MEASURING ECONOMIC GROWTH USING DATA ENVELOPMENT ANALYSIS

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Please cite this article as:
Škare, M. and Rabar, D., 2015. Measuring Economic Growth Using Data Envelopment Analysis. *Amfiteatru Economic,* 18(42), pp. 386-406

Abstract
Exploring and explaining development gaps between countries is an important theoretical and empirical task. This paper presents empirical studies related to economic growth and its determinants across countries, based on the use of data envelopment analysis method. It emphasizes the importance of this nonparametric approach to macroeconomic efficiency analysis and provides a broader and more comprehensive perspective to the researchers on this issue.

Keywords: efficiency, growth, productivity, data envelopment analysis, cross-country

JEL Classification: C60, D24, E32, O40, O47

1. Introduction

From the beginning of economics as a scientific discipline, economists have been trying to address the fundamental question of how to assess and improve the efficiency of economic systems. The ultimate aim is to improve living standards and quality of life and to eradicate poverty. Given this context, the most important is the concept of economic growth as the traditional concern of macroeconomics. Therefore, a crucial part of the economists' task is to find answers on how to accelerate it, which is conditioned by the comprehension of the factors that allow some countries to achieve higher rates of growth, and thus to provide themselves leadership position in the global rankings as measured by national production.

A wide range of studies shows that the economic growth is a complex macroeconomic phenomenon, which is why its sources and the extent of their influence, as well as the way of their contribution to the growth, have yet not been clearly understood, adequately conceptualised and fully explained. It could be partly attributed to the lack of a generalised or unifying theory, and the simplistic and very abstract way conventional economics approaches these issues (Artelaris et al., 2007). Therefore, efforts to make progress in

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clarifying these questions, which implies exploring and explaining development gaps between countries, remain an important theoretical and empirical task.

Despite its crucial importance, between the mid-1960s and mid-1980s research into economic growth went into relative decline compared to other areas of macroeconomics (see Laband and Wells, 1998). Over the last three decades, however, it has attracted increasing attention in both theoretical and applied empirical research. According to Xavier Sala-i-Martin, who is widely recognized as one of the world's leading economists in the field of economic growth, the most exciting aspect of the resurgence of interest in growth analysis has been the integration of theoretical and empirical research. He also believes that, in the new wave of research on economic growth, economists have taken economic theory more seriously when it comes to empirical studies, noting the work on convergence as a good example (Snowdon, 2006). However, many of the studies in the empirical growth literature, particularly the earlier ones, have focused on capital accumulation, largely ignoring productivity growth. Also, the use of traditional growth accounting, among other limitations, usually assumes that the production technology follows the suggested Cobb-Douglas form. Moreover, all changes in total factor productivity (TFP) are attributed to technological change. To redress all these issues, data envelopment analysis (DEA) has been suggested in the literature. DEA as a nonparametric alternative to traditional growth accounting, it is suitable for analysing productivity convergence based on frontier production functions. The use of this approach only requires the assumption about the returns to scale (RTS), and changes in TFP are decomposed into changes in the efficiency of production and technological changes.

The aim of this paper is to summarize the comprehensive literature in which DEA is applied as a nonparametric approach for measuring macroeconomic efficiency and determine the factors that affect it the most, along with the magnitudes of their impact. The paper is organized as follows. Section 2 briefly overviews modern efficiency measurement and gives a short description of the DEA method and its basic models, also listing their numerous extensions and relaxations. In the central and most comprehensive section 3, review of the literature on economic growth using DEA is presented. The overall conclusions of the study are brought out in the final section 4.

2. Data envelopment analysis

The assessment and improvement of efficiency have been the subject of great interest in many areas of human activity, and as such deserve close attention. Therefore, the efficiency measurement has become one of the most common subjects of debate in modern science on the application of mathematical methods in economic analysis. One such method, which is attracting a growing number of supporters, and at the same time is simple and enables an analysis of complex issues, is data envelopment analysis. Below, a brief overview of modern efficiency measurement and a short description of the DEA method are given (Rabar, 2013, p. 17-18).

Modern efficiency measurement begins in the 1950s with the classic paper on the measurement of productive efficiency, written by Farrell who drew upon the work of Koopmans, Debreu and Shephard. Koopmans (1951) was the first to define the concept of technical efficiency[1]. Debreu (1951) introduced distance functions as a way of modelling multiple-output technology and measuring the radial distance of a producer from a frontier in an output-expanding direction. Two years later, Shephard (1953) showed that the radial distance of a producer from a frontier can be measured in the same manner in an input-conserving direction. The association of distance functions with technical efficiency measures was crucial in the development of the efficiency measurement. Extending the work initiated by Koopmans and Debreu, Farrell (1957) was the first to measure empirically productive efficiency. In this context, he aptly noted (p. 253): "The problem of measuring the productive efficiency of an industry is important to both the economic theorist and the economic policy maker. If the theoretical arguments as to the relative efficiency of different economic systems are to be subjected to empirical testing, it is essential to be able to make some actual measurements of efficiency. Equally, if economic planning is to concern itself with particular industries, it is important to know how far a given industry can be expected to increase its output by simply increasing its efficiency, without absorbing further resources." Farrell further asserted that numerous attempts that have been made to solve mentioned problem failed to combine the measurements of the multiple inputs and outputs into any adequate measure of efficiency. He demonstrated how to define cost efficiency and how to decompose it into its technical and allocative components[2] that were then combined to provide a measure of total economic (overall) efficiency. These measures were intended to be quite general and thus applicable to any productive organization from a workshop to a whole economy, thereby allowing comparisons of entire countries or regions.

Although Farrell was able to formulate a multiple output case, he, unfortunately, confined his discussion and numerical examples to single output situations. His use of linear programming techniques eventually encouraged Charnes et al. (1978) to address some of the limitations of traditional benchmarking approaches by developing a non-parametric efficiency measurement technique named data envelopment analysis.

DEA methodology is derived from the classical microeconomic theory of production. It is used for evaluating the relative efficiency of operating entities of similar nature, i.e. of decision-making units (DMUs) that use the same multiple inputs and produce the same multiple outputs. The original question in the DEA-literature concerned the ways of measuring each unit's efficiency in production compared to a sample of peers, given observations on (possibly multiple) input and output quantities and, often, no reliable information on prices and no exact knowledge of the functional form of a production or cost function (Charnes and Cooper, 1985). Moreover, each variable can be expressed in different (usually non-congruent) measurement units. An a priori determination of input and output weights is also not required, but they are chosen by the method in a manner that assigns the best set of weights to each evaluated DMU. In this way, the subjective assessment of their importance is avoided, which contributes to the objectivity of analysis.

The whole procedure is based on empirical data on inputs and outputs of all observed DMUs, which should be included into a linear program that represents the selected DEA

[1] "A producer is technically efficient if, and only if, it is impossible to produce more of any output without producing less of some other output or using more of some input."

[2] Technical efficiency reflects the ability to obtain maximal output from a given set of inputs. Allocative (price) efficiency reflects the ability to use the inputs in optimal proportions, given their respective prices and the production technology.

model. Bounding inputs from below and outputs from above, it first establishes an empirical efficient production possibility frontier formed by a set of DMUs that exhibit best practices and are given a rating of '1'. Then it assigns the efficiency levels, ranging between 0 and 1, to other non-frontier units according to their distances to the efficient frontier. The degree of inefficiency is attributed to input excesses and/or output shortfalls that can be overcome by projecting onto the efficient frontier. In this way, the method combines and converts multiple inputs and outputs into a single efficiency index. Since spanned by the existing DMUs, the efficient frontier represents an achievable goal that inefficient DMUs should gain on. A multitude of models have been developed which are distinguished by the assumption of returns to scale (constant or variable), by the model orientation to (minimizing) inputs or (maximizing) outputs, by numerous extensions and relaxations.

Basic DEA models most commonly used in applications are CCR (Charnes et al., 1978) and BCC (Banker et al., 1984), named after initials of their authors. CCR model is built on the assumption of constant returns to scale (CRS) activities and yields an objective evaluation of overall efficiency. BCC model represents one of the various theoretical extensions that have been developed based on the original CCR model. Under the assumption of variable returns to scale (VRS)[3], it estimates pure technical efficiency at the given scale of operation and identifies whether increasing, decreasing or constant RTS possibilities are present for further exploitation[4].

Also, the DEA model can be adjusted to the strategy chosen by management and therefore oriented on input reduction (input-oriented model) or output augmentation (output-oriented model), while in both cases keeping other variables at their original levels. The distinction between differently oriented models results in different courses and thus in different projection values of an inefficient entity on the efficient frontier. Therefore, the distances from inefficient entity to its projections differ. Since smaller distance is usually easier to overcome, efficiency is not equally attainable by differently oriented models.

The problem of choosing between input and output orientation can be avoided with the use of a whole range of non-oriented models that DEA offers, among which may be mentioned the additive model, slack-based measure (SBM) model and multiplicative model. Although those models have the same production possibility set as the previously mentioned CCR and BCC models, they provide the ability of simultaneously minimizing inputs and maximizing outputs, while treating slacks directly in the objective function. Based on BCC model, Charnes et al. (1985) developed the additive model that is translation invariant in both the inputs and outputs, meaning that the translation of the original input or output values will result in the same optimal solution. The SBM model, proposed by Tone (2001), is an extension of the additive model with unit invariant[5] and monotone[6] efficiency measure. Charnes et al. (1982) developed the multiplicative model, in which the data were transformed using a logarithmic structure.

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[3] Since the CCR model was applicable only to processes with constant returns to scale, Banker et al. (1984) extended it in order to adapt it to processes with the assumption of variable returns to scale.

[4] The choice of returns to scale usually depends not only on theoretical assumptions, but also "on the context and purpose of the analysis, or whether short-run or long-run efficiency is under scrutiny" (Jacobs et al., 2006, p. 103).

[5] invariant with respect to the unit of measurement of each input and output item

[6] monotone decreasing in each input and output slack

Many theoretical papers in the field have modified the models to deal with problems that have occurred in practice. Cook and Seiford (2009) provided a sketch of some of the major research thrusts in DEA, with the focus primarily on methodological developments. Besides the previously mentioned basic ones, the authors reviewed various DEA models, including those that went beyond the usual definition of DEA, specifically discussing free disposal hull model, cross efficiency, least distance projections and invariance to data alterations. They went beyond the single level models by examining multilevel models, and also discussed various forms of multiplier restrictions used to constrain the frontier. The status of different types of variables, including non-discretionary, non-controllable, categorical, ordinal, imprecise, undesirable and flexible variables, was also reviewed. Data variation was also explored and included sensitivity analysis, probability-based models, window analysis and Malmquist models for capturing times series impacts on efficiency, and statistical inference issues surrounding the efficient frontier. The basic DEA results dichotomously classify the DMUs into efficient and inefficient. For various methodological and practical reasons, researchers and decision-makers are often interested to fully rank them to refine the evaluation. The ranking methods within the DEA context could be considered post-analyses since they do not replace the standard DEA models but rather provide added value (for a detailed discussion see Adler et al., 2002). Just a limited review of many desirable features that contributed to the rapid adoption of DEA models by practitioners is presented here.

Regardless of their type and orientation, extension or relaxation, the DEA models bring about a broad range of relevant and useful results. Among others, there is an efficiency measure for each entity of interest, and there are also sources and amounts of inefficiency. Besides, for inefficient units, DEA identifies the associated efficient virtual composite units on the frontier comprising of a relevant group of peers of efficient units (reference set) and the directions to these projected composite units (proposed improvements in each input and each output). This information is of utmost importance in helping policy makers in allocating resources more efficiently and in identifying directions for gain. Such a reputable range of results, along with the previously mentioned advantageous numerous features of the method itself, are the most common reasons for choosing DEA rather than traditional methods of measuring efficiency.

However, it would not be fair to omit to mention that, despite the advantages, the DEA also has several problems in the empirical applications, of which we will mention two. One of the main disadvantages of DEA is a commonly suggested rule of thumb, according to which the number of entities should be at least three times the number of indicators (for more detailed discussion see Sarkis, 2007). The reason for this requirement is an attempt to assure that the basic productivity models are more discriminatory thus achieving greater reliability of the efficiency results. Also, unlike general application of multi-criteria approaches to ex-ante problem areas where data are not readily available, especially if referring to a discussion of future technologies that do not yet exist, DEA provides an ex-post analysis of the past from which to learn (Adler et al., 2002).

Over the past thirty-some years since the appearance of the seminal work of Charnes et al. (1978), there has been an impressive growth in theoretical developments as well as in applications of the ideas to practical situations (Cook and Seiford, 2009). As a response to the need for adequate procedures to assess the relative efficiencies of multi-criterion systems and to provide improvement targets for such systems, this powerful methodology has been widely applied in management science. According to Liu et al. (2013), who surveyed the DEA literature by applying a citation-based approach, the field has accumulated approximately 4500 papers in ISI Web of Science database up through the year 2009. The same study identifies five active DEA subareas: "two-stage contextual factor evaluation framework", "extending models", "handling special data", "examining the internal structure" and "measuring environmental performance". While the papers in the first four subareas are studies of theoretical orientation, the papers in the last subarea are application works that refer to decision analysis problems in various areas such as schools, hospitals, banking, financial companies, hotels, airports, supplier's selection, retail organizations and nations. Such a broad spectrum of applications, including those in the context of macroeconomics, provides a useful illustration of the power of this approach that has been developed into a widely accepted academic field deserving close attention.

3. Review of literature on economic growth using data envelopment analysis

In the construction of a satisfactory empirical model of growth, one of the main areas of effort has concerned the identification of appropriate variables to include in the analysis. As a multidimensional phenomenon, economic growth has thus been studied using a variety of different indicators, ranging from gross domestic product (GDP), inflation and unemployment, as the primary variables, to a series of less used variables such as consumer price index, access to credit, business cycles. Consequently, a different selection of observed variables leads to different relative efficiency results that are additionally influenced by the choice of the model itself. Since that is critical for the research, the selection of inputs and outputs should reflect the interest of analysts and managers, qualifying the goal of conducting such an analysis, while the model should be selected as to be suitable for the process under consideration.

The foundations for the use of DEA as a tool of macroeconomic analysis were laid by Färe et al. (1994) who analysed productivity growth in 17 OECD countries over the period 1979-1988. Initially based on the Malmquist productivity index (MPI) introduced by Caves et al. (1982), the authors show how to account for productivity changes over time. Namely, they decompose productivity growth into two mutually exclusive and exhaustive components: changes in technical efficiency (catching up) and shifts in technology (innovation). Using GDP as the measure of aggregate output, and capital stock[7] and employment as the aggregate input proxies, the authors find that TFP growth in OECD countries was driven entirely by innovation resulting in technological progress while, by contrast, technical efficiency slightly deteriorated over time. Färe et al. were not the first to propose such a decomposition of productivity growth[8] but, unlike other approaches where the specification of a functional form for technology was required, their approach was nonparametric.

The same approach was adopted by Rao and Coelli (1998) as well as by Krüger et al. (2000). In the first paper, the output variable is real GDP per capita with the inputs being labour and capital per capita. The data cover 60 countries from all regions of the world for the period 1965-1990. For Latin America and North Africa/Middle East, negative annual TFP growth is observed while the highest TFP growth rate is of Asia. The authors report

[7] For example, see Nishimizu and Page (1982) and Bauer (1990).
[8] GDP and capital stock are measured in 1985 international prices.

several cases of technological regress, most of which were among African and Latin American countries. The second paper studies the 'East-Asian Miracle' from 1960 to 1990, dividing the data into two sub-periods – 1960-1973 and 1973-1990. The analysis covered 87 countries from all continents, classified into three groups – the G7, Latin America and a group of Newly Industrialized Countries (NICs). The output is GDP in international 1985 prices while inputs are labour and capital stock (constructed from investment data by use of the perpetual inventory method). With some minor exceptions, the study revealed the following results. Latin America experienced negative while G7 and NICs recorded positive average annual TFP growth. All three groups had on average positive change in technical efficiency, which was most prominent in NICs, suggesting rapid catching-up. Finally, all NICs and Latin American countries faced technological regress while, among the G7 countries, only five progressed technologically.

These papers have inspired a range of research studies examining various aspects of economic growth through the use of data envelopment analysis. A selective survey of the published literature is given below, and summarized in Table 1, placing the emphasis on countries, periods and indicators under consideration. The intention in selecting these case studies was to cover as many different countries, different times, different indicators and different DEA based efficiency benchmarking models as possible.

Lovell et al. (1995) studied the macroeconomic performance of 19 OECD countries over the period 1970-1990. In this interesting and frequently cited example in the international literature, macroeconomic performance was defined in terms of the ability of a country's macroeconomic managers to provide four services to their citizens: a high level of real GDP per capita, a low rate of inflation, a low rate of unemployment and a favourable trade balance[9]. Throughout the analysis emphasis was placed on a comparison of the performance of 14 European OECD countries and five non-European OECD countries. The authors used the nonradial extended additive DEA model to develop a best practice macroeconomic performance frontier and to measure the performance of each country in each year relative to the frontier. They then added two environmental disamenities (carbon and nitrogen emissions[10]) to the service list and repeated the analysis that showed that performance rankings changed and that the relative performance of the European countries declined.

Using the same set of methods and the same four macroeconomic indicators, Lovell and Pastor (1995) analysed the macroeconomic performance of 16 Ibero-American countries over the period 1980-1991. The data was then normalized to evaluate the quality of the macroeconomic management of each country. Venezuela and Mexico were identified as having had the strongest economies, and Nicaragua, Bolivia and Peru as having had the weakest economies. The analysis also identified the best-managed economies like those of Colombia, Mexico and Argentina, and the worst-managed economies as those of Peru, Bolivia and Nicaragua. Two of the three strongest economies also enjoyed relatively strong macroeconomic management. However, unfortunately for their citizens, it happens that the three weakest economies also suffered the worst macroeconomic management.

[9] GDP was measured in 1980 US dollars. Inflation rate was measured on an annual basis. Employment rate was defined as the ratio of civilian employment to the civilian labour force. Trade balance was defined as the ratio of the value of exports to the value of imports.

[10] Carbon emissions from energy use were measured in millions of tons per capita, while nitrogen emissions were measured in tons per square kilometre.

The gap between the healthiest and the weakest economies widened during the decade, a fact that was supported by the new extension of the conventional DEA model that was, in this paper (as well as in the previous one), referred to as Global Efficiency Measure.

Building on an earlier application of DEA to the ranking of the economic performance of the G-7 nations, Golany and Thore (1997) proposed to extend the calculations to take account of social variables such as education, health, and welfare policy as well. Based on three inputs (ratio of real domestic investment to real GDP; ratio of real government consumption expenditure, net of spending on defence and on education, to real GDP; ratio of public expenditure on education to nominal GDP) and four outputs (growth rate of per capita GDP; ratio of nominal social insurance and welfare payments to nominal GDP; 1 minus infant mortality rate ages 0-1; enrolment ratio for secondary education)[11], an empirical application was presented, rating 72 developed and developing countries by their economic and social performance during the period 1970 to 1985. Both in the context of the CCR and the BCC model, the efficiency rating and also a measure of returns to scale (increasing, constant or decreasing) were calculated for each country. The frequency of alternate optima, leaving the returns of scale indeterminate, was examined. For nations with increasing RTS, continued the long-run growth of both gross domestic product (GNP) and social performance was indicated, while for countries with decreasing RTS the result was just the opposite. The data for countries exhibiting constant RTS was further investigated using more accurate RTS analysis tools and, for some of these countries, the authors showed how the constant RTS characterization can be highly sensitive to changes in the data.

The statistical analysis based on the ranking techniques, offered in Brockett et al. (1999), expanded the potential benefit of DEA applications while retaining the robust nonparametric nature of the original DEA development. Combining DEA window-based analysis, rank matrix transformation and Kruskal-Wallis nonparametric analysis of variance test, the authors identified intertemporal performance trends using any one of several possible efficiency measures and tested the stability over time of the rank positions of the analysed units. These procedures were applied to data on three indicators reflecting the macroeconomic performance of 17 OECD nations in 1979-1988. Those were capital stock and employment as aggregate input proxies and GDP as a measure of aggregate output[12]. The analysis showed that Greece exhibited the worst performance and Denmark the best performance over the examined period. The U.S. did steadily better in its productivity efficiency than did Japan despite U.S. productivity growth exhibited a ‘slowdown’ relative to Japan. The results were discussed and contrasted with previous research in this area.

Forstner and Isaksson (2002) used DEA to construct a ‘world-technology frontier’ using data on 57 industrialized and developing countries[13] for the period 1980 to 1990, using

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[11] All the inputs and the first two outputs were averaged from 1970 to 1985, while the last two outputs referred to the year 1985.

[12] GDP and capital stock were measured in constant 1985 international prices. Employment was found using the real GDP per worker, and capital was obtained from the capital stock per worker.

[13] The sample included 22 OECD countries, 3 ‘Tiger’ economies of East Asia, 9 Sub-Saharan African countries and 23 other developing countries, mostly from Central and South America and from Asia.

labour and capital as inputs and real GDP as output[14]. Analysing TFP growth, measured by the use of output-oriented Malmquist index (assuming CRS), the authors showed that applying DEA in standard fashion resulted in a biased estimate of the change in technical efficiency, due to an implausible loss of memory about production techniques. Namely, when a country is located in a region where the world technology frontier is receding, it appears as performing exceptionally well in technical efficiency without actually having improved at all. To prevent this, an amendment to DEA, called Long-Memory DEA, was proposed. Its application yielded new results that were largely in line with common perceptions of growth patterns.

To see whether the transition to the market-based economy increased economic efficiency, technical progress and TFP, Deliktas and Balcilar (2005) examined the macroeconomic performance of countries in transition. The panel dataset on real GDP as output and labour and capital as inputs[15], for the period of 1991-2000, included 130 countries, but the analysis concentrated on the 25 transition countries (East European, Baltic and other former Soviet Union Countries). Using stochastic frontier analysis and, as confirmatory, DEA with VRS, the authors found that, with minor exceptions, the transition countries were well below the frontier. The results also showed that the transition to the market economy reduced inefficiency in the formerly planned economies. On the other hand, these countries have suffered from technical regress due to other factors, and this outweighed the effect of an increase in technical efficiency due to which a convergence among transition economies was found. The overall result has been an average TFP decline.

Escaith (2006) analysed the dynamics of economic growth in Latin America. Several techniques, including DEA, were used for extrapolating growth trends and applied to the regional situation. The Latin American and Caribbean (LAC) region was divided into three sub-regions – Mercosur and Chile, Andean Community and Mesoamerica, and examined in the period 1950-2005. The emphasis was placed on the period 1991-2005, which was split into three sub-periods – 1991-1997, 1998-2002 and 2003-2005. The first two sub-periods belong to the same economic cycle while the third one corresponds to a new cycle and the basic objective of this paper was to build some scenarios about its growth potential. Among other variables, capital stock, investment, productivity and GDP were included. These indicators were not discussed in detail, but an alternative framework was provided for measuring the potential economic growth. The results obtained from the empirical investigation pointed, among other things, that productive capacity has been debilitated by years of reduced investments, and TFP has not responded positively to the structural reforms.

Over the past few decades, countries of the Middle East and North Africa (MENA) have achieved variable levels of economic development. Ramanathan (2006) employed DEA to study the comparative performance of 18 MENA countries by considering three input ratios (undesirable outputs) – age dependency ratio, illiteracy rate and mortality rate, and four output ratios (desirable outputs) – labour-population ratio, life expectancy rate, percentage

[14] Values of GDP and capital were in international 1985 prices. Capital stock was non-residential capital only and was derived from capital stock per worker, while labour was derived from GDP per worker.

[15] GDP was measured in constant 1995 US dollars. Labour was measured as the total labour force**.** The capital stock was cumulatively calculated from gross capital formation (constant 1995 US dollars) by taking 1989 as the base year for the transition countries and 1985 for other countries.

of female teachers in primary education and GNP per capita. For 1999, Bahrain, Jordan, Kuwait, and the United Arab Emirates were identified as the most efficient. All are from the Middle East, with three being members of the Gulf Cooperation Council. Yemen was rated as the least efficient of all countries considered in the analysis. A regression analysis showed efficiency scores have a significant relationship with the wealth of the countries (in terms of GNP per capita) but do not have a significant link with the size of the countries (in terms of population). Further, a time series analysis using the Malmquist Productivity Index shows MENA countries achieved higher values of desired attributes, and lower values of unwanted attributes, in 1999 compared to 1998. During 1998-1999, technology change contributed more to the improvement of MPI than did technical efficiency change.

According to Kerekes (2007), the growth experience of virtually all but the very wealthy countries is best explained as a combination of high and low growth episodes. Therefore, there is a need to understand the responsible factors for growth regime changes, i.e. variations of the growth rates within countries. In this paper, the author aims at identifying the causes of growth transitions by combining a statistical method (Bai-Perron econometric technique), that is used to determine episodes of high and low growth, with a nonparametric approach to growth accounting (DEA), that is applied to derive the proximate causes of growth regime changes. The nonparametric growth accounting was based on data on capital stock, labour, investment and real GDP[16] from 105 countries with a population above one million for the period 1950-2004. Based on the assumption that the production technology exhibits CRS, results show that even in the medium run growth rate changes are the result of productivity changes whereas factor accumulation plays a minor role. Except for high-income countries productivity changes usually represent efficiency changes. A comparison of growth take-offs and growth collapses reveals that factor accumulation is even less necessary in periods of accelerating growth.

Mohamad and Said (2011) used DEA to estimate how well the nations of the Organization of the Islamic Cooperation (OIC) utilize their resources. Based on one input[17] and four outputs[18], the authors applied three versions of an output-oriented DEA model under the assumption of VRS to assess the relative macroeconomic performance of 54 OIC member countries for the period 2003-2007. The different model versions produced consistent results. Three fuel-exporting countries and four least-developed countries top the performance list with Iran and Yemen at the bottom. Of a subset of 33 fuel-exporting and medium-developed countries, nine (seven and two respectively) top the list. The results were analysed to identify the possible merits of efficiency and sources of inefficiency.

Škuflić et al. (2013) analysed the model of economic growth in 28 European countries, mostly EU members, in three different years (2000, 2004 and 2008) to determine

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[16] GDP was expressed in purchasing power parity in 2000 international dollars, and deflated using a Laspeyres index. Labour used in production was measured by the number of workers in the population. Total investment per period was derived multiplying the investment rate with GDP. The capital stock was calculated via the perpetual inventory method assuming a constant depreciation rate of 7%.

[17] total government consumption expenditure as a percentage of GDP

[18] the annual rate of growth of GDP, expressed in percentage; the ratio of merchandise exported to merchandise imported as a proxy for balance of trade; the rate of inflation as indicated by the rate of change of the consumer price index (CPI); the total labour participation rate measured as percentage of total population ages 15-64 years

the significant growth factors. They used output-oriented DEA model under the CRS assumption to distinguish between the countries that have applied efficient growth model from those that have not. Macroeconomic indicators used for the analysis of economic growth in this research are productivity and share of exports in GDP as inputs while outputs are represented by shares of gross wages and personal consumption in GDP and by GDP per capita. According to obtained results, Croatia ranks worst in terms of achieved efficiency, which could be attributed to the fact that, during the observed period, the other transition countries from the sample have been the EU members while Croatia has not. According to the obtained results, the authors concluded that the accession to the EU improves the country's efficiency.

In a cross section of 19 OECD countries, Afonso and St. Aubyn (2013) replaced the macroeconomic production function by a production possibility frontier, TFP being the composite effect of efficiency scores and possibility frontier changes. They considered one output (GDP, measured in units of national currency per PPS – purchasing power standard) and three inputs (human capital, public physical capital and private physical capital)[19], for the period 1970-2000 divided into three decades. The authors used a semiparametric analysis, computing Malmquist productivity indices and also resorting to stochastic frontier analysis. Based on output-oriented DEA under VRS, results showed that private capital was essential for growth, although public and human capital also contributed positively. The government effectiveness indicator[20] explained inefficiency suggesting, as expected, that better governance helps countries to achieve a better performance. Non-parametric and parametric results coincided quite closely countries movements vis-à-vis the possibility frontier, and on their relative distances to the frontier.

Recent discussions on the definition of growth in terms of welfare beyond GDP[21] suggest the necessity of developing new approaches to measuring the economic performance of national economies. According to Lábaj et al. (2014), the new concepts should take into account simultaneously economic as well as social and environmental aspects of economic development. Using seven output-oriented DEA models under the VRS assumption, the authors analysed the performance of 30 European countries, mostly EU members, for the year 2010. The models mutually differ in the choice of indicators and the efficiency concept. Thus, inputs included capital and labour, while outputs were classified into desirable outputs, represented by GDP, and undesirable outputs, represented by greenhouse gases emissions and income inequality measured by Gini index[22]. The overall efficiency was decomposed into ecological and socio-economic efficiency. Various model specifications allowed capturing different characteristics of economic development, thus showing different possibilities for economic policy to increase the efficiency.

Another contribution to the issue of growth regarding welfare beyond GDP is research on happiness as new research area and important new development in economics in recent

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[19] All four measures are also scaled by worker.

[20] It is the World Bank composite indicator that measures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies (Kaufmann et al., 2010).

[21] See, for example, Stiglitz et al. (2009).

[22] GDP and capital stock were measured in PPS, labour in thousands of persons employed, and greenhouse gases emissions in thousands of tons.

years. Considering both objective and subjective parameters[23], Debnath and Shankar (2014) analysed 130 countries over the period of ten years (2000-2009). Nations of various sizes, both rich and poor, with different economic standings in the world, with various culture and society, were studied. All the countries were clustered according to economy into three categories for which the relative happiness was then analysed using DEA. Since the objective was to maximize happiness as the output, a BCC output-oriented model was used. The authors proposed that only good governance cannot optimize the happiness because there are subjective parameters that are important to measure the happiness. In accordance, the results showed how the government can increase the happiness of the people by analysing their behaviour and expectations. Therefore, the definition of good governance must change from its existing characterization.

Research focus on countries' productivity and economic growth in recent years was shifted to studying the effects of some undesirable outputs related to environmental issues. Among the latest examples is the paper by Chiu et al. (2015), who selected 35 Asian countries during the period 2001 to 2005 and used the undesirable measure DEA model (proposed by Seiford and Zhu, 2002) to calculate and analyse those countries' productivity efficiency. The sample countries were divided into Newly Industrialized Asian Economies, Commonwealth of the Independent States and Mongolia, Developing Asia, the Middle East, and Advanced Economies. The input variables were the population and the amount of government investment while the output variables were GDP as desirable, and fossil-fuel CO2 emissions as undesirable. The analysis showed that most Middle Asia countries had the best efficiency scores. The numbers of best efficiency countries from 2001 to 2005 did not show a big variance, but the countries' ranking was obviously diverse. Big CO2 emissions countries, such as South Korea, Indonesia, India and China, did not have good efficiency like Japan. Each region had its best efficiency ranking countries, which had nothing to do with the character of a country. Small countries had the best efficiency scores while advanced countries had the best efficiency scores without CO2 emissions.

The data envelopment analysis is increasingly used in the field of composite indicators (CIs) construction. This application is known as the 'Benefit of the Doubt' approach (BoD). It was originally proposed by Melyn and Moesen (1991) to assess macroeconomic performance. In an attempt to capture the four dimensions of macroeconomic performance, upon which the OECD's "magic diamond" is based, with an unequal weighting of the single indicators, they introduced Leuven Index of Macroeconomic Performance (LIMEP). Such method is acceptable in the typical CI-context but lacks of consensus on, an appropriate weighting scheme. With some extensions, BoD has therefore been applied by some authors for the purpose of measuring and comparing the macroeconomic performance of nations.

[23] The four inputs were: (1) technical quality of governments which included government effectiveness, regulatory quality, rule of law and control of corruption; (2) democratic quality of governments which included voice and accountability, political stability and absence of violence; (3) government consumption which was expressed as a percentage of government consumption in total national consumption; (4) government expenditures which were expressed as a percentage of government expenditures in GDP. The two outputs were: (1) average happiness which represented worst/best possible life; (2) inequality in happiness which was expressed in terms of dispersion of happiness in nations under study.

Based on the above paper, Moesen and Cherchye (1998) presented a synthetic performance measure which merges the four previously mentioned separate dimensions (real growth, inflation, unemployment and the external account)[24], commonly used to summarise the economic performance of countries, into one single statistic. Using a DEA-inspired linear programming model that exhibits ‘benefit of the doubt weighting’, they investigated the performance of 20 OECD countries, half of which belongs to the EU, in two quinquennial periods, before (1987-1991) and after (1992-1996) the Maastricht Treaty. The results confirmed that the convergence criteria of this document have induced a relative performance deterioration in the EU-nations compared to the rest of the world, as was previously suggested in some studies.

Focusing on the construction of a CI for the knowledge-based economy, and in order to handle mixtures of exact and imprecise or missing data, Cherchye et al. (2011) evaluated 25 EU countries plus USA and Japan for the year 2004, discerning a ‘strong country in weak environment’ and ‘weak country in strong environment’ scenario resulting in respectively an upper and lower bound on countries’ performance. They amended the BoD method by extending it with a three-group classification system with countries subdivision upon resulting CI-intervals (i.e. benchmark countries, potential benchmark countries and countries open to improvement). From the dataset containing not less than 115 knowledge economy indicators, a subset of 23 (listed in Table 1) was selected[25], describing 97.4% of the variation in the overall set. Unsurprisingly, the results indicated that the USA and Japan outperformed EU countries, with the notable exception of Nordic countries. Southern European countries appeared to be at the bottom and to have considerable room for improvement in the knowledge-based economy-related policies.

The papers presented in Table 1 do not, of course, fully cover empirical literature on economic growth using data envelopment analysis. Some relevant articles may have been left out because they were out of reach of the authors, or they were analysing similar datasets as selected ones but were less frequent in the journals.

A common feature of the reviewed papers is their attempt to assess the overall macroeconomic performance of the countries under study. Aside from the works in which cross-country macroeconomic comparisons were made at this global level, DEA is often used for cross-national comparisons concerning macroeconomic performance but with an emphasis on a particular aspect that directly or indirectly contributes to this performance. Among the areas of socio-economic performance, that are most frequently the subject of cross-country empirical studies using DEA, are agriculture (Headey et al., 2010), healthcare (Cheng and Zervopoulos, 2014), education (Aristovnik, 2012), innovation (Guan and Zuo, 2014), etc., and most recently, eco-efficiency (Camarero et al., 2013)[26]. Despite the shift in

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[24] The single performance indicators were the average real GDP growth, the average change in the GDP deflator, the average unemployment rate, expressed as a percentage of the active population, and the average surplus (+) or deficit (-) on the current account as a percentage of GDP.

[25] All indicators were expressed in relative values (per capita or as a percentage of GDP or the like). As developed in relation to the Barcelona and Lisbon objectives, these indicators relate to seven thematic dimensions: (I) production and diffusion of ICT, (II) human resources, skills and creativity, (III) knowledge production and diffusion, (IV) innovation, entrepreneurship and creative production, (V) economic outputs, (VI) social performance, (VII) internationalisation.

[26] These particular papers were selected as quite recent and highly cited.

the focus of interest, the most important macroeconomic indicators were not excluded from consideration in any of these papers.

4. Conclusion

This paper brings a brief survey of the literature on the use of data envelopment analysis for evaluation of the macroeconomic performance of countries. It has revealed some valuable insights into the breadth of applications of this technique to cross-country comparisons.

The data shows that the number of evaluated countries ranges from 16 to 130. It is worth noting that the most analysed countries are OECD members, but also many other developed and developing countries receive some attention. Many of the indicators used in these studies overlap, coinciding with the most commonly used macroeconomic indicators such as GDP, capital and labour, which were however measured in different ways across studies. The number of indicators ranges between 3 and 23. The individual studies evaluate the macroeconomic performance of the countries over a period of one to fifty years, jointly covering the period 1950-2010.

Besides the basic DEA models, a lot of different variations and extensions have been developed to deal with a variety of applications. As can be seen, from the above description of the selected papers, a wide diversity of DEA approaches has been used for evaluation of macroeconomic efficiencies, such as Malmquist productivity index, window analysis, Long-Memory DEA, undesirable DEA model and benefit of the doubt. In some papers, these approaches were combined mutually or with one or more statistical methods. It should be noted that the papers are mainly based on time series analysis. Since productivity is considered a key source of economic growth, it is not surprising that many of the cited authors see economic growth through the prism of productivity, therefore investigating productivity changes over time.

We hope that these findings will assist researchers and practitioners in the field of economic growth and development in the appropriate choice of analytical method for their future studies, and in continuing to move the field forward.

Acknowledgments

This work has been fully supported by the Croatian Science Foundation as project no. 9481, “Modeling Economic Growth – Advanced Sequencing and Forecasting Algorithm.” Note: Any opinions, findings and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the Croatian Science Foundation.

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Appendix

Table no. 1: Summarized overview of empirical literature on economic growth using DEA

Author(s) and year	Sample	Period	Variables
Färe et al. (1994)	17 OECD countries	1979-1988	• Real capital • Labour • Real GDP
Lovell et al. (1995)	19 OECD countries	1970-1990	• Real GDP per capita • Inflation rate • Unemployment rate • Trade balance • Carbon emissions • Nitrogen emissions
Lovell and Pastor (1995)	16 Ibero-American countries	1980-1991	• Real GDP per capita • Inflation rate • Unemployment rate • Trade balance
Golany and Thore (1997)	72 developed and developing countries	1970-1985	• Ratio of real domestic investment to real GDP • Ratio of real government consumption expenditure, net of spending on defence and education, to real GDP • Ratio of government expenditure on education to nominal GDP • Growth rate of per capita GDP • Infant mortality rate ages 0-1 • Enrolment ratio for secondary education • Ratio of nominal social insurance and welfare payments to nominal GDP
Moesen and Cherchye (1998)	20 OECD Countries	1987-1996	• Real GDP growth • Change in the GDP deflator • Unemployment rate • Surplus or deficit on the current account

Author(s) and year	Sample	Period	Variables
Rao and Coelli (1998)	60 countries from all continents	1965-1990	• Labour per capita • Capital per capita • Real GDP per capita
Brockett et al. (1999)	17 OECD countries	1979-1988	• Capital • Employment • GDP
Krüger et al. (2000)	87 countries from all continents	1960-1990	• Labour • Capital • Real GDP
Forstner and Isaksson (2002)	57 industrialized and developing countries	1980-1990	• Labour • Capital • Real GDP
Deliktas and Balcilar (2005)	25 transition countries	1991-2000	• Labour • Capital • Real GDP
Escaith (2006)	LAC region countries	1991-2005	• Capital • Investment • Productivity • GDP
Ramanathan (2006)	18 MENA countries	1998-1999	• Age dependency ratio • Illiteracy rate • Mortality rate • Labour-population ratio • Life expectancy rate • Percentage of female teachers in primary education • GNP per capita
Kerekes (2007)	105 countries with population above 1 million	1950-2004	• Capital • Labour • Investment • Real GDP
Mohamad and Said (2011)	54 member countries of the OIC	2003-2007	• Total government consumption expenditure • GDP growth rate • Ratio of merchandise exported to merchandise imported • Inflation rate as indicated by the rate of change of the CPI • Total labour participation rate

Author(s) and year	Sample	Period	Variables
Cherchye et al. (2011)	27 countries (EU+USA+Japan)	2004	• ICT value added • SMEs ordering over the internet • Individuals using the Internet for banking • Pisa reading literacy of 15-year-olds • Total researchers • Participation in lifelong learning • Employed in creative occupations • BERD performed in service industries • EPO high-tech patent applications • Triadic patent families • Firm entries • GDP per capita • Early-stage venture capital • SMEs reporting non-technological change • GDP per capita in PPS • Real GDP growth rate • Total employment growth • Long-term unemployment rate • Hampered in daily activities because of chronic conditions • Rooms per person by tenure status and type of housing • Technology balance of payments • Co-authorship shares on international S&E articles • Foreign Ph.D. students
Škuflić et. al (2013)	28 European countries	2000 2004 2008	• Productivity • Share of exports in GDP • Share of gross wages in GDP • Share of personal consumption in GDP • GDP per capita

Author(s) and year	Sample	Period	Variables
Afonso and St. Aubyn (2013)	19 OECD countries	1970-2000	• Human capital per worker • Public physical capital per worker • Private physical capital per worker • GDP in PPS per worker • Governance effectiveness
Lábaj et al. (2014)	30 European countries	2010	• Capital in PPS • Labour • GDP in PPS • Greenhouse gases emissions • Gini index
Debnath and Shankar (2014)	130 rich and poor countries	2000-2009	• Technical quality of governments • Democratic quality of governments • Government consumption • Government expenditures • Average happiness • Inequality in happiness
Chiu et al. (2015)	35 Asian countries	2001-2005	• Population • Government investment • GDP • Fossil-fuel CO2 emissions