UNIVERSITY OF MACEDONIA
Interdepartmental Programme of Postgraduate Studies in Economic Science
Master in Economics

Master Thesis

Technical efficiency in higher education

A meta-regression analysis

Maria Papadimitriou **A. M.: M 13/12**

Supervisor Professor: Giannis Karagiannis

Thessaloniki

August 2013

The present was submitted in order to obtain Master's Degree in Economic Science with specialization in Applied Economics and Finance.

Table of Contents

Abstract

A meta-regression analysis including 163 both published and unpublished papers providing technical efficiency scores from higher education institutions was conducted in a worldwide base. The period under examination was from 1980 until 2012. The survey was based on a total of 8325 observations as some studies provide results from more than one method, for more than one country or for more than one year. The use of four different models and three different ways of estimation produced a total of 12 alternative models. All the alternative ways of estimation based on a meta-regression model framework and OLS (ordinary least square) was used as a methodological tool: In three alternative ways (a) equally weight each estimate (b) equally weight each paper/study (c) differently weight each estimate. By this econometric analysis the impact of various meta-independent variables in the mean technical efficiency score(s) among previously published studies is examined.

Introduction

The importance of higher education sector is blatant in a vast majority of countries worldwide. Education sector and more specifically higher education has attracted researchers from various fields mainly in an attempt of measuring the educational performance of institutions in higher education.

Due to the pioneer work of Farell (1957), who introduced the frontier methodology as a widely used tool in measuring economic efficiency, an extended assortment of methodological empirical frontier studies were introduced in the aftermath.

A representative and synoptic review for the available applications of the frontier efficiency measurement techniques literature to examine technical efficiency in education has been conducted by Worthington (2001). Obviously, the great efforts and interest that has been focused in measuring efficiency in higher education sector using the available frontier models is reflected in those reviews.

According to Farell (1957), economic efficiency is a simple measure of firm's efficiency and can be decomposed into two components: technical efficiency and allocative efficiency. Further elaboration reveals that technical efficiency can be defined as the ability of a firm or generally of a decision making unit to obtain maximal output from a given bundle of inputs and technology, where allocative efficiency reflects firm's success in using the inputs optimally given their respective prices and the production technology, (i.e. where the ratio of marginal products for each input pair is equalized to the ratio of their market prices), Coelli et al. (2005).

The combination of these two measures gives the Farell's framework as a measure of the total economic efficiency.

E.E = AE*TE

There are various methodologies and strategies which are applicable in the literature in order to measure technical efficiency. However, this issue stirs up a lot of controversy as the choice of a specific methodology can serious affect the estimated TE scores.

The main purpose here is to thoroughly examine the attributes of studies which estimate technical efficiency scores such as functional specification method of estimation, region, differences in the level of economic development etc. As a result a Meta-regression analysis of 163 frontier studies pertaining to technical efficiency measurement in the higher education sector is conducted.

Meta-regression analysis is a quantitative technique to identify a single summarized effect size which can be attributed to one or more characteristics of the studies involved Thomson and Higgins (2001).

The methodological differences and the specific characteristics of each involved study could potentially differentiate the empirical estimates of some indicators in our case the mean technical efficiency score.

Meta-regression not only recognizes the specification problem but also attempts to estimate its effects by modeling variations in selected econometric specifications. Meta-regression provides us with the means to analyze, estimate, and discount, when appropriate, the influence of alternative model specification and specification searches Stanley and Jarrell (1989).

Consequently some of the heterogeneity between efficiency scores estimates between different studies can be interpreted by using these differences across studies as explanatory variables (meta-independent variables) that account for relevant characteristics of an empirical study and explain the systematic variation from other results in literature in a regression model. Meta-regression aims to relate the size of effect to one or more characteristics of the studies involved.

In most cases these meta-independent variables tend to be dummy variables corresponding either the structure, the design of the data either the methodological characteristics stems from each surveyed study. The content of these variables are explained by Stanley, Doucouliagos and Jarrell (2008), and can be summarized in:

a) Socio-economic characteristics of the researchers (gender, income, funding resource etc.).

b) Measures of research quality.
c) Model adequacy and past research findings.

It was first introduced by Stanley and Jarrell (1989) and gradually evolved in a precious method in economics literature based on econometric techniques.

Methodological sketch of MRA

The key point in meta-regression analysis is that the wide variation among research findings based on information extracted from the studies themselves can be interpreted to an extent by the choice of methods, the particular attributes of the data or other specifications of the studies.

The first step should be the choice of the relevant metric for dependent variable. Some possible indicators could be:

a) Regression coefficients.
b) Elasticities.
c) Other calculated or estimated variables (e.g., wage gaps, economic returns, and efficiency or productivity levels).
d) t-statistics and/or the results of other statistical tests (e.g., likelihood ratio, Wald, or Lagrange multiplier).

The second step is the choice of moderator (meta-independent) explanatory variables. Suggestively could be used:

a) Type and characteristics of the data set (i.e. cross section or panel data).
b) Choice of estimation modeling (i.e. parametric non-parametric).
c) Model specification choices (i.e. functional form, orientation etc.)
d) Measures of the estimate's precision or accuracy.
e) Quality measures (specification tests passed, degrees of freedom).
f) Geographical orientation of the study.
g) Period covered by the study.
h) Researchers' characteristics (gender, institutional affiliations).

i) Type and quality of publication (quality of the journal).

Finally according to Stanley (2001), the main steps which are required in conducting meta-regression analysis estimation could be summarized in:

a) First and more importantly to involve all (as far as it is possible) the relevant studies.
b) Choice of the relevant metric for dependent variable.
c) Choice the appropriate moderator (meta-independent) explanatory variables.
d) Implementation of a careful econometric estimation.
e) Incur the meta-regression results to specification testing.

As far as the author is aware no exclusive meta-regression analysis exists in the field of efficiency measurement in higher education institutions globally. The only meta-regression analysis associated with efficiency in education is based in all levels of education (primary, secondary and tertiary education) by Haelermans (2009).

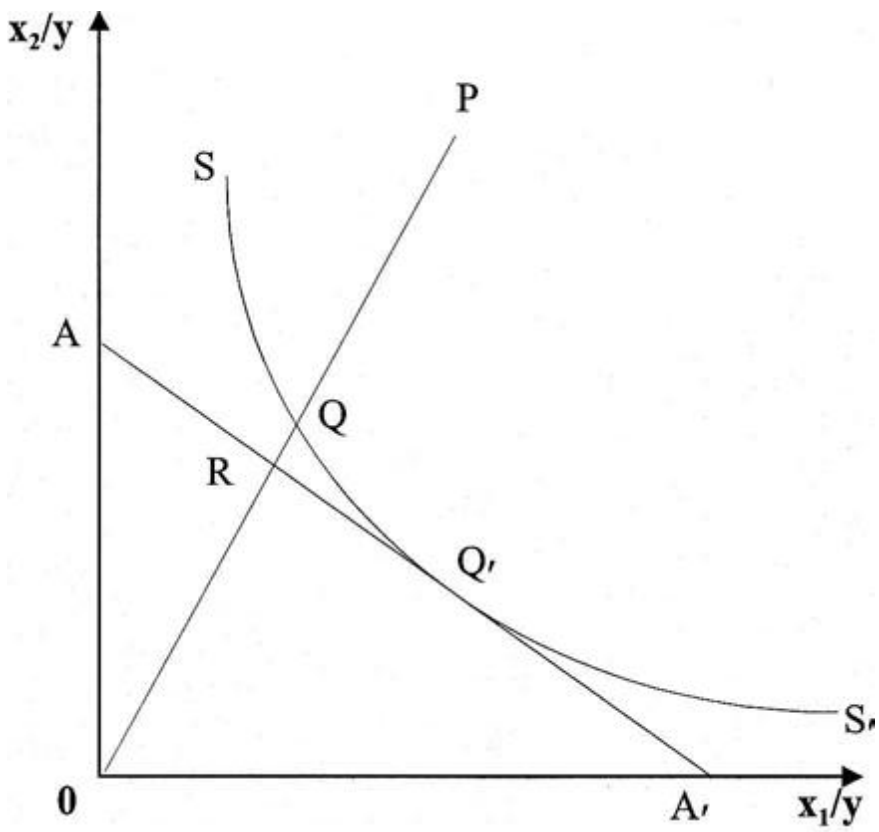
There are also few meta-regression analyses in the education sector mainly in different directions from efficiency measurements such as examining the effects of education in economic growth Benos and Zotou (2013), in gender inequality in China's education system Zeng et al. (2013).

It is also worth noted that meta-regression analysis is a widely used tool in studies associated with farming Bravo-Ureta et al. (2007), with agriculture Boys and Florax (2008), Karagiannis (2013), or other research fields such as in medicine Freemantle et al. (1999), Lambert et al (2001), Karkos et al. (2008).

Frontier Function Methodology a general overview

The first attempt to introduce a frontier production model was made by Farell (1957). The original framework was based in measuring Economic efficiency (EE) or production efficiency which can be decomposed into Technical (TE) and Allocative Efficiency (AE). The combination of this two components determine the Total economic efficiency.

His idea was illustrated by using a firm with two inputs (x_1, x_2) to produce a single output (q) as an outcome of this process given the production technology. He assumed constant returns to scale so it was feasible for the technology to be represented by the unit isoquant.



All firms which are fully efficient lied across the unit isoquant SS' (showing the alternative combinations of inputs that can be used to produce a given level of output). This isoquant allows the measurement of the technical efficiency as the fully efficient firms combine this frontier.

However firms which use quantities of (x_1, x_2) and produce an output like point P can be identified as technical inefficient firms.

The technical inefficiency here can be represented by the distance QP. Given the amount of output (q) all inputs have to be proportionally reduced by the distance QP to obtain a technical efficient production. Turning to percentage terms this reduction should be equal to QP/OP. As a result the technical efficiency of a firm is measured:

TE= OQ/OP

This ratio measures the proportion of (x_1, x_2) actually necessary to produce (q).

Consequently the difference 1- OQ/OP gives straightforwardly the technical inefficiency of the firm. More substantially it measures the proportion by which the firm's inputs should be reduced to obtain a given level of output (q) Coelli et al. (2005).

With regard to the second component named allocative efficiency (AE), it represents the ability of the firm to use its inputs optimally given their respective prices and the production technology when a firm is allocatively efficient the combination of inputs it used produce the maximum possible outputs.

Provided that the inputs price ratio is represented by the isoquant line A'A (where all the different combinations between inputs that can be purchased with a given cost outlay is illustrated). Then allocative efficiency can be calculated immediately as it is the ability of a firm to use its inputs optimally given the respective prices. At point P is given by the ratio OR/OQ. Consequently for point P the allocative inefficiency will be given as:

Allocative inefficiency= 1-OR/OQ

The distance RQ represents the reduction in production cost that should occur if the production occurred at point Q, where Q is an allocatively and technically efficient point contrary to Q' which is only technically efficient but allocatively inefficient point.

Overall, Total economic efficiency is demonstrated by the ratio OR/OP and total inefficiency is therefore 1- OR/OP Farell, (1957).

The last measure of efficiency that should be discussed here is scale efficiency which is based on the size of operation of each firm. It is possible that a firm is both technically and allocatively efficient but the scale of operation of the firm may not be optimal. Both firms which fall in increasing or decreasing returns of scale could improve their efficiency level by changing their scale of operations, (i.e keeping the same input mix but change the size of operations). If a production technology attain a globally constant return of scale technology then the firm is automatically scale

efficient and it does not need any modification on its size to be scale efficient. This a thorough definition about scale efficiency framework is given by (Balk, 2001).

A representative measure of scale efficiency (input-oriented) for a firm operating at a given mix of inputs and an output (q) was defined by Fare, Grosskopf and Roos, (1998).

$$SE(x,q) = \frac{TE\ CRS}{TE\ VRS}$$

Where TE_{crs} and TE_{vrs} represent Technical efficiency under constant and under variable returns of scale.

A great appeal in frontier function methodology is observed the last decades and this is more obvious considering the expansion of methodological and empirical frontier studies. This fact can be attributed mainly into two factors which are the close correspondence of frontier techniques with the theoretical framework and its consistency with the overall education production function approach (production, profit or cost function and with the notion of maximization or minimization.

This large number of frontier models can be classified into two basic categories parametric (such as the Cobb Douglas fitted to the data, such that no observed point should lie left or below it, known as the econometric approach) and non-parametric (piecewise-linear convex isoquant constructed such that no observed point should lie to the left or below it known as the mathematical programming approach to the frontier construction).

Parametric frontiers which rely on specific functional form can be clarified into deterministic and stochastic. The deterministic model assumes that any deviation from the frontier is due to inefficiency while the stochastic approach allows for statistical noise. Hence a fundamental problem the deterministic frontier model is that any measurement error and any of the source of stochastic variation in the dependent variable is embedded in the one sided component. As a result outliers can have obvious effects on the estimates and any shortcoming in the model specification may be misplaced into increased inefficiency measures Greene (1993).

Stochastic frontier production models incorporate a composed error structure with a two sided symmetric term and a one-sided component. The one sided component

represents inefficiency whereas the two sided error captures randomness (or statistical noise) which are outside of the control of the production unit.

Measurement errors could be included in this type of errors as well as econometric errors such as the specification of the model. Consequently stochastic frontier models fix the noise problem of the early deterministic frontier models. The usual assumption with the two component error structure is that inefficiencies follow a half normal distribution and the random errors are normally distributed Worthington (2001).

Stochastic frontier analysis tries to fix the omission of statistical noise of the deterministic models and gives a flexibility to estimate standard errors and to test hypothesis which where problematic with deterministic frontiers, as a result of certain violations in the max likelihood regularity condition Schmidt (1976).

Furthermore, by Jondrow et al. (1982), allows the calculation of individual firm's efficiency using stochastic frontier models. One of the limitations in the stochastic frontier models that still afflicts this method is the priory justification with regard to the distributional form of the one sided inefficiency term. Another classification of the econometric models used in the efficiency estimation is between primal and dual approaches which focus mainly in the behavioral assumptions of the model. Usually, in the past the most common choice by the researchers was the primal or direct estimation of the production function. However, due to biased and inconsistent estimates this method tend to be abandoned and an alternative method proved to be more suitable. Thus dual approaches were created which used cost or particularly profit function to minimize or maximize respectively.

In recent years, dual approaches became more and more popular due to its precious applications Kumbnakar (2001), Coelli et al. (2005).

a) It reflects a variety of behavioral objectives(cost minimization, profit maximization)
b) It accounts for multiple outputs
c) It is more convenient as it estimates both Technical Efficiency (TE) and Allocative Efficiency (AE) in the same time

The most important weakness of the dual approaches has been noted by (Greene, 1993) who has underlined the interpretation of the technical inefficiency measures that stems from dual model is not straight forward.

Apart from parametric models there are non-parametric models too. The most usual case in non-parametric models is Data Envelopment Analysis (DEA) technique. This method has both strengths and weaknesses. One of the most serious drawbacks here is that it does not allow for random noise derived from environmental heterogeneity, external shocks (exogenous), measurement error or omitted variables. As a result, every deviation from the frontier is attributed to inefficiency. A note working point around DEA use is the sensitivity of this method in some factors like the extreme observation, the number of observations as well as the number of inputs and outputs. These drawbacks are attributed to the fact that DEA is a deterministic model without random noise Ramanathan, (2003).

Another non-stochastic method which is less constrained in comparison with DEA is named "Free Disposal Hull" (FDH). In both methods any deviation of the frontier is a result of inefficiency Worthington (2001). However, FDH is less frequently applied in the education sector and this is obvious from the fact that only 3 of the 163 included studies in this survey have opted for FDH method. Agasisti (2011), Bonaccorsi et al. (2006), Fegg et al. (2004).

In spite of the extended use of frontier analysis techniques in the economic literature and the important advances that have been made among years there are many methodological questions that remain valid.

The main issue here is the examination of the effects of using different methodologies and the impacts of study specific characteristics on mean technical efficiency estimates. With regard to the alternative methodologies that can be applied the specific issues examined here include

a) Whether parametric deterministic or parametric stochastic frontiers produce different technical efficiency estimates than non-parametric studies.
b) Whether functional form has any effect on technical efficiency.
c) Whether technical efficiency from studies used primal approach differ from those used dual.
d) Whether the orientation of the model (input-output oriented models) or the returns of scale (constant vs variable returns of scale) may affect the

technical efficiency. Variable returns of scale (VRS) can be separated into increasing or decreasing returns of scale.

e) Whether dimensionality (sample size) and the number of inputs and outputs have a serious impact of technical efficiency.
f) Whether quality adjustment either in inputs or in outputs may have significant effects on technical efficiency.

Furthermore, study‘s specific characteristics are examined in an attempt to identify if some of them have significant impact on mean technical efficiency score. The dimension of these characteristics include

a) Whether technical efficiency varies according to the unit of analysis.
b) Whether geographical location generates a significant variation on mean technical efficiency.
c) Whether the income level of the examined country may influence the mean technical efficiency.
d) Whether private institutions perform better efficiency scores contrary to the public ones.
e) Whether published and unpublished papers may affect different technical efficiency.
f) Whether the papers published in higher quality journals have more serious impact on the mean technical efficiency score.

Data

An important consideration in the construction of the data base in studies using the Meta-regression analysis framework is to define a clear approach when literature is searched. To this end, a thorough search was conducted in 108 journals mainly associated with higher education institutions as well as journals with frontier analysis content. An extended literature search yielded to a total of 139 published papers in 69 different scientific journals during the period 1980-2012. Also 24 unpublished papers (working papers) where used from a total of 38 unpublished papers. It is vital to be noted that several other papers were retrieved (270) in the databases and journals included in the search. However, they were excluded due to inefficient information of the observed variables or due to characteristics that were not of interest in this survey.

Based on this sample a total of 8325 observations was collected as some papers report more than a separate year. The total number of the relevant papers was extracted exclusively from English literature covering the period 1980-2012.

Methodology

Introduction

The current econometric analysis consists of two parts, a theoretical and an empirical. The theoretical part includes each methodology that is used in the analysis. In specific, it is utilized the statistical method of descriptive statistics and econometric procedures, such as multiple regression analysis. The empirical part has the examined variables, tests and the findings that are utilized in the statistical analysis.

Theoretical Part

Descriptive Statistics

The purpose of descriptive statistical analysis is to describe the data that is possessed. Sometimes people distinguish between descriptive statistics and exploratory data analysis. Exploratory data analysis helps to understand what is happening in the data, while descriptive statistics aid to explain to other people what is happen in the data. While these two are closely related, they are not quite the same thing, and the best way of looking for something is not necessarily the best way of presenting it to others. In descriptive statistics analysis, we have used past trends in a timeline or we present basic statistical measures for the data (e.g. mean, standard deviation, percentages) Dafermos (2011).

Simple Regression Analysis

Regression analysis is a statistical tool for the investigation of relationships between variables. Usually, the investigator seeks to ascertain the causal effect of one variable upon another—the effect of a price increase upon demand, for example, or the effect of changes in the money supply upon the inflation rate. To explore such issues, the investigator assembles data on the underlying variables of interest and employs regression to estimate the quantitative effect of the causal variables upon the variable that they influence. The investigator also typically assesses the "statistical significance" of the estimated relationships, that is, the degree of confidence that the true relationship is close to the estimated relationship. Verbeek (2009).

A simple linear regression model is presented such as:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i,$$

Where Y is the dependent variable, β_o is the constant of the model, β_1 is the coefficient of the independent variable X, X is the independent variable and ε is the error term Halkos (2006).

Autocorrelation

Autocorrelation refers to the correlation of a time series with its own past and future values. Autocorrelation is also sometimes called "lagged correlation" or "serial correlation", which refers to the correlation between members of a series of numbers arranged in time. Positive autocorrelation might be considered a specific form of "persistence", a tendency for a system to remain in the same state from one observation to the next.

Heteroscedasticity

Heteroscedasticity occurs when the variance of the errors differs across observations i.e. variances are not constant.
Heteroscedasticity could be of two types:

1. Unconditional Heteroscedasticity: When variance does not systematically increase or decrease with changes in the value of independent variable. It is violation of assumption 4 but does not upholds any serious problems with regression.

2. Conditional Heteroscedasticity: It exists when error variance changes with the value of independent variable and it is more problematic.

Empirical Evidences

The current section presents the empirical findings of our research. In specific, it was used two statistical methods, descriptive statistics and multiple regression analysis. Descriptive statistics show initial statistic characteristic of the examined variables, such as the mean and the standard deviation. Moreover, it was utilized three different ways in order to estimate the results of the regression analysis. Each way consists of four econometric models. In specific, the methodology is displayed below in details.

Furthermore, it was used as dependent variable the mean technical efficiency score of a paper (MTES). The independent variables are the following:

When a meta-regression model framework is used it is common that the meta-independent variables will be represented by dummy variables. In this study 42 dummies will be used in an attempt to cover not only the alternative methodologies or model specification characteristics used in each study, but also additional determinant features. A representative sample are dummies pertaining to the country of origin of each study, the unit of analysis the quality of journal, the income level of the country and finally the profile of each institution which can be separated into public and private institutions.

More specifically, one dummy named parametric is used to separate between parametric and non-parametric methods. Additionally, there are four dummies according to the methodology each dummy used. To separate between deterministic and stochastic methods then the dummy deterministic is used. Turning to the specific method of each study dummy named SFA is determined for parametric non-deterministic models. Another two dummies named DEA and FDH are associated with non-parametric methods. It is noteworthy here that deterministic parametric frontier cases where not imported in this survey. Deterministic parametric frontiers assume that any observed deviation of the frontier is completely due to technical inefficiency contrary to stochastic parametric frontiers which are based on a

composed error model which allows us to differentiate between inefficiency and other stochastic influences. The latter assume a multiplicate composite error term, one symmetric component which captures the usual disturbances in econometrics and a one-sided error component which represent the frontier inefficiency, De Borger & Kerstens (1996).

Six dummy variables were used to define the specific characteristics of parametric models named primal and dual to distinguish between primal and dual approaches, CD and TL provided the functional form each study used. The abbreviation CD for Cobb Douglas and TL for Translog. Last but not least, two dummy variables named flexible and inflexible were used to separate the first order and second order flexible functional forms.

One dummy variable named Year Group was used to capture the year effect in accordance with the time period each study was conducted. Specifically, we used three separate year groups for the time periods: 1980-1989, 1990-1999, 2000-2012 which were weighted with 1, 2 and 3 respectively in an attempt to capture the tendency of MTEs changes as time elapses.

With regard to the institutions profile a dummy called private is used to separate public and private institutions. A dominant issue in each study is the mechanism assessing the quality in higher education. The literature on the production processes of education has already underlined that the quality of inputs and outputs matter for determining efficiency and effectiveness in this field Johnes (2006).

As a result the incorporation of quality adjustment measures in inputs and/or outputs could cause differences in the efficiency scores of each institution. Quality is not a one dimensional but rather a multi-dimensional concept, quality of teaching, quality of research, quality as a combination of activities etc. To this end, a dummy variable was used to define if a quality adjustment mechanism in inputs and/or outputs was incorporated by the researcher.

Another factor that may matter is regionality issues associated with the country of origin of each study. An overwhelming majority of literature comes from European countries or countries from the North America. The frequency of data in other continents like Africa is more than low. As a result, six dummies were used to capture the regionality effects.

The income level of each country may be an indicator of the relative expenses each country attributes in education. According to the World Bank the income level of a country is determined by each gross national product (GNP) per capital which is the value of all final goods and services produced in a country in one year (gross domestic product) plus income that residents have received from abroad minus income claimed by nonresidents divided by its population. In high income countries educational attainment is greatest. This is mainly true because of superior infrastructure and the political pressure placed on policy makers within these countries contrary to middle or low income countries. Consequently, four dummies were used to clarify the studies according to income level of each country of origin based on the World Bank classification.

A total of eight dummies are defined to discern the unit of analysis of each study. There is a variety of units that were analyzed. However the most common practice was studies using as a unit of analysis universities departments and colleges. Least common were studies using efficiency assessment in faculty members, administration and library services or assessment per countries higher education.

A highly discussed dimension in most surveys is the publication bias that many of them may suffer from. This is a selection bias which can arise because much of the research with respect to a specific subject may remain unpublished or unreported due to the mistrust many editors and researchers show to results that are less frequent or include contradictions compare to the traditional literature. Sometimes, this selection bias may be an outcome of misevaluation of the results, Haelermans (2009). That is why a dummy named published was included to capture if the relative study was published or unpublished. A further clarification in published papers was done according to the quality of journal each paper stems from. This clarification was based in the list of scientific journals published by Katranidis (2009). A total of four dummies were defined to capture the four different qualities of journals.

Another dimension that should be tested is whether models which include more inputs and outputs might lead to significantly higher efficiency scores, Haelermans (2009). That is why a dummy for the aggregate number of inputs and outputs was created. The last two dummies search the differences arise between studies pertaining to the returns of scale and the orientation (input-output oriented).

A dummy variable named CSR accounts for studies using constant returns of scale contrary to studies with variable returns of scale (VRS) (increasing-decreasing returns of scale).When an economy virtualize constant returns of scale means that a proportionate increase in all inputs result in the same proportionate increase in outputs (e.g. doubling all inputs leads to exactly twice as much output). In an increasing returns of scale economy a proportionate increase in inputs leads to a more than proportionate increase in output and finally when a production function exhibits decreasing returns of scale the proportionate increase in output is less than the proportionate increase of inputs, Coelli et al. (2005).

The last dummy should be clearly defined here is that named orientation and is regarded with the input or output oriented measures. When technical efficiency is measured using an input oriented model a firm reduce its input quantities proportionally without changing the output quantities produced. Alternatively, in output oriented measures of technical efficiency the question is how much can output quantities be proportionally expanded without altering the input quantities used.

During the econometric analysis, it was decided to include three alternative ways of modelling estimation. In specific, the empirical analysis is based on Stanley (2001). It should be pointed out that the basic models remain unchanged but the dependent variable (MTES) was replaced by others which are similar. At the first method, the variable MTES was equally weighted by treating each alternative estimate as an observation even if they arrived from the same study. This way offers more weight to studies with multiple estimates. Additionally, at the second method, the dependent variable ($MTESw_1$) was equally weighted, as each study is treated as a single observation in the sample regardless the number of alternative estimates each study provides. Therefore, it is able to select one of these estimates or the average of the multiple estimates (we use the average from many comparable estimates). Finally, the third alternative way tries to differently weight each estimation. Each weight here is extracted according to the total number of estimates each study contains so that the aggregation of weights in each study be equal to unit (third way – variable $MTESw_2$). The three alternative ways are used in order to observe the actual differences at our results.

Descriptive Statistics

The next tables present the descriptive statistics of these studies. A total of 163 studies were included in the analysis where 152 of them applied deterministic models and 19 stochastic models. This discrepancy between the sum of deterministic and stochastic studies (171 studies) and the reported number of included papers (163 studies) is due to the fact that some studies applied more than one techniques. Generally, the majority of studies rely on deterministic frontiers and the use of DEA. More specifically, 149 cases using DEA, 19 cases using SFA and 3 cases using FDH were retrieved.

Table 1 shows that the average mean technical efficiency for all deterministic models is 81.94% compare to 91,13% for all stochastic models. A comparison between the average mean technical efficiency of parametric and non-parametric estimates demonstrates that the latter (83.56%) are lower than the former (91.13%). The standard deviation do not indicate significant deviations as it ranges between 0.25-0.26. A significant difference is observed between the average mean technical efficiency of DEA and SFA models recorded 91.13% and 81.94% respectively.

Another interesting difference in average mean technical efficiency is that between primal (76.21%) and dual models (93.9%) where the latter presents indeed higher rate. Turning to the effect of functional form Cobb Douglas recorded lower average mean technical efficiency (57.98%) compare to Translog. Between flexible and inflexible functional forms the discrepancy in average mean technical efficiency is more than obvious. The first one reached 93.76% and the second one only 57.98%.

Table 1

	MEAN	**MAX**	**MIN**	**STANDARD DEVIATION**	**MODE**	**OBSERVATIONS**	**Number of cases**
PARAMETRIC	0,911354	3,97	0,143	0,252219	0,93	653	19
Non-Parametric	0,835667	6,193	0,049	0,26776	1	3655	152
SFA	0,911354	3,97	0,143	0,252219	0,93	653	19

DEA	0,819427	6,193	0,0008	0,293801	1	7525	149
FDH	1,094806	2,314	0,54	0,299953	1	98	3
PRIMAL	0,762168	1,052	0,143	0,25785	1	95	7
DUAL	0,939036	3,97	0,179	0,242744	0,991	552	12
DETERMINISTIC	0,819427	6,193	0,0008	0,293801	1	7525	152
FLEXIBLE	0,937653	3,97	0,179	0,233349	0,93	605	17
INFLEXIBLE	0,579875	0,91	0,143	0,248181	0,35	48	2
CD	0,579875	0,91	0,143	0,248181	0,35	48	3
TL	1,155557	3,97	0,676	0,378575	1	131	6

Table 2 summarizes the average mean technical efficiency according to the geographical region where the study took place. Despite the fact that the larger number of cases is in Europe (82 cases) North America (USA, Canada) performs better with regard to average mean technical efficiency (96,67%) contrary to Europe's 78,73%. Also, Latin America, Africa and Australia recorded more than 83% in average mean technical efficiency. The only continent accounts for less than 79% is Europe. It should be pointed that there were three cases: there were data from more than one regions.

Table 2

Region	MEAN	MAX	MIN	STANDARD DEVIATION	MODE	Obs.	Number of cases
OVERALL SAMPLE	0,862992	6,193	0,0008	0,075951	1	8325	163
North America	0,966792	6,193	0,296	0,305511	1	1178	21
Latin America	0,839023	1	0,143	0,22266	1	129	2
Asia	0,836706	2,632	0,0008	0,310217	1	1864	42
EU	0,787377	3,97	0,055	0,285889	1	4644	82
Australia	0,893277	1	0,388	0,120636	1	397	9
Africa	0,854779	1,035	0,243	0,185389	1	113	4

Turning to the unit of analysis, **table 3** displays the results for the average mean technical efficiency according to the unit each study examined. The most common units of analysis are the university and department units with 70 and 41 cases respectively. Their AMTEs gap is wide and amounts to a difference of 7%. Another important point here is that colleges present higher AMTEs (89.98%) than universities' AMTEs 85.96%. The remaining categories (Faculty, Administration Services, Library Services, Vocational institutes) apart from the country unit of analysis show rates under 80% in AMTEs.

Table 3

Unit of Analysis	MEAN	MAX	MIN	STANDARD DEVIATION	MODE	OBSERVATIONS	Number of cases
OVERALL	0,8181	6,193	0,012	0,0927	1	8325	163
UNIVERSITY	0,8596	6,193	0,0008	0,3339	1	4203	70
DEPARTMENT	0,7927	1,002	0,012	0,2227	1	2618	41
FACULTY	0,6702	1,25	0,049	0,2733	1	452	14
COLLEGE	0,8998	1,163	0,43	0,1241	1	461	7
LIBRARY	0,7943	1	0,291	0,2039	1	172	6
VOCATIONAL	0,7464	1	0,031	0,2516	1	243	2
ADMINISTRATION	0,6876	0,734	0,621	0,0591	-	3	2
COUNTRY	1,0942	2,328	0,614	0,3098	1	173	5

In **table 4** a further clarification is given for the Average Mean Technical Efficiency according to the income level each under study country has. The highest figures are recorded by Upper Middle Income countries (86.92%). Whereas the high income level countries lied third (82.74%) despite that they aggregate more cases. The remaining countries which fall in the low income countries category reach 85.58% in average mean technical efficiency outperforming better form the high income. In this level of analysis there were only two cases where more than one income levels were used.

Table 4

Income level	MEAN	MAX	MIN	STANDARD DEVIATION	MODE	OBSERVATIONS	Number of cases
OVERALL	0,825426	6,193	0,0008	0,06236	1	8325	163
HIC	0,827418	6,193	0,012	0,288125	1	6369	116
UMIC	0,869244	2,632	0,0008	0,346849	1	1114	22
MIC	-	-	-	-	-	-	
LMIC	0,858882	1,167	0,245	0,19601	1	441	9
LIC	0,74616	1	0,031	0,265204	1	401	14

Table 5

	MEAN	MAX	MIN	STANDARD DEVIATION	MODE	OBSERVATIONS	Number of cases
Private	0,8607	4,071	0,031	0,289136	1	1184	12
Public	0,8378	6,193	0,012	0,247458	1	6173	105
Quality-Adjustment	0,8506	2,882	0,031	0,23275	1	3060	54
Non-quality Adjustment	0,8714	6,193	6,193	0,277783	1	1986	104
Published	0,8622	6,193	0,00080	0,276509	1	7089	138
Unpublished	0,6496	1	0,031	0,315698	1	1236	25
Input oriented	0,8574	2,882	0,012	0,267406	1	3486	70
Output oriented	0,8571	6,193	0,0008	0,282942	1	4104	82
CRS	0,7214	1,865	0,0008	0,301408	1	2278	50
VRS	0,8767	6,193	0,0490	0,298244	1	5155	71

Table 5 summarizes the Average Mean technical Efficiency with regard to the profile of the institution, the classification about quality adjusted input and output, the orientation of the study and finally the returns of scale each study has implemented. It is obvious that the most studies focused in public institutions (105) however they perform lower than the private ones (83.78%) compared to (86.07%). It should me also noted that there were 25 cases which presented data for both private and public institutions and 21 cases were no exact information was extracted.

The vast majority of studies in this survey were cases without quality adjusted inputs and outputs (104) compare to only 54 cases where researchers had the availability of data to use quality adjusted inputs and/or outputs. The important fact here is that studies without quality adjustment show higher AMTEs (87.14%) than those which incorporate quality measures (85.06%).

The magnitude of published studies is indeed larger (138 cases) compare to only 25 unpublished cases. It has to be pointed that the AMTEs rate shows significant discrepancy between these two categories with the former reaching 86.22% and the latter 64.96%.

Furthermore, no significant deviation in AMTEs is observed between input and output oriented studies as in both of them the AMTEs is approximately at 85%.

An interesting pattern is observed regarding the returns of scale each study used. Studies with variable returns of scale (increasing /decreasing returns of scale) outperform the AMTEs rates of studies with constant returns of scales. It is notable here that 24 cases used both techniques and 18 cases provided no relative information.

Table 6

Quality of the paper	**MEAN**	**MAX**	**MIN**	**STANDARD DEVIATION**	**MODE**	**OBSERVATIONS**
Quality A	1,1902	2,882	0,133	0,449419	1	231

Quality B	0,8540	6,193	0,0008	0,268814	1	2103
Quality C	0,8125	3,97	0,167	0,258266	1	1544
Quality D	0,7988	1	0,012	0,222203	1	1189

In **table 6** differences in AMTEs are reported across the qualities of journals. Journals fall in A Quality level overshoot the other three categories despite the fact that they account for fewer observations.

Table 7

YEAR GROUP	MEAN	MAX	MIN	STANDARD DEVIATION	MODE	OSERVATIONS
1980-1889	0,7797	1,035	0,012	0,216225	1	1539
1990-1999	0,8999	2,882	0,111	0,701985	1	2623
2000-2013	0,8021	2,882	0,111	0,42052	1	4163

Table 7 suggests that the second year group 1990-1999 records the highest AMTEs (89.91%) among the other two groups. The interesting fact here is that as time elapses after 2000 the AMTEs falls significantly and a possible explanation may be that after 2000 not enough new knowledge was introduced to the literature but a reuse of the existing one is observed.

Multiple Regression Analysis

During this section of the thesis, it is important to mention the econometric models which are used in order to present the empirical results. In specific, each model is displayed below. Also, it is mentioned that four different models were estimated having as dependent variable the mean technical efficiency score (MTES) as well as its variations. In addition, it is important to mention that there is not detected any problems of autocorrelation and heteroscedasticity in the models. The autocorrelation was checked by using Breusch–Godfrey test. Also, the heteroscedasticity was checked by utilizing the White-test. At the end, it is pointed out that the Ordinary-Least-Square (OLS) method is used in order to produce the results of the regression analysis and the confidence interval of the analysis is equal to 95%.

Meta-regression Model

Observations of technical efficiency scores in higher education were collected from a wide variety of journals the economic literature provides. This technical efficiency scores serve as the dependent variable in a series of meta-regressions. A set of 41 meta-independent variables were used as explanatory variables.

Based on a simple OLS model the meta-regression can be written as:

$$\text{Mean Technical Efficiency} = a_0 + \sum_{i=1}^{j} \beta_j D_{ji} + \mu_i$$

Where D_{ji} is a dummy variable for the meta-independent variable j (j=1,2,…..,J) and estimate point i (i=1,2,….,N), β_i gives the impact of study attribute j on the effect size, and μ_i is the error term.

First Model

The first model is presented below:

$MTES_i$ = f (UOA_VOCATIONAL, UOA_UNIVERSITY, UOA_LIBRARY, UOA_FACULTY, UOA_COUNTRY, UOA_COLLEGE, UOA_ADMINISTRATION, UOA_DEPARTMENT, REG_AFRICA, REG_ASIA, REG_AUSTRALIA, REG_EU, REG_LATIN_AMERICA, REG_NORTH_AMERICA, QUALITY_ADJUSTMENT,

QUALITY_A, QUALITY_B, QUALITY_C, QUALITY_D, YEAR_GROUP, CONSTANT).

This model is constructed according to criteria of interest each researcher has and criteria associated with the availability of data in each region (country) for the different inputs and outputs.

Also, it is important to mention that the dependent variable (MTES, $MTESw_1$, and MTESw2) changes when alternative way of estimation is used.

First way

The mean technical efficiency score (dependent variable – MTES) was calculated without any weight.

Variable	Coefficient	Std. Error	t-Statistic	Prob*
UOA_VOCATIONAL	0.307587	0.123868	2.483175	0.0130
UOA_UNIVERSITY	0.466252	0.122423	3.808527	0.0001
UOA_LIBRARY	0.306425	0.123711	2.476946	0.0133
UOA_FACULTY	0.317700	0.123121	2.580381	0.0099
UOA_COUNTRY	0.814703	0.124223	6.558398	0.0000
UOA_COLLEGE	0.489838	0.122831	3.987896	0.0001
UOA_ADMINISTRATION	0.365249	0.198567	1.839421	0.0659
UOA_DEPARTMENT	0.380960	0.122252	3.116193	0.0018
REG_AFRICA	0.519086	0.124440	4.171383	0.0000
REG_ASIA	0.544251	0.121983	4.461679	0.0000
REG_AUSTRALIA	0.592484	0.122743	4.827012	0.0000
REG_EU	0.439492	0.121839	3.607166	0.0003
REG_LATIN__AMERICA	0.469906	0.124205	3.783312	0.0002
REG_NORTH__AMERICA	0.618919	0.121867	5.078651	0.0000
QUALITY_ADJUSTM	0.039052	0.006601	5.916331	0.0000

ENT				
QUALITY_A	0.284735	0.019623	14.51002	0.0000
QUALITY_B	0.016044	0.007987	2.008841	0.0446
QUALITY_C	0.013279	0.008731	1.520809	0.1283
QUALITY_D	-0.058510	0.009769	-5.989208	0.0000
YEAR_GROUP	-0.048712	0.005226	-9.321687	0.0000

**95% confidence interval*

The table above presents the empirical results of the regression analysis. The findings show that two independent variables seems to be statistically insignificant and therefore they do not have any impact on the dependent variable. In specific, the university administration does not influence the mean technical efficiency score (MTES) because the probability value is above 5% (P=6.59%) and thus the null hypothesis must be accepted. In addition, when the quality of a paper is C, then it will not influence the MTES. Furthermore all the statistical significant independent variables associated with the unit of analysis (vocational institutes, university, library, faculty, country, college, and department) present positive meta-regression coefficients, consequently each of them inflates the mean technical efficiency score.

The same pattern is repeated for the dummies (independent variables) that control the regionality impact, as the total meta-regression coefficients seem to have positive impact to the MTES. Also, it is pointed out that the variables quality D and year group have negative impact on the dependent variable MTES. Overall in this model the unit of analysis, the region of origin of each study, the quality of the journal and the year of the study affect the MTES.

Second Way

The mean technical efficiency score (dependent variable – MTESw1) was calculated by selecting for each study only the average of the individual estimates each study contains.

Variable	Coefficient	Std. Error	t-Statistic	Prob*
UOA_VOCATIONAL	-0.060754	0.182968	-0.332046	0.7399

UOA_UNIVERSITY	0.088759	0.182546	0.486230	0.6268
UOA_LIBRARY	-0.069691	0.183080	-0.380662	0.7035
UOA_FACULTY	-0.037899	0.182765	-0.207363	0.8357
UOA_DEPARTMENT	0.004291	0.182638	0.023495	0.9813
UOA_COUNTRY	0.441157	0.183125	2.409043	0.0160
UOA_COLLEGE	0.123593	0.182386	0.677644	0.4980
UOA_ADMINISTRATION	-0.008855	0.210873	-0.041994	0.9665
REG_AFRICA	0.417914	0.093627	4.463602	0.0000
REG_ASIA	0.443942	0.092119	4.819235	0.0000
REG_AUSTRALIA	0.489192	0.092643	5.280384	0.0000
REG_EU	0.340137	0.092003	3.697004	0.0002
REG_LATIN__AMERICA	0.373327	0.093452	3.994846	0.0001
REG_NORTH__AMERICA	0.521246	0.092012	5.664982	0.0000
QUALITY_ADJUSTMENT	0.039804	0.004454	8.936668	0.0000
QUALITY_A	0.283649	0.013270	21.37472	0.0000
QUALITY_B	0.015755	0.005389	2.923320	0.0035
QUALITY_C	0.014499	0.005892	2.460626	0.0139
QUALITY_D	-0.059826	0.006592	-9.075405	0.0000
YEAR_GROUP	-0.050425	0.003529	-14.28864	0.0000
C	0.478636	0.204563	2.339800	0.0193

**95% confidence interval*

The table above presents the empirical findings of the second way. It was discovered that there is no statistically significance between the dependent variable ($MTESw_1$) and the type or characteristic of the educational institution. However, the institution's administration has no influence (prob=96.65%) on the mean technical efficiency score. On the other hand, the country seems to have statistically positive impact (prob=1.6%) on the dependent variable. Also, any other independent factor is statistically significant according to the results of the table above. The regionality

impact continues to exist and inflates the MTES. The same apply for the papers quality as well as the year effect.

Third way

The mean technical efficiency score (dependent variable – $MTESw_2$) was calculated by using as weight the ratio 1/number of estimates in each paper.

Variable	Coefficient	Std. Error	t-Statistic	Prob*
UOA_VOCATIONAL	-0.014315	0.034584	-0.413910	0.6790
UOA_UNIVERSITY	-0.012510	0.034504	-0.362562	0.7169
UOA_LIBRARY	-0.000636	0.034605	-0.018379	0.9853
UOA_FACULTY	-0.004863	0.034546	-0.140763	0.8881
UOA_DEPARTMENT	-0.014938	0.034522	-0.432712	0.6652
UOA_COUNTRY	0.006919	0.034614	0.199880	0.8416
UOA_COLLEGE	-0.012638	0.034474	-0.366595	0.7139
UOA_ADMINISTRATION	0.437216	0.039859	10.96917	0.0000
REG_AFRICA	-0.155533	0.017697	-8.788572	0.0000
REG_ASIA	-0.167085	0.017412	-9.595954	0.0000
REG_AUSTRALIA	-0.164446	0.017511	-9.390877	0.0000
REG_EU	-0.172242	0.017390	-9.904531	0.0000
REG_LATIN__AMERICA	-0.174194	0.017664	-9.861453	0.0000
REG_NORTH__AMERICA	-0.170018	0.017392	-9.775715	0.0000
QUALITY_ADJUSTMENT	0.000621	0.000842	0.737562	0.4608
QUALITY_A	0.012160	0.002508	4.847958	0.0000

QUALITY_B	0.003557	0.001019	3.491717	0.0005
QUALITY_C	0.000643	0.001114	0.577498	0.5636
QUALITY_D	-0.000137	0.001246	-0.110000	0.9124
YEAR_GROUP	0.000200	0.000667	0.300107	0.7641
C	0.196828	0.038666	5.090482	0.0000

**95% confidence interval*

It is observed that the utilization of the third way produces more coefficients which are not statistically significant instead of the first way. In specific, it was discovered that the mean technical efficiency score does not be influenced by the factors which are related to the type of educational institution. Therefore, the MTES does not be influenced if an educational institution is a vocational institute or a university. In addition, if the paper provides efficiency scores accessing the library department then it has no impact on MTES. Also, the MTES seems to be totally independent by any influences from using as a unit of analysis faculties, departments, countries and colleges. In addition, the quality adjustment coefficient is statistically insignificant and therefore it does not influence the dependent variable. At the end, the independent variables 'quality C, quality D and year group' seems to have no effect on the dependent variable. The only independent variables which still remain statistically significant regardless of the way of estimation are the variables capture regionality effects.

Second Model

The second model is displayed below:

$MTES_i = f\ (PARAMETRIC,\ DETERMINISTIC,\ DEA,\ FDH,\ ORIENTATION,\ AGREG\_INPUTOUTPUT,\ PRIVATE,\ CONSTANT)$

This model aims to explain the methodological influences in MTES. This features are in the discretion of each researcher.

Also, it is important to mention that the dependent variable (MTES, MTESw1, and MTESw2) changes when alternative way of estimation is used.

First way

The mean technical efficiency score (dependent variable – MTES) was calculated without any weight.

Variable	Coefficient	Std. Error	t-Statistic	Prob*
PARAMETRIC	-0.041960	0.013234	-3.170511	0.0015
DETERMINISTIC	-0.140488	0.013331	-10.53859	0.0000
DEA	-0.003564	0.014342	-0.248535	0.8037
FDH	0.211226	0.043291	4.879199	0.0000
ORIENTATION	-0.023404	0.006594	-3.549192	0.0004
AGREG__INPUTOUTPUT	0.005767	0.000602	9.583767	0.0000
PRIVATE	0.020584	0.009137	2.252754	0.0243
C	0.940849	0.011777	79.88821	0.0000

**95% confidence interval*

The table above present the results of the regression analysis. It was discovered that each independent factor is statistically significant except the DEA variable because its probability value is below 5% (prob=80.37%). The variables 'parametric', 'deterministic' and 'orientation' seems to influence negative the mean technical efficiency score. As a result these meta-independent variables deflate the MTES. Each other independent variable (FDH, AGREG_INPUTOUTPUT, PRIVATE) has statistically significant positive impact on the dependent variable (MTES). The statistical significance of the variable private reveals that when private institutions are analyzed this inflates the MTES (positive impact).

Second Way

The mean technical efficiency score (dependent variable – MTESw1) was calculated by selecting for each study only the average of the individual estimates each study contains.

Variable	Coefficient	Std. Error	t-Statistic	Prob*
DETERMINISTIC	-0.116082	0.163963	-0.707975	0.4790
DEA	-0.016932	0.165520	-0.102299	0.9185
FDH	0.216443	0.030966	6.989662	0.0000
PARAMETRIC	-0.055613	0.023714	-2.345120	0.0190
ORIENTATION	-0.016345	0.004064	-4.021546	0.0001
AGREG__INPUTOUTPUT	0.005007	0.000425	11.77794	0.0000
PRIVATE	0.020483	0.005257	3.896244	0.0001
C	0.934653	0.023307	40.10102	0.0000

**95% confidence interval*

The results of the second way support that the mean technical efficiency score is not influenced by the 'deterministic' and 'DEA' independent variables. Also, the first method was found that DEA variable is not statistically significant and therefore it has no impact on the MTES variable and the same pattern is revised here again. The remaining variables tend to remain statistically significant.

Third way

The mean technical efficiency score (dependent variable – $MTESw_2$) was calculated by using as weight the ratio 1/number of estimates in each paper.

Variable	Coefficient	Std. Error	t-Statistic	Prob*
PARAMETRIC	0.009662	0.001745	5.538273	0.0000
DETERMINISTIC	0.776285	0.001607	483.1311	0.0000
DEA	-0.767470	0.001885	-407.1761	0.0000
FDH	0.018914	0.001727	10.95271	0.0000
ORIENTATION	0.001343	0.000836	1.606378	0.1082
AGREG__INPUTOUTPUT	0.000189	5.78E-05	3.274480	0.0011
PRIVATE	-0.001241	0.000846	-1.467115	0.1424
C	0.005917	0.001474	4.014334	0.0001

**95% confidence interval*

The third way produces different results. The orientation seems to not influence the mean technical efficiency score (prob=10.82%). Also, the same effect was discovered for the profile of the education institution (private). The only variable from those which are statistically significant and influences negative the mean technical efficiency score (MTES) is DEA.

Third Model

The third model is displayed below:

$MTES_i = f\ (QUALITY\_A,\ QUALITY\_B,\ QUALITY\_C,\ QUALITY\_D,\ PUBLISHED,\ LIC,\ HIC,\ LMIC,\ CONSTANT)$

This model tries to interpret the impact of the journals' quality as well as the impact each country income level has in MTES.

Also, it is important to mention that the dependent variable (MTES, MTESw1, and MTESw2) changes when alternative way of estimation is used.

First way

The mean technical efficiency score (dependent variable – MTES) was calculated without any weight.

Variable	Coefficient	Std. Error	t-Statistic	Prob*
QUALITY_A	0.285213	0.019210	14.84713	0.0000
QUALITY_B	-0.052002	0.008804	-5.906769	0.0000
QUALITY_C	-0.092152	0.009488	-9.712844	0.0000
QUALITY_D	-0.124917	0.010297	-12.13125	0.0000
PUBLISHED	0.251311	0.009947	25.26377	0.0000
LIC	-0.131344	0.016448	-7.985543	0.0000
HIC	-0.056479	0.009218	-6.127347	0.0000
LMIC	-0.054119	0.015806	-3.424000	0.0006
C	0.710898	0.011020	64.50964	0.0000

**95% confidence interval*

The table above presents the empirical results of regression analysis for the third model. In specific, every coefficient seems to be statistically significant because the probability value is below of 5%. In addition, each independent variable influences negative the mean technical efficiency score. However, only two independent variables have positive impact on the dependent variable. In specific, if a paper is published in a journal ranked with quality A, then the MTES would increase. The same effect was discovered for the variable 'published'.

Second Way

The mean technical efficiency score (dependent variable – MTESw1) was calculated by selecting for each study only the average of the individual estimates each study contains.

Variable	Coefficient	Std. Error	t-Statistic	Prob*
QUALITY_A	0.285477	0.013150	21.70912	0.0000
QUALITY_B	-0.051989	0.006027	-8.626617	0.0000
QUALITY_C	-0.091632	0.006495	-14.10862	0.0000
QUALITY_D	-0.124190	0.007049	-17.61847	0.0000
PUBLISHED	0.250532	0.006810	36.79144	0.0000
LIC	-0.128570	0.011259	-11.41904	0.0000
HIC	-0.055771	0.006310	-8.838785	0.0000
LMIC	-0.053386	0.010820	-4.934149	0.0000
C	0.710687	0.007544	94.20907	0.0000

**95% confidence interval*

This second model is more stable and it follows the results of the first method. Therefore, these findings supports the empirical evidences of the first model. More importantly here neither variable is statistically insignificant. At last the variables published and if a paper is published in a journal ranked as quality A continue to have positive impact into the MTES.

Third way

The mean technical efficiency score (dependent variable – $MTESw_2$) was calculated by using as weight the ratio 1/number of estimates in each paper

Variable	Coefficient	Std. Error	t-Statistic	Prob*
QUALITY_A	0.013609	0.003549	3.835087	0.0001
QUALITY_B	0.001298	0.001065	1.218982	0.2229
QUALITY_C	-0.002418	0.001330	-1.817960	0.0691
QUALITY_D	0.001872	0.000838	2.232723	0.0256
PUBLISHED	0.001237	0.001379	0.896941	0.3698

LIC	0.012288	0.001895	6.486001	0.0000
HIC	-0.000408	0.001208	-0.337460	0.7358
LMIC	0.002999	0.001365	2.197759	0.0280
C	0.014648	0.001766	8.295113	0.0000

**95% confidence interval*

The third way does not produce the same results than the first method. In specific, there are more variables which are statistically insignificant according to the statistical criteria. The MTES does not seem to be influenced by the quality B and C of journal. In addition, if a country has higher income or the paper is published, these factors have no impact on MTES.

Fourth Model

The fourth model is displayed below:

$MTES_i = f\ (TL,\ SFA,\ CD,\ QUALITY\_ADJUSTMENT,\ AGREG\_INPUTOUTPUT,\ YEAR\_GROUP,\ CSR,\ DUAL\ CONSTANT)$

This model aims to explain the methodological influences in MTES. More specifically it is thoroughly examined how the specific characteristic of parametric models i.e model specification (like the functional form, the approached used) can differentiate the MTES results. This features are in the discretion of each researcher.

Also, it is important to mention that the dependent variable (MTES, $MTESw_1$, and MTESw2) changes when alternative way of estimation is used.

First way

The mean technical efficiency score (dependent variable – MTES) was calculated without any weight.

Variable	Coefficient	Std. Error	t-Statistic	Prob*

TL	0.455951	0.035785	12.74145	0.0000
SFA	-0.364639	0.053328	-6.837718	0.0000
CD	0.138956	0.068194	2.037670	0.0416
QUALITY_ADJUSTMENT	0.041425	0.007359	5.629334	0.0000
AGREG__INPUTOUTPUT	0.010671	0.000762	14.00799	0.0000
YEAR_GROUP	-0.040536	0.005245	-7.728681	0.0000
CSR	-0.159320	0.007501	-21.24037	0.0000
DUAL	0.379968	0.051198	7.421569	0.0000
C	0.889135	0.014985	59.33367	0.0000

**95% confidence interval*

The table above displays the empirical results of the first way in the fourth econometric model. Each independent variable is statistically significant and therefore it influences the dependent variable. Every independent factor influences positive the mean technical efficiency score, except the SFA, CSR and the year group. The important finding here is that the aggregation of inputs and outputs inflate (positive impact) in the MTES and this is in accordance with the findings by Healermans (2009), that the use of more outputs might lead to higher efficiency scores. It should be also noted that the dummy which controls the effects in MTES when quality adjusted inputs and outputs are used, in this model remains statistically significant and inflates (positive impact) the MTES contrary to the first model where it was statistically insignificant. The use of Cobb Douglas or Translog functional form seems to inflate the MTES. Also, the use of dual approaches seems to have positive effects on MTES. Finally, the variable which controls the year effect reveals that the closer the study is to the present the more negative is the impact on

MTES.

Second Way

The mean technical efficiency score (dependent variable – MTESw1) was calculated by selecting for each study only the average of the individual estimates each study contains.

Variable	Coefficient	Std. Error	t-Statistic	Prob*
TL	0.212207	0.025748	8.241723	0.0000
SFA	-0.122622	0.038370	-3.195771	0.0014
CD	0.054450	0.049067	1.109706	0.2672
QUALITY_ADJUSTMENT	0.036756	0.005295	6.941912	0.0000
AGREG__INPUTOUTPUT	0.009652	0.000548	17.60990	0.0000
YEAR_GROUP	-0.039079	0.003774	-10.35535	0.0000
CSR	-0.160963	0.005397	-29.82453	0.0000
DUAL	0.134391	0.036838	3.648187	0.0003
C	0.896995	0.010782	83.19182	0.0000

**95% confidence interval*

The use of second way creates the same results as the first way. However, the Cobb-Douglas functional form seems to be statistically insignificant (prob=26.72%) and therefore the use of this specific functional form does not influence the mean technical efficiency score (MTES). It is also important to be pointed out that the dummy variable which captures each year group effects in MTES is statistically significant, consequently the closer the year group to the present the more negative is the effect in MTES. It should be also pointed out that in both first and second way the use of constant returns of scale deflates the MTES.

Third way

The mean technical efficiency score (dependent variable – $MTESw_2$) was calculated by using as weight the ratio 1/number of estimates in each paper.

Variable	Coefficient	Std. Error	t-Statistic	Prob*
TL	-0.001404	0.003957	-0.354756	0.7228
SFA	0.032452	0.009351	3.470346	0.0005

CD	-0.028520	0.012465	-2.287928	0.0222
QUALITY_ADJUSTMENT	0.000515	0.000990	0.520917	0.6024
AGREG__INPUTOUTPUT	0.000267	8.62E-05	3.098497	0.0020
YEAR_GROUP	0.001174	0.000617	1.901925	0.0572
CSR	0.005428	0.001003	5.413766	0.0000
DUAL	-0.029511	0.008882	-3.322460	0.0009
C	0.009817	0.001702	5.769470	0.0000

**95% confidence interval*

In addition, the table above shows the findings of the second way. In specific, the third method produces different results than the previous way. Hence, the independent factors, such as Translog functional form, quality adjustment and year group seems to be statistically insignificant. At the end, it was discovered important differences concerning of the sign of the coefficient (negative or positive). More specifically, a sign change is observed in both CRS and Dual coefficients turned their signs becoming positive and negative respectively compare to the first two ways.

Empirical Conclusions

From an overall perspective, this survey reveals precious findings not only about the effects of each meta-independent variable on MTES but also the differences that arises across the three alternative ways of estimation.

Generally, the first way of estimation where the mean technical efficiency score (dependent variable – MTES) was calculated without any weight produces the most statistically significant variables in comparison with the two alternative ways. The third way where mean technical efficiency score (dependent variable – $MTESw_2$) was calculated by using as weight the ratio 1/number of estimates in each paper produced the fewer statistically significant variables.

As an overview of all four models and their different ways of estimation, the most important findings are summarized below. The variable which controls year effects has a negative impact on MTES across the models. Turning to the method of estimation, DEA and SFA produce different results as the former is statistically

insignificant apart from the third way when the latter is statistically significant having a negative effect on MTES. It is really remarkable that the unit of analysis of each study has no impact on MTES across the models (statistically insignificant). Private institutions seem to inflate the MTES as well as the variable which controls the aggregation of inputs and outputs (the more inputs-outputs are used the more MTES is inflated). Regardless the classification of each country income level, the effect on MTES is negative. In most cases the variables which capture quality adjustment measures in inputs and/or outputs as well as the orientation of the used method are statistically significant, with the former inflating the MTES and the latter deflating the dependent variable. The effect each functional form may have on MTES is controversial as it varies not only in the statistical significance but also in the effect may have (negative or positive) on MTES. Published papers seem to have a positive contribution to MTES contrary to unpublished papers. However, we could not come to conclusions about the effect the quality of the journal, each paper was published, may have due to the fact that both the statistical significance and the sign of the coefficient vary across the model and its way. The two last variables which are statistically significant across the different ways of estimation are the variables which control the constant or variable returns of scale and the one that discerns primal or dual approaches. However, the effect may have on MTES is controversial as it can be both negative and positive.

The econometric results suggest that studies come from North America generate higher MTES estimates compare to the other regions. The studies which contain DEA models yield lower estimates in MTES than studies follow SFA models. In addition, studies focusing on private institutions on average have highest level of MTES as well as studies using college as a unit of analysis. Last but not least, published paper tends to outperform better on average MTES than unpublished one.

A vital body of literature has emerged the last decades on technical efficiency measurement in higher education. The proliferation of these empirical studies predicated for a better organization of these empirical findings which reveal mixed results depending on the merit of the various methodologies have been developed across the years. As a result, the meta-regression analysis applied here attempts to integrate this extended range of empirical findings and enlighten the effects of

alternative methodological assumption as well as data particularities and other study case specificities in higher education technical efficiency measures.

In my view, additional work that incorporates an extension of the applied methodological framework of meta-regression analysis can be made by using random effects and fixed effects meta-regression analysis. This extension can cover and produce a better understanding of the possible result differences that may be attributed in paper-specific effects (heterogeneity across studies).

References

Abbott, M. and C. Doucouliagos. A Data Envelopment Analysis of the Efficiency of Victorian TAFE Institutes, *Australian Economic Review*, 2002, 35, 55–69.

Abbott, M. and C. Doucouliagos. Competition and efficiency: Overseas students and technical efficiency in Australian and New Zealand universities, *Education Economics*, 2009, 17, 31-57.

Abbott, M. and C. Doucouliagos. Technical and Scale Efficiency of Vocational Education and Training Institutions: The Case of the New Zealand Polytechnics, *New Zealand Economic Paper*,1999, Working paper NO. 22.

Abbott, M. and C. Doucouliagos. The efficiency of Australian universities: A data envelopment analysis, *Economics of Education Review*, 2003, 22, 89-97.

Abbott, M. and C. Doucouliagos. Total factor productivity and efficiency in Australia colleges of advanced education, *Journal of Educational Administration*, 2001, 39, 384-393.

Abou-Warda, S.H. Quality in Egyptian Higher Education Context: DEA Approach to Enhancement of Internal Quality Assurance Systems in Technical Departments, *Arab Journal of Administrative Sciences*, 2011, 18, 165-194.

Abramo, G., Cicero, T. and C.A. D'Angelo. A field-standardized application of DEA to national-scale research assessment of universities, *Journal of Informetrics*, 2011, 5, 618-628.

Abramo, G., D'angelo, C.A. and F. Pugini. The measurement of Italian Universities' research productivity by a non-parametric-bibliometric methodology, *Scientometrics*, 2008, 76, 225-244.

Afonso, A. and M. Santos. A dea approach to the relative efficiency of Portuguese public universities, *Portuguese Journal of Management Studies*, 2008, 67-87.

Agasisti, T. and A. Dal Bianco. Reforming the university sector: effects on teaching efficiency-evidence from Italy, *Higher Education*, 2009, 57, 477-498.

Agasisti, T. and C. Perez-Esparrells. Comparing efficiency in a cross-country perspective: the case of Italian and Spanish state universities, *Higher Education*, 2010, 59, 85-103.

Agasisti, T. and C. Salerno. Assessing the Cost Efficiency of Italian Universities, *Education Economics*, 2007, 15, 455-471.

Agasisti, T. and G. Johnes. Beyond frontiers: comparing the efficiency of higher education decision making units across more than one country, *Education Economics*, 2009, 17, 59-79.

Agasisti, T. and G. Johnes. Cost structure, efficiency and heterogeneity in US higher education: An empirical analysis. *Lancaster University Management School* Working Paper 2009/013.

Agasisti, T. and G. Johnes. Heterogeneity and the evaluation of efficiency: the case of Italian universities, *Applied Economics*, 2010, 42, 1365-1375.

Agasisti, T. Performances and spending efficiency in higher education: a European comparison through non-parametric approaches, *Education Economics*, 2011, 19, 199-224.

Agasisti, T., Dal Bianco, A., Landoni, P., Sala, A. and M. Salerno. Evaluating the Efficiency of Research in Academic Departments: an Empirical Analysis in an Italian Region, *Higher Education Quarterly*, 2011, 65, 267–289.

Agha, S.R., Kuhail, I., Abdelnabi, N., Salem, M. and A. Ghanim. Assessment of academic department's efficiency using data envelopment analysis, *Journal of Industrial Engineering and management*, 2011, 4, 301-325.

Ahn, T., Charnes, A. and W.W. Cooper. Some statistical and dea evaluations of relative efficiencies of public and private institutions of higher learning? *Socio-Economic Planning Sciences*, 1988, 22, 259-269.

Anderson, T.R., Daim, T.U. and F.F. Lavoie. Measuring the efficiency of university technology transfer, *Technovation*, 2007, 27, 306-318.

Andersson, C., Antelius, J., Mansson, J. and K. Sund. Technical Efficiency and Productivity at Higher Education Institutions –Some problems and some solutions.

Anupong Wongchai, Wen-Bin Liu and Ke-Chung Peng. DEA Metafrontier Analysis on Technical Efficiency Differences of National Universities in Thailand.

Arcelus, F.J. and D.F. Coleman. An efficiency review of university departments, *International Journal of Systems Science*, 1997, 28, 721-729.

Archibald, R.B. and D.H. Feldman. Graduation Rates and Accountability: Regressions Versus Production Frontiers, *Research in higher education*, 2008, 49, 80-100.

Aristovnik, A. and A. Obadic, The funding and efficiency of higher education in Croatia and Slovenia: a non-parametric comparison, *Munich Personal RePEc Archive*, 2011 No. 31466.

Avkiran, N.K. Investigating technical and scale efficiencies of Australian Universities through data envelopment analysis, *Socio-Economic Planning Sciences*,2001, 35, 57-80.

Balk, B.M. Scale efficiency and productivity change, *Journal of productivity analysis*, 2001, 15, 159-183.

Barros, C.P., Guironnet, J.P. and N. Peypoch. Productivity growth and biased technical change in French higher education, *Economic Modelling*, 2011, 28, 641-646.

Beasley, J. Comparing University Departments, *Omega*, 1990, 18, 171-183.

Beasley, J. E. Determining Teaching and Research Efficiencies, *Journal of the Operational Research Society*, 1995, 46, 441-452.

Belete B. Evaluating the efficiencies of university faculties: Adjusted data envelopment analysis. Paper for Accounting and Finance Association of Australia and New Zealand (AFAANZ) 2009 *Conference*, Adelaide, Australia, 5 – 7 July 2009.

Benos, N. and S. Zotou. Education and economic growth. A Meta-regresion analysis. *Munich personal RePEC Archive (MPRA)*, 2013, 46143.

Bergantino, A. S., Capozza, C. and F. Porcelli. Measuring Teaching Efficiency of the Italian University System: the Role of Market Structure. A two step DEA analysis at faculty level.

Bergantino, A. S., Capozza, C. and F. Porcelli. The Role of Market Structure in Determining the Efficiency of the Italian University System: a DEA analysis at faculty level.

Bonaccorsi, A., Daraio, C. and L. Simar. Advanced indicators of productivity of universities. An application of robust nonparametric methods to Italian data, *Scientometrics*, 2006, 66, 389-410.

Boys, K.A and R. Florax. Meta-Regression Estimates for CGE Models: A Case Study for Input Substitution Elasticities in Production Agriculture. Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Portland, July 29 – August 1, 2007.

Bradley, S., Johnes, J. and A. Little. Measurement and determinants of efficiency and productivity in the further education sector in England, *Bulletin of Economic Research*, 2010, 62, 0307-3378.

Bravo-Ureta, B.E., Solis, D., Moreiro Lopes, V.H., Maripani, G.F. Thiam, A. and T. Rivas. Technical efficiency in farming a Metaregression analysis. *Journal of productivity analysis*, 2007, 27, 57-79.

Breu, T.M. and R.L. Raab. Efficiency and Perceived Quality of the Nation's "Top 25" National Universities and National Liberal Arts Colleges: An Application of Data Envelopment Analysis to Higher Education, *Socio-Economic Planning Sciences*, 1994, 28, 33-45.

Carrington, R., Coelli, T. and D.S. Prasada Rao. The performance of Australian universities: conceptual issues and preliminary results, *Economic Papers*, 2005, 24, 145-163.

Castano, M.C.N. and E.C. Cabanda. Performance evaluation of the efficiency of Philippine Private Higher Educational Institutions: application of frontier approaches, *International Transactions in Operational Research*, 2007, 14, 431-444.

Castano, M-C.N. and E. Cabanda. Sources of Efficiency and Productivity Growth in the Philippine State Universities and Colleges: A Non-Parametric Approach, *International Business & Economics Research Journal*, 2007, 6, 79-90.

Casu, B. and E. Thanassoulis, Evaluating cost efficiency in central administrative services in UK universities, *Omega*, 2006, 34, 417-426

Casu, B., Shaw, D. and E. Thanassoulis. Using a Group Support System to Aid Input-Output Identification in DEA, *Journal of the Operational Research Society*, 2005, 56, 1363-1372.

Celik, O. and A. Ecer. Efficiency in accounting education: evidence from Turkish Universities, *Critical Perspectives on Accounting*, 2009, 20, 614-634.

Chang, D., Wu, C., Ching, G. and C. Tang. An evaluation of the dynamics of the plan to develop first-class universities and top-level research centres in Taiwan, *Asia Pacific Education Review*, 2009, 10, 47-57.

Chapple, W., Lockett, A., Siegel, D. and M. Wright. Assessing the relative performance of U.K. university technology transfer offices: parametric and non-parametric evidence, *Research Policy*, 2005, 34, 369-384.

Chen, J.K. and I.S. Chen. Inno-Qual efficiency of higher education: Empirical testing using data envelopment analysis, *Expert Systems with Applications*, 2011, 38, 1823-1834.

Cherchye, L. and P.V. Abeele. On research efficiency a micro-analysis of Dutch university research in Economics and Business Management, *Research Policy*, 2005, 34, 495-516.

Çınar, Y. Research and Teaching Efficiencies of Turkish Universities and Heterogeneity Considerations: Application of 'Multi-Activity DEA' and 'DEA by Sequential Exclusion of Alternatives' Models.

Coelli, T.J, Rao, D.S.P, O' Donnell C.J. and G.E. Battese. An introduction to efficiency and productivity analysis, 2nd edition, *Springer*, 2005, XVII, 350.

Çokgezen, M. Technical efficiencies of faculties of economics in Turkey, *Education Economics*, 2009, 17, 81-94.

Colbert, A., Levary, R.R. and M.C. Shaner. Determining the relative efficiency of MBA programs using DEA, *European Journal of Operational Research*, 2000, 125, 656-669.

Cunha, M. and V. Rocha. On the Efficiency of Public Higher Education Institutions in Portugal: An Exploratory Study. N. 468 September 2012

Dafermos, V. Social Statistics and Research Methodology with SPSS. *Ziti Press*, 2011.

De Borger, B. and K. Kerstens. Cost efficiency of Belgian local governments: A comparative analysis of FDH, DEA and econometric approaches. *Regional science and urban economics*, 1996, 26, 148-170.

De Witte, K. and N. Roggea. Accounting for exogenous influences in performance evaluations of teachers, *Economics of Education Review*, 2011, 30, 641-653.

Dharmapala, P.S. and H.M. Saber. Resource allocation within academic units DEA and goal programming approach with an application to an Arabian Gulf university. *Benchmarking: An International Journal*, 2007, 14, 202-210.

Doyle, J. and R. Green. Efficiency and Cross-efficiency in DEA: Derivations, Meanings and Uses, *Journal of the Operational Research Society*, 1994, 45, 5, 567-578.

Doyle, J.R. and R.H. Green. Self and peer appraisal in higher education, *Higher Education*, 1994, 28, 241-264.

Duh, R.R., Chen, K.T., Lin, R.C. and L.C. Kuo, Do internal controls improve operating efficiency of universities? Annals of operation research, 2011, DOI 10.1007/s10479-011-0875-6.

Dyckhoff, H., Dirksen, A. and E. Mbock. Measuring balanced efficiency with DEA: New approach and case study of German business schools' research performance.

Eckles, J.E. Evaluating the Efficiency of Top Liberal Arts Colleges, *Research in higher eduaction*, 2010, 51, 266-293.

Emrouznejad, A. and E. Thanassoulis. A mathematical model for dynamic efficiency using data envelopment analysis, *Applied Mathematics and Computation*, 2005, 160, 363-378.

Fandel, G. On the performance of universities in North Rhine-Westphalia, Germany: Governments redistribution of funds judged using DEA efficiency measures, *European Journal of Operational Research*, 2007, 176, 521-533.

Farell, M.J. The measurement of productivity efficiency, *Journal of the Royal Statistical Society*, Series A, CXX, Part 3, 253-290.

Farre, R., Grosskopf, S. and P. Roos. Malmquist productivity indexes: A survey of theory and practice, in R. Farre S. Grosskopf and R.R. Russell (Eds.), Index Numbers: Essays in Honor of Sten Malmquist, Kluwer Academic Publishers, Boston.

Fathi, B., Ahmadi, M. and T. Torabi. The Measuring of the efficiency of Islamic Azad University in Iran Using Data Envelopment Analysis (DEA) (Case study: Azad University Branches in region five).

Feng, Y.J., Lu, H. and K. Bi. An AHP/DEA method for measurement of the efficiency of R&D management activities in universities, *International Transactions in Operational Research*, 2004, 11, 181-191.

Flegg, A.T. and D.O. Allen. Congestion in the new British Universities: A further analysis, *Journal of the Operations Research Society of Japan*, 2009, 52, 186-203.

Flegg, A.T. and D.O. Allen. Does Expansion Cause Congestion? The Case of the Older British Universities, 1994–2004, *Education Economics*, 2007, 15, 75-102.

Flegg, A.T. and D.O. Allen. Using Cooper's Approach to Explore the Extent of Congestion in the New British Universities, *Economic Issues*, 2007, 12, 47-81.

Flegg, A.T., Allen, D.O., Field, K. and T.W. Thurlow. Measuring the efficiency of British universities: a multi-period data envelopment analysis, *Education Economics*, 2004, 12, 231-249.

Freemantle N., Cleland, J., Young, P. and J. Mason. β Blockade after myocardial infarction: systematic review and meta regression analysis. *BMJ: British Medical Journal*, 1999, 318.

Fu, T.T. and M.Y. Huang. Measuring the Performance and Relative Efficiency of Departments in the College of Commerce using DEA, *Forth workshop on knowledge economy and electronic commerce*, 42-62.

Fu, T-T and Y-H. Lu. Heterogeneous Output Quality and Efficiency Evaluation of Polytechnic Higher Education Institutions via DEA.

Gimenez, V.M. and J.L. Martınez. Cost efficiency in the university: A departmental evaluation model, *Economics of Education Review*, 2006, 25, 543-553.

Glass, J.C., McCallion, G., McKillop, D.G., Rasaratnam, S. and K.S. Stringer. Implications of variant efficiency measures for policy evaluations in UK higher education, *Socio-Economic Planning Sciences*, 2006, 40, 119-142.

Glass, J.C., McKillop, D.G. and G. O'Rourke. Evaluating the productive performance of UK universities as cost-constrained revenue maximizers: an empirical analysis, *Applied Economics*, 2002, 34, 1097-1108.

Glass, J.C., Mckillop, D.G. and G. O'Rourke. Productivity growth in UK accountancy departments 1989-96, *Financial Accountability & Management*, 1997, 13, 0267-4424.

Greene, W. The econometric approach to efficiency analysis. In: Fried HO, Lovell CAK, Schmidt SS (EDS) The measurement of productive efficiency: techniques and applications. Oxford University Press, 1993, 68–119.

Gwendolyn N. de Guzman M.C. and E. Cabanda. Selected Private Higher Educational Institutions In Metro Manila: A DEA Efficiency Measurement, *American Journal of Business Education*, 2009, 2, 97-108.

Haelermans C. A Meta-regression Analysis of education efficiency scores, *TIER working paper*, 2009, 11/09.

Haksever, C. and Y. Muragishi. Measuring Value in MBA Programmes, *Education Economics*, 1998, 6, 11-25.

Halkos, G. Econometrics – Empircal Applications in Eviews, Minitab, SPSS & Excel. *Gkiourdas Press*, 2006

Halkos, G., Tzeremes, N. and S. Kourtzidis. A DEA approach for measuring university departments' efficiency, *Munich Personal RePEc Archive*, 2010, No. 24029.

Halkos, G.E., Tzeremes, N.G. and S.A. Kourtzidis. Measuring Public Owned University Departments' Efficiency: A Bootstrapped DEA Approach, *Journal of Economics and Econometrics*, 2012, 55, 1-24.

Hanke, M. and T. Leopoldseder. Comparing the Efficiency of Austrian Universities a Data Envelopment Analysis Application, *Tertiary Education and Management*, 1998, 4, 191-197.

Hsiao, H.C., Shen, C.H., Chou, C.M., Chen, S.C. and L.Y. Chang. The relationship between programme management efficiency and evaluation results in an institute of technology: a Taiwanese case, *World Transactions on Engineering and Technology Education*, 2009, 7, 169-175.

Hsu, M. K., Chao, G. H., and James, M. L. An efficiency comparison of MBA programs: Top 10 vs non-top 10. *Journal of Education and Business, May/June*, 2009, 269-274.

Izadi, H., Johnes, G., Oskrochi, R. and R. Crouchley. Stochastic frontier estimation of a CES cost function: the case of higher education in Britain, *Economics of Education Review*, 2002, 21, 63-71.

Jenkins, L. and M. Anderson. A multivariate statistical approach to reducing the number of variables in data envelopment analysis, *European Journal of Operational Research*, 2003, 147, 51-61.

Johnes, G. and A. Schwarzenberger. Differences in cost structure and the evaluation of efficiency: the case of German universities, *Education Economics*, 2011, 9, 487-499.

Johnes, G. and J. Johnes. Higher education institutions' costs and efficiency: Taking the decomposition a further step, *Economics of Education Review*, 2009, 28, 107-113.

Johnes, G. and J. Johnes. Measuring the Research Performance of UK Economics Departments: An Application of Data Envelopment Analysis, *Oxford Economic Papers, New Series*, 1993, 45, 332-347.

Johnes, G. and M. Salas-Velasco. The determinants of costs and efficiencies where producers are heterogeneous: the case of Spanish universities, *Economics Bulletin*, 2007, 4, 1-9.

Johnes, G. Education and economic growth. Lancaster university management school, working paper, 2006/019

Johnes, G. Scale and technical efficiency in the production of economic research, *Applied Economics Letters*, 1995, 2, 7-11.

Johnes, G. The Costs of Multi-product Organizations and the Heuristic Evaluation of Industrial Structure, *Socio-Economic Planning Sciences*, 1998, 32, 199-209.

Johnes, G. The Management of Universities Scottish Economic Society/Royal Bank of Scotland Annual Lecture, *Scottish Journal of Political Economy*, 1999, 46, 505–522.

Johnes, G., Johnes J. and Thanassoulis, E. An analysis of costs in institutions of higher education in England, *Studies in Higher Education*, 33, 527-549.

Johnes, J. Measuring efficiency and input substitutability: Evidence from the English higher education sector over a period of expansion.

Johnes, J. and G. Johnes, Research Funding and Performance in U.K. University Departments of Economics: A Frontier Analysis, *Economics of Education Review*, 1995, 14, 301-314.

Johnes, J. and L. Yu. Measuring the research performance of Chinese higher education institutions using data envelopment analysis, *China Economic Review*, 2008, 19, 679-696.

Johnes, J. Data envelopment analysis and its application to the measurement of efficiency in higher education, *Economics of Education Review*, 2006, 25, 273-288.

Johnes, J. Efficiency and Input and Output Substitutability in English Higher education. 1996/97 to 2007/08: A Parametric Distance Function Approach.

Johnes, J. Efficiency and productivity change in the English higher education sector from 1996/97 to 2004/5, *The Manchester School*, 2008, 76, 653-674.

Johnes, J. Measuring efficiency: a comparison of multilevel modelling and data envelopment analysis in the context of higher education, *Bulletin of Economic Research*, 2006, 58, 0307-3378.

Johnes, J. Measuring teaching efficiency in higher education: An application of data envelopment analysis to economics graduates from UK Universities 1993, *European Journal of Operational Research*, 2006, 174, 443-456.

Jondrow, J., Lovell, C.A.K., Materov, S. and P. Schmidt. On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics*, 1982, 19, 233–238.

Kantabutra, S. and J.C.S. Tang. Efficiency Analysis of Public Universities in Thailand, *Tertiary Education and Management*, 2010, 16, 15-33.

Kao, C. and H.T. Hung. Efficiency analysis of university departments: An empirical study, *Omega*, 2008, 36, 653-664.

Kao, C. and S.T. Liu, Data Envelopment Analysis with Missing Data: An Application to University Libraries in Taiwan, *Journal of the Operational Research Society*, 2000, 51, 897-905.

Kao, C. and Y. Lin. Comparing University Libraries of Different University Size, *International Journal of Libraries and Information Services*, 1999, 49, 150-158.

Kao, C. and Y.C. Lin. Evaluation of the university libraries in Taiwan: total measure versus ratio measure, *Journal of the Operational Research Society*, 2004, 55, 1256-1265.

Kao, C., Liu, S.T. and H.L. Pao. Assessing improvement in management research in Taiwan, *Scientometrics*, 2012, 92, 75-87.

Karagiannis G. Metaregression Analysis of Agricultural Productivity Studies. Working paper No 152262, Proceedings Issues, 2013: Productivity and Its Impacts on Global Trade, June 2-4, 2013. Seville, Spain from International Agricultural Trade Research Consortium.

Karkos, C.D., Sutton, A.J., Bown, M.J. and R.D. Sayers. A Meta-analysis and Metaregression Analysis of Factors Influencing Mortality after Endovascular Repair of Ruptured Abdominal Aortic Aneurysms. *European Journal of Vascular & Endovascular Surgery*, 2011, 42, 775-786.

Katharaki, M. and G. Katharakis. A comparative assessment of Greek universities' efficiency using quantitative analysis, *International Journal of Educational Research*, 2010, 49, 115-128.

Katos, A. Econometrics. *Zygos*, 2004.

Katranidis, S. List of scientific journal, *University of Macedonia press*, 2009

Kempkes G. and C. Pohl, The efficiency of German universities–some evidence from nonparametric and parametric methods, *Applied Economics*, 2010, 42, 2063-2079.

Khan, M.S. and S.S. Sreekuma. Service quality evaluation of technical institutions using data envelopment analysis, *International Journal of Productivity and Quality Management*, 2008, 3, 127-143.

Klumpp, M. European Universities Efficiency Benchmarking, *EAIR 34th Annual Forum in Stavanger*, Norway, 2012.

Koksal, G. and B. Nalcaci. The relative efficiency of departments at a Turkish engineering college: A data envelopment analysis, *Higher Education*, 2006, 51, 173-189.

Kong, W.H. and T.T. Fu. Assessing the performance of business colleges in Taiwan using data envelopment analysis and student based value-added performance indicators, *Omega*, 2012, 40, 541-549.

Kong, W-H. and T-T. FU. Investigating Output Weights of Peer Reviewers in the University Performance Assessment: A DEA Cross Efficiency Study.

Korhonen, P., Tainio, R. and J. Wallenius. Value efficiency analysis of academic research, *European Journal of Operational Research*, 2001, 130, 121-132.

Kounetas, K., Anastasiou, A., Mitropoulos, P. and I. Mitropoulos. Departmental efficiency differences within a Greek university: An application of a DEA and Tobit analysis, *International Transactions in Operational Research*, 2011, 18, 545-559.

Kuah, C.T., Wonga, K.Y. and M.K. Tiwari. Knowledge sharing assessment: An Ant Colony System based Data Envelopment Analysis approach, *Expert Systems with Applications*, 2013, 40, 3137-3144.

Kumbhakar, S.C. Estimation of profit functions when profit is not maximum. *American Journal of Agriculture Economics*, 2001, 83, 1-19.

Lambert PC, Sutton AJ, Abrams KR. And D.R. Jones. A comparison of summary patient-level covariates in meta-regression with individual patient data meta-analysis. *Journal of clinical epidemiology*, 2002, 55, 86-94.

Leitner, K.H., Prikoszovits, J., Schaffhauser-Linzatti, M., Stowasser R. and K. Wagner, The impact of size and specialisation on universities' department

performance: A DEA analysis applied to Austrian universities, *Higher Education*, 2007, 53, 517-538.

Lenton, P. The cost structure of higher education in further education colleges in England, *Economics of Education Review*, 2008, 27, 471-482.

Li, L. Research of Universities' Input-Output Efficiency Basing on DEA, International Conference on Information, *Business and Education Technology*, 2013, 1180-1183.

Lin, H.T. Efficiency measurement and ranking of the tutorial system using IDEA, *Expert Systems with Applications*, 2009, 36, 11233-11239.

Lissitsa, A., Coelli, T. and D.S. Prasada Rao Agricultural economics education in Ukrainian agricultural universities: an efficiency analysis using data envelopment analysis.

Liu, L., Lee, C. and G. Tzeng. DEA Approach for the Current and the Cross Period Efficiency for Evaluating the Vocational Education, *International Journal of Information Technology & Decision Making*, 2004, 3, 353-374.

Lu, T. and W. YanBai. The Study of the DEA Method Model for University Teaching Quality Assessment and Benefit Analysis, *Physics Procedia*, 2012, 25, 1187-1191.

Madden, G., Savage, S. and S. Kemp. Measuring Public Sector Efficiency: A Study of Economics Departments at Australian Universities, *Education Economics*, 1997, 5, 153-168.

Martin, E. An application of Data Envelopment Analysis in the performance assessment of the Zaragoza university departments.

Martín, E. Efficiency and Quality in the Current Higher Education Context in Europe: an application of the data envelopment analysis methodology to performance assessment of departments within the University of Zaragoza, *Quality in Higher Education, 2006*, 12, 57-79.

Martins Costa, E., De Sousa Ramos, F. and H. Ramos de Souza. Static versus dynamic dea in federal higher education institutions – ifes.

McMillan, M.L. and W.H. Chan, University Efficiency: A Comparison and Consolidation of Results from Stochastic and Non-stochastic Methods, *Education Economics*, 2006, 14, 1-30.

McMillan, M.L., and Datta, D. The relative efficiency of Canadian universities: A DEA perspective. *Canadian Public Policy*, 1998, *24*(4), 485-511.

Miranda, R., Gramani, M.C. and E. Andrade. Technical efficiency of business administration courses: a simultaneous analysis using DEA and SFA, *International Transactions in Operational Research*, 2012, 19, 847-862.

Monaco, L. Measuring Italian university efficiency: a non-parametric approach, *Munich Personal RePEc Archive*, 2012, No. 37949.

Moreno, A.A. and R. Tadepalli. Assessing Academic Department Efficiency at a Public University, *Managerial and Decision Economics, 2002, 23, 385-397.*

Ng, Y.C. and S. Li. Efficiency and productivity growth in Chinese universities during the post-reform period, *China Economic Review*, 2009, 20, 183-192.

Ng, Y.C. and S.K. Li. Measuring the Research Performance of Chinese Higher Education Institutions: An Application of Data Envelopment Analysis, *Education Economics*, 2000, 8, 139-156.

Obadić, A. and A. Aristovnik. Relative efficiency of higher education in Croatia and Slovenia: an international comparison, *Amfiteatru Economic*, 2011, 8, 362-376.

Parteka, A. and J. Wolszczak-Derlacz. Dynamics of productivity in higher education: Cross-European evidence based on bootstrapped Malmquist indices, *Journal of Productivity Analysis*, DOI 10.1007/s11123-012-0320-0.

Ramanathan, R. An introduction to data envelopment analysis: a tool for performance management. *SAGE Publications*, 2003

Ray, S.C., and Y. Jeon. Reputation and efficiency: A non-parametric assessment of America's top-rated MBA programs, *European Journal of Operational Research*, 2008, 189, 245-268.

Robst, J. Do state appropriations influence cost efficiency in public higher education? *Applied Economic Letters*, 2000, 7, 715-719.

Rouyendegh, B.D. The DEA and Intuitionistic Fuzzy TOPSIS Approach to Departments' Performances: A Pilot Study, *Journal of Applied Mathematics*, 2011, Article ID 712194.

Salerno, C. What we know about the efficiency of higher education institutions: The best evidence.

Sarafoglou, N. and K. Haynes. University productivity in Sweden: a demonstration and explanatory analysis for economics and business programs. *The Annals of Regional Science*, 1996, 30, 285-304.

Sarrico, C.S. and R.G. Dyson. Restricting virtual weights in data envelopment analysis, *European Journal of Operational Research*, 2004, 159, 17-34.

Sarrico, C.S. and R.G. Dyson. Using DEA for Planning in UK Universities-An Institutional Perspective, *Journal of the Operational Research Society*, 2000, 51, 789-800.

Sav, G.T. Four-Stage DEA Efficiency Evaluations: Financial Reforms in Public University Funding, *International Journal of Economics and Finance*, 2013, 5, 24-33.

Schmidt, P. Sickles RC Production frontiers and panel data. *Journal of Business & Economic Statistics*, 1984, 2, 367–374.

Sellers-Rubio, R., Mas-Ruiz, F.J. and A.B. Casado-Díaz. University Efficiency: Complementariness versus Trade-off between Teaching, Research and Administrative Activities, *Higher Education Quarterly*, 2010, 64, 373-391.

Shim, W. Applying DEA Technique to Library Evaluation in Academic Research Libraries, *Graduate School of Library and Information Science*, 2003, 51, 312-32.

Siegel, D.S., Waldman, D. and A. Link. Assessing the impact of organizational practices on the relative productivity of university technology transfer offices: an exploratory study, *Research Policy*, 2003, 32, 27-48.

Sinuany-Sterna, Z., Mehrez, A. and A. Barboys. Academic departments' efficiency via DEA, *Computers & Operations Research*, 1994, 21, 543-556.

Soares de Mello, J.C.C.B., Gomes, E.G., Meza, L.A., Soares de Mello, M.H.C. and A.J.R. Soares de Mello. Engineering post-graduate programmes: a quality and productivity analysis, *Studies in Educational Evaluation*, 2006, 32, 136-152.

Sohn, S.Y. and Y. Kim. DEA based multi-period evaluation system for research in academia, *Expert Systems with Applications*, 2012, 39, 8274-8278.

Sreekumar, S. and S.S. Mahapatra. Performance modeling of Indian business schools: A DEA-neural network approach, *Benchmarking: An International Journal*, 2011, 18, 221-239.

Stanley, T.D. and S.B. Garrell. Meta-regression analysis: A quantitative method of literature surveys, *Journal of economic surveys*, 1989, 3, 54-67.

Stanley, T.D. Wheat from Chaff: Meta-analysis as quantitative literature review, *Journal of economic perspectives*, 2001, 15, 131-50.

Stanley, T.D., Doucouliagos C. and S.B. Garrell. Meta-regression analysis as the socioeconomics of economics research. *Journal of socioeconomics*, 2008, 37, 276-92.

Stevens, P.A. A Stochastic Frontier Analysis of English and Welsh Universities, *Education Economics*, 2005, 13, 355-374.

Tajnikar, M. and J. Debevec. Funding system of full-time higher education and technical efficiency: case of the University of Ljubljana, *Education Economics*, 2008, 16, 289-303.

Tauer, L.W., Fried, H.O. and W.E. Fry. Measuring Efficiencies of Academic Departments within a College, *Education Economics*, 2007, 15, 473-489.

Taylor, B. and G. Harris. Relative efficiency among South African universities: A data envelopment analysis, *Higher Education*, 2004, 47, 73-89.

Thanassoulis, E., Kortelainen, M., Johnes, G. and J. Johnes. Costs and efficiency of higher education institutions in England: a DEA analysis, *Journal of the Operational Research Society*, 2011, 62, 1282-1297.

Thompson, S.G and J.P.T. Higgins. How should meta-regression analyses be undertaken and interpreted? *Statistics in Medicine*, 2002, 21, 1559-73.

Thursby, J.G. and S. Kempb. Growth and productive efficiency of university intellectual property licensing, *Research Policy*, 2002, 31, 109-124.

Tomkins, C. and R. Green. An experiment in the use of data envelopment analysis for evaluating the efficiency of UK university departments of accounting, *Financial Accountability & Management*, 1988, 4, 0267-4424.

Tóth, R. Using DEA to evaluate efficiency of higher education, *Applied Studies in Agribusiness and Commerce*, 79-82.

Turner, D. Benchmarking in universities: league tables revisited, *Oxford Review of Education*, 2005, 31, 353-371.

Tyagi, P., Yadav, S.P. and S.P. Singh. Relative performance of academic departments using DEA with sensitivity analysis, *Evaluation and Program Planning*, 2009, 32, 168-177.

Ulutas, B.H. Assessing the relative performance of university departments: Teaching vs. Research, *Istanbul University Econometrics and Statistics e-Journal*, 2011, 13, 125-138.

Verbeek, M. A guide to modern Econometrics. *West Sussex: John & Wiley Press*, 2009.

Wang, W-K. and H-C. Huang. Measuring the Relative Efficiency of European MBA Programs: A Comparative analysis of DEA, SBM, and FDH Model.

Warning, S. Performance Differences in German Higher Education: Empirical Analysis of Strategic Groups, *Review of Industrial Organization*, 2004, 24, 393-408.

Wolszczak-Derlacz, J. and A. Parteka. Efficiency of European public higher education institutions: a two-stage multi-country approach, *Scientometrics*, 2011, 89, 887-917.

Wonsik Shim and P. B. Kantor A Novel Economic Approach to the Evaluation of Academic Research Libraries.

Wonsik Shim, P.B. Kantor. Evaluation of digital libraries: A DEA approach

Worthington, A.C. An Empirical Survey of Frontier Efficiency Measurement Techniques in Education, *Education Economics*, 2001, 9, 245-268.

Worthington, A.C. and B.L. Lee. Efficiency, technology and productivity change in Australian universities, 1998–2003, *Economics of Education Review*, 2008, 27, 285-298.

Xiang-Yang, S., Li, Z. and L. Qi-Gang. An Approach for Evaluating Journals of Universities or Colleges Based upon Multi-layer Efficiency DEA, *Physics Procedia*, 2012, 25, 678-686.

Yang, F., Ang, S., Xia, Q. and C. Yang. Ranking DMUs by using interval DEA cross efficiency matrix with acceptability analysis, *European Journal of Operational Research*, 2012, 223, 483-488.

Zhu H. Evaluation and Analysis of Regional Higher Education Performance Based on DEA.

Zing, J., Pang, X., Zhang, L., Medina, A. and S. Roselle. Gender inequality in education in China a Meta-regression analysis, 2013, DOI: 10.1111/coep.12006.