The Dynamic of Technological Capabilities of Countries: A Dual Approach Using Composite Indicators Data Envelopment Analysis

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WORKING PAPER

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Abstract

One of the main characteristics of the technological capabilities of countries has always been their uneven distribution across the countries. This paper explores the dynamic of technological capabilities for a sample of 42 countries over the period 1995-2007 introducing some methodological novelties. The results suggest that a process of convergence of technological capabilities has occurred to some extent. However, this has not been complete as some countries are still unable to reach a balanced growth in the different components of technological capabilities. We conclude by arguing that the production of technology can no longer be considered a privilege of a few advanced countries. This is going to bear consequences in the global arena in terms of trade, international division of labour and technological specialization**.**

Key words **-** technological capabilities, globalization of technology, composite indicators, data development analysis, 42 cross-country comparisons, large emerging countries

1. INTRODUCTION

One of the main characteristics of the technological capabilities of countries has always been their uneven distribution. In fact, a few countries (namely, the United States, Europe and Japan) have accounted for the world lion's share of technological capabilities. In the last two decades, two issues have persistently interested the community of scholars studying the technological capabilities of countries: *i.* how to provide an overall measure of technological capabilities at the national level (i.e. a number), aggregating different dimensions (variables) of the innovation activity (Grupp & Schubert, 2010; OECD, 2007); *ii.* the global dynamic of technology, and in particular whether a process of global convergence is occurring, or, instead, a club of a few advanced countries is still responsible for the major production of technology and innovation (Archibugi & Iammarino, 2002; Porter et al., 2009; Tassey, 2008).

The long standing attractiveness of these two topics relies on the belief that technology is a *conditio sine qua non* for long-term growth and catching-up. The other fundamental premise is that the process of technology adoption and diffusion does not occur in a spontaneous way as the neoclassical theory claimed, but requires an explicit and costly effort. This paper aims to explore the dynamic of technological capabilities (convergence versus divergence, catching-up versus falling behind) for a sample of 42 countries over the period 1995-2007. To accomplish this task we introduce some methodological novelties, which allow us to identify and qualify the main trends that underpinned this process.

The use of composite indicators to summarize in a synthetic way the overall technological capabilities of a nation has come to remarkable prominence over the last decade. This approach has been largely adopted by several scholars, international organizations and policy makers (OECD, 2007).[1] The development of a methodology to measure technological capabilities at the national level is a demanding task for two main reasons. First, innovation is multidimensional in nature, as it encompasses different activities ranging from basic research to design and engineering (Kline & Rosenberg, 1986). Second, these measures are often indirect since the phenomenon they are trying to capture is "intangible and not directly observable" (Grupp & Schubert, 2010, p. 68). Moreover, the various sources of innovation are *complementary* rather than *interchangeable,* as often implicitly assumed behind the structure of the composite indicators. Infrastructures devoid of a sufficiently qualified labour force will be useless and vice versa (Abramovitz, 1989; Maddison, 1991). Additionally, qualified human resources are key in the process of adoption and adaptation of technology developed abroad (Bell & Pavitt, 1997; World Bank, 1998). Finally, along with the revolution of the Information and Communication Technologies (ICTs), tapping global knowledge has become an imperative (Rifkin, 2000; World Bank, 1998).

Composite indicators (simple or weighted averaging) have been used to express in a single aggregate measure the technological capabilities of countries (Archibugi & Coco, 2004). More recently Cherchye et al. (2007) introduced a "benefit of the doubt" indicator based on Data Envelopment Analysis (DEA) techniques. The rational for the introduction of this last index is that the weights are chosen endogenously by the linear program associated to the DEA technique. Composite indicators and DEA indicators are two of the three main methodologies surveyed by Grupp and Schubert (2010) in a recent study (the other being based on principal components and here excluded from the discussion for reasons of space). The two methodologies give rise to different results and different ranking of countries, raising the question of which one of the two indicators should be used in practice.

Our first contribution, methodological in nature, is to provide a link between these two methodologies. We exploit duality theory (see Fare and Primont, 1995) to establish a link between the weighted average composite indicator and the DEA indicator. In this way we are able to give an explanation of the observed differential between the composite indicator and the DEA indicator. Far from being a failure of the methodology, this difference is able to highlight the different trajectories of technological capabilities growth for the different countries. This new methodological interpretation gives us the opportunity to investigate in some detail the different aspects of the process of globalization of technology over the last 15 years. Our empirical results suggest that a process of convergence of technological capabilities has occurred to some extent. However, this has not been complete as some countries are still unable to reach a balanced growth in the different components of technological capabilities. We conclude by arguing that the production of technology and innovation can no longer be considered a privilege of a few countries belonging to the Triad. This is going to bear, in the opinion of the authors, relevant consequences in the global arena.

The paper is organized as follows. Section 2 gives the basic conceptual background of the analysis. In section 3 we explain the rationale behind the selection of variables and describe the dataset. Section 4 is devoted to the presentation of the methodology. Section 5 shows the results of the analysis, while Section 6 concludes.

2. BACKGROUND: TECHNOLOGICAL CAPABILITIES AND CATCHING-UP

The fundamental importance of technological innovation as a driver for long-run growth has been made clear by a large body of studies (for a review see Verspagen, 2005). A related stream of empirical papers has shown that differences in technology are a fundamental source of different growth rates across countries (Castellacci, 2008; Fagerberg, 1994; Fagerberg & Godinho, 2005; Pianta, 1995). Additionally, Fagerberg and Verspagen (2002) find that the importance of technological innovation vis-à-vis the importance of institutions for economic growth has increased lately. This is in tune to what argued from an historical perspective by Mokyr (2002) who argues that technological innovation is more likely to explain over time development differences vis-à-vis institutions which instead are more relevant regarding cross-section differences. Having saying that, the problem has been shifted to identify how lagging-behind countries can close the technology gap through catching-up processes.

In this respect, technological capabilities have demonstrated to play a crucial role. The technological capabilities approach departs from the neoclassical approach in which technology is freely available for lagging behind countries. The cornerstone of studies dealing with technological capabilities is the assumption that countries differ in their capacity to absorb and adapt technology developed abroad. Processes of imitation and adoption are costly, require previous knowledge and skills, and imply learning (Abramovitz, 1986; Bell & Pavitt, 1997; Cohen & Levinthal, 1990; Gerschenkron, 1962; Lall, 1992; Perez & Soete, 1996). In a nutshell, imitation is far to be a simple plug-in process, whilst it rather requires a big deliberate effort and the presence of endogenous capabilities. Differences in technological capabilities lie at the heart of the explanation of why countries have a diverse ability to catch up advanced countries by imitating and adopting foreign advanced technology (Abramovitz, 1986; Archibugi & Pietrobelli, 2003; Castellacci, 2008; Fagerberg et al., 2007; Figueiredoa, 2008; Iammarino et al., 2008; Patel & Pavitt, 1994).

One of the first attempts to address technological capabilities at the country level has been made by Lall (1992). Lall's measures of national technological capabilities include several variables grouped in three main dimensions including "structure and performance" (i.e. growth, export GDP and so on), "education" and "science and technology". Archibugi and Coco (2004) developed an index of technological capabilities for a large number of both developed and developing countries relative to two periods of time (1990 and 2000). Their index is divided into three main dimensions, the "creation of technology", the "technological infrastructures" and the "development of human skills". By comparing the two years they point out the important growth of the Asian tigers, Taiwan, South Korea, Hong Kong, Singapore, and also the remarkable improvement of China and India but limited to the technological infrastructures. The Georgia Tech Technology Policy and Assessment Center has developed the High-Tech Indicators not just to measure the current technological capabilities, but to forecast how the present capabilities can lead to secure quotas of high-tech exports (Roessner et al. 1996). This indicator is composed of four input indicators which reflect national propensity for future technology-based competitiveness, and three output indicators. These indicators are built through a combination of an expert opinion survey and hard data. Finally, recent studies have showed that countries tend to group in homogeneous groups – clubs - according to their characteristics of technological capabilities and growth trajectories (Castellacci & Archibugi, 2008; Castellacci 2008).

3. THE GLOBAL CAPABILITIES INDEX (GLOCAP)

The last 15 years have seen at least two main structural phenomena in the international arena: first, the emerging of a group of Asian economies in terms of growth and technological change; second, the explosion and diffusion of ICT technology at mass level. Both these effects cannot be captured using cross-sectional analysis (that is static in nature). Also, previous exercises in building composite indicators of technological capabilities (Archibugi & Coco, 2004) have to be updated in order to account for the importance of the new technologies. We address these issues by using a panel data that covers, basically, the period of time in which both the previous phenomena occurred. We follow (Archibugi & Coco, 2004) in grouping our variables into three main categories or pillars: *Business Innovation, Knowledge&Skills, Infrastructures*. This study deviates from (Archibugi & Coco, 2004) introducing the number of PC and internet users explicitly in the analysis as well as in dividing R&D expenditures in business R&D and public R&D in order to point out their relative contribution. Additionally, it uses a balanced panel dataset which allows a more robust dynamic analysis. In Table 1 the nine variables feeding into the Global Capabilities Index (GloCap) and the data sources are presented grouped in three pillars. In the following we discuss them in detail.

--- TABLE 1 ---

Business innovation

The importance attached to the business sector in carrying out innovation is straightforward. To capture the innovative performance of firms both patents and Business R&D (BERD) are used. Patents have been largely used for accounting commercial purpose generated technological innovation (Griliches, 1990). At such, they can be considered a “tolerable assumption” (Schmookler, 1962) of the innovative activities of firms. We use the “triadic patents” which correspond to patents filed at the European Patent Office (EPO), the United States Patent and Trademark Office (USPTO) and the Japan Patent Office (JPO), for the same invention, by the same applicant or inventor (OECD, 2008; , 2004). The advantage of using this particular family of patent is twofold. First, they are a reliable tool for cross-country comparison, given that they include the three more important and natural patent office in the world. Second, the underlying innovation related to a patent filed in the three most important offices across the world is more likely to be valuable (in commercial terms, loosely defined) with respect to an innovation protected only in one single office.

R&D expenditures have also been largely considered as a measure of input of the innovative effort of the firms (OECD, 2002). It represents the natural candidate as a complementary measure with respect to patents for at least two reasons. First, patent intensity can largely differ across industrial sectors (Cohen et al., 2000). Consequently, cross-countries differences in terms of patent intensity can reflect a different industrial structure. Second, patents by definition are not capable to capture service innovation, while in advanced countries services have been dramatically growing in importance in terms of innovation investment and knowledge creation and exploitation. The growing of R&D expenses in the service sector (Miles, 2005; OECD, 2005) calls for the use of this indicator as a reliable proxy to capture the innovation effort in this sector.

Knowledge&skills

Human resources, in terms of education, knowledge and skills are considered a fundamental ingredient within the wide concept of absorptive capacity (OECD 2003). The literature dealing with growth has largely recognized the importance of these factors by introducing them in its models. Howitt (2000) shows that cross-country differences in the returns to investments to human capital are key to explain the dynamic of absorptive capacity. Azariadis and Drazen (1990) argue that difference in growth rates can be explained by the presence of threshold externalities in the accumulation of human and physical capital. In brief, the quality of the human resources is key not only to generate knowledge but also, and crucially for emerging economies, for enabling imitation and adoption of technology developed elsewhere (World Bank, 1998).

Three variables are used for this pillar: researchers, scientific articles and Public R&D.[2] The variable "total researchers in R&D" is expected to reflect the magnitude of human resources with high-skills involved in formal scientific-based and technological-based activities, both in the public and in the private sector. The variable "scientific and technical articles" represents the magnitude of the generation of codified knowledge. Specifically, it reflects the knowledge generated in the universities and public-funded research centres. However, it also reflects knowledge generated in the private sector which over the last years have been publishing an increasing share of scientific and technical articles. Finally, Public R&D gives account of the resources devoted to formal research activities by the public sector, including both governmental institutions and higher education institutions.

Infrastructures

The importance attached to capital and technological infrastructures has also been recognised to be a fundamental *conditio* for countries to develop (World Bank, 1998). This has increasingly become a necessary requirement with the revolution of the new information and communication technologies (ICTs) which has profoundly changed the way people do things, leading to fundamental changing in the organizational structure of the firm, their business models, the channels for the sharing and diffusion of knowledge across countries (Castells, 1996). Within this environment, being connected has become a necessary condition for countries to access knowledge created and circulated across the globe (Rifkin, 2000). Personal computers, fixed-line and mobile phones and the number internet users should capture all together the quality of the network and infrastructures of a country to tap global knowledge.[3] Additionally, we added fixed capital aiming at capturing the physical infrastructure which can be key especially at the beginning of catching-up processes (Pianta, 1995).

4. METHODOLOGY: COMPOSITE INDICATORS AND DATA ENVELOPMENT ANALYSIS

According to Cherchye et al. (2005), there are at least three main problems which need to be addressed when constructing composite indicators: *i.* the choice of the single "ingredients"; *ii.* the pre-treatment of the data (i.e. the process of normalization); *iii.* how the single indicators will merge into a single metric (that is the choice of the appropriate weights scheme). The first point has been addressed in section 3. To address the other points we need to introduce some formal notation. At every time $t = 1,...,T$, for every country $k = 1,...,K$, each variable $m = 1,...,M$ is observed. We collect all this information into a set of T matrices (one for each time period):

$$\mathbf{Y}^t = \left[Y^t_{km}\right]$$

where Y^t_{km} is the value of variable m for country k at time t. This means that along row k we observe all the values assumed by the variables for country k at time t. Pre-treatment of data has basically been done using one of the following procedures (small y is the standardized variable) (Nardo et al., 2005):

1. Range Standardization: $y_{km}^t = \frac{Y_{km}^t - Y_m^{\min}}{Y_m^{\max} - Y_m^{\min}}$ where $Y_m^{\min}$ is the minimum value variable m assumes in the dataset and $Y_m^{\max}$ is the maximum value variable m assumes in the dataset;
2. Z-Standardized: $y_{km}^t = \frac{Y_{km}^t - Y_m^{mean}}{std(Y_m)}$, where Y_m^{mean} is the mean value of variable m in the dataset;
3. Mean adjusted: $y_{km}^t = \frac{Y_{km}^t}{Y_m^{mean}}$;
4. Maximum adjusted: $y_{km}^t = \frac{Y_{km}^t}{Y_m^{\max}}$;

Now, it is possible to show (see Lovell and Pastor, 1995) that DEA is not invariant to transformation 1) and 2), but it is invariant to transformations 3) and 4) (rescaling of the original values). This means that the DEA indicator ("benefit of the doubt" indicator) gives the same value if applied to the original variables or to 3) and 4), but it gives a different value if applied to 1) and 2). In our opinion, this is a sufficient reason to reject 1) and 2) from our standardization exercise. Transformations 3) and 4) both return dimensionless variables. We chose transformation 4) on the basis of the fact that the variables also range between zero and one and this facilitates the localization of the best performers along each variable as well giving a good intuitive proxy of the "level" of each country with respect to the best performer.

The construction of a composite indicator requires the specification of a vector of weights $\mathbf{p} = [p_1, ..., p_M]$ to be used in the aggregation (the weights are assumed to be positive and sum up to one $\sum_m p_m = 1$). The composite indicator will be:

$$C_k^t = \sum_{m=1}^{M} p_m y_{km}^t$$

A quite controversial issue arises from the choice of the effective weights to be used in such a formula (Grupp & Mogee, 2004; Grupp & Schubert, 2010). Before going trough the explanation of the actual weights we used in practice, let us establish some formal relationship between such and index and the DEA index. The result will be presented for any set of weights chosen, so that it will be perfectly general (i.e., it holds for any possible vector of positive weights that sum up to one). In the appendix we also introduce a generalization of the method here presented where the composite indicator assume a CES functional form (incorporating the linear as special case).

We define the Technological Capabilities Set (S) as the piecewise linear envelope of the observed dataset:

$$S = \{y : y \leq zY, z \geq 0\}$$

Associated to this set, we define the Technological Capabilities Frontier (TCF) as the set of Koopmans efficient points:

$$TCF = \left\{ y : \forall 0 < \theta < 1, \frac{y}{\theta} \notin S \right\}$$

--- FIGURE 1 ---

A graphical representation can improve the understanding of these notions. In Figure 1 a simple case is considered where 5 countries (Sweden, Usa, Netherlands, Argentina and Brazil) are evaluated with respect to two dimensions (Articles and Patents). The set of feasible values for the considered variables (S) will be all the area limited by the axis and the bold black line. This means that a point outside this area is infeasible (given this set of observations). From the figure it is possible to note that while USA, Sweden and Netherlands lie along the bold black line (the TCF), Argentina and Brazil lie in the interior of the set S. In fact the first 3 countries define the TCF. As it is easy to check, for these countries it is not possible to expand proportionally all the variables and still stay in the feasible set S. On the contrary Argentina and Brazil can expand proportionally their variables. For example Argentina can move from its place to point a onto the TCF. This means that Argentina shows a deviation from the efficient frontier

TCF. DEA is precisely used to identify the magnitude of this deviation and to build the linear envelope that constitutes the frontier (the bold line).

Now, using a composite indicator gives us some additional information. In the two dimensional example of figure 1, the weights can be represented as a straight line. The further this line lies on the right the higher the value of the associated composite indicator. In the example, Sweden shows the maximum value of the composite indicator for the given weights. It is important to note that while the DEA indicator gives the same value for USA and Sweden, the composite indicator gives different values. In fact DEA signals deviation from Koopman efficiency that is a very weak and general notion of efficiency. USA is Koopmans efficient (it has less article but more patents than Sweden), but it is not the country that maximizes the value of the composite indicator for the given exogenous weights. This difference in the composite indicator is given by the distance between the two straight lines passing trough US and Sweden. And this difference is totally due to a Compositional effect, namely the different proportion in which articles and patents are in Sweden and USA. From the figure it is easy to check that for Argentina the case is different. In fact, the difference in the composite indicator (distance between the straight dashed lines) is partly due to a pure deviation from the TCF and partly to a Compositional effect, i.e. a deviation from the optimal proportion of articles and patents represented by Sweden.

The graphical representation suggests that there are two very different effects operating: one is due to a proportional deviation from the TCF and the other one due to a deviation from the optimizing composition of the variables along the TCF. These two effects can be measured and related to each other by the following procedure. The deviation from the TCF can be measured solving the following linear programming problem for each observation k at each period of time t:

$$
\begin{aligned}
DEA_k^t &= \min_{z,\lambda} \lambda \\
s.t.\quad & \frac{y_{km}^t}{\lambda} \le \sum_{j=1}^{K} z_j y_{jm}^t \,, \quad \forall k = 1,\ldots,K \\
& z_j \ge 0\,, \quad \forall j = 1,\ldots,K
\end{aligned}
$$

This linear programming problem is searching for the maximum proportional expansion of the observed variables such to place observation k onto the TCF. Therefore, for example, this index will return a value of one for USA in the previous example, but a value that is less than one for Argentina and Brazil. One of the attractive features of the DEA index is that it is bounded in the unit interval $0 < DEA_k^t < 1$, assumes a value equal to one when the country is onto the TCF and a value of zero if all the variables observed for the given country are zero. These are quite useful properties. One of the shortcomings of using such an index is that it gives the same value to observations that are on the TCF. This is where the composite indicator steps in a useful way. Introducing a set of weights $\mathbf{p} = [p_1,..., p_M]$ allows demarcating the performance of countries on the TCF. It is possible to define a linear program that search for the maximum value achievable with the given exogenous weights in the set S:

$$
\begin{aligned}
C_{\max}^t &= \max_{z,y} \sum_{m=1}^{M} p_m y_m \\
s.t.\quad & y_m^t \le \sum_{j=1}^{K} z_j y_{jm}^t \,, \quad \forall k = 1,\ldots,K \\
& z_j \ge 0\,, \quad \forall j = 1,\ldots,K
\end{aligned}
$$

Now, for each given country it is possible to define a composite index of technological capabilities as the ratio between the observed index and the maximum achievable index:

$$
CE_k^t = \frac{C_k^t}{C_{\max}^t}
$$

This composite indicator will be bounded between zero and one allowing for an easy interpretation. Moreover we are now in a position to establish a link between the composite indicator and the DEA indicator. From duality theory (see, for example, Fare & Primont, 1995) we know that

$$CE_k^t \leq DEA_k^t$$

This result is quite remarkable and has been greatly underestimated in the literature. One of the consequences of this result is that any composite indicator (for any choice of weights) cannot reach its maximum unless the DEA indicator is equal to one. In other words, DEA catching-up is a prerequisite for any other type of convergence; or, catching-up for any type of composite indicator (for any choice of weights) is observable only if the DEA indicator shows catching-up.

Besides that, the gap between the two indicators has a quite simple interpretation, measuring the deviation between the observed composition of the variables and the ideal composition. Following figure 1, Argentina can first expand proportionally its variables to point *a* to reach the TCF. This will also proportionally increase the value of its composite indicator; but point *a* does not represent the best. In fact, Argentina can change the composition of its variables from a more patent intensive to a more article intensive pattern, moving along the TCF and reaching the maximum value represented by Sweden. Thus the deviation between the DEA indicator and the composite indicator is a signal of how much the composition of the variables is close to the best composition. Formally it is possible to define such a deviation in a residual way as:

$$AE_k^t = \frac{CE_k^t}{DEA_k^t}$$

This index is bounded between zero and one, with one signalling optimal composition. Since all this analysis has been put forward keeping the weights fixed, we also get a very accurate understanding of the role of the weights in defining the composite indicator: the weights actually select the ideal composition along the TCF. Associated to each vector of weights, we have a different optimal composition along the TCF. This is represented by a different slope of the dashed lines in the two variables example.

Now, we are prepared to see what happen between two time periods. From t to t+1 the change in the composite indicator can be decomposed as:

$$\Delta C_k^{t+1} = \Delta DEA_k^{t+1} \cdot \Delta AE_k^{t+1} \cdot \Delta F^{t+1}$$

where $\Delta DEA_k^{t+1} = \dfrac{DEA_k^{t+1}}{DEA_k^{t}}$ is the change in the *DEA index*, $\Delta AE = \dfrac{AE_{t+1}}{AE_t}$ is the change in the *Compositional index*, $\Delta F^{t+1} = \dfrac{C_{\max}^{t+1}}{C_{\max}^{t}}$ is the change in the maximal achievable value of the composite indicator and represents a measure of how much the TCF shifted between the two time periods (TCF shift trend). These three indexes signal very different underlying phenomena. *DEA index* change takes a value greater (smaller) than one if the country is closer (farther) to the TCF frontier at time t+1 with respect to time t (the country is catching-up the TCF, or vice versa). The *Compositional index* change takes a value greater (smaller) than one if the composition of the variables for the country is closer (farther) from the optimal composition. The TCF shift trend takes a value larger (smaller) than one if the best country has improved (deteriorated) the values of its variables. All these indexes take a value of one if no change is observed.

It is worth reminding that all these indexes are relative indexes. A country can fall behind while just keeping a constant value of its variables. This is due to the fact that the TCF is moving over time and countries need to improve just to avoid a worsening. Also, a country showing a constant value of the *DEA index* and of the *Compositional index*, still will have a positive growth in the observed variables due to the TC component. This means that the TC component measures the global trend in the growth of variables.

As said before, the TC components will signal if there was a global trend in the variables, i.e. if at the end of the period countries are globally more productive in the production of innovation than they were at the beginning. Thus the catching-up issue will regard basically the other two components. Table 2 summarizes the four typologies of catching-up processes that we are able to single out.

TABLE 2

Since the indexes are calculated for every country, we are able to disentangle the trajectory of every single country. To have an overall measure of the global dynamics we test the convergence hypothesis on the *GloCap index*, the *DEA index* and the *Compositional index*.

5. THE GLOBAL DYNAMIC OF TECHNOLOGICAL CAPABILITIES

The choice of the weighing scheme

Due to the duality result established in the previous section, we are now in a position to make a reasonable choice for the weights to use for the GloCap. Since the DEA index is always larger than the composite indicator index, choosing the set of weights implies identifying a target country on the TCF. In other words, we are seeking a reference country among those which present a value for the DEA index equal to 1 (this means they are on the TCF). To give some highlights on this issue, let us have a look to the countries that compose the TCF in 1995 (DEA index equals 1).

TABLE 3

By looking at the pillar composition in Table three, one easily checks that Sweden is the most "equilibrated" country in terms of pillar composition. The superior performance of Israel with respect to Sweden in Pillar two (due to a value for public R&D that is out of the norm), is traded off by a sharp decrease in Pillar one, and in Pillar three to a lesser extent. The main point here is that

Sweden will be dominating the other countries in terms of the composite indicator index for a large set of different weights. In other terms, in order to choose Israel as the target country onto the TCF frontier, one has to pick up very extreme values of the weights to give a premium to the Pillar two. This is, of course, unreasonable, since choosing extreme values for the weights means leaning towards a non equilibrated composition of the pillars. This would be in contrast with the predominating idea, among innovation scholars, that innovation process requires the presence of complementary technological capabilities (pillar equilibration).[4] As a result from a sensitive analysis, we found that Sweden gets the highest score of the GloCap for several alternative choices of the weights. Based on this evidence, we choose to set the following set of weights: 0.three for the Pillar one, 0.three for the Pillar two, 0.4 for the Pillar three. Pillars are unweighted averages and this implies that we are implicitly evaluating market oriented innovation (pillar one) more than the other variables.

The results of the empirical analysis

In this section the results of the empirical analysis are presented. In Figure 2 we plot the *GloCap Index* change over the 13 years period and the *GloCap Index$_{95}$*. An overall process of convergence in technological capabilities across the considered countries arises to some extent. A good deal of the countries which were lagging behind at the beginning of the period exhibit faster rates of growth and vice versa. However, one does not observe convergence for all the countries. The presence of a moderate convergence process is confirmed by the correlation rate between the ranking of the *GloCap Index* change and the ranking of the *GloCap Index$_{95}$* which is equal to -0.52 (Table 1A in the Appendix). The second point which is worth-stressing is the large variability of rates of growth across lagging behind countries. Countries like Lithuania, China, Poland and Brazil which show similar scores relative to *GloCap Index$_{95}$* exhibit very different rates of growth.

--- FIGURE 2 ---

As illustrated in Section 4, the *GloCap Index* can be decomposed in two main components, the *DEA index* change and the *Compositional index*. As we already explained, the *DEA Index* change provides an "objective" measure of the expansion of a country's technological capabilities. The *Compositional index* is instead a measure of the "correctness" of the balance between the three pillars composing the *GloCap*. In Figure 3 we report the same exercise provided in Figure 2 but with regards to the two main component of the *GloCap Index* change, the *DEA index* and the *Compositional index*. The differences between the two graphs are striking. As far as the *DEA index* is concerned, a clear and linear process of convergence emerges as confirmed by the correlation rate between the ranking of the *DEA index* change and the ranking of the *DEA index*$_{95}$ which is equal to -0.74 (Table 1A in the Appendix). The only countries which show a *DEA index* change lower than one are the Russian Federation, Australia and the United States, while all the others are above one. This suggests that nearly all the considered countries have been improving their level of technological capabilities, that is they have been catching-up the *TCF*. Crucially, the rate of growth of the *DEA indicator* is directly proportional do the distance to the TFC at the beginning of the considered period. That is, the larger the technological gap of a country, the faster the catching-up processes has occurred. It is also worth stressing that among the nations experiencing faster rates of growth there are the BRICS countries, namely China, India, Brazil and South Africa (with the exception of the Russian Federation) together with two other large emerging economy like Turkey and Mexico.

--- FIGURE 3 ---

If we look at the second graph reporting the dynamic of the *Compositional index*, a complete different picture arises. Specifically, across the lagging behind countries there is evidence of a process of convergence for some of them, while conversely, other laggard countries exhibit a clear process of divergence. The lack of a significant process of convergence as a whole is confirmed by the correlation rate between the ranking of the *Compositional index* change and the ranking of the *Compositional index*$_{95}$ which is equal to -0.13 (Table 1A in the Appendix). In this case, nearly half of the considered countries lie above the value of one which reflects a relative worsening of the balance of the three pillars of the *GloCap*. It is also clear that the cross-country variability is remarkably high concerning the laggard countries, while it tends to reduce progressively moving towards more advances nations. As far as the BRICS countries are concerned, in this case only China and the Russian Federation are above one (together with Mexico and Turkey), while India, Brazil and South Africa are far below one.

In Figure 4 the *DEA index* change is plotted against the *Compositional index* change.[5] In this way we are able to distinguish four groups of countries according to the characteristics of their catching-up processes over the considered period:

- The *unbalanced catch-up group*: these countries show a remarkable growth in terms of *DEA index* change over the considered period. However, they did not manage to improve the composition of their technological capabilities, as they score below one in terms of *Compositional index* change thus highlighting a deterioration of their balance of technological capabilities among the three *GloCap* pillars. This group includes the largest part of developing and emerging countries, namely three BRICS countries (Brazil, India and South Africa) and nearly all of the EU New Member States, together with Argentina;
- The *balanced catch-up group*: in this group countries show a good performance both in terms of *DEA index* change as well as relative to the *Compositional index* change. In other terms, they have managed to narrow the gap with the *TCF* and at the same time they have improved the allocation of their technological capabilities. Only five countries are included in this group: three large emerging economies, such as China, Mexico and Turkey, and the

two Baltic countries included in the sample which have also recently joined the EU, Estonia and Lithuania;

- The *re-allocating group:* countries belonging to this group show a low performance in terms of *DEA index* change. However, they have succeeded in re-allocating their technological capabilities toward a more efficient composition. This group includes a good deal of countries which are not the leader in technological capabilities but can no longer be considered emerging countries, such as some European countries, advanced Asian nations like Singapore and Korea Republic, and Australia and New Zealand;
- The *leader group:* finally, countries included in these groups are the leaders whose technological leadership appears to have been increasingly eroded by the other countries. This group includes the most technological advanced countries in the world.

--- FIGURE 4 ---

6. CONCLUSIONS

This article's aim was to explore the dynamic of technological capabilities for a large set of countries using a novel methodological approach. In this section we point out the contribution in terms of methodology, we then discuss the main results and finally consider some consequences which have a bearing in terms of policy.

From a methodological perspective, the exploitation of duality theory gave us the opportunity to go inside the black box of the choice of weights. We showed that the choice of weights in the composite indicator formula corresponds to the choice of a compositional target onto the technological capabilities frontier . This basically means that the choice of weights is equivalent to the choice of the target country among the countries having a DEA score equal to one. This greatly reduces the complexities associated to the choice of weights, since the researcher can now look to the variables associated only to a small number of countries (eight in our sample). We also showed that among the countries with a full DEA score, only Sweden shows a reasonable equilibrated value across the three pillars, thus justifying the choice of weights used in the analysis. Thanks to the duality result discussed in this paper, the divergence between DEA ("benefit of the doubt") and any composite indicator that uses positive weights found a sharp - and extremely useful in economic terms - interpretation as compositional effect. This compositional effect signals a deviation from the "optimal" equilibrated composition among pillars and to our knowledge has been introduced in this study for the first time. On overall, our approach suggests that composite indicators and DEA indexes can be seen (and used) as complementary rather than substitute methodologies.

The analysis shows that a process of convergence in technological capabilities has occurred to some extent for the 42 considered countries over the period 1995-2007 (Figure 2). By looking at the first graph of the Figure 3 one can observe a clear pattern of convergence in terms of *DEA Index*. More specifically, the speed of the catching-up processes is directly proportional to the size of the gap with the TCF at the beginning of the period. Countries which were far away from the TCS exhibit faster rates of growth in technological capabilities. In this sense, the presence of a large gap seems to represent a good opportunity to spur catching-up processes for lagging behind nations. Two large blocks of countries have been considerably improving their performance: the BRICS countries (with the exception of the Russian Federation), and the EU New Member States. In a nutshell, there is no doubt that the TCF is these days more crowded with respect to the 1995.

We were also able to further qualify this process by looking at the dynamic of the balance of the different components of the GloCap. By looking at the second graph of the Figure 3, one can also observe that no convergence occurred in terms of the *Compositional Index*. While countries tend to close their technological gap over time, they seem to do that in very different ways. We then divided countries in two main groups (Figure 4) according to the nature (balanced/unbalanced) of their catch-up process. One overall, it arises that among the countries narrowing their technological gap the unbalanced catching-up process is predominant. That is, a great deal of emerging countries have been improving their technological capabilities over this period but they also ended up with a worsening relative to their balance among the three pillars. In particular, three large emerging economies such as China, Mexico and Turkey, along with two Baltic Republic, Estonia and Lithuania, exhibit a balanced catch-up process. On the other side, three BRICS countries, namely Brazil, South Africa and India, together with another large economy like Argentina and several of the New EU Member States show an unbalanced process of catch-up. As already stressed, innovation capabilities of the private sector, human resources and technological infrastructures are growth ingredients profoundly complementary in nature. This provides an important clue about the different typologies of catching-up processes we have indentified here.

We conclude arguing that the dynamic of technological capabilities across the countries over the last decades lends some support towards the end of the hegemony of the Triad – Unites States, Europe and Japan. Among the countries which are catching-up, one has to keep in mind that some of them are very large economies and therefore their relative improvement bears remarkable consequences in absolute terms across the global arena. It is just worth mentioning that Brazil, China, India, Mexico and Turkey account for the 70 per cent of the labour force of our sample. These countries have demonstrated to be increasingly integrated in the international trade and included in the global supply chain of the multinational enterprises (UNCTAD, 2005, 2006). There are no evident reasons suggesting that in the following years this process should come to an end. In the opinion of the authors, this is likely to bear substantial consequences in terms of international trade, international division of labour, evolution of technological specialization and structural changes.

REFERENCES

Abramovitz, M. (1986). Catching up, forging ahead, and falling behind. *Journal of Economic History, 46*(2), 385-406.

Abramovitz, M. (1989). *Thinking about growth.* Cambridge: Cambridge University Press.

Archibugi, D. & Coco, A. (2004). A new indicator of technological capabilities for developed and developing countries (ArCo). *World Development, 32*(4), 629-54.

Archibugi, D. & Iammarino, S. (2002). The globalization of technological innovation: Definition and evidence. *Review of International Political Economy, 9*(1), 98-122.

Archibugi, D. & Pietrobelli, C. (2003). The globalisation of technology and its implications for developing countries. Windows of opportunity or further burden? *Technological Forecasting and Social Change, 70*(9), 861-84.

Azariadis, C. & Drazen, A. (1990). Threshold externalities in economic development *Quarterly Journal of Economics, 105*(2), 501-26.

Bell, M. & Pavitt, K. (1997) Technological accumulation and industrial growth: Contrasts between developed and developing countries. In Archibugi, D. & Michie, J. (Eds.), *Technological accumulation and industrial growth: Contrasts between developed and developing countries.* Cambridge: Cambridge University Press.

Castellacci, F. (2008). Technology clubs, technology gaps and growth trajectories. *Structural Change and Economic Dynamics, 19*(4), 301–14.

Castellacci, F. & Archibugi, D. (2008). The technology clubs: The distribution of knowledge across nations. *Research Policy, 37(10),* 1659-1673.

Castells, M. (1996). *The rise of the network society: The information age: Economy, society and culture vol 1. The information age* Oxford: Blackwell Publisher.

Cerulli, G. & Filippetti, A. (2010). The usefulness of STI composite indicators: an empirical application to 42 countries. Paper presented at the ENID Conference, March 2010, Paris.

Cherchye, L., Moesen, W. & van Puyenbroeck, T. (2005). Legitimately diverse, yet comparable: On synthetising social inclusion performance in the EU. *Journal of Common Market Studies, 42*(5), 429-44.

Cohen, W. M. & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128-52.

Cohen, W. M., Nelson, R. R. & Walsh, J. P. (2000). Protecting their intellectual assets: Appropriability conditions and why us manufacturing firms patent (or not). *NBER Working Paper*

Fagerberg, J. (1994). Technology and international differences in growth rates. *Journal of Economic Literature, 32*(3), 1147-75.

Fagerberg, J. & Godinho, M. M. (2005) Innovation and catching-up. In Fagerberg, J., et al. (Eds.), *Innovation and catching-up.* Oxford: Oxford University Press.

Fagerberg, J., Srholec, M. & Knell, M. (2007). The competitiveness of nations: Why some countries proper while others fall behind. *World Development, 35*(10), 1595-620.

Fagerberg, J. & Verspagen, B. (2002). Technology-gaps, innovation-diffusion and transformation: An evolutionary interpretation. *Research Policy, 31*(8-9), 1291-304.

Fare, R. & Primont, D. (1995). Multi-output production and duality: theory and applications. Kluwer Academic Publishers.

Figueiredoa, P. N. (2008). Industrial policy changes and firm-level technological capability development: Evidence from northern brazil. *World Development, 36*(1), 55-88.

Gerschenkron, A. (1962). *Economic backwardness in historical perspective.* Cambridge MA: The Belknap Press.

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Literature, 28*(4), 1661-707.

Grupp, H. & Mogee, M. E. (2004). Indicators for national science and technology policy: How robust are composite indicators? *Research Policy, 33*(1373-84.

Grupp, H. & Schubert, T. (2010). Review and new evidence on composite innovation indicators for evaluating national performance. *Research Policy, 39*(1), 67-78.

Howitt, P. (2000). Endogenous growth and cross-country income differences. *Econometrics, 15*(4), 59-81.

Iammarino, S., Padilla-Pérez, R. & von Tunzelmann, N. (2008). Technological capabilities and global–local interactions: The electronics industry in two Mexican regions. *World Development, 36*(10), 1980-2003.

Kline, S. J. & Rosenberg, N. (1986) An overview of innovation. In Landau, R. & Rosenberg, N. (Eds.), *An overview of innovation.* Washington D.C.: National Academy Press.

Lall, S. (1992). Technological capabilities and industrialization. *World Development, 20*(2), 165-86.

Lovell C.A.K., Pastor J.T. (1995). Units invariant and translation invariant DEA models. Operations Reserach Letteres, 18, 147-151.

Maddison, A. (1991). *Dynamic forces in capitalist development* Oxford: Oxford University Press.

Miles, I. (2005) Innovation in services. In Fagerberg, J., et al. (Eds.), *Innovation in services.* Oxford Oxford University Press.

Mokyr, J. (2002). *The gifts of Athena. Historical origins of the knowledge economy.* Princeton: Princeton University Press.

Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffman, A. & Giovannini, E. (2005) *Handbook on costructing composite indicators: Methodology and user guide*, OECD Statistics Working Paper 2005/3.

OECD (2008) *Compendium of patent statistics*, OECD.

OECD (2007) *Science, technology and innovation indicators in a changing world*. Paris: Oecd

OECD (2005) *Growth in service. Fostering employment, productivity and innovation*, Oecd.

OECD (2004) *Triadic patent families methodology*. Paris: Oecd

OECD (2003) *The sources of growth in Oecd countries*. Paris: Oecd

OECD (2002). *The measurement of scientific and technological activities. Proposed standard practice for survey of research and experimental development: Frascati manual.* Paris: Oecd

Patel, P. & Pavitt, K. (1994). Uneven (and divergent) technological accumulation among advanced countries: Evidence and a framework of explanation. *Industrial and Corporate Change, 3*(3), 759-87.

Perez, C. & Soete, L. (1996) Catching up in technology: Entry barriers and windows of opportunities. In Shin, J. S. (Eds.), *Catching up in technology: Entry barriers and windows of opportunities.* London: Routledge.

Pianta, M. (1995). Technology and growth in Oecd countries. *Cambridge Journal of Economics, 19*(1), 175–88.

Porter, A., Newman, N. C., Roessner, D., Johnson, D. M. & Jin, X.-Y. (2009). International high tech competitiveness: Does china rank number 1? *Technology Analysis & Strategic Management, 21*(2), 173-93.

Rifkin, J. (2000). *The age of access: The new culture of hypercapitalism, where all of life is a paid-for experience.* London: Penguin.

Roessner, J.D., Porter, A.L., Newman, N., Cauffiel, D. (1996). Anticipating the future high-tech competitiveness of nations: indicators for twenty-eight countries. *Technological Forecasting and Social Change 51(2)*, 133–149.

Schmookler, J. (1962). Economic sources of inventive activity. *Journal of Economic History, March*(1-20.

Tassey, G. (2008). Globalization of technology-based growth: The policy imperative. *The Journal of Technology Transfer, 33*(6), 560-78.

UNCTAD (2006). *World Investment Report 2006. FDI from Developing and Transition Economies: Implications for Development.* New York, Unctad.

UNCTAD (2005). *World Investment Report 2005. Transnational Corporations and the Internationalization of R&D.* New York, Unctad.

Verspagen, B. (2005) Innovation and economic growth. In Fagerberg, J., et al. (Eds.), *Innovation and economic growth.* Oxford, UK: Oxford University Press.

World Bank (1998) *World development report. Knowledge for development*, The World Bank.

Appendix A: robustness analysis

All the previous analysis is based on the assumption that the composite indicator has a linear structure. This could be considered restrictive. In this appendix we show that all the previous analysis can be settled in a very general specification. We start by defining the composite indicator C using a CES aggregator function:

$$C(\mathbf{y},\mathbf{p})=\left(\sum_{m=1}^{M} p_m{}^{1/s}\, y_m{}^{s-1/s}\right)^{\frac{s}{s-1}}$$

The CES function incorporates as special cases the Cobb-Douglas function (s=1), the Leontief function ($s \to 0$) and the linear function ($s \to \infty$). This means that the parameter s is a calibration parameter to choose the degree of convexity of the function: the more it is convex the less allow for substitution. Now for any aggregator function like that we can solve the following non-linear problem:

$$\begin{aligned} C^t_{\max} &= \max_{z,y} C(\mathbf{y},\mathbf{p}) \\ s.t. \quad y^t_m &\le \sum_{j=1}^{K} z_j y^t_{jm} \ , \quad \forall k = 1,\ldots,K \\ z_j &\ge 0 \ , \quad \forall j = 1,\ldots,K \end{aligned}$$

and use it to define a composite indicator dual to the DEA index. We did it for the limiting case of the Leontief aggregator function. In this case the function becomes:

$$C^t_k = \min\{y^t_{k1},\ldots,y^t_{kM}\}$$

The Leontief aggregator function gives a very stringent notion of ideal composition, penalizing any deviation from the complete balanced composition $y^t_{k1} = y^t_{k2} = \ldots = y^t_{kM}$. The results are not significantly different from the ones obtained with the linear aggregator function, but add a lot on the side of computation. Results of this analysis are available on request and are omitted for reasons of space.

Appendix B: tables and figures

Table 1. *The three pillars and nine variables feeding into the index, and the relative data sources*

Pillar	**Variable**	**Data Source**
Business innovation	Triadic patents	OECD
	Business R&D (BERD)	OECD, UNCTAD
Knowledge&skills	Total researchers in R&D (FTE)	OECD
	Scientific and technical articles	WDI (World Bank)
	Public R&D (PUBRD): Government Intramural Expenditure on R&D (GOVERD) + Higher Education Expenditure on R&D (HERD)	OECD, UNCTAD
	Labour force with tertiary education *(variable omitted due to high correlation)*	WDI (World Bank)
	S&T enrolment in tertiary programmes *(variable omitted due to high correlation)*	UNESCO
Infrastructures	Personnel computers	WDI (World Bank)
	Fixed-line and mobile telephones	WDI (World Bank)
	Internet users	WDI (World Bank)
	Fixed capital	WDI (World Bank)
	Broadband subscribers *(variable omitted due to high correlation)*	WDI (World Bank)

Figure 1. *An example of the Technological Capabilities Set and the TCF*

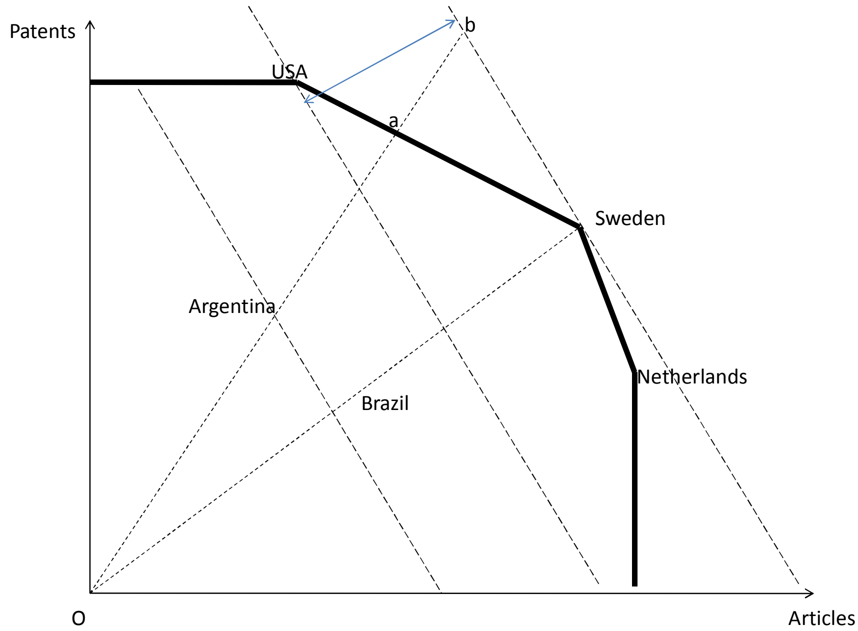


Table 2. *The four typologies of catching-up processes*

	DEA index > 1	DEA index < 1
Compositional Index > 1	Balanced catching-up	Composition improving
Compositional Index < 1	Unbalanced catching-up	Falling behind

Table 3. *The three pillars scores in 1995 relative to countries on the TCF*

Country	Pillar 1	Pillar2	Pillar3
Finland	0.399	0.472	0.258
France	0.311	0.433	0.209
Iceland	0.129	0.438	0.196
Israel	0.307	0.75	0.206
Japan	0.486	0.451	0.267
Netherlands	0.323	0.466	0.228
Norway	0.177	0.447	0.274
Sweden	0.584	0.547	0.242
Switzerland	0.626	0.49	0.289
United States	0.394	0.474	0.257

Figure 2. *Convergence in technological capabilities over the period 1995-2007 (42 countries)*

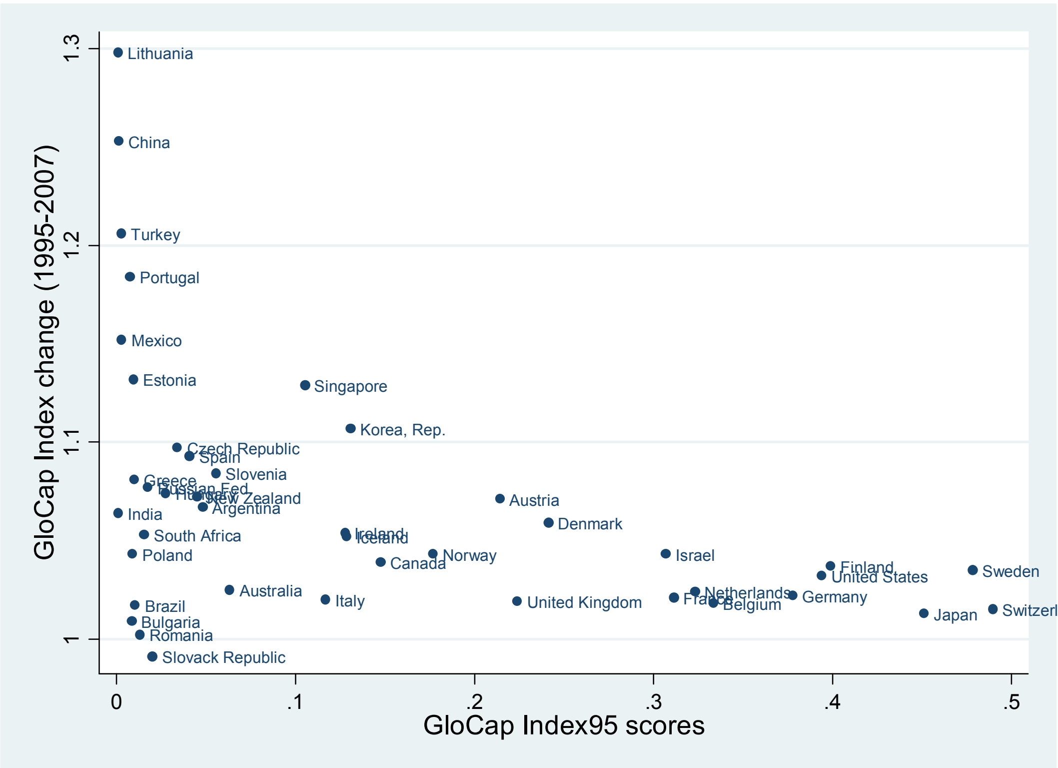


Figure 3. *Convergence in DEA index and Compositional index over the period 1995-2007, (42 countries)*

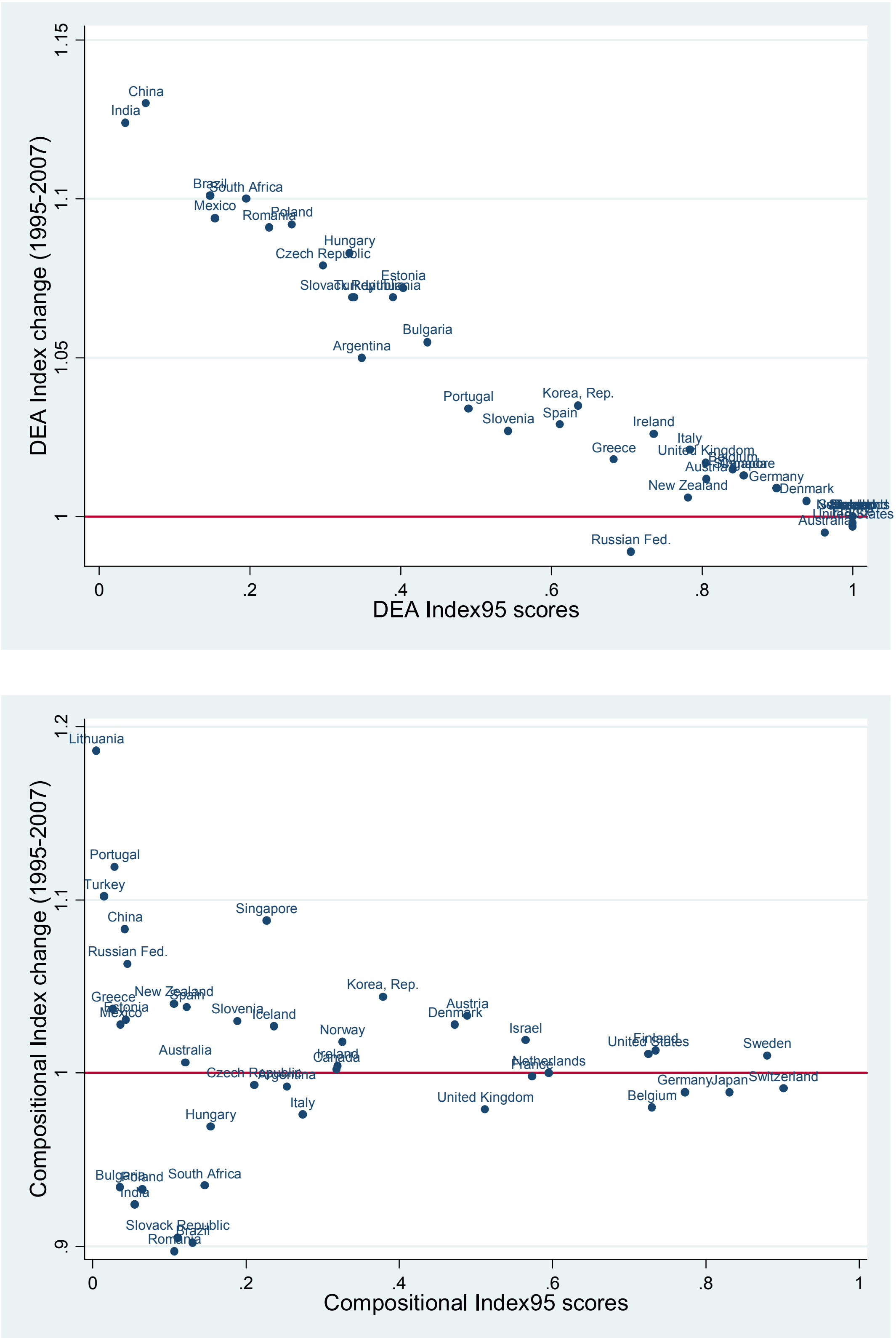
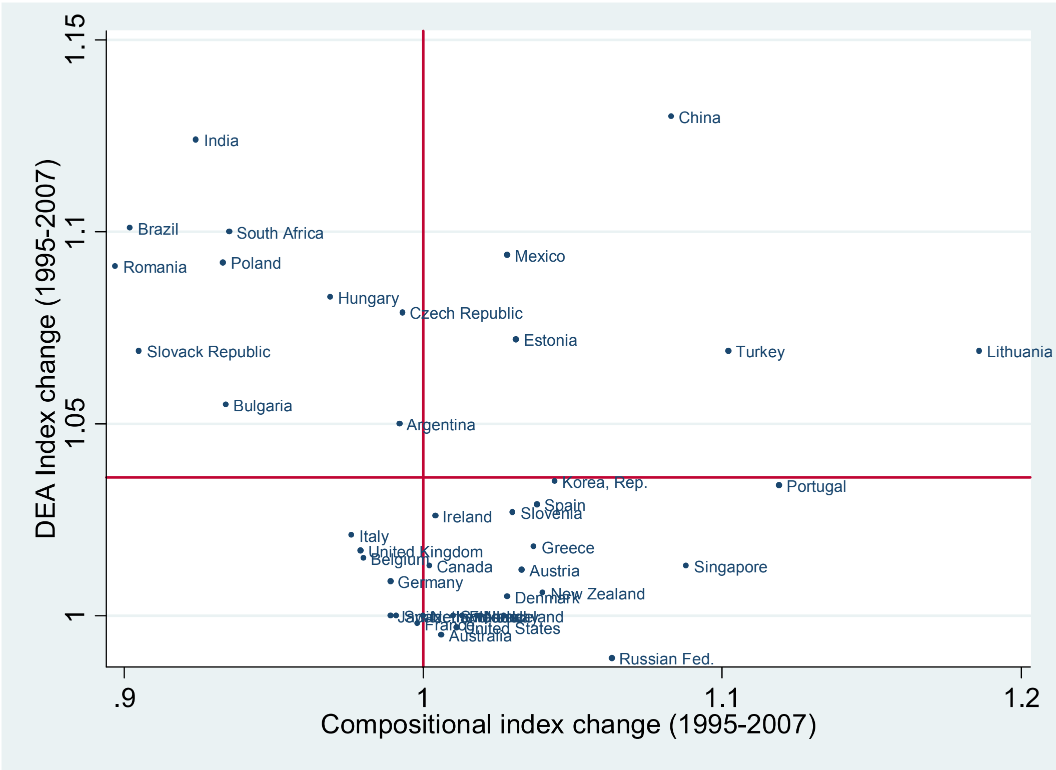


Figure 4. *The dynamic of DEA index and compositional index over the period 1995-2007, (42 countries)*



Note: y-axis crosses at the average value

Table A1. *Indexes scores and rankings, (42 countries ranked by GloCap Index 2007)*

	Index scores						Rankings					
Country	GloCap Index95	GloCap Index2007	DEA Index 95	DEA Index2007	Compositional Index95	Compositional Index2007	GloCap Index95	GloCap Index2007	DEA Index95	DEA Index2007	Compositional Index95	Compositional Index2007
Sweden	0.436	0.750	1.000	1.000	0.969	1.000	2	1	1	1	2	1
Israel	0.400	0.708	1.000	1.000	0.889	0.944	3	2	1	1	3	2
Switzerland	0.450	0.701	1.000	1.000	1.000	0.935	1	3	1	1	1	3
Finland	0.364	0.695	1.000	1.000	0.809	0.927	5	4	1	1	5	4
Japan	0.388	0.659	1.000	1.000	0.862	0.879	4	5	1	1	4	5
Denmark	0.302	0.636	0.939	1.000	0.715	0.848	10	6	12	1	11	7
Singapore	0.204	0.633	0.856	1.000	0.530	0.844	18	7	14	1	22	8
US	0.363	0.632	1.000	0.967	0.807	0.871	6	8	1	18	7	6
Norway	0.297	0.614	1.000	1.000	0.660	0.819	12	9	1	1	14	10
Netherlands	0.328	0.609	1.000	1.000	0.729	0.812	7	10	1	1	9	11
Germany	0.327	0.605	0.899	1.000	0.808	0.807	8	11	13	1	6	12
Austria	0.240	0.585	0.805	0.933	0.663	0.836	16	12	17	20	13	9
Belgium	0.301	0.570	0.842	1.000	0.794	0.760	11	13	16	1	8	13
France	0.307	0.558	1.000	0.980	0.682	0.759	9	14	1	16	12	14
Iceland	0.248	0.545	1.000	1.000	0.551	0.727	15	15	1	1	19	16
Korea, Rep.	0.157	0.529	0.637	0.961	0.548	0.734	22	16	24	19	20	15
UK	0.259	0.520	0.805	0.979	0.715	0.708	13	17	17	17	10	17
Canada	0.254	0.519	0.856	1.000	0.659	0.692	14	18	14	1	15	18
Ireland	0.184	0.484	0.735	1.000	0.556	0.645	20	19	21	1	18	22
Australia	0.218	0.453	0.963	0.905	0.503	0.667	17	20	11	22	25	19
Italy	0.183	0.433	0.784	1.000	0.519	0.577	21	21	19	1	23	24
New Zealand	0.190	0.408	0.782	0.842	0.540	0.646	19	22	20	27	21	21
Spain	0.127	0.385	0.613	0.859	0.460	0.598	24	23	25	24	29	23
Slovenia	0.136	0.371	0.542	0.752	0.558	0.658	23	24	26	29	17	20
Estonia	0.070	0.343	0.404	0.933	0.385	0.490	32	25	29	20	33	26
Czech Rep.	0.078	0.300	0.297	0.737	0.584	0.543	28	26	35	32	16	25
Hungary	0.075	0.291	0.332	0.859	0.502	0.452	31	27	34	24	26	29
Greece	0.094	0.279	0.683	0.849	0.306	0.438	25	28	23	26	39	30
Slovack Rep.	0.077	0.260	0.336	0.750	0.509	0.462	29	29	33	31	24	28
Lithuania	0.053	0.258	0.390	0.866	0.302	0.397	35	30	30	23	40	33
Portugal	0.078	0.256	0.491	0.728	0.353	0.469	27	31	27	34	35	27
Poland	0.054	0.223	0.255	0.735	0.471	0.405	34	32	36	33	28	32
Argentina	0.076	0.200	0.349	0.627	0.484	0.425	30	33	31	36	27	31
Turkey	0.034	0.188	0.339	0.751	0.223	0.334	37	34	32	30	42	40
Bulgaria	0.061	0.187	0.437	0.828	0.310	0.301	33	35	28	28	38	41
Russian Fed.	0.085	0.182	0.705	0.619	0.268	0.392	26	36	22	37	41	35
Romania	0.034	0.164	0.225	0.641	0.336	0.341	38	37	37	35	36	39
Mexico	0.026	0.135	0.153	0.454	0.378	0.396	40	38	39	40	34	34
Brazil	0.028	0.130	0.147	0.465	0.423	0.373	39	39	40	39	32	37
South Africa	0.037	0.130	0.194	0.610	0.424	0.284	36	40	38	38	31	42
China	0.009	0.078	0.063	0.268	0.317	0.388	41	41	41	41	37	36
India	0.007	0.039	0.036	0.143	0.432	0.364	42	42	42	42	30	38

[1] A very comprehensive reviews and contribution about the methodology of the composite indicators can be found on the ISPRA website http://composite-indicators.jrc.ec.europa.eu/.

[2] We also tested the inclusion of other two variables, "labour force with tertiary education" and "S&T enrolment in tertiary programmes". We decided to rule them out on the ground of a very high correlation with the other three variables of the pillar and due to some data missing. However, given the results we obtained we can think *as if* they were included in the second pillar.

[3] Initially we also included broadband subscribers, but also in this cases we decided to rule it out because of a large overlapping with other variables within the same pillar.

[4] For a discussion about the complementarity and the use of a consistent methodology see Cerulli & Filippetti, 2010.

[5] The graph has been divided in order to highlight countries with a *Compositional index* larger and lower than one. Concerning the *DEA index* we preferred to divide countries according to their performance with respect to the average, given that nearly all of them present a DEA index larger than one, while in this way we are able to point out those showing a better performance.