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*by*

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**Abstract**

In this paper using Data Envelopment Analysis (DEA) we evaluate the influence of national culture on education policy efficiency for 20 OECD countries. For that reason bootstrap techniques have been employed in order to produce biased corrected efficiency scores and confidence intervals are been calculated. By using probabilistic approaches it conditions the effect of national cultural values on the obtained countries' educational efficiencies. The empirical results indicate that the efficiency of education policy is mainly influenced from differences of individualistic and masculinity values among the countries. However the results clearly indicate that education policy reforms must be based outside those national cultural bounds in order to support national economies on their foreseen challenges.

**Keywords:** Data Envelopment Analysis, Education, Linear programming, Statistics

**JEL Codes:** C6, C14, I21

## I. Introduction

According to Lucas (1988) literature has emphasized the importance of human capital as an endogenous factor of production to explain economic growth. According to literature education is a vital component of human capital both by increasing individuals' productivity and by benefiting the society (Mimoun and Raies, 2010; Fanti and Gori, 2010). However, education at the tertiary level seems to have a crucial role in enhancing competitiveness, since it creates, incorporates and disseminates progress in knowledge that then makes it possible to increase productivity in various productive areas.

Abbott & Doucouliagos (2003) and Johnes (2006) investigated the efficiency of higher education in the UK, whereas Joumady and Ris (2005) using DEA methodology compared different Higher Education institutions through 8 European countries in order to evaluate their impact on graduates' skills to labour market requirements. In addition, Mancebón and Muñiz (2008) estimated the differences of the efficiency of Spanish public and private high schools using DEA methodology founding that the better academic results in private schools seem to be exclusively due to their having pupils with a more favourable background for the educational process. Furthermore, Johnes (2006) using DEA and multilevel modelling (MLM) to a data set of 54,564 graduates from UK universities in 1993 assesses whether the choice of technique affects the measurement of universities' performance. Johnes found that the rankings of universities derived from the DEA efficiencies which measure the universities' own performance are not strongly correlated with the university rankings derived from the university effects of the multilevel models.

Furthermore, Flegg et al. (2004) evaluated the technical efficiency of 45 British Universities using Malmquist productivity indexes evaluating student to staff ratio and reforms of public spending in British Higher Education policies. These researches raise the question of educational systems' efficiency and to a certain extent to their contribution to economic development through their provision of educated labour. As such policy makers have an essential role to play by promoting greater articulation between academic activity, programmes and activities throughout countries.

However, the research question in hand is what makes a country's educational system "efficient"? What are the uncontrollable mechanisms that interfere with such a policy orientation and implication? According to Gimenez et al (2007) not many studies have examined at a national level educational systems in terms of their efficiency of transforming their expenses into improving outcomes. Thanassoulis and Dunstant (1994) suggest that the evaluation of an educational system should include attributes and values that favour workplace and social integration. Bradley et al. (2010) using data for nearly 200 further education providers in England to investigate the level of efficiency and change in productivity over the period 1999–2003. They found that the local unemployment rate has an effect on provider efficiency. To the authors' believes the way that societies in different countries think, behave and act is the predetermined frame that shapes educational policies and their efficiencies, because education (especially tertiary education) is perceived and oriented differently in different cultures. Culture in addition contains the ways of living which are built up by a group of human beings and transmitted from and generation to another.

Accordingly, Hofstede (1980) suggests that culture is a collective mental programming which is difficult to change; if it changes at all, it does so slowly. As such this study tries to answer two questions; firstly it tries to establish if there is a link between countries' national cultures and education policy efficiency. As a second step it tries to establish the effect of national cultural characteristics on countries' education policies efficiency. Therefore, we will be able to determine how and under which cultural circumstances educational policies can be more "efficient" in a country. In order to do so this paper provides a nonparametric analysis by employing the latest developments in DEA methodology comparing twenty OECD countries' education investment policies by measuring their efficiency. In addition it calculates the effect of uncontrollable factors to educational system policies by using Hofstede's cultural dimensions (Hofstede 1980)[1].

## II. Data

Our study investigates the efficiency of twenty OECD countries' higher education investment policies[2]. Even though employment itself is enhanced by other

[1] Hofstede had distributed to IBM's employees all over the world the same questionnaire in order to analyse the key characteristics of their cultures. The database he created was covering employees in 72 national subsidiaries, 38 occupations, 20 languages, and at two points in time: around 1968 and around 1972. Altogether, there were more than 116000 questionnaires with over 100 standardized questions each.

[2] The OECD countries under consideration are Australia, Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Iceland, Ireland, Italy, Japan, Korea, Mexico, Netherlands, Poland, Spain, Sweden, UK, USA.

factors including education, we only investigate the efficiency of different countries utilizing specific resources/policies (inputs) in order to stimulate to produce qualified/ educated labour. Finally, Bee and Dolton (1985) suggest that production function estimation can be applied to the education industry. Our data set concerns the year 2002 and it is drawn from the OECD (2004) database. Since there is much heterogeneity among the examined countries' educational policies, we tried to include only those inputs/output(s) that are common and have been used from several studies.

The study uses three inputs: 1) SEE = School expectancy for all levels of education combined. 2) RSS = Ratio of students to teaching staff in educational institutions. This ratio is calculated as the total number of full-time equivalent students divided by the total number of full-time equivalent educational personnel. 3) NTH = Number of teaching hours per year. Teaching time is defined as the number of hours per year that a full-time teacher teaches a group or class of students according to the formal policy in the country.

Finally one output have been used: 1) SURT = Survival rate at the tertiary level. This is defined as the proportion of new entrants to the specified level of education who successfully complete a first qualification. It is calculated as the ratio of the number of students who are awarded an initial degree to the number of new entrants to the level n years before, n being the number of years of full-time study required to complete the degree.

In general, the inputs we are using describe the basic elements of long-term education investment policies which can be defined as a common target among the countries under examination. Furthermore, the proposed output tries to evaluate the outcome of those policies in terms of graduates. In general terms this input/output framework represents the ability of an educational system with a given resources (provided from education investment policies) to provide educated labour according to market and labour demands in the "right" time having altogether a positive impact on countries growth economic and social welfare.

Moreover, in order to establish the effect of cultural characteristics on education policies' performance the paper uses Hofstede's cultural dimensions. Hofstede is the most widely cited author in the field with the most methodologically supported quantification of cultural characteristics (Swierczek, 1994). Given this fact we adopt in our study Hofstede's cultural dimensions having in mind the critique made by several authors regarding the methodology and the diachronically validity of those cultural dimensions (Triandis, 1982; Shackleton and Ali, 1990; Sondergaard, 1994). The four cultural dimensions as introduced by Hofstede (1980) are described next.

*1) Power Distance (PDI)* = Power distance index informs us on dependence relationships in a country. Specifically, this index can be defined as the extent to which the less powerful members of institutions (families, schools) and organizations (places where people work) in a country expect and accept that power is unequally distributed. Inequalities within a society can be realized in the different social classes (lower, middle, higher), which differ in their access to and opportunities for the benefits from the advantages of societies, one of which is education. A higher education is expected to make someone at least middle class. At the same time education determines the occupations one can expect to undertake. PDI are lower for occupations needing a higher education. For countries scoring low on PDI this implies that students will become more independent of teachers as they go on with their studies. In high PDI countries students remain dependent on teachers even in the higher education levels.

*2) Uncertainty Avoidance (UAI):* The uncertainty avoidance index refers to differences between countries on uncertainty avoidance which can be defined as the extent to which members of a culture feel threatened or uncertain of unknown situations. Students from strong UA countries expect teachers to be experts who know everything and have an answer fro everything. Students from weak UA countries accept a teacher who probably ignores an answer to a question. They respect teachers who are sincere and straight to them.

*3) Masculinity and Femininity (MAS):* ranges from ''societies in which social gender roles are clearly distinct'' to ''societies in which social gender roles overlap'' (Hofstede, 1980, p.82). Failing in school is a disaster in a masculine culture. Failure in school in a feminine culture is a relatively minor incident. On the masculine side teachers' brilliance and academic reputations and students' academic performance are the dominant factors. Whereas, on the feminine side teachers' friendliness and social skills and students' social adaptation play a bigger role.

*4) Individualism versus collectivism (IDV):* ranges from ''societies in which the ties between individuals are loose'' to ''societies in which people from birth onwards are integrated into strong, cohesive in-groups'' (Hofstede, 1980, p. 51). In a individualistic and collectivism society the purpose of education is perceived differently. In the former it aims at preparing the individual for a place in a society of other individuals. This means learning to cope with new unknown, unforeseen situations. The purpose of learning is less to know how to do, as to know how to learn. In collectivism society there is a stress on adaptation to the skills and virtues necessary to be an acceptable group member. This leads to a premium on the products of tradition. Students in a collectivism society must learn how to do things in order to participate in a society. Finally, in a individualistic society the holder of a degree/ diploma not only improves the holder's economic growth but also his or her self-respect. However in collectivism society a diploma or a degree is an honor to the holder which entitles them to be associated with higher-status groups. The social acceptance which comes with a diploma is much more important than the individual self- respect that comes with mastering a subject.

## III. Methodology

### *III.1 Performance measurements*

The first DEA estimator first was introduced from Farrell (1957) to measure technical efficiency. However DEA became more popular when introduced by Charnes *et al* (1978) in order to estimate $\Psi$ and allowing constant returns to scale (CCR model). The production set $\Psi$ constraints the production process and is the set of physically attainable points $(x, y)$ :

$$\Psi = \left\{ (x, y) \in \Re_{+}^{N+M} \middle| x \;\; can \;\; produce \;\; y \right\} \quad (1),$$

where $x \in \Re_{+}^{N}$ is the input vector and $y \in \Re_{+}^{M}$ is the output vector. Later, Banker et al. (1984) introduced a DEA estimator allowing variable returns to scale (BCC model). The CCR model uses the convex cone of $\hat{\psi}_{FDH}$ to estimate $\Psi$, where as the BCC model uses the convex hull of $\hat{\psi}_{FDH}$ to estimate $\Psi$. In this paper we use input oriented models since the decision maker through different governmental policies can have greater control over the inputs compared to the outputs used (Halkos and Tzeremes, 2010).

Following the notation by Simar and Wilson (2008), the CCR model developed by Charnes *et al* (1978) can be calculated as:

$$\hat{\Psi}_{CRS} = \left\{ \begin{array}{l} (x, y) \in \Re^{N+M} \left| y \leq \sum_{i=1}^{n} \gamma_i y_i ; x \geq \sum_{i=1}^{n} \gamma_i x_i \quad for \;\; (\gamma_1, ... \gamma_n) \right. \\ such \;\; that \;\; \gamma_i \geq 0, i = 1, ... n \end{array} \right\} \quad (2).$$

The BBC model developed by Banker *et al* (1984) allowing for variable returns to scale can then be calculated as:

$$\hat{\Psi}_{VRS} = \left\{ \begin{array}{l} (x,y) \in \Re^{N+M} \left| y \le \sum_{i=1}^{n} \gamma_i y_i ; x \ge \sum_{i=1}^{n} \gamma_i x_i \quad for \ (\gamma_1, \ldots \gamma_n) \right. \\ such \ \ that \ \ \sum_{i=1}^{n} \gamma_i = 1; \ \gamma_i \ge 0, i = 1, \ldots n \end{array} \right\} \tag{3.}$$

Then the input oriented efficiency score based on the Farrell (1957) measure for a unit operating at the level $(x, y)$ can be obtained by plugging in $\hat{\Psi}_{DEA}$ in equation:

$$\theta(x,y) = \inf \left\{ \theta \middle| (\theta x, y) \in \Psi \right\} \tag{4}$$

*III.2 Bias correction using the bootstrap technique*

According to Dyson and Shale (2010) bootstrap procedures produce confidence limits on the efficiencies of the units in order to capture the true efficient frontier within the specified interval. As a result the main drawbacks concerning their inability to conduct statistical inference will disappear (Halkos and Tzeremes, 2010). In addition Simar and Wilson (1998, 2000, 2008) suggest that DEA estimators were shown to be biased by construction. They introduced an approach based on bootstrap techniques (Efron, 1979) to correct and estimate the bias of the DEA efficiency indicators.

Then the bootstrap bias estimate for the original DEA estimator $\hat{\theta}_{DEA}(x,y)$ can be calculated as:

$$B\hat{I}AS_B\left(\hat{\theta}_{DEA}(x,y)\right) = B^{-1}\sum_{b=1}^{B}\hat{\theta}^*_{DEA,b}(x,y) - \hat{\theta}_{DEA}(x,y) \tag{5.}$$

Furthermore, $\hat{\theta}^*_{DEA,b}(x,y)$ are the boot strap values and $B$ is the number of bootstrap reputations. Then a biased corrected estimator of $\theta(x,y)$ can be calculated as:

$$\begin{aligned} \hat{\hat{\theta}}_{DEA}(x,y) &= \hat{\theta}_{DEA}(x,y) - B\hat{I}AS_B\left(\hat{\theta}_{DEA}(x,y)\right) \\ &= 2\hat{\theta}_{DEA}(x,y) - B^{-1}\sum_{b=1}^{B}\hat{\theta}^*_{DEA,b}(x,y) \end{aligned} \tag{6.}$$

However, according to Simar and Wilson (2008) this bias correction can create an additional noise and the sample variance of the bootstrap values $\hat{\theta}^*_{DEA,b}(x,y)$ need to be calculated. The calculation of the variance of the bootstrap values is illustrated below:

$$\hat{\sigma}^2 = B^{-1}\sum_{b=1}^{B}\left[\hat{\theta}^*_{DEA,b}(x,y) - B^{-1}\sum_{b=1}^{B}\hat{\theta}^*_{DEA,b}(x,y)\right]^2 \quad (7).$$

We need to avoid the bias correction illustrated in (6) unless:

$$\frac{\left|\widehat{BIAS}_B(\hat{\theta}_{DEA}(x,y))\right|}{\hat{\sigma}} > \frac{1}{\sqrt{3}} \quad (8).$$

Finally, the $(1-\alpha)$ $x$ 100 - percent bootstrap confidence intervals can be obtained for $\theta(x,y)$ as:

$$\frac{1}{\hat{\delta}_{DEA}(x,y) - nc^*_{1-a/2}} \leq \theta(x,y) \leq \frac{1}{\hat{\delta}_{DEA}(x,y) - nc^*_{a/2}} \quad (9).$$

*III.3 Testing for the existence of constant or variable returns to scale*

After producing the biased corrected estimators (both for CCR and BCC models) the problem in hand appears between the choice of the adoption or not of the assumption of constant or variable returns to scales. Following Simar and Wilson (2002) bootstrap techniques can be used in order to test for the adoption of results between the Constant Returns to Scale (CRS) against the Variable Returns to Scale (VRS) such as: $H_0 : \Psi^{\theta}$ is globally CRS against $H_1 : \Psi^{\theta}$ is VRS. The test statistic mean of the ratios of the efficiency scores is then provided by:

$$T(X_n) = \frac{1}{n}\sum_{i=1}^{n}\frac{\hat{\theta}_{CRS,n}(X_i,Y_i)}{\hat{\theta}_{VRS,n}(X_i,Y_i)} \quad (10).$$

Then the *p-value* of the null-hypothesis can be obtained:

$$p - value = prob(T(X_n) \leq T_{obs} \left| H_0 \right. \; is \;\; true) \quad (11)$$

where $T_{obs}$ is the value of T computes on the original observed sample $X_n$ .Then the *p-value* can be approximated by the proportion of bootstrap values of $T^{*b}$ less the original observed value of $T_{obs}$ such as:

$$p - value \approx \sum_{b=1}^{B}\frac{I\left(T^{*b} \leq T_{obs}\right)}{B} \quad (12).$$

*III.4 Testing the effect of external 'environmental' factors on the efficiency scores*

In order to analyse the effect of cultural dimensions (PDI, IDV, MAS, UAI) on the efficiency scores obtained we follow the probabilistic approach developed by Daraio and Simar (2005b, 2007). They suggest that the joint distribution of (X,Y) conditional on the environmental factor Z=z defines the production process if Z=z. The efficiency measure can then be defined as:

$$\theta(x, y|z) = \inf\left\{ \theta \middle| F_X(\theta x|y, z) > 0 \right\} \quad (13),$$

where $Fx(x|y,z) = \Pr ob(X \le x | Y \ge y, Z = z)$. Then a kernel estimator can be defined as follows:

$$\hat{F}_{X|Y,Z,n}(x|y,z) = \frac{\sum_{i=1}^{n} I(x_i \le x, y_i \ge y) K((z - z_i)/h)}{\sum_{i=1}^{n} I(y_i \ge y) K((z - z_i)/h)} \quad (14),$$

where K(.) is the Epanechnikov kernel[3] and $h$ is the bandwidth of appropriate size. The density of Z has been calculated based into the two stage approach proposed by Daraio and Simar (2005a, 2005b). In the first stage we calculated $h$ using the likelihood cross validation criterion, using a k-NN (k-nearest-neighbor) method (Silverman, 1986). Then in the second step the local bandwidths obtained are expanded by a factor $1 + n^{-1/(p+q)}$ in order to take into account the dimensionality of $x$ and $y$, and the sparsity of points in larger dimensional spaces[4]. Therefore, we obtain a conditional DEA efficiency measurement defined as:

$$\hat{\theta}_{DEA}(x, y|z) = \inf\left\{ \theta \middle| \hat{F}_{X|Y,Z,n}(\theta x|y, z) > 0 \right\} \quad (15).$$

However, Daraio and Simar (2007) suggested that when the environmental variables are highly correlated then this can lead to biased efficiency estimates of the conditional frontiers. Therefore, the results need to be treated with scepticism. Since cultural dimensions are highly correlated (Hofstede, 1980), we follow Cherchye et al. (2007) suggesting the Mahalanobis transformation (Mardia et al., 1979) in order to decorrelate the environmental variables. Then a sequential kernel estimation can be applied as if all environmental variables were independently distributed.

[3] Also other kernels from the family of continuous kernels with compact support can be used.

[4] For crucial discussion on kernel selection and bandwidth choices see Daraio and Simar (2005a, 2005b, 2007).

Then in order to establish the influence of an environmental variable on the efficiency scores obtained a scatter of the ratios $\frac{\hat{\theta}_n(x, y|z)}{\hat{\theta}_n(x, y)}$ against Z (in our case as mentioned there are four external factors) and its smoothed non parametric regression lines it would help us to analyse the effect of Z on the efficiency scores. For this purpose we use the nonparametric regression estimator introduced by Nadaraya (1964) and Watson (1964) as:

$$\hat{g}(z) = \frac{\sum_{i=1}^{n} K(\frac{z - Z_i}{h}) \left( \frac{\hat{\theta}_n(x, y|z)}{\hat{\theta}_n(x, y)} \right)}{\sum_{i=1}^{n} K(\frac{z - Z_i}{h})} \quad (16).$$

If this regression is increasing it indicates that Z is unfavourable to the countries' educational efficiency whereas if it is decreasing then it is favourable. When the Z is unfavourable then the environmental factor (in our case countries' cultural values) acts like an extra undesired output to be produced demanding the use of more inputs in production activity. In the opposite case the environmental factor plays a role of a substitutive input in the production process giving the opportunity to save inputs in the activity of production.

## IV. Empirical Results and Conclusions

Following the results from the tests described in equations 10 to12 the paper identifies that from the problem in hand the BCC model which allows variables returns to scale is more appropriate. In our application we have three input factors and one output factor and we obtained for this test a p-value of 0,043 < 0,05 (with B=2000) hence, we reject the null hypothesis of CRS. Therefore, the results adopted for our study are based on the BCC model assuming variable returns to scale[5]. The efficiency results obtained are presented in Table 1.

Analytically, Table 1 presents the efficiency scores of the twenty countries, the biased corrected efficiency scores and the 95-percent confidence intervals: lower and upper bound obtained by B=2000 bootstrap replications using the algorithm described previously. As reported the efficient countries (i.e. efficient score =1) are reported to be: Iceland, Japan, Korea, Mexico, Sweden and the United States. Whereas countries with higher scores (i.e. more than 0.9) are reported to be: Finland, France, Germany,

[5] All the results obtained from CRS model are available upon request

Italy, and Spain. However, the results obtained are biased and therefore following equation (8) the biased corrected results need to be adopted for our analysis.

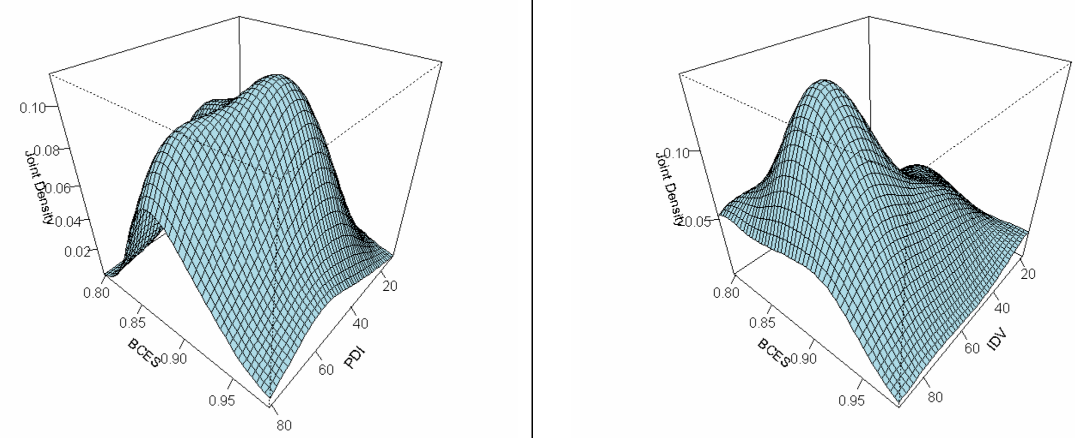
According to the biased corrected efficiency measures the countries with the higher educational efficiency scores (i.e. > 0.9) are reported to be: Iceland, Italy, Japan, Korea, Mexico, Spain, Sweden and the United States. Adopting the methodology proposed by Daraio and Simar (2005b, 2007) we created four conditional BCC educational efficiency estimators taking into account the influence of the four external variables used (i.e. PDI, IDV, MAS, UAI).

**Table 1**: Efficiency scores of countries' educational systems

| Country | VRS | Bias-Corrected | bias | std | lower | upper |
|---|---|---|---|---|---|---|
| Australia | 0.83 | 0.80 | -0.0417 | 0.0006 | 0.77 | 0.83 |
| Austria | 0.89 | 0.86 | -0.0356 | 0.0006 | 0.82 | 0.89 |
| Belgium | 0.88 | 0.87 | -0.0168 | 0.0001 | 0.84 | 0.88 |
| Czech Republic | 0.92 | 0.87 | -0.0566 | 0.0019 | 0.81 | 0.91 |
| Denmark | 0.89 | 0.86 | -0.0345 | 0.0006 | 0.82 | 0.89 |
| Finland | 0.91 | 0.87 | -0.0460 | 0.0009 | 0.83 | 0.91 |
| France | 0.91 | 0.89 | -0.0267 | 0.0003 | 0.86 | 0.91 |
| Germany | 0.91 | 0.88 | -0.0389 | 0.0005 | 0.84 | 0.90 |
| Iceland | 1.00 | 0.92 | -0.0827 | 0.0029 | 0.85 | 1.00 |
| Ireland | 0.83 | 0.81 | -0.0363 | 0.0005 | 0.78 | 0.83 |
| Italy | 0.91 | 0.90 | -0.0163 | 0.0001 | 0.87 | 0.91 |
| Japan | 1.00 | 0.92 | -0.0822 | 0.0028 | 0.85 | 1.00 |
| Korea | 1.00 | 0.98 | -0.0173 | 0.0002 | 0.95 | 1.00 |
| Mexico | 1.00 | 0.92 | -0.0829 | 0.0030 | 0.84 | 1.00 |
| Netherlands | 0.87 | 0.85 | -0.0351 | 0.0005 | 0.81 | 0.87 |
| Poland | 0.89 | 0.87 | -0.0212 | 0.0002 | 0.85 | 0.89 |
| Spain | 0.95 | 0.92 | -0.0300 | 0.0005 | 0.88 | 0.94 |
| Sweden | 1.00 | 0.94 | -0.0663 | 0.0015 | 0.88 | 1.00 |
| United Kingdom | 0.83 | 0.80 | -0.0488 | 0.0009 | 0.76 | 0.83 |
| United States | 1.00 | 0.92 | -0.0851 | 0.0028 | 0.85 | 1.00 |

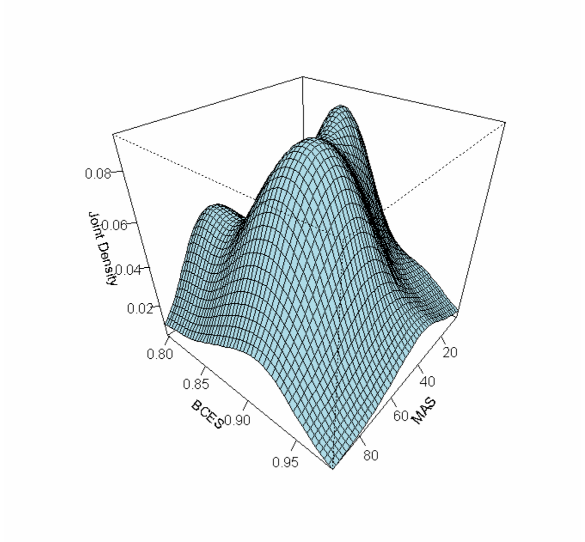
In Figure 1 we plot the estimated joint PDF using the "normal reference rule-of-thumb" approach for bandwidth selection and a second order Gaussian kernel (Silverman, 1986). The joint PDF have been obtained for biased corrected efficiency scores (BCES) and the cultural dimensions (PDI, IDV, MAS and UAI). The bandwidths obtained are 0.02817140 (BCES), 12.74876 (PDI), 12.98705 (IDV), 15.93267 (MAS) and 14.89975 (UAI). In Figure 1, Subfigure 1a reveals the joint density between the biased corrected efficiency scores (under the VRS hypothesis) and the power distance cultural values which indicate a somewhat equalled based distribution having the probability mass at  efficiency values between 0.85 to 0.9 regardless the value of PDI. In contrast to Subfigure 1a, Subfigure 1b reveals that the joint density between BCES and IDV a somewhat "right-angled" distribution having probability mass at lower efficiency scores and high individualistic values. In Subfigure 1c illustrates the joint density of BCES and countries' masculinity values. The Subfigure 1c reveals that higher probability mass is around 0.9 efficiency levels regardless the MAS values. Finally, Subfigure 1d we observe again (as Subfigure 1b) a "right-angled" distribution having probability mass low efficiency scores and high UAI values. The joint density distribution reveals important characteristics of the present data, however their not incorporate the effect of the external factors (in our case the cultural values) to the efficiency scores under consideration.

**Figure 1:** Joint density plots of biased corrected efficiency scores (BCES) and the cultural dimensions (PDI, IDV, UAIO, MAS)

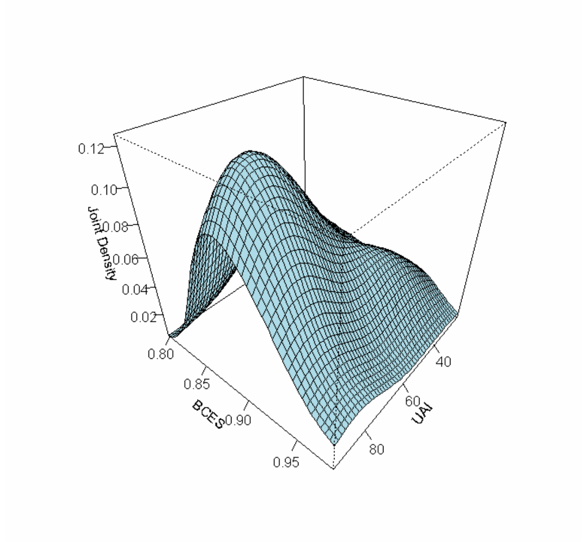



1a

1b




1c

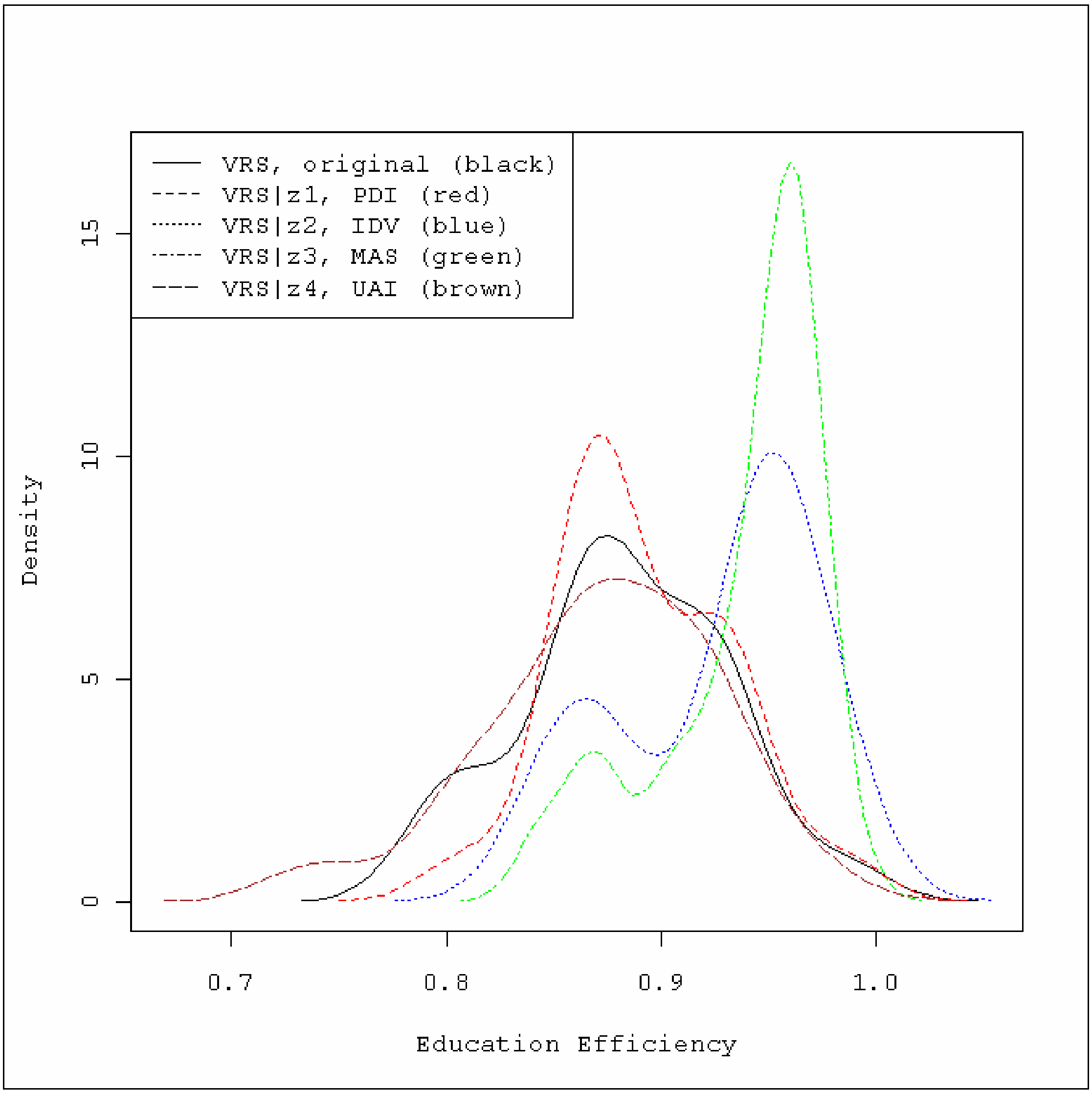



1d

In addition to Figure 1, Figure 2 provides us with kernel density plots of the conditional educational efficiency values[6] (see equations 13-15). Each graph illustrates the conditional unbiased DEA estimator based on the effect of each cultural value. For the calculation of the four density estimates we have used the "normal reference rule-of-thumb" approach for bandwidth selection (Silverman 1986) and a second order Gaussian kernel. It appears that the estimates conditioned to cultural values under the effect of masculine and individualist cultures appear to be leptokurtic compared to the effect of power distance and uncertainty avoidance values which are appear to be platykurtic. The leptokurtic distributions indicate that there is a rapid fall-off in the density as we move away from the mean. Furthermore, the pickedness of the distribution suggests a clustering around the mean with rapid fall around it. As such it appears that MAS and IDV cultural values in a society influencing more countries' education policy performance.

[6] The analytical results of the conditional DEA estimators are available upon request

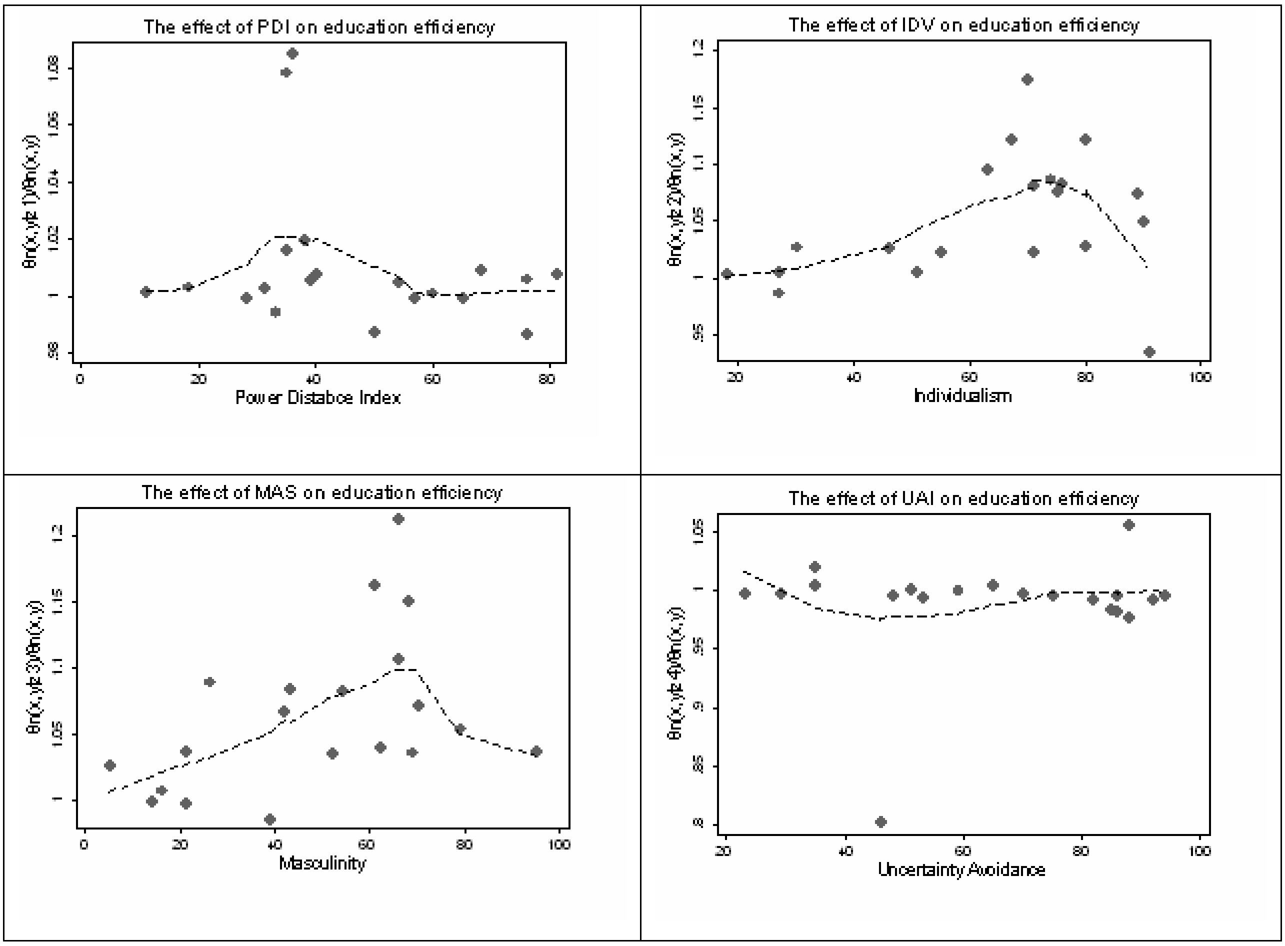
**Figure 2:** Kernel density functions of countries' educational efficiencies derived from conditional BCC DEA frontiers using Gaussian Kernel and the appropriate bandwidth




Following, the approach introduced by Daraio and Simar (2005b, 2007) and described previously Figure 3 illustrates the effect of the four external variables on countries' educational performance. As can be realised by Figure 3, IDV and MAS have a negative effect on countries' efficiency performances up to a point which in turn after that point the effect appears to be positive. As such the differences between countries' with masculine and feminine values seem to bound the education investment policies and thus countries' education efficiency, failing to foreseen the changes needed in order to adopt educational policies to the new global environment.

Similarly, the differences between the individualist and the collectivist society and the way they perceive the purpose of education can lead to inefficient education policies. The effect of PDI seem to have mixed results according to the different levels of PDI values indicating again that educational process and thus the policies associated are perceived differently between the societies with lower and higher PDI values. Finally, UAI values seem to be rather neutral on countries' efficiency levels. The results clearly indicate that the effect of national culture on countries educational policies is crucial by determining the way governments shape their policies, their perceptions and the role of the tertiary education on the economy.

**Figure 3:** Graphical representation of the global effect of cultural dimensions on countries' educational efficiency




## V. Conclusion

According to Dyson and Shale (2010) there is a need of studies applying the theoretical developments of OR into realistic scenarios. In addition the majority of the studies are giving more emphasis on the 'research' element of OR and too little on the 'operational'. Following those lines we apply the latest techniques incorporating uncertainty and external (environmental) variables into a real performance measurement problem in an aggregated level. For the first time to our knowledge, this paper tests the influence of national culture on countries' educational policies performance. By incorporating the latest developments of DEA techniques this study illustrates how the efficiency can be measured under the influence of factors which are not in the control of the decision making units. Additionally, the question if national culture influences education policy performance is answered. The results reveal that national culture can shape the way policy makers perceive and recognise the role of higher education in an economy and thus they act differently.

By using nonparametric techniques and efficiency bias correction methods we analysed those effects showing that individualist and masculinity values appear to influence more countries' education policy performance. However, the results need to be treated with scepticism since our intension wasn't to indicate whether a national culture is better than another but rather how national cultures can interfere in policy perceptions regarding education and its role in the "new global" society. As the new world economy changes, the ability to have efficient education policies and thus a "healthy" educational system is crucial. Since the international and global context is changing rabidly based on international economic situations, extreme values and beliefs in different national cultures need to be avoided when policies to educational systems are been designed and applied.

Culture in addition contains the ways of living which are built up by a group of human beings and transmitted from one generation to another. Accordingly, Hofstede (1980) suggests that culture is a collective mental programming which is difficult to change; if it changes at all, it does so slowly. As such educational systems in order to cope with higher demands must be based outside those national cultural bounds in order to support national economies on their foreseen challenges.

## V. References

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