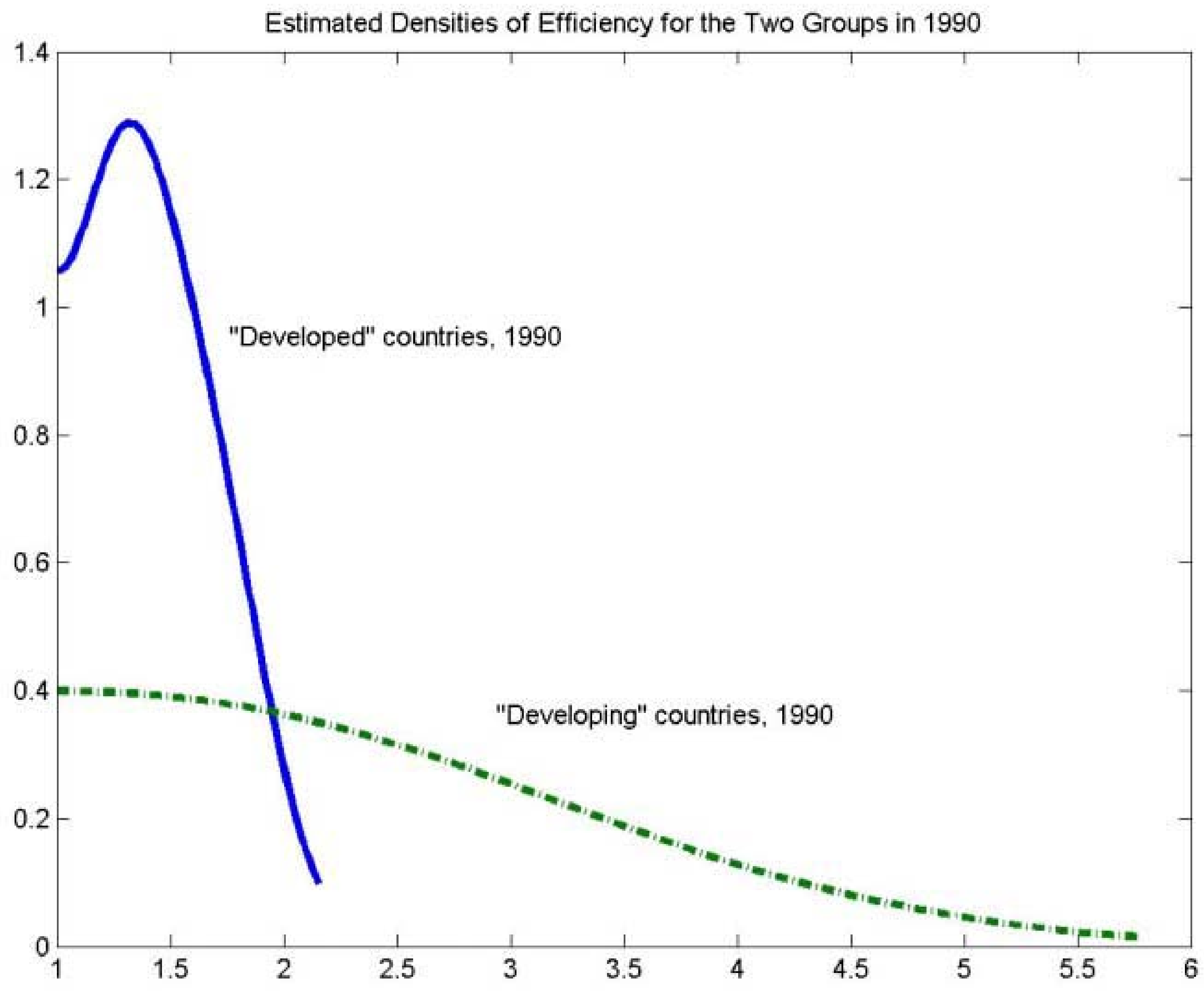
[11]Notes: Number of bootstrap iterations is 2000. For the test, we use the Gaussian kernel and Silverman (1986) adaptive bandwidth estimator, $h = 0.9An^{-1/5}$ (where $A = \min(\sqrt{var(u)}, iqr(u)/1.349)$, where $iqr(u)$ is the interquartile range of random variable u, which density is estimated.)

Estimated Densities of Efficiency for the "Developing" countries: 1965 vs 1990




Estimated Densities of Efficiency for the "Developed" countries: 1965 vs 1990
"Developed" countries, 1990
"Developed" countries, 1965
1.4
1.2
1
0.8
0.6
0.4
0.2
0
1
1.5
2
2.5


Estimated Densities of Efficiency for the Two Groups in 1965
"Developed" countries, 1965
"Developing" countries, 1965
1.4
1.2
1
0.8
0.6
0.4
0.2
0
1
2
3
4
5
6
7


Estimated Densities of Efficiency for the Two Groups in 1990
"Developed" countries, 1990
"Developing" countries, 1990
1.4
1.2
1
0.8
0.6
0.4
0.2
0
1
1.5
2
2.5
3
3.5
4
4.5
5
5.5
6