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Abstract

The paper assesses the efficiency of public expenditures in decreasing the unequal distribution of education in developing countries over the period 1980–2010. For this purpose, we use partial frontier estimator to compute output and input efficiency scores. Moreover, we analyze the determinants of education output efficiency by using Exponential Fractional Regression Models (EFRM).

The results show that on average, developing countries can reduce their education inequality by 30% without changing their public expenditures on education. Developing countries improved their output efficiency over the study period. However, their input efficiency has decreased relatively slightly since 2005. The results also show that logarithm of GDP and its square, urbanization, government stability and democracy are the main determinants of education output efficiency for both logit and Cloglog specifications.

Keywords

Public Spending, Efficiency, Education Inequality, Partial Frontier Method, EFRM

JEL Codes

H52, I20, C14, C25, C23

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1 INTRODUCTION

Education, one of the fundamental human and children rights is essential for sustainable development and for ending poverty. Economists have recognized the role played by education on economic growth and well-being. Thus, the human capital theory (Becker, 1985) has highlighted the importance of education in individual productivity. Following Becker, the endogenous growth theory (Romer, 1986, 1990; Lucas, 1988)[1] identified education as the engine of economic growth[2].

However, neoclassical and endogenous growth theories ignored any impact of the inequitable distribution of human capital on the growth process (Sauer and Zagler, 2014). Yet, inequitable distribution of education is harmful for growth and economic development. In fact, education inequality may affect negatively economic growth via the demographic mechanisms (greater inequality in the distribution of education is related to greater fertility, lower life expectancy, and lower rates of investment in human capital) or via credit market constraints (human capital inequality coupled with credit market constraints may also negatively influence investment and growth)[3]. Moreover, many empirical works (Castelló and Doménech, 2002; Castelló-Climent, 2010a, b; Checchi, 2000; Fan et al., 2001) have highlighted the negative impact of education inequality on economic performance and poverty.

Over the last decades, education has expanded dramatically in most developing countries. In some countries, this expansion has been at historically unprecedented rates (The World Bank, 2017). This period is also characterized by the decrease of education inequality (Castelló-Climent and Doménech, 2014). However, the level of education inequality remains high in many developing countries particularly in South Asia and Sub Saharan Africa[4].

To attain equitable distribution of education, governments can increase the level of public funding allocated to this sector or improve the efficiency of public expenditures. The increase in public expenditures, mostly funded through taxation, can create distortion in the allocation of resources and constraints economic growth. The improvement of public expenditures efficiency becomes crucial. According to Chan and Karim (2012), "Public

[1] See Sauer and Zagler (2014)

[2] Sauer and Zagler (2012)

[3] Galor and Zeira (1993)

[4] See Castelló-Climent and Doménech (2014, p.8)

spending efficiency is defined as the ability of the government to maximize its economic activities given a level of spending, or the ability of the government to minimize its spending given a level of economic activity". In other words, efficiency of a producer (non-profit or profit organizations) consists in doing a comparison between observed and optimal value of its outputs and inputs. Inputs refer to the monetary and non-monetary resources employed to produce outputs (Mandl et al., 2008). Outputs are those results that are achieved immediately after implementing an activity[5] (products); they are goods or services produced by the government. Outcomes, which can be considered as mid-term results, are the difference made by the outputs (Moreno-Enguix and Lorente Bayona, 2017). In other words, they are the final objectives to achieve and often linked to welfare or growth objectives (Mandl et al., 2008). In the case of public sector, outcomes are the goals that the government wants to achieve with the outputs.

Economic efficiency has technical and allocative components. Technical efficiency is defined as the capacity and willingness of an economic unit to produce the maximum possible output from a given bundle of inputs and a technology[6] (or uses minimal inputs to produce a given level of output). It refers to the ability to avoid waste (Fried et al., 2008). Allocative efficiency is defined as the ability and willingness of an economic unit to equate its specific marginal value product with its marginal cost (Kalirajan and Shand, 1999). In other words, the allocative efficiency measures a Decision Making Unit's (DMU) success in choosing an optimal set of inputs with a given set of input prices[7]. According to Mandl et al. (2008), allocative efficiency reflects the link between the optimal combination of inputs, taking into account costs and benefits, and the output achieved. It is the ability to combine inputs and/or outputs in optimal productions in light of prevailing prices[8]. Optimal proportions satisfy the first–order conditions for the optimization problem assigned to the production unit. The measurement of allocative efficiency requires information on inputs prices and that is controversial.

Output-oriented efficiency expresses the efficiency of a DMU for a given level of inputs while on the other hand input-oriented efficiency represents the efficiency of a DMU for a given level of output. Thus, countries with low input-oriented efficiency could reduce their

[5] Moreno-Enguix and Lorente Bayona (2017)

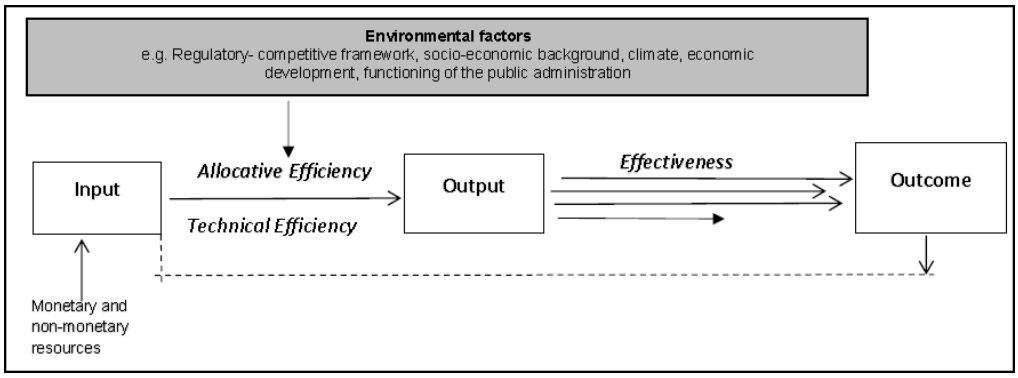
[6] Kalirajan and Shand (1999, p.149)

[7] See Daraio and Simar (2007)

[8] Fried et al. (2008, p.20)

expenditures without lowering their performance while countries with low output-oriented efficiency might increase their performance without increasing their expenditures (Christl et al., 2018).

Figure 1: Conceptual framework of efficiency and effectiveness



Source : Mandl et al. (2008, p.3)

Many reasons justify the interest of economic studies and international organizations (e.g., International Monetary Fund and The World Bank) in public expenditures efficiency. First, it facilitates comparison across similar economic units, i.e., it indicates relative efficiency. Second, where measurement reveals variations in efficiency among economic units, further analysis can be undertaken to identify the factors causing such variations. Third, such analyses bear policy implications for the improvement of efficiency (Kalirajan and Shand, 1999). In fact, studies that measure public expenditures efficiency, contribute to highlight best practices and to draw implication on public sector reforms. In a context of macroeconomic constraints (which limit countries' scope for expenditure increases) and fiscal discipline, public expenditures efficiency could be used as an indicator to evaluate the effectiveness of public policy. Finally, improving public expenditures efficiency can improve accountability.

Many empirical studies were interested in the measurement of efficiency of public expenditures in education (Gupta and Verhoeven, 2001; Christiaensen et al., 2002; Afonso and Aubyn, 2006; Afonso et al., 2005, 2010b; Herrera and Pang, 2005; Fonchamnyo and Sama, 2016; Gavurova et al., 2017). These studies offer several techniques to measure efficiency (specifically technical efficiency) which can be classified into parametric and nonparametric. Although some of these studies were focused on the determinants of efficiency, they have given limited attention to education distribution. Thus, this paper assesses empirically the technical efficiency

of public expenditures in improving the distribution of education in developing countries. In fact, technical efficiency permits to identify opportunities for improvements in the way resources are converted into outputs, and to identify inefficiencies in the mix of production factors. To assess the efficiency scores, we use a nonparametric partial frontier estimator which is more robust than the previous estimators (e.g., Data Envelopment Analysis and Free Disposal Hull). We also analyze the determinants of the output–oriented efficiency scores using fractional regression models (FRM) which is the most natural way of modelling bounded proportional response variables.

The paper is structured as follow. Section2 reviews the literature in the efficiency of education public expenditures. Section3 presents the methods used for measuring efficiency and the originality of our estimator. Section4 discusses the data and results. The last section concludes.

2 Literature Review

The theme of efficiency has been analysed since Adam Smith's pin factory (Daraio and Simar, 2007). However, the first rigorous analytical approach to the measurement of efficiency in production originated with the work of Koopmans (1951) and Debreu (1951) and empirically applied by Farrell (1957). An important contribution to the development of efficiency and productivity analysis has been done by Shephard's models of technology and the concept of distance functions (Shephard, 1970, 1953, 1974)[9].

There is an abundant literature on the efficiency of education public expenditures. These studies, mostly quantitative, are relying on parametric and nonparametric approach. Thus, Clements (2002) assessed the efficiency public expenditures on education in European Union. He applied Free Disposal Hull (FDH) method by comparing countries of European Union to the "best practices" observed in the OECD[10]. His study used expenditure per student (in purchasing parity-adjusted dollar) and teacher to student ratio as input variables and international standardized test (TIMSS, Trend in International Mathematics and Science Study) as output variable. He found that 25 percent of education spending is wasteful in European Union relative to the "best

[9] Daraio and Simar (2007, p.16)

[10] Organisation for Economic Co-operation and Development

practices". This result showed that educational performance could be improved without necessarily increasing educational public spending. Eugéne (2007) by using the same method assessed the efficiency of the Belgian general government in health care, education, public order and safety and general public services. He concluded that Belgian education system is more expensive but lead to better results than the European average.

FDH was also used by Gupta and Verhoeven (2001) to assess the efficiency of government expenditure on education (measured by per capita education spending in purchasing power parity (PPP)) and health[11] in 37 African countries, both in relation to each other and in comparison with countries in Asia and the Western Hemisphere. This study covered the period 1984–1995. The authors showed that on average, governments in African countries are less efficient in the provision of education (primary school enrolment, secondary school enrolment, and adult illiteracy) and health (life expectancy, infant mortality, and immunizations against measles and DPT[12]) services than countries in Asia and the Western Hemisphere. But education and health spending in Africa have become more efficient during this period. The results also suggest that improvements in educational attainment and health output in African countries require more than higher budgetary allocations.

Some authors adopted the Data Envelopment Analysis (DEA) method to assess public expenditure on education. Thus, Kirjavainen and Loikkanen (1998) used the nonparametric DEA method to study the efficiency among 291 Finnish senior secondary schools. They also explained the degree of inefficiency (100 - efficiency score) by a statistical Tobit model. Their results showed that private schools were inefficient relative to public schools. They also highlighted that school size does not affect efficiency. Following the same methodology, Afonso and Aubyn (2006) addressed the efficiency of public expenditure on the provision of education services by comparing the output (PISA[13] Indicators) from the educational system of 25 mostly OECD countries with resources employed (teachers per student, time spent at school) during the period 2000-2002. They estimated a semi-parametric model of the education production process using a two-stage procedure. By regressing DEA output scores on nondiscretionary variables, using both Tobit and a single and double bootstrap procedure, they showed that inefficiency was strongly related to

[11] Measured by per capita health spending in PPP

[12] Diphtheria–Pertussis–Tetanus

[13] Program for International Student Assessment

GDP per capita and adult educational attainment. Gavurova et al. (2017) by using DEA compared the relative efficiency of government expenditures on secondary education in selected European countries in 2015. They found that average efficiency (output-oriented) was 0.955 and highlighted a relative high efficiency in evaluated countries.

DEA was also employed by Yogo (2015) for public spending assessment (precisely input oriented technical efficiency) of 77 developing countries in health, education and infrastructure over the period 1996–2012. He also examined the effect of ethnic diversity (fractionalization and polarization measures) on the efficiency of public spending by using a censored Tobit regression model. Two main findings have been drawn. First, barely 12% of the sample of countries under study makes an efficient use of public expenditures. Second, no matters the level of aggregation, ethnic polarization is positively associated with higher efficiency. Fonchamnyo and Sama (2016), in an article analysing the efficiency of public spending in the education and health sectors in three selected Central Africa countries (Cameroon, Central African Republic and Chad) applied DEA approach to compute efficiency scores. They used in a second stage panel data Tobit and fractional logit regression to determine the effect of institutional and economic factors on public expenditures efficiency on education and health sectors. They showed that Cameroon is the most efficient country. Their results also indicate that budgetary and financial management impacts positively and significantly efficiency scores while corruption has a negative and significant effect.

Yotova and Stefanova (2017), in a study on efficiency of tertiary education expenditure used the DEA method. Their study covered nine European Union member States from Central and Eastern Europe (Bulgaria, the Czech Republic, Estonia, Latvia, Lithuania, Hungary, Poland, Romania, and Slovenia). They employed tertiary educational attainment (age group 25-34 years), employment rate of population with tertiary education (age group 25-29 years) and population with tertiary education not at risk of poverty and social exclusion (age group 25-49) as output indicators and total expenditure on tertiary education[14] as input indicator. The authors concluded that Latvia is the most efficient country in comparative perspective in the area of the tertiary education expenditure and achieved direct and indirect output results.

[14] Total expenditure on tertiary education is calculated as the sum of public expenditure and private expenditure ofhouseholds

Some research used both FDH and DEA methods to compute efficiency scores. For instance, Afonso and Aubyn (2004) address the efficiency in education and health sectors for a sample of OECD countries by applying nonparametric FDH and DEA methods. They used the performance of 15-year-olds in the PISA (reading, mathematics and science literacy scales) in 2000 as output indicator. As for inputs measures, they used the annual expenditures on secondary education per student in 1999. The results suggest that the average input efficiency in education sector varies between 0.520 and 0.610, depending on method used[15]. They used the same methodology to assess efficiency in health and education in an article published in 2005. In the educational case, they employed physical input indicators (the total intended instruction time in public institutions in hours per year for the 12 to 14 years old and the number of teachers per student in public and private institutions for secondary education). As an output, they used PISA indicators. The results showed that the average input efficiency vary between 0.859 and 0.886, depending on method used.

Herrera and Pang (2005) estimated the efficiency frontiers for nine education output indicators (gross and net primary school enrolment, gross and net secondary school enrolment, literacy of youth, average years of school, first level complete, second level complete, and learning scores) and four health output indicators (life expectancy at birth, immunization against DPT and measles, disability-adjusted life expectancy) based on a sample of 140 countries from 1996 to 2002. In the case of education, they used public spending per capita on education (in constant 1995 US PPP dollars) and non-monetary factors of production such as the ratio of teachers to students. They also applied nonparametric FDH and DEA methods to compute efficiency scores and sought to identify empirical regularities that explain cross-country variation in the efficiency scores by using a Tobit panel approach. Their results showed that higher expenditure levels, larger wage bill, income inequality, HIV/AIDS and aid are negatively associated with efficiency scores. In contrast, urbanization is positively associate to efficiency score.

Moreno-Enguix and Lorente Bayona (2017) designed Public Expenditures Efficiency Indexes (PEEI), both for total expenditure and sectoral expenditures (including education), by using single synthetic indicators. These indexes were developed for 35 developed countries in 2012. The Public Expenditures Efficiency Index by sector is computed mathematically as the ratio between the sectoral public

[15] The output average efficiency varies between 0.942 (FDH) and 0.966 (DEA)

performance and government expenditure in the sector considered (in percentage of GDP). Performance on Education is a synthetic index of primary (average of two normalized scores[16]) and higher (average of two normalized scores) education. Their results showed that corruption and democracy do not influence efficiency in education. Their study follows Afonso et al. (2005) who used the same methodology to compute Public Sector Performance and Public Sector Efficiency (PSE) indicators comprising a composite and seven sub-indicators (administrative, education[17], health, public infrastructure, distribution, stability and economic performance), for 23 industrialized countries.

Parametric method was also used for evaluating efficiency public spending on education. Jayasuriya and Wodon (2003) assessed efficiency in education and health spending using stochastic frontier estimator on a sample of 76 countries from 1990 to 1998. Per capita GDP, per capita expenditures on education and adult literacy rate employed as input variables. As for education output variable, they used net primary enrolment rate. The production frontiers can vary by region. In a second stage the authors explained efficiency by bureaucracy quality, corruption and urbanization. The results suggest large differences among countries (and among regions) in efficiency, and a substantial correlation in the efficiency measures obtained for the two indicators (education and health). An analysis of the determinants of the efficiency measures suggests that bureaucratic quality and urbanization both have strong positive impacts on efficiency while the impact of corruption is not statistically significant.

Grigoli (2014) used a hybrid approach to examine public expenditure efficiency in secondary education for emerging and developing economies. This method was designed by Wagstaff and Wang (2011). This method allows to take advantage of the strengths of DEA and SFA while avoiding their weaknesses. Grigoli's results suggests that education expenditure is inefficient in many emerging and developing economies, especially in Africa. He also finds that reallocating expenditure to hire more teachers could improve the efficiency of public education spending where student-to-teacher ratios are high.

In short, the literature on the efficiency of public expenditure on education is based on a variety of methods to compute efficiency scores and to analyse their determinants.

[16] Primary education enrolment rate and Quality of primary education

[17] This index contains secondary school enrolment and educational attainment indicators

3 Methods for Measuring Efficiency

There are two types of public spending efficiency measurement. Macro measurements which aim to evaluate the efficiency of total public spending. They attempt to measure, or rather to get some ideas of the benefits from higher public spending. Micro measurements aim at measuring the efficiency of a particular category of public spending. They attempt to determine the relationship between spending and benefits in a particular budgetary function or even sub-function (i.e., health spending or the efficiency of spending in hospitals, or spending for protection against malaria, aids, etc.)[18].

Numerous techniques have been developed to compute efficiency scores. These methods are based on the concept of efficiency frontier (productivity possibility frontier). In other words, the method consists in estimating a production, cost or profit function. Efficiency scores of Decision-Making Units (DMUs) are measured by their distance to an estimated production function (the frontier). A production function is a mathematical representation of the technology that transforms inputs into outputs. The two most widely used methods are parametric (stochastic or deterministic) or non-parametric (essentially deterministic).

3.1 The parametric methods

The parametric approach assumes a specific functional form for the relationship between the inputs and the outputs as well as for the inefficiency term incorporated in the deviation of the observed values from the frontier (Herrera and Pang, 2005). It assumes that a function giving maximum possible output as a function of certain inputs (or minimum cost of producing that output given the prices of the inputs). This approach can be either deterministic or stochastic.

A very common parametric method is the Stochastic Frontier Analysis (SFA) approaches. There are two main estimation strategies here. The first strategy is based on an error components model which assumes that the error term has two components, one for random errors (assumed to follow a normal distribution) and one non-negative represents the technical inefficiency (Aigner et al., 1977; Meeusen and van Den Broeck, 1977). Initially applied to cross-section data, the SFA was

[18] See Afonso et al. (2010b)

extended to panel data with Battese and Coelli (1992, 1995); Kumbhakar and Wang (2005); Kumbhakar et al. (2014) etc. The second strategy is the fixed effect approach used by Evans et al. (2000). In this method, frontier intercept[19] is represented by a constant and the non-negative component of the error term are the country-specific inefficiencies. The country with the highest intercept is considered as best performer and taken as the reference country (the frontier) and the distance from this maximum, gives a measure of technical efficiency (Evans et al., 2000; Jayasuriya and Wodon, 2003).

SFA offers the possibility to find out whether the deviation of a DMU's actual output from its potential output is mainly because it did not use the best practice techniques or is due to external random factor (Kalirajan and Shand, 1999). It permits to test statistically various hypotheses concerning technology's modelling and characteristics of DMU–specific efficiency measures[20]. SFA offers flexibility in modeling various specific aspects of production such as production and marketing risk. SFA facilitates decomposition of economic efficiency into technical and allocative efficiency. SFA also takes care of potential bias introduced by extreme observations (Christiaensen et al., 2002). However, it imposes a parametric structure on the production function and on the distribution of efficiency which potentially introduces other bias.

Other methods were used to estimate a frontier via resolving a linear or quadratic programming (Aigner and Chu, 1968), corrected ordinary least squares (Richmond, 1974) or maximum likelihood (Afriat, 1972). These methods are named the parametric deterministic approach or "full frontier models". This approach assumes that inefficiency is explained by all deviations from the frontier[21] (Herrera and Pang, 2005; Fried et al., 2008). Since this method is deterministic, the results are sensitive to outliers. The main drawback of parametric method is the possibility of imposing an inappropriate structure on the technology. (Hollingsworth et al., 1999).

[19] Constant – non negative component of the error term

[20] Kalirajan and Shand (1999, p.168)

[21] The distance of a DMU from the frontier

3.2 Nonparametric methods

The nonparametric approach calculates the frontier directly from the data without imposing specific functional restrictions on the production technology. This approach was pioneered by Farrell (1957). This method is generally dominated by deterministic approach and use an outer envelope that encompasses all observations is constructed. In other words, under the nonparametric approach, a best practice frontier is constructed from the observed inputs and outputs as a piecewise linear technology (Grosskopf, 1986). In this approach the restrictions placed on the technology vary widely but can be less restrictive than those used to date in the parametric approach.

Free Disposal Hull

One common nonparametric method to establish the production frontier is the Free Disposal Hull (FDH) approach. It is defined as a piecewise linear reference technology, constructed on the basis of observed input-output combinations that satisfies the following axioms: The first states that a semi-positive output cannot be obtained from a null input vector — thus excluding free production — and that any non-negative input results at least in a zero output. The second implies that finite inputs cannot produce infinite outputs. The third (known as strong free disposability or positive monotonicity assumption) guarantees that an increase in inputs cannot result in a decrease in outputs. The fourth axiom is postulated for mathematical convenience which cannot be contradicted by any empirical observation. The last axiom implies that any reduction in outputs remains producible with the same amount of inputs. This assumption allows for variable returns to scale (De Borger et al., 1994). In this method, technical efficiency is measured as the distance between an observed production unit and the postulated production frontier (the isoquant). This method was first proposed by Deprins et al. (1984), FDH requires minimal assumptions with respect to the production technology (e.g., absence of convexity). It allows for a direct measurement of the relative efficiency of government spending among countries (Gupta and Verhoeven, 2001). From a managerial viewpoint, the major advantage of the FDH is that the resulting efficiency measures are related to an observed production unit[22]. But its main drawback is due to the partial ordering based on the vector dominance reasoning. This implies that the

[22] De Borger et al. (1994, p.657)

approach may be sensitive both to the number and distribution of the observations in the data set, and to the number of input and output dimensions considered (De Borger et al., 1994). FDH does not permit to make a distinction between random factors that may affect production (for example, rainfall in agricultural production) and actual inefficiency (Christiaensen et al., 2002). Finally, the method is not robust to outliers or extreme data points.

Data Envelopment Analysis

Data Envelopment Analysis (DEA) is another common nonparametric deterministic approach to estimating production frontiers. In this approach, linear programming methods are used to construct a linear envelope to bind the data (construct the frontier) relative to which efficiency measures can be calculated. In contrast to FDH, DEA assumes convexity of the production possibility set implying that linear combinations of best-observed production results lie on or below the production possibility frontier (Christiaensen et al., 2002; Herrera and Pang, 2005). According to Aragon et al. (2005), the convexity assumption is widely used in economics but is not always valid. DEA also assumes the free disposability of the production frontier. This technique, originating from Farrell's (1957) seminal work and popularized by Charnes et al. (1978) was initially born in operations research for measuring and comparing the relative efficiency of a set of DMUs[23]. DEA permits to analyse each DMU separately and to measure relative efficiency with respect to the entire set being evaluated. It also solves problems using standard techniques of linear programming (Seiford, 1996). However, DEA is sensitive to extreme values and outliers (an atypical observation or a data point outlying the cloud of data points).

Partial frontiers Methods

An alternative nonparametric estimator of the "efficiency frontier" which is more robust to extreme values, noise or outliers than the standard DEA and FDH was proposed by the literature (Cazals et al., 2002; Aragon et al., 2005; Daraio and Simar, 2005; Daouia and Ruiz-Gazen, 2006; Daouia and Simar, 2007; Daouia and Gijbels, 2011; Tauchmann, 2012; Christl et al., 2018). The underlying idea of this method is to estimate a partial frontier well inside the cloud of data points but near the upper frontier[24] (Daouia and Gijbels, 2011). Two alternatives have been used to

[23] Murillo-Zamorano (2004)

[24] In contrast to envelopment methods (DEA and FDH) which envelop all the data

estimate partial frontier:

The order-m estimator (or conditional order-m estimator) introduced by Cazals et al. (2002) is based on the concept of expected minimum production function (or expected maximum production function). This estimator generalizes FDH by adding a layer of randomness to the computation of efficiency scores. Rather than benchmarking a DMU by the best performing peer in the sample at hand, order-m is based on the idea of benchmarking the DMU by expected best performance in a sample of m peers[25]. In other words, the method consists to estimate a frontier of a discrete order–m ∈ N* [26](instead of estimating the full frontier), which increases with respect to m to achieve the efficient frontier ϕ when m ~ ∞[27]. This estimator shares the same asymptotic properties as the FDH estimator but is less sensitive to outliers and/or extreme values (Daouia and Simar, 2007; Daouia and Ruiz-Gazen, 2006).

The quantile-frontier of order–α (or order-α estimator) suggested by Aragon et al. (2005) is also a generalization of FDH. The idea is to replace the concept of "discrete" order–m partial frontier by a "continuous" order-α partial frontier where α ∈]0, 1] corresponds to the level of an appropriate nonstandard conditional quantile frontier (Daouia and Simar, 2007). From an economic point of view, α gives the production threshold exceeded by 100(1 − α)% all production units using less than x as inputs. The order-α estimator is fast to compute, easy to interpret and can be useful in terms of practical efficiency analysis. It does not envelop all the observed data points and has at least the same statistical properties as the order-m estimator. Moreover, according to Daouia and Ruiz-Gazen (2006) and Aragon et al. (2005) order-α has better robust property than order-m. Note that there exists a relationship between α and m[28] such that

$$\alpha(m) = 1\frac{1}{2}^{\frac{1}{m}} \qquad (1)$$

Partial frontiers and related measures of efficiency show some interesting statistical properties together with several "appealing" economic features that deserve some comments (Daraio and Simar, 2007).

First, partial frontier estimators do not envelop all the data points. Consequently, these robust measures of frontiers and the related efficiency scores

[25] Tauchmann (2012, p.463)

[26] A set of all integers $m \geq 1$

[27] Daouia and Ruiz-Gazen (2006, p.1234–1235)

[28] Daouia and Gijbels (2011, p.149)

are less influenced and hence more robust to extreme values and outliers. This property permits to avoid one of the more important limitation of the traditional nonparametric estimators related to their deterministic nature[29].

Second, because of their statistical properties these robust estimators do not suffer of the curse of dimensionality shared by most nonparametric estimators and by the DEA/FDH efficiency estimators (Daraio and Simar, 2007). This property is very important for empirical works since it allows to work with samples of moderate size and do not require large samples to avoid imprecise estimation (e.g., large confidence intervals)[30].

Third, and even more important is the economic interpretation of order–m measures of efficiency, and the appealing notion of order-α, in particular α measures of efficiency. Indeed, the parameter m has a dual nature. It is defined as a "trimming" parameter for the robust nonparametric estimation. It also defines the level of benchmark one wants to carry out over the population of firms. Based on this nature, Daraio and Simar (2007) have proposed to use m in its dual meaning to provide both robust estimations and a potential competitors analysis.

Given that partial frontiers methods do not impose specific functional restrictions on the production technology, are robust estimators and do not suffer from the curse of dimensionality (compared to FDH and DEA estimators), we will use partial frontier methods specially the order–m estimator to estimate our production boundary.

Note that a hybrid method to measuring efficiency was proposed by Wagstaff and Wang (2011) which blends both DEA and SFA approach. This approach allows to deal with heterogeneity across groups, as different frontiers are constructed for different groups of countries. It also uses a LOWESS method, which helps dealing with the measurement error, data outliers, and stochastic nature of the problem at hand.

4 Data and Results Analysis

4.1 Data

We use a panel dataset of 67 developing countries[31] from 1980 to 2010. Two groups

[29] DaraioandSimar(2007,p.78)

[30] DaraioandSimar(2007,p.78)

[31] Low and middle income countries according to The World Bank

of variables are considered: those used in estimating the production frontier for education distribution and those used in the analysis for the determinants of efficiency.

4.1.1 Production frontier

The first group of variables includes one output (education Gini index by age and gender for persons over 15) and one input variable (Per capita education spending by the government in purchasing power parity (PPP)). The education Gini index is from Crespo-Cuaresma et al. (2012, 2013) dataset. This indicator measures inequality in educational attainment by age and gender at the global level and captures access to education. In this paper, we use the index for both men and women. This quinquennial index covers 175 countries from 1960 to 2010. It used IISA/VID (International Institute for Applied Systems Analysis/Vienna Institute of Demography) global database of populations by age, sex, and levels of education. This IISA/VID dataset was developed by applying the demographic methodology of multi- state population projection (see Lutz and Samir (2011); Samir et al. (2010); Lutz and Goujon (2001)). Crespo-Cuaresma et al. (2012, 2013) computed the Gini index of education by applying the following formula:

$$GiniEC_{\alpha,s} = \frac{1}{\ddot{y}_{\alpha,s}} \sum_{i=2}^{4} \sum_{j=1}^{i-1} |y_{\alpha,s,i} - y_{\alpha,s,j}| p_{\alpha,s,i} p_{\alpha,s,j} \qquad (2)$$

Where $y_{\alpha,s,i}$ is the cumulative duration of schooling for the level of education i in the age group α with sex s and $p_{\alpha,s,i}$ is the corresponding share of the population with that level of education. $\ddot{y}_{\alpha,s}$ denotes the mean value of years of schooling, given by

$$\ddot{y}_{\alpha,s} = \sum_{i=1}^{n} p_{\alpha,s,i} y_{\alpha,s,i}$$

Four educational attainment levels have been considered by Crespo-Cuaresma et al.: no formal education (i = 1), primary education (i = 2), secondary education (i = 3) and tertiary education (i = 4). The education Gini coefficient is between 0 to 1. A value of 0 indicates a perfectly equally distributed education structure (this case corresponds to a situation in which the whole population attains the same education level). A value of 1 indicates a perfect unequal distribution (in this case, one person

completes for example tertiary education, while the rest of the population does not attain any formal schooling)[32].

As Afonso et al. (2010a), we compute the output variable ($GiniEC^{T}_{\alpha,s}$) by transforming the education Gini index as follow:

$$GiniEC^{T}_{\alpha,s} = 1 - GiniEC_{\alpha,s}$$

This transformation is used to insert increasing outputs as the desired objective, given that higher Gini coefficients imply a greater inequality.

We used Per capita education public expenditures in purchasing power parity (PPP) as our input measure. This indicator is computed as the product of the shares of public expenditure on education in percentage of GDP[33] and real GDP per capita at chained PPPs in US Dollars[34]. We computed GDP per capita by dividing GDP by population from PWT database. In fact, expenditure-side real GDP allows comparison of relative living standards across countries and across years (Feenstra et al., 2015). Then, using per capita PPP education public expenditures permits a more accurate cross-country comparison of the domestic shadow costs of the resource allocation for education than conventional US dollar measures and GDP ratios (Gupta and Verhoeven, 2001).

Private expenditures, including activities of Non Governmental Organizations (NGOs), may also be taken into account. But these data are not available. Physical inputs such as the numbers of teachers, pupil-teacher ratio, average class size, number of instruction hours and the use and availability of computers can also be considered to estimate the production frontier[35]. However, these indicators are either unavailable or contain missing data for many developing countries.

4.1.2 Non-discretionary factors

The second group of variables are used to analysis the determinants of education output efficiency score. These variables determine the heterogeneity across countries and influence performance and efficiency. These variables are

[32] Sauer (2016)

[33] From International Monetary Fund (IMF) database (World Economic Outlook and Government Financial Statistics)

[34] From Penn World Table 9.1 (PWT 9.1) dataset

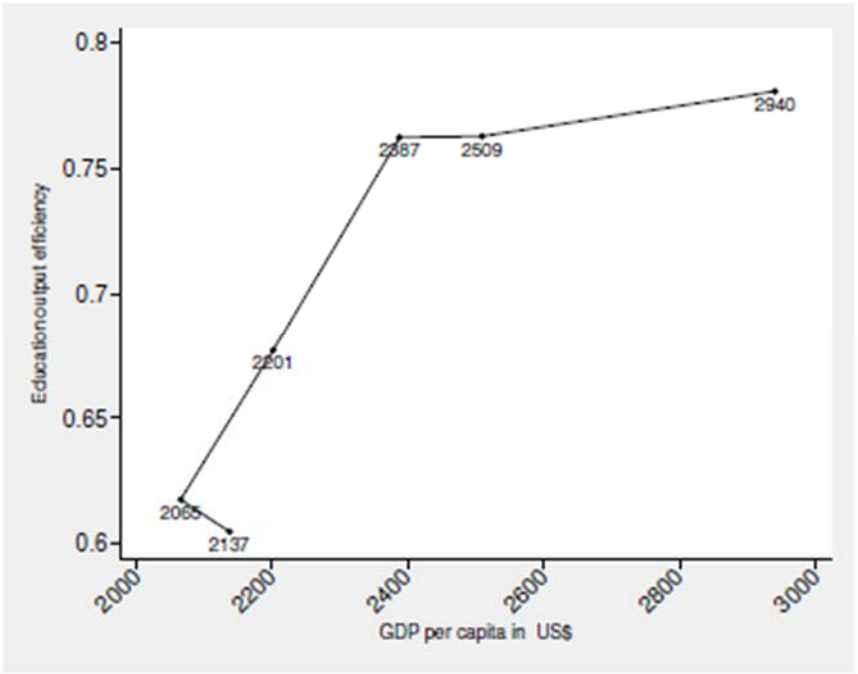
[35] See Afonso and Aubyn (2006); ?

called “environmental” or nondiscretionary or “exogenous” inputs. They include: *The logarithm of real GDP per capita, the square of the logarithm of real GDP per capita, Urbanization, Trade openness, Foreign Direct Investment, Financial Development, Net Official development assistance, Corruption, Government stability and Democracy*.

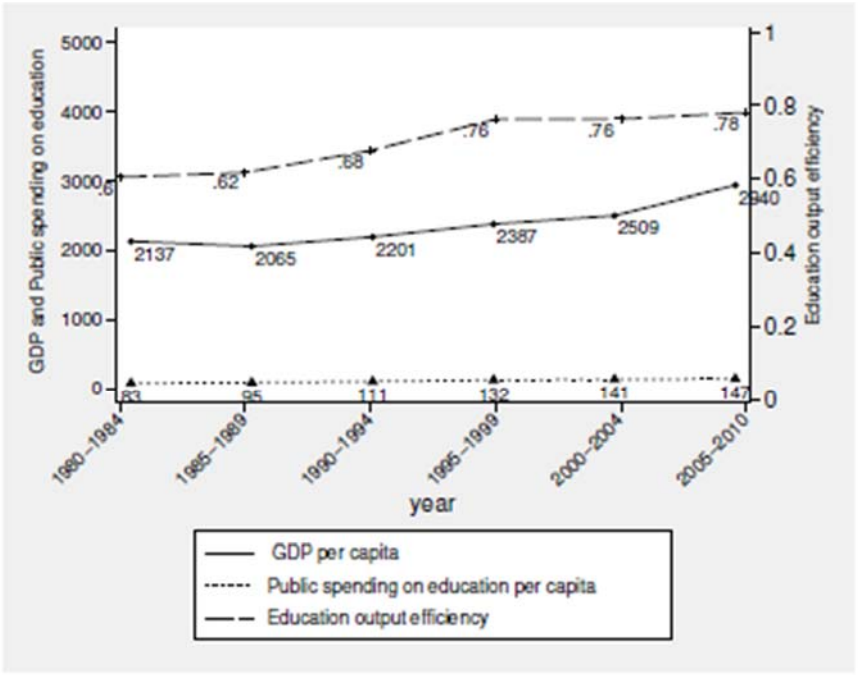
The logarithm of real GDP per capita: This variable aims to proxy the physical capital stock which facilitates an efficient production of public goods and services, but which may also facilitate monitoring of policy makers (Afonso et al., 2010b). A higher level of public expenditures efficiency is associated with a higher level of GDP per capita. We also use the square of the logarithm of real GDP per capita (logGDPSq). In fact, the relationship between the education output efficiency score and GDP per capita is not linear as shown by figure 1a. We can hypothesize that a drop of GDP per capita was followed by an increasing of education efficiency score during the 1980s (see figure 1b). This may be due to the economic policy reforms adopted by the governments and following the Washington Consensus. In fact, these reforms include fiscal discipline and the reordering public expenditures priorities. Since 1990, we notice that improvement of education output efficiency is followed by the rise of GDP per capita.

Figure 2: Relationship between GDP per capita and education's output efficiency

(a) Education's output efficiency and GDP per capita



(b) Education output efficiency, GDP per capita and public spending on education



Source: Authors

Urbanization refers to urban population in percentage of total population. The clustering of public servants makes cheaper to provide services in urban areas. So higher degree of urbanization should result in higher efficiency (Herrera and Ouedraogo, 2018).

Trade openness (sum of exports and imports as a share of GDP): This indicator proxies the degree of international competition over labour and capital (Afonso et al., 2010b). It also measures the level of integration in the world economy. According to Hauner and Kyobe (2010), trade openness could increase public spending efficiency by increasing competitive pressure on the domestic economy, including the government, as well as increasing exposure to the outside world[36]. We expect that higher international trade compels the government to become more market oriented and hence increases government efficiency (Rayp and Van De Sijpe, 2007).

Foreign Direct Investment (FDI), net inflows (% of GDP): According to Rayp and Van De Sijpe (2007), the sign of the inflow of FDI is a priori ambiguous. In fact, as a proxy of integration in the world economy, higher of FDI inflows may forces the government to be behave in a more free market compatible way and to comply with higher performance standards that multinational corporations expect. However according to Todaro and Smith (2003), FDI in developing countries may also be linked to rent extraction and rent sharing between the political elite and foreign corporations, leading to favouritism, corruption… and, ultimately, less efficiency[37].

Financial Development Index (FD): This overall index of financial development is an aggregation of financial institutions (banks, insurance companies, mutual funds, and pension funds) and financial markets (stock and bond markets) sub-indices. This index is defined as a combination of depth (size and liquidity of markets), access (ability of individuals and companies to access financial services) and efficiency (ability of institutions to provide financial services at low cost and with sustainable revenues, and the level of activity of capital markets)[38]. This index is available with annual frequency from 1980 onwards. [39] A better developed financial system could prevent the manipulation of financial system, thus putting more pressure on the government to control its budget by working in an efficient manner.

[36] Rayp and Van De Sijpe (2007, p.370)

[37] Rayp and Van De Sijpe (2007, p.370)

[38] Čihák et al. (2012, 2013); Svirydzenka (2016)

[39] It is available for 180 countries but not available for Zimbabwe

Furthermore, a better–developed financial systems could make it easier to domestically finance deficits (Rayp and Van De Sijpe, 2007).

Net Official development assistance (ODA) received in percentage of Gross National Income (GNI). This variable represents disbursement flows (net of repayment of principal) that meet the Development Assistance Committee (DAC) definition of ODA. To the extent that countries do not have to incur the burden of taxation, they may not have the incentive to use resources in the most cost-effective way. Another channel through which aid financing may affect efficiency is the volatility and unpredictability of its flows. Given that this financing source is more volatile than other types of resources (Bulíř and Hamann, 2003), it is difficult to undertake medium-term planning (Herrera and Pang, 2005). In this case, we expect a negative association between aid and public expenditures efficiency.

Corruption: This variable assess corruption within the political system (Howell, 2012). A higher values of corruption index indicates a decreased prevalence of corruption. Corruption distorts the economic and financial environment, reduces the efficiency of government and business by enabling people to assume positions of power through patronage rather than ability and introduces inherent instability in the political system (Jayasuriya and Wodon, 2003). Moreover, corruption breeds waste of public funds. Higher values of corruption index indicate a decreased prevalence of corruption. In other words, low level of corruption rises public spending efficiency.

Government stability: This variable assesses both the government's ability to carry out its declared program(s), and its ability to stay in office. The risk rating assigned is the sum of three subcomponents (Government Unity, Legislative Strength and Popular Support). Each subcomponent has a maximum score of four points and a minimum score of 0 points. A score of 4 points equates to "Very Low Risk" and a score of 0 points to "Very High Risk" (How- ell, 2012). The ICRG Government stability index is between 1 (the lowest level of government strength) to 12 (the higher level of government strength). Political instability can complicate consistent budgetary planning and undermine efficiency (Hauner and Kyobe, 2010). Since ICRG provides ratings for 140 countries, Corruption and Government stability are not avail- able for some countries (Benin, Burundi, Chad, Lesotho, Mauritania, Mauritius, Nepal and Rwanda).

Democracy measured by the polity2 indicator. This index is a combination of democracy and autocracy indicators of polity IV. Additionally, to autocracy and

democracy, polity2 includes interruption[40], interregnum[41] and transition[42] periods. The polity2 score ranges from-10 (highly autocratic), to 10 (highly democratic) and is available since 1800. To make the interpretation easier, we normalized the polity2 score from 0 (highly autocratic) to 1 (highly democratic) by using a Min-Max formula. Indeed, voting is the fundamental link between citizens and politicians. A high turnout may reduce inefficiencies in public service provision through more efficient monitoring of politicians. In other words, a high turnout may give politicians incentives to implement policies that improve efficiency Borge et al. (2008).

The input and environmental variables have been averaged over 5 years periods (respectively 1980-1984, 1985-1989, 1990-1994, 1995-1999, 2000-2004 2005-2010) because the output data are quinquennial. Notice that for the second stage regression, we then use an education output efficiency score strictly lower than 1 (because the econometric estimator used does not accommodate the value 1). We then used an unbalanced dataset of 55 developing countries over the period 1980-2010. Summary statistics and sources for all variables are presented in table1.

Table 1: Summary Statistics of key variables

Variable	Definition	mean	sd	min	max	N	Sources
First stage regression							
Output							
GiniEC15	Gini index of education 15 year and over	0.48	0.22	0.13	0.95	402	Crespo-Cuaresma et al.(2012,2013)dataset
GiniEC15T	Transformed education Gini index	0.52	0.22	0.053	0.87	402	Authors computing
Input							
rgdpe_pop	Real GDP per capita at chained PPPs in US Dollars	3021	2243.5	532.7	12517.2	402	Authors computing with PWT 9.1 data
goveducgdp	Government spending on education in percentage of GDP	3.69	1.65	1.21	15	402	IMF databases
goveducgdp_ppp	Real public spending on education per capita at chained PPPs in US Dollars	118	110.7	11.8	637.6	402	Authors computing
Education efficiency							
effiEduc_output23	Education spending output Efficiency Score	0.70	0.27	0.071	1.05	402	Authors computing
effiEduc_input23	Education spending input Efficiency Score	0.51	0.35	0.071	1.65	402	Authors computing
Second stage regression							
effiEduc_output23	Education spending output Efficiency Score	0.65	0.25	0.071	1.00	301	Authors computing
logGDP	Logarithm of GDP per capita at constant 2010 US Dollars	7.36	1.05	5.21	9.41	288	Computing with World Bank WDI [43]
logGDPSq	Logarithm of real per capita GDP squared	55.3	15.5	27.2	88.6	288	Computing with World Bank WDI
Urbanrate	Urban rate	1.83	2.52	-5.28	25.8	291	World Bank WDI
Trade openness	Trade openness in percentage of GDP	0.19	0.11	0	0.62	301	World Bank WDI
FD	Financial Development	61.4	32.3	12.9	210.0	283	IMF financial development database
ODA	Net Official development assistance (ODA) received (% of GNI)	42.9	18.4	8.16	84.0	301	World Bank WDI
Corruption	Corruption	2.59	0.98	0	6	293	International Country Risk Guide (ICRG)
Government Stability	Government Stability	7.05	2.04	1	11	293	International Country Risk Guide (ICRG)
Democracy	Normalized Polity2 democracy Index	0.53	0.31	0.0100	1	299	Polity IV database

Source: Authors' calculation

[40] Occupation by a foreign country

[41] Falling down of political authority

[42] Period between two political regimes that are substantially different

4.2 Empirical strategy

As said in subsection 3.2, we use partial frontier approaches (or conditional efficiency model) especially, the order-m estimator to estimate our production boundary. We compute efficiency scores for output and input oriented for each period. We set the value of m equal to 23. This value permits to get the lower share of super-efficient DMUs (after stimulated many samples of m DMUs). The method authorizes DMUs to be above the production frontier (i.e., efficiency score higher than 1). We test the sensibility of the order–m estimators (effiEduc_output23 and effiEduc_input23) to other values of m, by using Pearson correlation test (nonlinear correlation test) and Spearman's rank correlation test. The alternative values of m are respectively 17[43] and 50[44]. In the same vein, we also test the sensibility of the order-m estimator to alternative order–α estimator. A correlation coefficient (or a rank correlation coefficient) close to one and significant means that the DMU's efficiency (or its rank) are not significantly influenced by m values or order-α estimator. The order-m estimator allows some DMUs to lie outside the efficiency frontier (super-efficient countries). Hence, unlike the other methods, the efficiency score in the order-m method can be greater than one.

In the second stage we regress the output efficiency score (effiEduc_output) on a set of exogenous variables (named environmental variables) by using Fractional Regression Models (FRMs). The bounded nature of efficiency scores and in some cases, the possibility of nontrivial probability mass accumulating at one or both boundaries imply that fractional regression models must be applied in this context. The standard linear regression model is not appropriate since it does not guarantee that the predicted values of the dependent variable are restricted to the unit interval (Ramalho et al., 2010, 2011). Moreover, given that the dependent variable is strictly bounded from above and below, it is in general unreason- able to assume that the effect of any explanatory variable is constant throughout its entire range[45]. Tobit approach is also traditionally used to estimate efficiency score. However, there are some problems with this approach. First, only in the two-limit Tobit model, the predicted values of dependent variable are restricted to the unit interval. But that approach can only be applied when observations are with in both limits, which is

[43] Corresponding to one fourth of the sample

[44] Corresponding to three fourths of the sample

[45] Ramalho et al. (2011)

often not the case. Second, the Tobit model is appropriate to describe censored data in the interval [0, 1] but its application to data defined only in that interval is problematic. Observations at the boundaries of a fractional variable are a natural consequence of individual choices and not of any type of censoring. Finally, the Tobit model is very stringent in terms of assumptions, requiring normality and homoskedasticity of the dependent variable, prior to censoring (Ramalho et al., 2011). Fractional regressions models were first suggested by Papke and Wooldridge (1996). This seminal paper was followed by several extensions (Ramalho et al., 2010, 2011; Ramalho and Ramalho, 2017; Ramalho et al., 2018; Ramalho, 2019). Recently, Ramalho et al. (2016, 2018) and Ramalho (2019) developed a new class of estimators based on a transformation of logit and complementary loglog (cloglog) fractional regression models into a form of exponential regression (EFRM) with multiplicative individual effects and time-variant heterogeneity from which six alternative GMM estimators (including four alternative GMM fixed-effects estimators) have been proposed. These estimators are robust to heterogeneity (time-variant and time-invariant) and can accommodate endogenous explanatory variables. In this paper, we use the pooled fixed-effects (GMMpfe) estimator allowing explanatory variables and individual effects to be correlated.

We then use the following econometric specification:

$$y_{it} = G(x_{it}\theta + \alpha_i + \upsilon_{it})$$

Where υ_{it} denotes time-varying unobserved heterogeneity and G is assumed to have a logit $\left(G(\cdot) = \frac{exp(\cdot)}{1+exp(\cdot)}\right)$ or cloglog $\left(G(\cdot) = 1 - exp^{-exp(\cdot)}\right)$ specification. y_{it} is the dependent variable and x_{it} the matrix of explanatory variables. α_i is the vector of individual-specific intercepts and θdenotes the vector of parameters. Note that the EFRM accommodates the value zero of dependent variable. However, it is not defined for its upper boundary.

4.3 Results Analysis

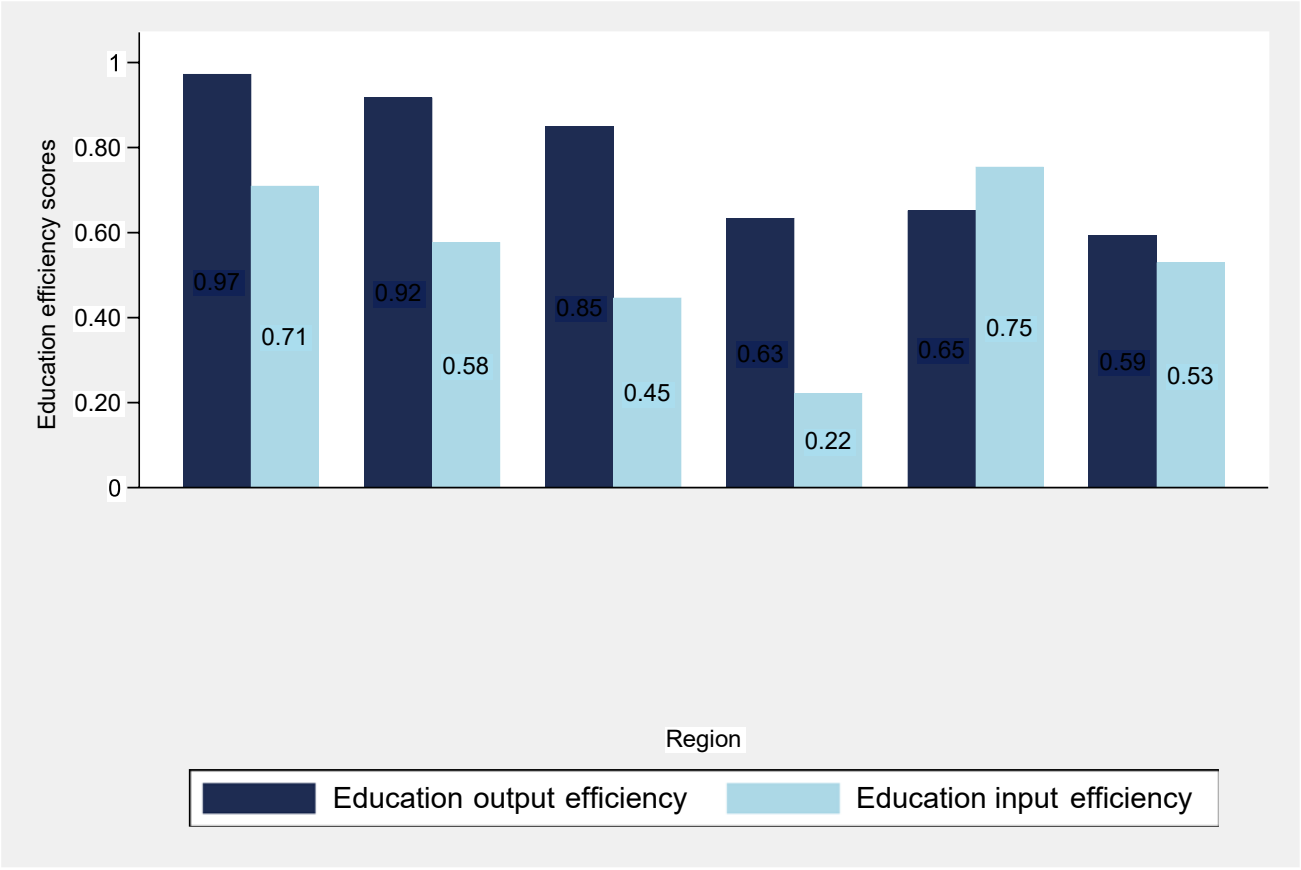
4.3.1 Efficiency scores

Appendix F provides output and input efficiency scores for each country and each period. The analysis of efficiency scores provides the following results:

The average output technical efficiency score is relatively high (0.70). This suggests that developing countries might increase their output (then reduce their education

inequality) by 30% without changing their public expenditure on education. East Asia and Pacific, Europe and central Asia and Latin America and Caribbean have the highest levels of output efficiency scores over the study period. As for Sub-Saharan Africa, its output efficiency score is the lowest (0.59). However, its input efficiency score (0.53) is higher than the average input efficiency score (0.51). Middle East and North Africa's (MENA) countries have the lowest in-put efficiency score (0.22). In general, (except South Asia) the output efficiency score is higher than the input efficiency score[46] (see figure3).

Figure 3: Average score of efficiency by regional sub-sample

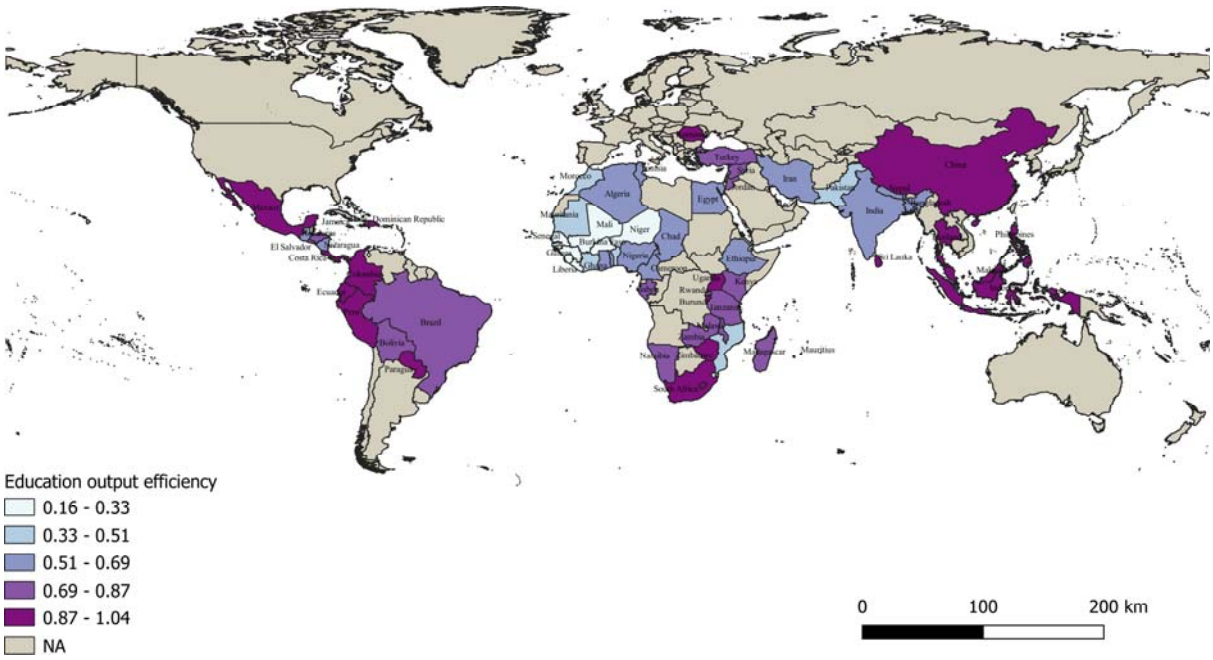


Source: Authors

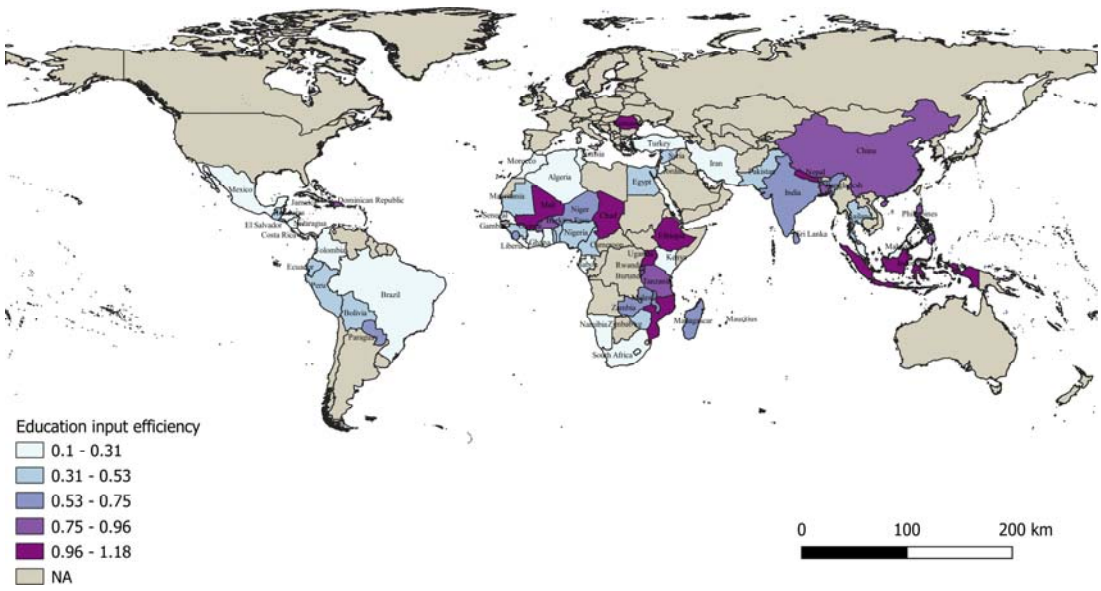
[46] Herrera and Ouedraogo (2018) also find the same result

Figure 4: Geographical representation of education efficiency scores

(a) Education output efficiency



(b) Education input efficiency

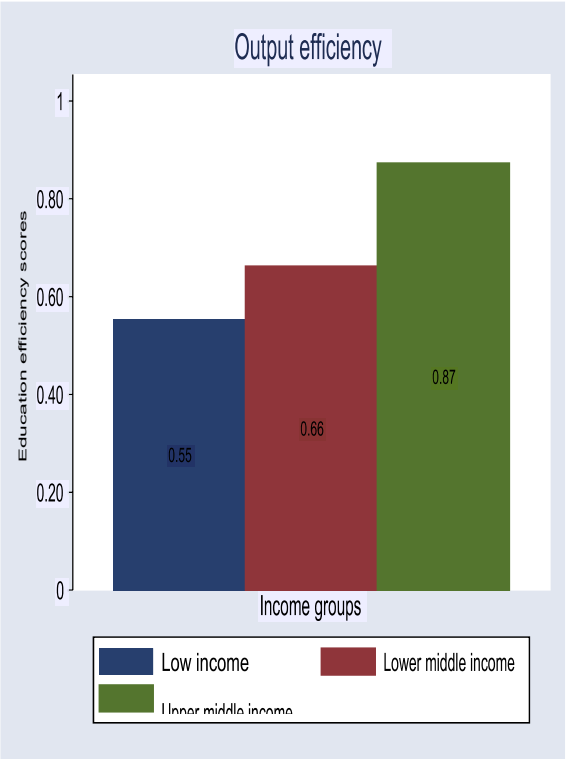


Source: Authors

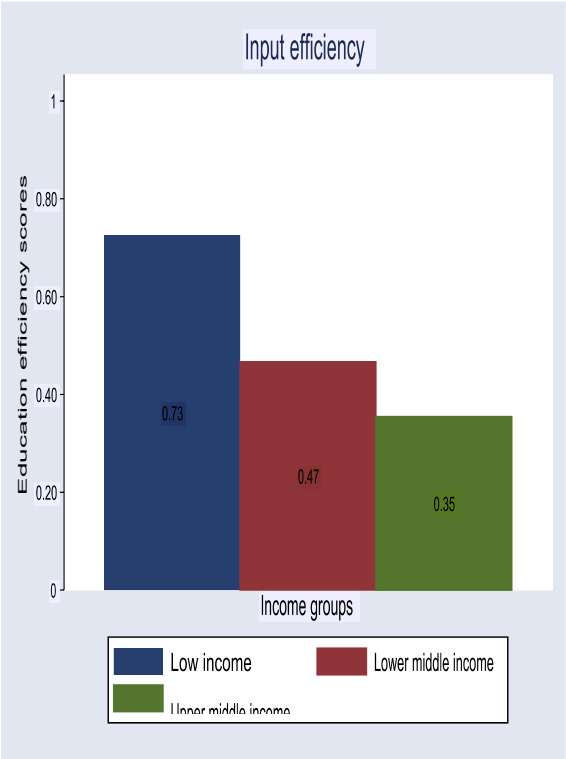
Low-income countries have the lowest level of output efficiency (0.55). However, they have the highest level of input efficiency (0.73). In the same vein, upper middle-income countries have the highest level of output efficiency (0.87) but the lowest level of input efficiency (0.35). Figures 5a and 5b provide the average output and input efficiency score by income group.

Figure 5: Average score of efficiency by income group

(a)Output Efficiency



(b) Input Efficiency

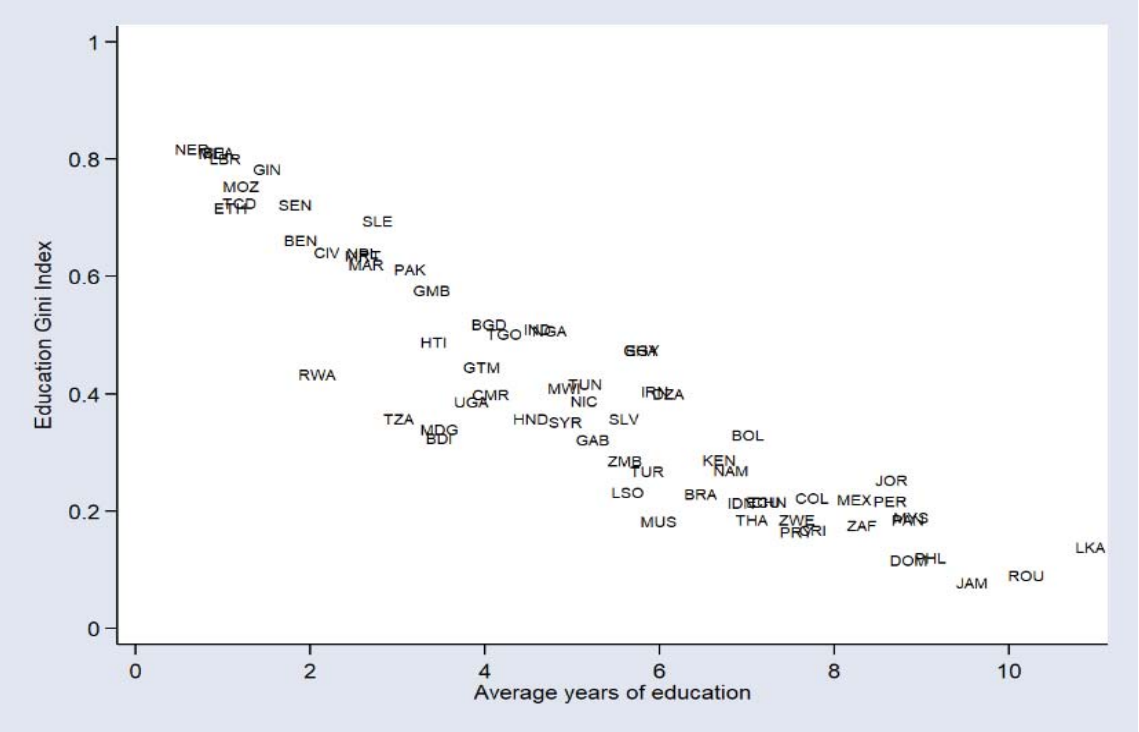


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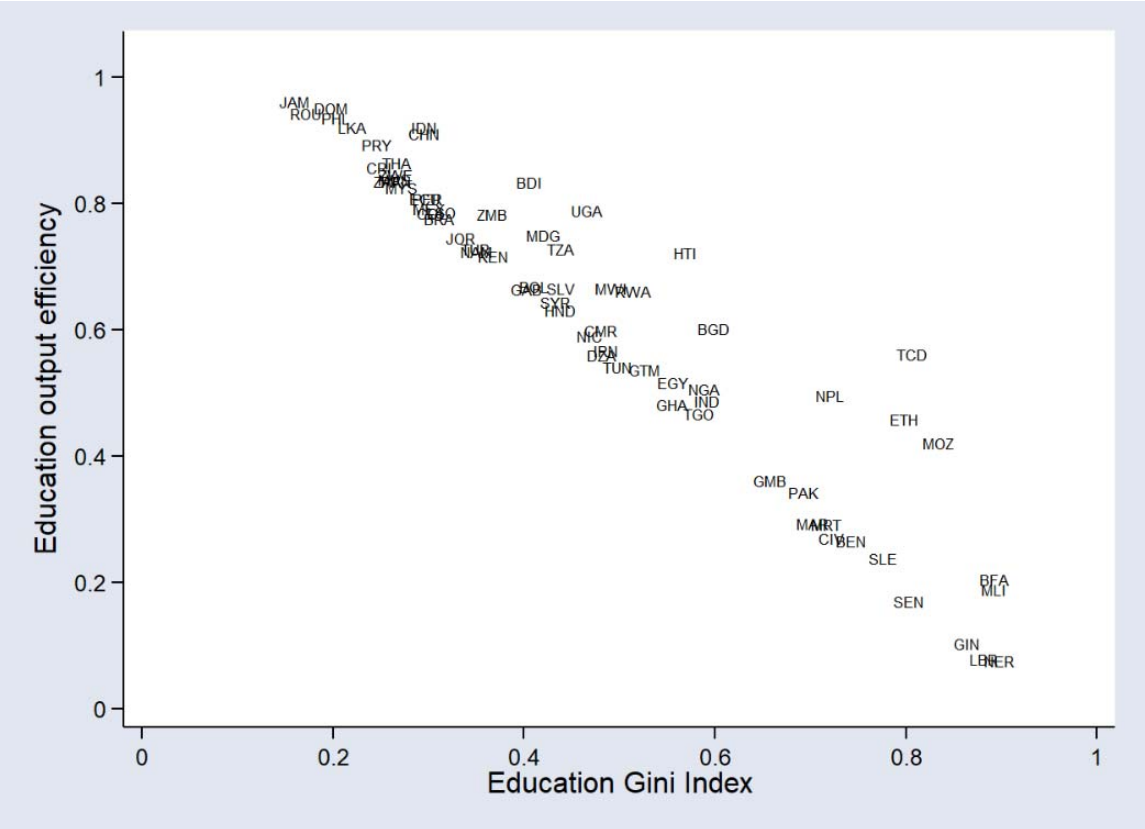
Countries with high level of education output efficiency (e.g., Sri Lanka, Jamaica and Romania) have higher educational attainment level and better education equality. Conversely, countries with low educational attainment level (e.g., Guinea, Liberia and Niger) have higher education inequality and lower education output inefficiency (see figures 6a, 6b and 6c). Then, we can hypothesize that the level of educational attainment is linked to the level of education output efficiency.

Figure 6: Relation between Education output efficiency, education inequality and Education

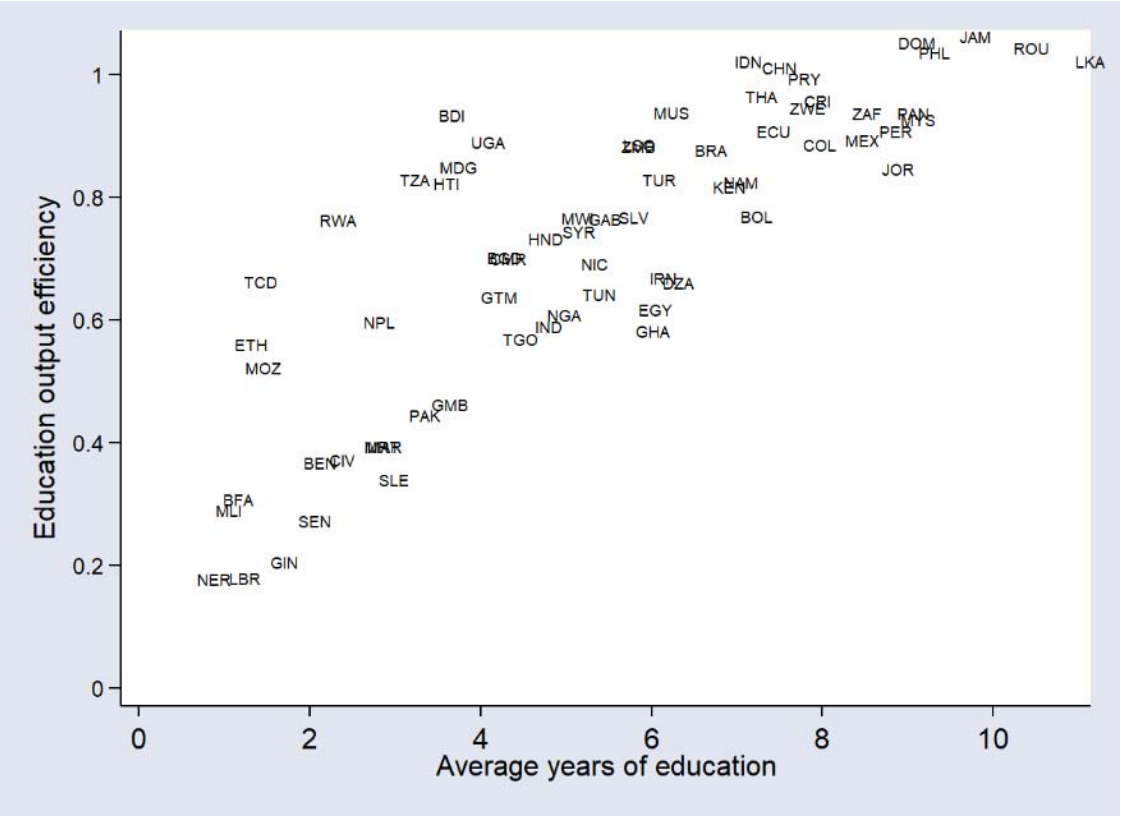
(a) Correlation: Education inequality Average year of education



(b) Correlation: Education output efficiency Education inequality



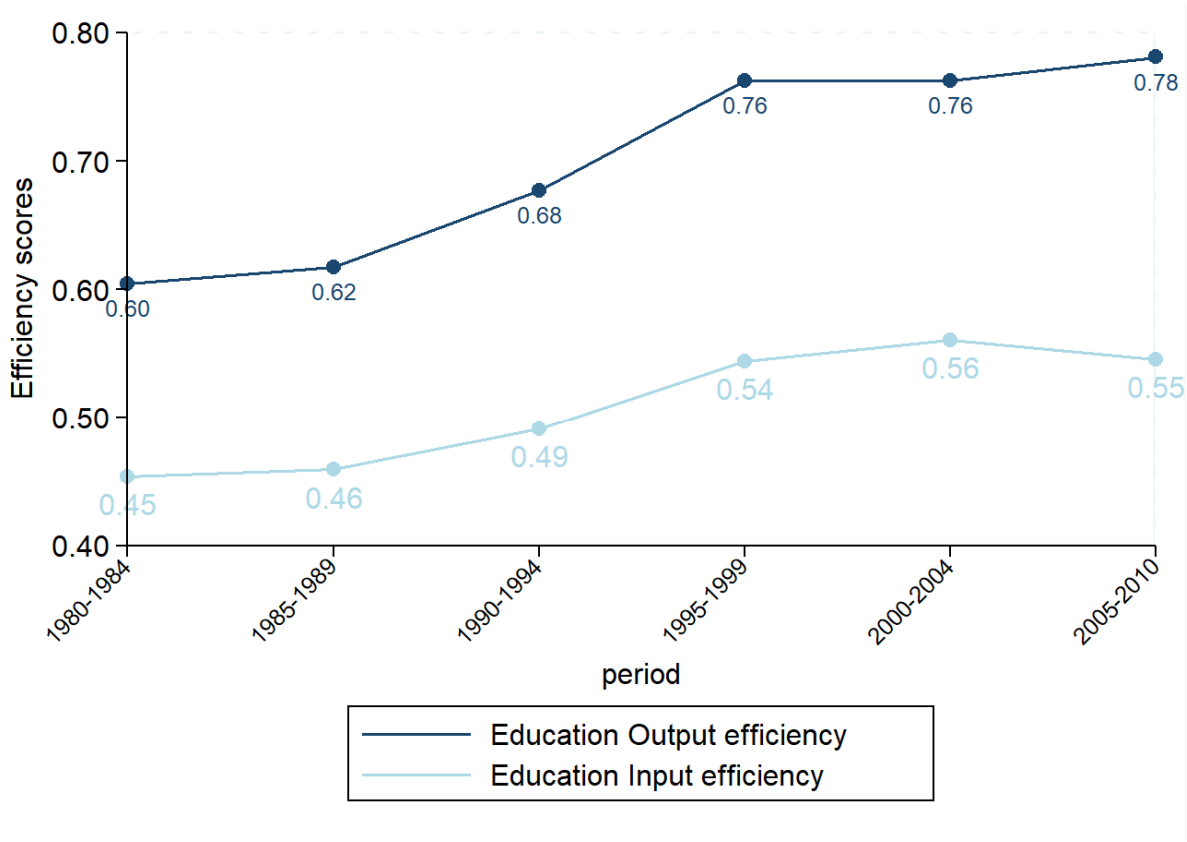
(c) Correlation: Education output efficiency Average year of education



Source: Authors

Table2 and table3 provide the evolution of output and input efficiency scores over the study period. The results show that the output efficiency scores have increased (figure6 and table2). Regarding input efficiency, there is an improvement from 1980 to 2004 and a slightly decrease since 2005 (see figure6 and table3).

Figure 7: Evolution of Output and Input efficiency score



Source: Authors

Table 2: Evolution of efficiency scores output oriented

Periods	mean	p50	sd	cv	min	max	p25	p75	iqr
1980-1984	0.60	0.63	0.28	0.47	0.071	1.05	0.38	0.83	0.45
1985-1989	0.62	0.66	0.28	0.46	0.089	1.05	0.35	0.86	0.52
1990-1994	0.68	0.72	0.26	0.38	0.13	1.05	0.50	0.89	0.39
1995-1999	0.76	0.84	0.24	0.32	0.16	1.04	0.64	0.95	0.30
2000-2004	0.76	0.83	0.25	0.32	0.19	1.04	0.65	0.95	0.29
2005-2010	0.78	0.86	0.23	0.29	0.21	1.05	0.69	0.94	0.25
Total Sample	0.70	0.76	0.27	0.38	0.071	1.05	0.50	0.92	0.42
Numberofobservations	402								

Source: Authors

Table 3: Evolution of efficiency scores input oriented

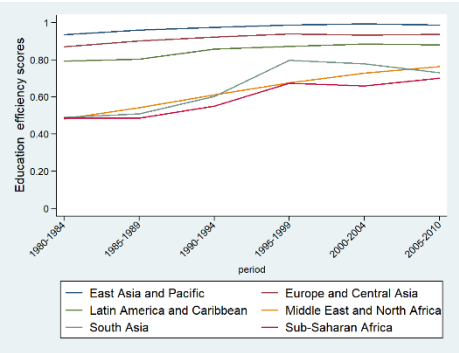
Periods	mean	p50	sd	cv	min	max	p25	p75	iqr
1980-1984	0.45	0.32	0.35	0.76	0.071	1.33	0.17	0.65	0.49
1985-1989	0.46	0.34	0.35	0.75	0.076	1.45	0.16	0.68	0.51
1990-1994	0.49	0.38	0.35	0.71	0.077	1.44	0.20	0.81	0.61
1995-1999	0.54	0.40	0.37	0.68	0.083	1.25	0.22	0.95	0.73
2000-2004	0.56	0.44	0.36	0.65	0.082	1.65	0.29	0.90	0.61
2005-2010	0.55	0.50	0.34	0.62	0.093	1.48	0.25	0.79	0.54
Total Sample	0.51	0.40	0.35	0.69	0.071	1.65	0.20	0.80	0.60
Number of observations	402								

Source: Authors' calculation

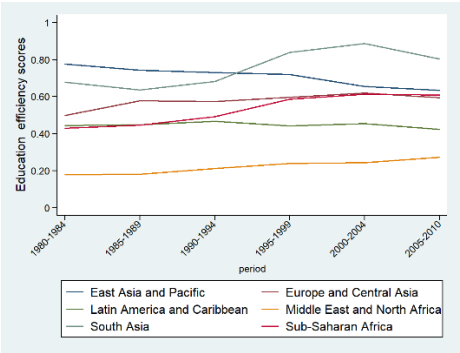
Sub-Saharan Africa, South Asia, Europe and Central Asia have improved their output efficiency scores (see figure8). There is also an improvement of output efficiency in lower and upper middle-income countries (see figure9a).

Figure 8: Evolution of output and input efficiency by region

(a) Output Efficiency



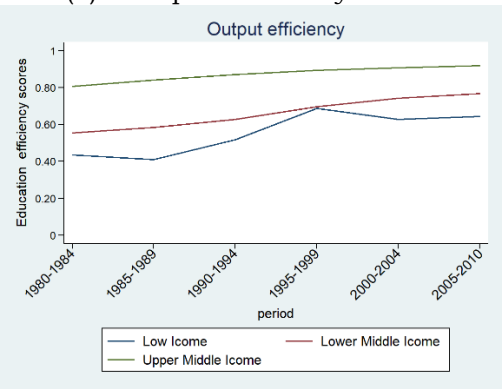
(b) Input Efficiency



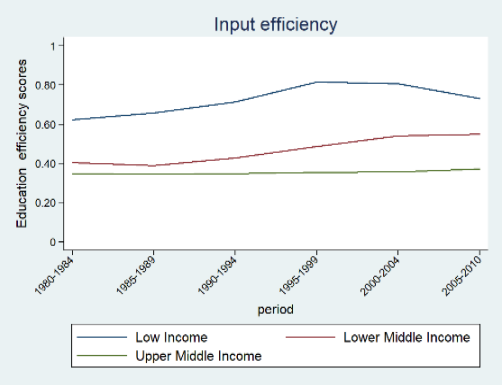
Source: Authors

Figure 9: Evolution of output and input efficiency by icome group

(a) Output Efficiency



(b) Input Efficiency



Source: Authors

The sensibility tests (Pearson and Spearman's rank correlation tests) of the order-m estimators (effiEduc_output23 and effiEduc_input23) to other value of m and to order-α estimators (EffiEducalpha_output and EffiEducalpha_input) are significant (at 1%) and close to 1 (see table4 and 5. Consequently, the output and input order-m estimators are robust (DMU's efficiency score (or its rank) are not significantly influenced by the values of m or order–α estimator).

Table 4: Sensibility of output efficiency score to other values of m and order–α estimator

Pearson correlation test

	effiEduc_output23	effiEduc_output17	effiEduc_output50	effialpha_output
effiEduc_output23	1.000			
effiEduc_output17	0.999*	0.999*		
effiEduc_output50	0.999*	0.999*	1.000	
effialpha_output	0.999*	0.999*	0.999*	1.000

Spearman correlation test

	effiEduc_output23	effiEduc_output17	effiEduc_output50	effialpha_output
effiEduc_output23	1.000			
effiEduc_output17	0.9994*	1.000		
effiEduc_output50	0.9991*	0.9983*	1.000	
effialpha_output	0.9975*	0.9966*	0.9985*	1.000

Source Authors' calculation.
Note: *p< 0.01

Table 5: Sensibility of input efficiency score to other values of m and to order alpha estimator

Pearson correlation test

	effiEduc_input23	effiEduc_input17	effiEduc_input50	effialpha_input
effiEduc_input23	1.000			
effiEduc_input17	0.997*	1.000		
effiEduc_input50	0.991*	0.982*	1.000	
effialpha_input	0.986*	0.978*	0.991*	1.000

Spearman correlation test

	effiEduc_input23	effiEduc_input17	effiEduc_input50	effialpha_input
effiEduc_input23	1.000			
effiEduc_input17	0.9979*	1.000		
effiEduc_input50	0.9945*	0.9895*	1.000	
effialpha_input	0.9907*	0.9856*	0.9940*	1.000

Source Authors 'calculation.
Note: *p< 0.01

4.3.2 Determinants of Education's output efficiency score

Table 6 shows the main determinants of education spending's output efficiency for logit and CLoglog specifications. These results lead the following remarks:
The logarithm of real GDP per capita has a positive and significant effect on public expenditures efficiency for logit and Cloglog specifications. The square of the logarithm of the real per capita GDP decreases public expenditures efficiency on education for both specifications.

Urbanization ratio, financial development, government stability and democracy impact positively and significantly public spending efficiency on education for both specifications.

Corruption has a non-significant impact on education output efficiency for both specifications. However, it lowers public expenditures efficiency on education.

Contrary to expectation, trade openness has a negative, but non-significant impact on education output efficiency. Net ODA has a negative and non-significant effect on education output efficiency.

FDI has a negative and non-significant impact on education output efficiency for logit specification but a positive and non-significant impact for Cloglog specification. In general, the coefficients for logit specification are higher than the coefficients for Cloglog specification (in absolute value).

Table 6: Determinant of education output efficiency

Variables	Logit	Cloglog
logGDP	6.222***	3.609***
	(2.047)	(0.950)
logGDPSq	-0.448***	-0.251***
	(0.139)	(0.065)
Urbanrate	0.043***	0.023***
	(0.010)	(0.006)
FD	2.874***	1.235***
	(0.912)	(0.467)
Trade	-0.103	-0.121
	(0.233)	(0.115)
ODA	-0.619	-0.141
	(0.559)	(0.351)
FDI	-0.436	0.131
	(1.394)	(0.688)
Corruption	0.016	0.013
	(0.055)	(0.041)
Government Stability	0.063***	0.045***
	(0.020)	(0.011)
Democracy	0.591***	0.362***
	(0.193)	(0.124)
Number of observations	266	266
Number of Countries	52	52

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

5 CONCLUSION

Developing countries are facing high education inequality with limited resources to reduce it. Thus, the assessment of public expenditures efficiency is crucial in these countries.

This paper aims two objectives. First, it assesses the efficiency of public expenditures with the focus on the output and measured as an improvement of the distribution of education in developing countries. Second, it identifies the factors determining education output efficiency.

The paper uses a sample of 67 developing country to compute education output and input efficiency from 1980 to 2010. As for identifying the determinants of education output efficiency, the paper employs unbalanced panel data.

To estimate the efficiency scores of public expenditures on education, the paper uses nonparametric partial frontier method especially order-m estimator. This method is more robust to extreme values or outliers than the other nonparametric estimators (specifically, FDH and DEA). To analyse the factors determining education output efficiency, the paper employs exponential Fractional Regression Model (EFRM).

The results show that, on average, developing countries might reduce their education inequality by 30% without changing their amount of public expenditures on education. Education output efficiency is very low in sub-Saharan Africa and low-income countries. The level of education output efficiency may be due to level of educational attainment.

Regarding education input efficiency, the results indicate that developing countries could reduce their education public expenditures by 49% to achieve the same results. Middle East and North Africa and Upper middle-income countries have the lowest level of education input efficiency.

Developing countries have achieved significant progress in improving their education output efficiency. Their education input efficiency has improved from 1980 to 2004 but has since 2005 decreased slightly.

From EFRM results, the paper finds that education output efficiency is determined by economic factors (logarithm of GDP and its square). A high ratio of urbanization permits to easily provide education services in an efficient manner. Good governance (government stability and democracy) lead to high efficiency. A high financial development is also beneficial for education output efficiency.

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Appendix

A Descriptive statistics of education output efficiency scores by region

Regions	mean	p50	sd	cv	min	max	p25	p75	iqr
East Asia & Pacific	0.97	0.99	0.046	0.047	0.91	1.02	0.95	1.00	0.057
Europe & Central Asia	0.92	0.92	0.15	0.17	0.81	1.02	0.81	1.02	0.22
Latin America & Caribbean	0.85	0.87	0.12	0.15	0.62	1.04	0.75	0.93	0.18
Middle East & North Africa	0.63	0.64	0.14	0.22	0.37	0.83	0.60	0.73	0.13
South Asia	0.65	0.58	0.22	0.33	0.42	1.00	0.57	0.68	0.11
Sub-Saharan Africa	0.59	0.62	0.26	0.43	0.16	0.93	0.35	0.82	0.47
Total Sample	0.70	0.75	0.24	0.34	0.16	1.04	0.56	0.89	0.33
Number of Country	67								

Source Authors' calculation

B Descriptive statistics of education input efficiency scores by region

Regions	mean	p50	sd	cv	min	max	p25	p75	iqr
East Asia & Pacific	0.71	0.87	0.36	0.50	0.19	1.09	0.52	0.87	0.35
Europe & Central Asia	0.58	0.58	0.56	0.97	0.18	0.97	0.18	0.97	0.79
Latin America & Caribbean	0.45	0.34	0.33	0.74	0.096	1.18	0.20	0.62	0.42
Middle East & North Africa	0.22	0.17	0.14	0.62	0.11	0.49	0.14	0.33	0.19
South Asia	0.75	0.73	0.23	0.30	0.50	1.04	0.58	0.93	0.35
Sub-Saharan Africa	0.53	0.45	0.31	0.59	0.11	1.09	0.28	0.77	0.50
Total Sample	0.51	0.43	0.32	0.64	0.096	1.18	0.21	0.77	0.57
Number of Country	67								

Source Authors' calculation

C Descriptive statistics of education output efficiency scores by income level

Income groups	**mean**	**p50**	**sd**	**cv**	**min**	**max**	**p25**	**p75**	**iqr**
Low income	0.55	0.55	0.26	0.47	0.16	0.93	0.32	0.80	0.48
Lower middleincome	0.66	0.68	0.21	0.32	0.25	1.02	0.56	0.80	0.23
Upper middleincome	0.87	0.89	0.12	0.14	0.62	1.04	0.81	0.95	0.14
Total sample	0.70	0.75	0.24	0.34	0.16	1.04	0.56	0.89	0.33
Number ofCountry	67								

D Descriptive statistics of education output efficiency scores by income level

Income groups	mean	p50	sd	cv	min	max	p25	p75	iqr
Low income	0.73	0.77	0.30	0.42	0.27	1.18	0.44	1.01	0.57
Lower middle income	0.47	0.43	0.26	0.55	0.15	1.09	0.29	0.58	0.28
Upper middleincome	0.35	0.20	0.31	0.87	0.096	1	0.16	0.52	0.37
Total sample	0.51	0.43	0.32	0.64	0.096	1.18	0.21	0.77	0.57
Number of Country	67								

E list of country used

Country for which efficiency scores is computed	Region	Second stage regression
Algeria	Middle East & North Africa	Algeria
Bangladesh	South Asia	Bangladesh
Benin	Sub-Saharan Africa	
Bolivia	Latin America & Caribbean	Bolivia
Brazil	Latin America & Caribbean	Brazil
Burkina Faso	Sub-Saharan Africa	Burkina Faso
Burundi	Sub-Saharan Africa	Burundi
Cameroon	Sub-Saharan Africa	Cameroon
Chad	Sub-Saharan Africa	
China	East Asia & Pacific	China
Colombia	Latin America & Caribbean	Colombia
Costa Rica	Latin America & Caribbean	Costa Rica
Cote d'Ivoire	Sub-Saharan Africa	Cote d'Ivoire
Dominican Republic	Latin America & Caribbean	
Ecuador	Latin America & Caribbean	Ecuador
Egypt	Middle East & North Africa	Egypt
El Salvador	Latin America & Caribbean	El Salvador
Ethiopia	Sub-Saharan Africa	Ethiopia
Gabon	Sub-Saharan Africa	Gabon
Gambia	Sub-Saharan Africa	Gambia
Ghana	Sub-Saharan Africa	Ghana
Guatemala	Latin America & Caribbean	Guatemala
Guinea	Sub-Saharan Africa	Guinea
Haiti	Latin America & Caribbean	Haiti
Honduras	Latin America & Caribbean	Honduras
India	South Asia	India
Indonesia	East Asia & Pacific	Indonesia
Iran (Islamic Republic of)	Middle East & North Africa	Iran (Islamic Republic of)
Jamaica	Latin America & Caribbean	

Country for which efficiency scores is computed	Region	Second stage regression
Jordan	Middle East & North Africa	Jordan
Kenya	Sub-Saharan Africa	Kenya
Lesotho	Sub-Saharan Africa	
Liberia	Sub-Saharan Africa	Liberia
Madagascar	Sub-Saharan Africa	Madagascar
Malawi	Sub-Saharan Africa	Malawi
Malaysia	East Asia & Pacific	Malaysia
Mali	Sub-Saharan Africa	Mali
Mauritania	Sub-Saharan Africa	
Mauritius	Sub-Saharan Africa	
Mexico	Latin America & Caribbean	Mexico
Morocco	Middle East & North Africa	Morocco
Mozambique	Sub-Saharan Africa	Mozambique
Namibia	Sub-Saharan Africa	Namibia
Nepal	South Asia	
Nicaragua	Latin America & Caribbean	Nicaragua
Niger	Sub-Saharan Africa	Niger
Nigeria	Sub-Saharan Africa	Nigeria
Pakistan	South Asia	Pakistan
Panama	Latin America & Caribbean	Panama
Paraguay	Latin America & Caribbean	Paraguay
Peru	Latin America & Caribbean	Peru
Philippines	East Asia & Pacific	
Romania	Europe & Central Asia	Romania
Rwanda	Sub-Saharan Africa	
Senegal	Sub-Saharan Africa	Senegal
Sierra Leone	Sub-Saharan Africa	Sierra Leone
South Africa	Sub-Saharan Africa	South Africa
Sri Lanka	South Asia	Sri Lanka
Syrian Arab Republic	Middle East & North Africa	Syrian Arab Republic

Country for which efficiency scores is computed	Region	Second stage regression
Thailand	East Asia & Pacific	Thailand
Togo	Sub-Saharan Africa	Togo
Tunisia	Middle East & North Africa	Tunisia
Turkey	Europe & Central Asia	Turkey
Uganda	Sub-Saharan Africa	Uganda
United Republic of Tanzania	Sub-Saharan Africa	United Republic of Tanzania
Zambia	Sub-Saharan Africa	Zambia
Zimbabwe	Sub-Saharan Africa	
Number of Country	67	55

Source: Authors

F Education Efficiency Scores

Country	ID	code	period	Output effeciency	Input effeciency
Algeria	1	DZA	1980-1984	0.45	0.13
Algeria	1	DZA	1985-1989	0.54	0.13
Algeria	1	DZA	1990-1994	0.63	0.12
Algeria	1	DZA	1995-1999	0.69	0.10
Algeria	1	DZA	2000-2004	0.75	0.10
Algeria	1	DZA	2005-2010	0.79	0.09
Bangladesh	2	BGD	1980-1984	0.49	0.82
Bangladesh	2	BGD	1985-1989	0.50	0.78
Bangladesh	2	BGD	1990-1994	0.54	0.94
Bangladesh	2	BGD	1995-1999	0.92	1.02
Bangladesh	2	BGD	2000-2004	0.91	1.03
Bangladesh	2	BGD	2005-2010	0.73	0.98
Benin	3	BEN	1980-1984	0.24	0.38
Benin	3	BEN	1985-1989	0.26	0.38
Benin	3	BEN	1990-1994	0.31	0.38
Benin	3	BEN	1995-1999	0.37	0.52
Benin	3	BEN	2000-2004	0.43	0.47
Benin	3	BEN	2005-2010	0.48	0.50
Bolivia	4	BOL	1980-1984	0.61	0.32
Bolivia	4	BOL	1985-1989	0.67	0.32
Bolivia	4	BOL	1990-1994	0.74	0.35
Bolivia	4	BOL	1995-1999	0.79	0.33
Bolivia	4	BOL	2000-2004	0.83	0.36
Bolivia	4	BOL	2005-2010	0.86	0.29
Brazil	5	BRA	1980-1984	0.80	0.30
Brazil	5	BRA	1985-1989	0.84	0.16
Brazil	5	BRA	1990-1994	0.86	0.17
Brazil	5	BRA	1995-1999	0.88	0.17
Brazil	5	BRA	2000-2004	0.89	0.25

Country	ID	code	period	Output effeciency	Input effeciency
Brazil	5	BRA	2005-2010	0.88	0.20
Burkina Faso	6	BFA	1980-1984	0.52	1.08
Burkina Faso	6	BFA	1985-1989	0.12	0.97
Burkina Faso	6	BFA	1990-1994	0.24	0.87
Burkina Faso	6	BFA	1995-1999	0.38	0.98
Burkina Faso	6	BFA	2000-2004	0.24	0.71
Burkina Faso	6	BFA	2005-2010	0.23	0.64
Burundi	7	BDI	1980-1984	0.93	0.86
Burundi	7	BDI	1985-1989	0.90	0.95
Burundi	7	BDI	1990-1994	0.88	1.00
Burundi	7	BDI	1995-1999	1.02	1.09
Burundi	7	BDI	2000-2004	0.99	1.03
Burundi	7	BDI	2005-2010	0.78	0.60
Cameroon	8	CMR	1980-1984	0.54	0.37
Cameroon	8	CMR	1985-1989	0.58	0.38
Cameroon	8	CMR	1990-1994	0.66	0.54
Cameroon	8	CMR	1995-1999	0.76	0.66
Cameroon	8	CMR	2000-2004	0.77	0.44
Cameroon	8	CMR	2005-2010	0.78	0.40
Chad	9	TCD	1980-1984	0.17	0.63
Chad	9	TCD	1985-1989	0.23	0.90
Chad	9	TCD	1990-1994	0.45	0.96
Chad	9	TCD	1995-1999	1.00	1.14
Chad	9	TCD	2000-2004	1.00	1.65
Chad	9	TCD	2005-2010	1.00	1.21
China	10	CHN	1980-1984	0.84	0.65
China	10	CHN	1985-1989	1.00	0.65
China	10	CHN	1990-1994	1.00	0.81
China	10	CHN	1995-1999	1.04	1.05
China	10	CHN	2000-2004	1.04	1.05
China	10	CHN	2005-2010	1.04	1.03

Country	ID	code	period	Output effeciency	Input effeciency
Colombia	11	COL	1980-1984	0.84	0.31
Colombia	11	COL	1985-1989	0.85	0.33
Colombia	11	COL	1990-1994	0.86	0.17
Colombia	11	COL	1995-1999	0.88	0.18
Colombia	11	COL	2000-2004	0.87	0.20
Colombia	11	COL	2005-2010	0.89	0.22
Costa Rica	12	CRI	1980-1984	0.96	0.17
Costa Rica	12	CRI	1985-1989	0.95	0.14
Costa Rica	12	CRI	1990-1994	0.95	0.17
Costa Rica	12	CRI	1995-1999	0.93	0.19
Costa Rica	12	CRI	2000-2004	0.92	0.15
Costa Rica	12	CRI	2005-2010	0.91	0.17
Cote d'Ivoire	13	CIV	1980-1984	0.24	0.12
Cote d'Ivoire	13	CIV	1985-1989	0.29	0.14
Cote d'Ivoire	13	CIV	1990-1994	0.33	0.14
Cote d'Ivoire	13	CIV	1995-1999	0.38	0.17
Cote d'Ivoire	13	CIV	2000-2004	0.41	0.26
Cote d'Ivoire	13	CIV	2005-2010	0.45	0.25
Dominican Republic	14	DOM	1980-1984	1.04	1.00
Dominican Republic	14	DOM	1985-1989	1.05	1.00
Dominican Republic	14	DOM	1990-1994	1.05	1.00
Dominican Republic	14	DOM	1995-1999	1.04	1.00
Dominican Republic	14	DOM	2000-2004	1.02	0.82
Dominican Republic	14	DOM	2005-2010	1.00	0.76
Ecuador	15	ECU	1980-1984	0.86	0.17
Ecuador	15	ECU	1985-1989	0.86	0.27
Ecuador	15	ECU	1990-1994	0.88	0.38
Ecuador	15	ECU	1995-1999	0.91	0.24
Ecuador	15	ECU	2000-2004	0.91	0.48
Ecuador	15	ECU	2005-2010	0.92	0.51
Egypt	16	EGY	1980-1984	0.44	0.48

Country	ID	code	period	Output effeciency	Input effeciency
Egypt	16	EGY	1985-1989	0.46	0.45
Egypt	16	EGY	1990-1994	0.55	0.47
Egypt	16	EGY	1995-1999	0.66	0.57
Egypt	16	EGY	2000-2004	0.71	0.49
Egypt	16	EGY	2005-2010	0.77	0.47
El Salvador	17	SLV	1980-1984	0.68	0.61
El Salvador	17	SLV	1985-1989	0.67	0.53
El Salvador	17	SLV	1990-1994	0.72	0.53
El Salvador	17	SLV	1995-1999	0.76	0.51
El Salvador	17	SLV	2000-2004	0.82	0.70
El Salvador	17	SLV	2005-2010	0.83	0.56
Ethiopia	18	ETH	1980-1984	1.00	1.21
Ethiopia	18	ETH	1985-1989	0.22	1.09
Ethiopia	18	ETH	1990-1994	0.45	1.03
Ethiopia	18	ETH	1995-1999	0.70	1.10
Ethiopia	18	ETH	2000-2004	0.44	0.93
Ethiopia	18	ETH	2005-2010	0.44	0.69
Gabon	19	GAB	1980-1984	0.57	0.17
Gabon	19	GAB	1985-1989	0.66	0.12
Gabon	19	GAB	1990-1994	0.73	0.14
Gabon	19	GAB	1995-1999	0.80	0.13
Gabon	19	GAB	2000-2004	0.83	0.14
Gabon	19	GAB	2005-2010	0.88	0.24
Gambia	20	GMB	1980-1984	0.31	0.15
Gambia	20	GMB	1985-1989	0.35	0.16
Gambia	20	GMB	1990-1994	0.40	0.22
Gambia	20	GMB	1995-1999	0.46	0.26
Gambia	20	GMB	2000-2004	0.53	0.39
Gambia	20	GMB	2005-2010	0.62	0.42
Ghana	21	GHA	1980-1984	0.46	0.12
Ghana	21	GHA	1985-1989	0.49	0.17

Country	ID	code	period	Output effeciency	Input effeciency
Ghana	21	GHA	1990-1994	0.52	0.17
Ghana	21	GHA	1995-1999	0.59	0.22
Ghana	21	GHA	2000-2004	0.64	0.29
Ghana	21	GHA	2005-2010	0.68	0.24
Guatemala	22	GTM	1980-1984	0.55	0.40
Guatemala	22	GTM	1985-1989	0.54	0.51
Guatemala	22	GTM	1990-1994	0.60	0.48
Guatemala	22	GTM	1995-1999	0.64	0.44
Guatemala	22	GTM	2000-2004	0.68	0.43
Guatemala	22	GTM	2005-2010	0.69	0.32
Guinea	23	GIN	1980-1984	0.11	0.19
Guinea	23	GIN	1985-1989	0.13	0.30
Guinea	23	GIN	1990-1994	0.18	0.40
Guinea	23	GIN	1995-1999	0.20	0.37
Guinea	23	GIN	2000-2004	0.24	0.41
Guinea	23	GIN	2005-2010	0.27	0.36
Haiti	24	HTI	1980-1984	0.49	0.94
Haiti	24	HTI	1985-1989	0.52	1.14
Haiti	24	HTI	1990-1994	1.00	1.44
Haiti	24	HTI	1995-1999	1.00	1.25
Haiti	24	HTI	2000-2004	1.00	1.23
Haiti	24	HTI	2005-2010	0.81	1.08
Honduras	25	HND	1980-1984	0.63	0.25
Honduras	25	HND	1985-1989	0.66	0.22
Honduras	25	HND	1990-1994	0.72	0.34
Honduras	25	HND	1995-1999	0.73	0.36
Honduras	25	HND	2000-2004	0.76	0.33
Honduras	25	HND	2005-2010	0.78	0.29
India	26	IND	1980-1984	0.45	0.43
India	26	IND	1985-1989	0.46	0.48
India	26	IND	1990-1994	0.50	0.45

Country	ID	code	period	Output effeciency	Input effeciency
India	26	IND	1995-1999	0.59	0.60
India	26	IND	2000-2004	0.69	0.74
India	26	IND	2005-2010	0.72	0.76
Indonesia	27	IDN	1980-1984	1.00	1.33
Indonesia	27	IDN	1985-1989	1.00	1.45
Indonesia	27	IDN	1990-1994	1.02	1.27
Indonesia	27	IDN	1995-1999	1.01	1.13
Indonesia	27	IDN	2000-2004	1.02	0.76
Indonesia	27	IDN	2005-2010	0.97	0.62
Iran (Islamic Republic of)	28	IRN	1980-1984	0.46	0.10
Iran (Islamic Republic of)	28	IRN	1985-1989	0.54	0.12
Iran (Islamic Republic of)	28	IRN	1990-1994	0.62	0.10
Iran (Islamic Republic of)	28	IRN	1995-1999	0.69	0.11
Iran (Islamic Republic of)	28	IRN	2000-2004	0.77	0.29
Iran (Islamic Republic of)	28	IRN	2005-2010	0.80	0.34
Jamaica	29	JAM	1980-1984	1.05	1.00
Jamaica	29	JAM	1985-1989	1.04	1.00
Jamaica	29	JAM	1990-1994	1.05	1.00
Jamaica	29	JAM	1995-1999	1.03	1.00
Jamaica	29	JAM	2000-2004	1.04	1.00
Jamaica	29	JAM	2005-2010	1.05	1.00
Jordan	30	JOR	1980-1984	0.68	0.08
Jordan	30	JOR	1985-1989	0.76	0.08
Jordan	30	JOR	1990-1994	0.82	0.14
Jordan	30	JOR	1995-1999	0.87	0.20
Jordan	30	JOR	2000-2004	0.90	0.17
Jordan	30	JOR	2005-2010	0.92	0.18
Kenya	31	KEN	1980-1984	0.66	0.17
Kenya	31	KEN	1985-1989	0.72	0.17
Kenya	31	KEN	1990-1994	0.78	0.25
Kenya	31	KEN	1995-1999	0.84	0.34

Country	ID	code	period	Output effeciency	Input effeciency
Kenya	31	KEN	2000-2004	0.88	0.47
Kenya	31	KEN	2005-2010	0.91	0.46
Lesotho	32	LSO	1980-1984	0.80	0.38
Lesotho	32	LSO	1985-1989	0.83	0.23
Lesotho	32	LSO	1990-1994	0.84	0.25
Lesotho	32	LSO	1995-1999	0.89	0.24
Lesotho	32	LSO	2000-2004	0.92	0.35
Lesotho	32	LSO	2005-2010	0.93	0.31
Liberia	33	LBR	1980-1984	0.10	0.13
Liberia	33	LBR	1985-1989	0.12	0.16
Liberia	33	LBR	1990-1994	0.14	0.20
Liberia	33	LBR	1995-1999	0.16	0.26
Liberia	33	LBR	2000-2004	0.19	0.39
Liberia	33	LBR	2005-2010	0.26	0.52
Madagascar	34	MDG	1980-1984	0.67	0.35
Madagascar	34	MDG	1985-1989	0.71	0.43
Madagascar	34	MDG	1990-1994	0.83	0.61
Madagascar	34	MDG	1995-1999	0.96	1.03
Madagascar	34	MDG	2000-2004	0.91	0.91
Madagascar	34	MDG	2005-2010	0.90	0.84
Malawi	35	MWI	1980-1984	0.68	0.65
Malawi	35	MWI	1985-1989	0.69	0.62
Malawi	35	MWI	1990-1994	0.70	0.64
Malawi	35	MWI	1995-1999	0.73	0.62
Malawi	35	MWI	2000-2004	0.78	0.68
Malawi	35	MWI	2005-2010	0.90	0.65
Malaysia	36	MYS	1980-1984	0.82	0.18
Malaysia	36	MYS	1985-1989	0.87	0.20
Malaysia	36	MYS	1990-1994	0.91	0.21
Malaysia	36	MYS	1995-1999	0.93	0.21
Malaysia	36	MYS	2000-2004	0.95	0.15

Country	ID	code	period	Output effeciency	Input effeciency
Malaysia	36	MYS	2005-2010	0.96	0.18
Mali	37	MLI	1980-1984	0.13	0.86
Mali	37	MLI	1985-1989	0.13	1.05
Mali	37	MLI	1990-1994	0.25	1.10
Mali	37	MLI	1995-1999	0.66	1.14
Mali	37	MLI	2000-2004	0.25	0.90
Mali	37	MLI	2005-2010	0.21	0.83
Mauritania	38	MRT	1980-1984	0.23	0.47
Mauritania	38	MRT	1985-1989	0.27	0.33
Mauritania	38	MRT	1990-1994	0.33	0.31
Mauritania	38	MRT	1995-1999	0.41	0.35
Mauritania	38	MRT	2000-2004	0.46	0.38
Mauritania	38	MRT	2005-2010	0.55	0.42
Mauritius	39	MUS	1980-1984	0.87	0.11
Mauritius	39	MUS	1985-1989	0.90	0.17
Mauritius	39	MUS	1990-1994	0.93	0.23
Mauritius	39	MUS	1995-1999	0.94	0.25
Mauritius	39	MUS	2000-2004	0.93	0.32
Mauritius	39	MUS	2005-2010	0.94	0.25
Mexico	40	MEX	1980-1984	0.83	0.11
Mexico	40	MEX	1985-1989	0.86	0.12
Mexico	40	MEX	1990-1994	0.88	0.08
Mexico	40	MEX	1995-1999	0.88	0.08
Mexico	40	MEX	2000-2004	0.89	0.08
Mexico	40	MEX	2005-2010	0.90	0.10
Morocco	41	MAR	1980-1984	0.26	0.16
Morocco	41	MAR	1985-1989	0.31	0.15
Morocco	41	MAR	1990-1994	0.35	0.18
Morocco	41	MAR	1995-1999	0.40	0.20
Morocco	41	MAR	2000-2004	0.45	0.18
Morocco	41	MAR	2005-2010	0.48	0.13

Country	ID	code	period	Output effeciency	Input effeciency
Mozambique	42	MOZ	1980-1984	0.19	0.93
Mozambique	42	MOZ	1985-1989	0.19	1.10
Mozambique	42	MOZ	1990-1994	0.37	1.02
Mozambique	42	MOZ	1995-1999	1.00	1.22
Mozambique	42	MOZ	2000-2004	0.39	0.91
Mozambique	42	MOZ	2005-2010	0.87	1.01
Namibia	43	NAM	1980-1984	0.70	0.12
Namibia	43	NAM	1985-1989	0.76	0.08
Namibia	43	NAM	1990-1994	0.80	0.09
Namibia	43	NAM	1995-1999	0.83	0.09
Namibia	43	NAM	2000-2004	0.86	0.13
Namibia	43	NAM	2005-2010	0.88	0.14
Nepal	44	NPL	1980-1984	0.25	1.07
Nepal	44	NPL	1985-1989	0.30	1.05
Nepal	44	NPL	1990-1994	0.62	1.03
Nepal	44	NPL	1995-1999	1.00	1.21
Nepal	44	NPL	2000-2004	0.70	1.07
Nepal	44	NPL	2005-2010	0.60	0.81
Nicaragua	45	NIC	1980-1984	0.60	0.08
Nicaragua	45	NIC	1985-1989	0.63	0.08
Nicaragua	45	NIC	1990-1994	0.65	0.12
Nicaragua	45	NIC	1995-1999	0.68	0.16
Nicaragua	45	NIC	2000-2004	0.72	0.21
Nicaragua	45	NIC	2005-2010	0.75	0.23
Niger	46	NER	1980-1984	0.07	0.32
Niger	46	NER	1985-1989	0.09	0.37
Niger	46	NER	1990-1994	0.13	0.49
Niger	46	NER	1995-1999	0.20	0.64
Niger	46	NER	2000-2004	0.22	0.75
Niger	46	NER	2005-2010	0.23	0.79
Nigeria	47	NGA	1980-1984	0.38	0.19

Country	ID	code	period	Output effeciency	Input effeciency
Nigeria	47	NGA	1985-1989	0.44	0.34
Nigeria	47	NGA	1990-1994	0.50	0.29
Nigeria	47	NGA	1995-1999	0.56	0.33
Nigeria	47	NGA	2000-2004	0.65	0.43
Nigeria	47	NGA	2005-2010	1.00	1.14
Pakistan	48	PAK	1980-1984	0.31	0.50
Pakistan	48	PAK	1985-1989	0.32	0.44
Pakistan	48	PAK	1990-1994	0.37	0.44
Pakistan	48	PAK	1995-1999	0.45	0.56
Pakistan	48	PAK	2000-2004	0.55	0.59
Pakistan	48	PAK	2005-2010	0.55	0.48
Panama	49	PAN	1980-1984	0.90	0.16
Panama	49	PAN	1985-1989	0.92	0.17
Panama	49	PAN	1990-1994	0.92	0.20
Panama	49	PAN	1995-1999	0.93	0.26
Panama	49	PAN	2000-2004	0.91	0.18
Panama	49	PAN	2005-2010	0.93	0.22
Paraguay	50	PRY	1980-1984	1.02	1.01
Paraguay	50	PRY	1985-1989	0.96	0.83
Paraguay	50	PRY	1990-1994	0.98	0.81
Paraguay	50	PRY	1995-1999	0.96	0.56
Paraguay	50	PRY	2000-2004	0.96	0.45
Paraguay	50	PRY	2005-2010	0.96	0.33
Peru	51	PER	1980-1984	0.82	0.29
Peru	51	PER	1985-1989	0.85	0.35
Peru	51	PER	1990-1994	0.89	0.25
Peru	51	PER	1995-1999	0.91	0.33
Peru	51	PER	2000-2004	0.93	0.43
Peru	51	PER	2005-2010	0.94	0.50
Philippines	52	PHL	1980-1984	1.03	1.00
Philippines	52	PHL	1985-1989	1.01	0.79

Country	ID	code	period	Output effeciency	Input effeciency
Philippines	52	PHL	1990-1994	1.02	0.76
Philippines	52	PHL	1995-1999	1.02	0.66
Philippines	52	PHL	2000-2004	1.02	1.00
Philippines	52	PHL	2005-2010	1.02	1.01
Romania	53	ROU	1980-1984	1.00	0.83
Romania	53	ROU	1985-1989	1.02	1.00
Romania	53	ROU	1990-1994	1.03	1.00
Romania	53	ROU	1995-1999	1.04	1.00
Romania	53	ROU	2000-2004	1.03	1.00
Romania	53	ROU	2005-2010	1.03	1.00
Rwanda	54	RWA	1980-1984	0.55	0.60
Rwanda	54	RWA	1985-1989	0.66	0.68
Rwanda	54	RWA	1990-1994	0.69	0.85
Rwanda	54	RWA	1995-1999	0.93	0.95
Rwanda	54	RWA	2000-2004	0.81	0.86
Rwanda	54	RWA	2005-2010	0.82	0.68
Senegal	55	SEN	1980-1984	0.17	0.23
Senegal	55	SEN	1985-1989	0.20	0.28
Senegal	55	SEN	1990-1994	0.23	0.32
Senegal	55	SEN	1995-1999	0.27	0.32
Senegal	55	SEN	2000-2004	0.30	0.31
Senegal	55	SEN	2005-2010	0.33	0.20
Sierra Leone	56	SLE	1980-1984	0.21	0.57
Sierra Leone	56	SLE	1985-1989	0.27	0.60
Sierra Leone	56	SLE	1990-1994	0.28	0.55
Sierra Leone	56	SLE	1995-1999	0.31	0.56
Sierra Leone	56	SLE	2000-2004	0.38	0.50
Sierra Leone	56	SLE	2005-2010	0.47	0.59
South Africa	57	ZAF	1980-1984	0.83	0.07
South Africa	57	ZAF	1985-1989	0.88	0.09
South Africa	57	ZAF	1990-1994	0.91	0.10

Country	ID	code	period	Output effeciency	Input effeciency
South Africa	57	ZAF	1995-1999	0.95	0.14
South Africa	57	ZAF	2000-2004	0.96	0.15
South Africa	57	ZAF	2005-2010	0.97	0.50
Sri Lanka	58	LKA	1980-1984	0.95	0.58
Sri Lanka	58	LKA	1985-1989	0.97	0.44
Sri Lanka	58	LKA	1990-1994	0.99	0.54
Sri Lanka	58	LKA	1995-1999	1.02	0.80
Sri Lanka	58	LKA	2000-2004	1.04	1.00
Sri Lanka	58	LKA	2005-2010	1.04	1.00
Syrian Arab Republic	59	SYR	1980-1984	0.60	0.14
Syrian Arab Republic	59	SYR	1985-1989	0.65	0.16
Syrian Arab Republic	59	SYR	1990-1994	0.71	0.35
Syrian Arab Republic	59	SYR	1995-1999	0.76	0.37
Syrian Arab Republic	59	SYR	2000-2004	0.80	0.37
Syrian Arab Republic	59	SYR	2005-2010	0.84	0.61
Thailand	60	THA	1980-1984	0.99	0.72
Thailand	60	THA	1985-1989	0.93	0.63
Thailand	60	THA	1990-1994	0.94	0.59
Thailand	60	THA	1995-1999	0.94	0.55
Thailand	60	THA	2000-2004	0.94	0.31
Thailand	60	THA	2005-2010	0.94	0.34
Togo	61	TGO	1980-1984	0.36	0.27
Togo	61	TGO	1985-1989	0.43	0.24
Togo	61	TGO	1990-1994	0.50	0.27
Togo	61	TGO	1995-1999	0.59	0.37
Togo	61	TGO	2000-2004	0.69	0.46
Togo	61	TGO	2005-2010	0.73	0.56
Tunisia	62	TUN	1980-1984	0.49	0.18
Tunisia	62	TUN	1985-1989	0.55	0.18
Tunisia	62	TUN	1990-1994	0.60	0.14
Tunisia	62	TUN	1995-1999	0.66	0.13

Country	ID	code	period	Output effeciency	Input effeciency
Tunisia	62	TUN	2000-2004	0.70	0.11
Tunisia	62	TUN	2005-2010	0.74	0.09
Turkey	63	TUR	1980-1984	0.74	0.17
Turkey	63	TUR	1985-1989	0.78	0.16
Turkey	63	TUR	1990-1994	0.81	0.15
Turkey	63	TUR	1995-1999	0.84	0.19
Turkey	63	TUR	2000-2004	0.83	0.24
Turkey	63	TUR	2005-2010	0.85	0.19
Uganda	64	UGA	1980-1984	0.72	1.16
Uganda	64	UGA	1985-1989	0.73	0.86
Uganda	64	UGA	1990-1994	0.75	1.07
Uganda	64	UGA	1995-1999	1.01	1.17
Uganda	64	UGA	2000-2004	1.00	1.12
Uganda	64	UGA	2005-2010	1.00	1.16
United Republic of Tanzania	65	TZA	1980-1984	0.65	0.47
United Republic of Tanzania	65	TZA	1985-1989	0.68	0.49
United Republic of Tanzania	65	TZA	1990-1994	0.80	0.59
United Republic of Tanzania	65	TZA	1995-1999	0.81	0.84
United Republic of Tanzania	65	TZA	2000-2004	1.00	1.18
United Republic of Tanzania	65	TZA	2005-2010	0.90	1.07
Zambia	66	ZMB	1980-1984	0.69	0.16
Zambia	66	ZMB	1985-1989	0.75	0.16
Zambia	66	ZMB	1990-1994	0.81	0.37
Zambia	66	ZMB	1995-1999	0.91	0.83
Zambia	66	ZMB	2000-2004	1.02	1.31
Zambia	66	ZMB	2005-2010	1.00	1.48
Zimbabwe	67	ZWE	1980-1984	0.82	0.23
Zimbabwe	67	ZWE	1985-1989	0.87	0.30
Zimbabwe	67	ZWE	1990-1994	0.91	0.29
Zimbabwe	67	ZWE	1995-1999	0.97	0.40
Zimbabwe	67	ZWE	2000-2004	0.99	0.41

Country	ID	code	period	Output effeciency	Input effeciency
Zimbabwe	67	ZWE	2005-2010	1.00	0.36

Source: Authors' calculation