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by

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**Abstract**

This paper contributes to the link between social and cultural factors with countries innovation performance. By measuring 25 countries' innovation efficiency with the use of conditional and unconditional DEA (Data Envelopment Analysis) frontiers the paper provides empirical evidence of the effect of culture on countries' innovation efficiency. Particularly, conditional and unconditional full frontier models are used alongside with bootstrap techniques in order to determine the effect of national culture on countries' innovation performance. The study illustrates how the recent developments in efficiency analysis and statistical inference can be applied when evaluating such issues. The results reveal that national culture has an impact on countries' innovation efficiency. Analytically, the results indicate that higher PDI (power distance index), IDV (individualism) and UAI (uncertainty avoidance) values have a negative effect on countries innovation efficiency, whereas masculinity values appear to have a positive effect on countries innovation performance.

**Keywords:** National culture; Innovation efficiency; Conditional efficiency; Bootstrap procedures.
**JEL Classification:** C02, C14, C61, O14, Z13

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## 1. Introduction

Economic literature directly measures a country's levels of entrepreneurial performance through the country's entrepreneurial activity. The latter has well been recognised for its contribution in the process of economic growth. Baumol (1968) emphasising the impact of countries' entrepreneurial performance stated that capital accumulation and labour force alone cannot explain a substantial proportion of countries' output. In addition Leinbenstein (1968) suggested that entrepreneurship is a significant variable in the development process. Among those lines, Banerjee and Newman (1993) provide evidence that economic development may be associated with increased entrepreneurship, while Iyigun and Owen (1998) demonstrate that economic development is associated with a decline in the number of entrepreneurs relative to professionals.

This study uses the terms innovation and innovation performance by adopting Evans' view of a 'dynamic entrepreneurship', which is the ability of combining the means of production in 'new', 'innovative' ways (Evans, 1949). But these innovations whether they are technological or a modification of 'ways' in an industry require 'entrepreneurial initiative' (Baumol, 1968). This 'entrepreneurial initiative', which has an effect on countries' entrepreneurial performance, is subject to countries' different social and cultural elements (Cohran, 1960; Soltow, 1968).

Based on this view, Evans and Leighton (1989) have emphasised that sociological and psychological literature on entrepreneurship contains useful insights that can be incorporated in economic modelling. Granovetter (1985) suggests that social and cultural values affect the functioning of markets. Lee and Peterson (2000) stressed the fact that entrepreneurship and innovation 'fits' better with some cultures than with others. Singh (1995) emphasizes the fact that cross-cultural research in entrepreneurship can provide us with useful insights of practice and policy evaluation. Therefore, culture-dependent relationships in innovation and entrepreneurship can be emphasised (Tiessen, 1997).

However, most of the cross-cultural studies have been criticized for their lack of methodological maturity, data collection and analysis (George and Zahra, 2002; Coviello and Jones, 2004; Engelen et al. 2009). In addition Lynn et al. (1996) describe innovation community as an interaction between of social and economic relationships. According to Guice (1999) suggest that social studies of science and technology are mainly concerned with technical practice and not on the supportive social environment and culture.

Our study, tries to provide empirical evidence of the link between cultural values and countries' innovation performance. To our knowledge only one study tried to obtain empirical evidence between R&D investment and national culture (Vaskarelis, 2001). In contrast with the studies using parametric and non-parametric techniques measuring countries' innovation/R&D efficiency (Wang and Huang, 2007; Hollanders and Esser, 2007; Fu and Yang, 2009), this study uses the new advances in conditional DEA measurement (Daraio and Simar, 2005; 2007) and the inferential approach introduced by Simar and Wilson (1998, 2000) to investigate such a link.

## 2. Measuring innovation efficiency

Different cross country studies have used DEA analysis in order to measure countries' relative efficiency of R&D activities. Most of them perceive the R&D/knowledge generation activity for every country as a production process. Pakes and Griliches (1984) and Griliches (1990) based on the production process illustrate countries' innovation activities as a product of some observable measures of resources such as such as R&D expenditures or the number of research scientists. In turn innovation is measured by a proxy of economic valuable knowledge, the patents count.

Similarly, Wang and Huang (2007) by using DEA analysis measured the relative efficiency of R&D activities across 30 countries. Then they used Tobit regressions for controlling the external environment. They found that less than one-half of the countries are fully efficient in R&D activities and that more than two-thirds are at the stage of increasing returns to scale. In addition most countries appear to have an advantage on producing SCI cum EI publications than in generating patents. Hashimoto and Haneda (2008) used a DEA – Malmquist index in order to measure total factor R&D efficiency changes of 10 Japanese pharmaceutical firms for the time period of 1983–1992. By using R&D expenditure (billion yen a year) as input and number of patents, pharmaceutical sales and operating profit as outputs. They found that R&D efficiency of Japanese pharmaceutical industry has almost monotonically gotten worse throughout the study decade.

Similar to our study Hollanders and Esser (2007) used a DEA analysis using the scores from the European Innovation Scoreboard (EIS) for the year 2007 includes three categories of innovation inputs (innovation drivers, knowledge creation and innovation and entrepreneurship) and two categories of outputs (applications and intellectual property). In contrast with the previous studies Fu and Yang (2009) developed a patent production frontier is estimated for a panel of 21 OECD countries over the 1990–2002 period using Stochastic Frontier Analysis. The results indicate the existence between Europe and the world leaders in terms of basic patenting capacity with institutional factors being significantly associated with the patenting efficiency of an economy.

Given the need for studies linking the social environment with technical innovations, Vaskarelis (2001) have examined the impact of national culture on R&D investment for 50 selected countries. He stresses the role of national culture as a major determinant of R&D activity. By using Hofstede's power distance index (PDI) Vaskarelis found evidence that the lower the power distance in a society the higher its investment of R&D. According to Pavitt (1998), societal factors influencing the rate and direction of technical change. Finally, Howells (1995) suggests that technological knowledge can be described as socially distributed cognitive knowledge (p. 890).

**3. Data**

In order to measure countries' innovation efficiency we use data from the European Innovation Scoreboard 2007 Database (EIS, 2007) for 25 countries as in the study by Hollanders and Esser (2007). In addition three composite indexes as inputs and two composite indexes as outputs are used. These five indexes include 25 indicators derived mainly from Eurostat and OECD. Table 1 presents the descriptive statistics of the inputs and outputs used alongside with cultural/ environmental factors influencing countries' innovation performance.

More analytically, innovation inputs cover three innovation dimensions: Innovation drivers measure the structural conditions required for innovation potential; Knowledge creation measures the investments in R&D activities, considered as key elements for a successful knowledge-based economy; and Innovation & entrepreneurship measures the efforts towards innovation at firm level. Innovation outputs cover two innovation dimensions: Applications measures the performance expressed in terms of labour and business activities and their value added in innovative sectors; and intellectual property measures the achieved results in terms of successful know-how (EIS, 2007).

As can be observed from table 1 (looking at the standard deviation values) there are a lot of heterogeneities between countries. In order to capture the effect of culture on countries' innovation performance we use the four cultural dimensions as introduced by Hofstede (1980): power distance (PDI, $Z_1$); individualism versus collectivism (IDV, $Z_2$); masculinity versus femininity (MAS, $Z_3$); and uncertainty avoidance (UAI, $Z_4$). Power distance ($Z_1$) can be defined as ''the extent to which the less powerful members of institutions and organizations within a country expect and accept that power is distributed unequally'' (Hofstede 1980, p.28). Individualism versus collectivism ($Z_2$) 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'' (p. 51). Masculinity versus femininity ($Z_3$) ranges from ''societies in which social gender roles are clearly distinct'' to ''societies in which social gender roles overlap'' (p. 82). Finally, Uncertainty avoidance ($Z_4$) ''the extent to which the members of a culture feel threatened by uncertain or unknown situations'' (p. 113).

**Table 1**: Descriptive statistics of inputs, outputs and cultural variables used

| **Variables** | *Average* | *Min* | *Max* | *Std* |
|---|---|---|---|---|
| *Innovation drivers (input)* | 0.48 | 0.12 | 0.82 | 0.20 |
| *Knowledge creation (input)* | 0.39 | 0.03 | 0.91 | 0.22 |
| *Innovation & Entrepreneurship (input)* | 0.44 | 0.20 | 0.89 | 0.17 |
| *Applications (output)* | 0.44 | 0.21 | 0.73 | 0.14 |
| *Intellectual property (output)* | 0.29 | 0.00 | 1.00 | 0.28 |
| **Cultural Factors** | *Average* | *Min* | *Max* | *Std* |
| *PDI (Z1)* | 49.48 | 11.00 | 104.00 | 21.44 |
| *IDV (Z2)* | 62.08 | 27.00 | 91.00 | 17.47 |
| *MAS (Z3)* | 51.88 | 5.00 | 110.00 | 24.14 |
| *UAI (Z4)* | 69.24 | 23.00 | 112.00 | 24.12 |

## 4. Methodology

### *4.1 Performance measurements*

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

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

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 for variable returns to scale (BCC model). The CCR model uses the convex cone of $\hat{\psi}_{FDH}$ (Deprins et al., 1984) to estimate $\Psi$, whereas the BCC model uses the convex hull of $\hat{\psi}_{FDH}$ to estimate $\Psi$. Since inputs are our primary decision variables, we use input oriented models since the decision maker through different governmental investment policies have greater control over the inputs compared to the outputs used (Halkos and Tzeremes, 2010a, 2010b). The input oriented efficiency score based on the Farrell (1957) for a unit operating at the level (x, y)is defined as:

$$\theta(x, y) = \inf \left\{ \theta \middle| (\theta x, y) \in \Psi \right\} \qquad (2)$$

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

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

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

$$\hat{\Psi}_{VRS} = \left\{ \begin{array}{l} (x, y) \in \Re^{N+M} \left| y \le \sum_{i=1}^{n} \gamma_i y_i ; x \ge \sum_{i=1}^{n} \gamma_i x_i \quad for \quad (\gamma_1, \ldots \gamma_n) \right. \\ such \quad that \quad \sum_{i=1}^{n} \gamma_i = 1; \; \gamma_i \ge 0, i = 1, \ldots n \end{array} \right\} \qquad (4).$$

*3.2 Bias correction using the bootstrap technique*

According to Simar and Wilson (1998, 2000) 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. Therefore, the bootstrap bias estimate for the original DEA estimator $\hat{\theta}_{DEA}(x,y)$ can be calculated as:

$$\widehat{BIAS}_B\left(\hat{\theta}_{DEA}(x,y)\right) = B^{-1}\sum_{b=1}^{B}\hat{\theta}^*_{DEA,b}(x,y) - \hat{\theta}_{DEA}(x,y) \quad (5).$$

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

$$\hat{\hat{\theta}}_{DEA}(x,y) = \hat{\theta}_{DEA}(x,y) - \widehat{BIAS}_B\left(\hat{\theta}_{DEA}(x,y)\right) = 2\hat{\theta}_{DEA}(x,y) - B^{-1}\sum_{b=1}^{B}\hat{\theta}^*_{DEA,b}(x,y) \quad (6).$$

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:

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

In addition we need to avoid the bias correction illustrated in (6) unless:

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

By expressing the input oriented efficiency in terms of the Shephard (1970) input distance function as $\hat{\delta}_{DEA}(x,y) \equiv \frac{1}{\hat{\theta}_{DEA}(x,y)}$ we can construct bootstrap confidence intervals for $\hat{\delta}_{DEA}(x,y)$ as:

$$\left[\hat{\delta}_{DEA}(x,y) - \hat{\alpha}_{1-a/2}, \hat{\delta}_{DEA}(x,y) - \hat{\alpha}_{a/2}\right] \qquad (9).$$

*3.3 Testing for constant and variable returns to scale*

According to 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:

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

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

$$p - value = \Pr ob(T(X_n) \leq T_{obs} \mid H_0 \quad is \quad true) \qquad (11)$$

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

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

*3.4 Testing the effect of external (environmental/uncontrollable) factors on the efficiency scores*

In order to analyse the effect of external variables (cultural values) on the efficiency scores obtained we follow the probabilistic approach developed by Daraio and Simar (2005, 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:

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

where $Fx(x|y,z) = \Pr ob(X \leq x|Y \geq y, Z = z)$. Daraio and Simar then suggested a kernel estimator defined as follows:

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

where K(.) is the Epanechnikov kernel and *h* is the bandwidth of appropriate size. We have used kernel with compact support (Epanechnikov) as suggested by Daraio and Simar (2005). Furthermore, for the calculation of bandwidth we used the two stage data driven approach as proposed by Daraio and Simar (2007). As a first step we used the likelihood cross validation criterion based on K-NN method (Silverman 1986). As a second step we take into account for the dimensionality of x and y, and the sparsity of points in larger dimensional spaces we expand the local bandwidths *hZi* by a factor, increasing with *(p + q)* but decreasing with n[1]. Therefore, we obtain a conditional DEA efficiency measurement defined as:

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

Then in order to establish the influence of an environmental variable on the efficiency scores obtained a scatter of the ratios $Q = \frac{\hat{\theta}_n(x, y|z)}{\hat{\theta}_n(x, y)}$ against Z (in our case

[1] For more discussion on kernel selection and bandwidth choices see Daraio and Simar (2005, 2007)

as mentioned there are four external factors) and its smoothed nonparametric regression lines would help us to analyse the effect of Z on the efficiency scores. If the smoothed nonparametric regression is increasing it indicates that Z is unfavourable to efficiency and when this regression is decreasing then is favourable to efficiency. Finally, in order to construct the smoothed nonparametric regression we use the estimator introduced by Nadaraya (1964) and Watson (1964):

$$\hat{g}(z) = \frac{\sum_{i=1}^{n} K(\frac{z - Z_i}{h})Q}{\sum_{i=1}^{n} K(\frac{z - Z_i}{h})} \qquad (16).$$

## 5. Empirical Analysis

Following the methodology proposed by Simar and Wilson (2002) we investigate our results for the existence of returns to scale. In our application we have three input factors and two outputs and we obtained for this test a p-value of 0.0001< 0.05 (with B=2000) hence, we reject the null hypothesis of CRS. Therefore, the results adopted in our study are based on the VRS model assuming variable returns to scale[2]. Tables 2 provide the innovation efficiency scores derived from the convex analysis. Furthermore, table 2 provides the results of VRS analysis adopting the correction of bias using the methodology proposed by Simar and Wilson (1998, 2000). From the sample of 25 under the VRS assumption only eight countries appear to be efficient (efficiency score =1). These countries are Austria, Estonia, Finland, Hungary, Malta, Netherlands, Slovenia and the USA.

However when looking at the bias corrected efficiency results we realise that the efficiency scores are in many cases considerably lower. For instance for the case of Estonia the unbiased efficiency score is 0.803 with lower bound (LB) of 0.635 and upper bound (UB) of 0.989 confidence interval of 95%. Following the rule presented

[2] The results obtained under the CRS assumption are available upon request

in equation (8) then the bias corrected efficiencies must be preferred compared to the original estimates.

As such the countries with higher innovation efficiency scores are reported to be: Switzerland (0.912), France (0.899), Malta (0.894), Austria (0.871), Hungary (0.858), Poland (0.855), Finland (0.815), Slovenia (0.805), the United States (0.804), Estonia (0.803) and the Netherlands (0.803). The countries with lower innovation efficiency scores are reported to be Ireland (0.327), the United Kingdom (0.455), Luxembourg (0.472), Greece (0.528), Denmark (0.562), Bulgaria (0.579), Germany (0.582), Spain (0.590) and Romania (0.597).

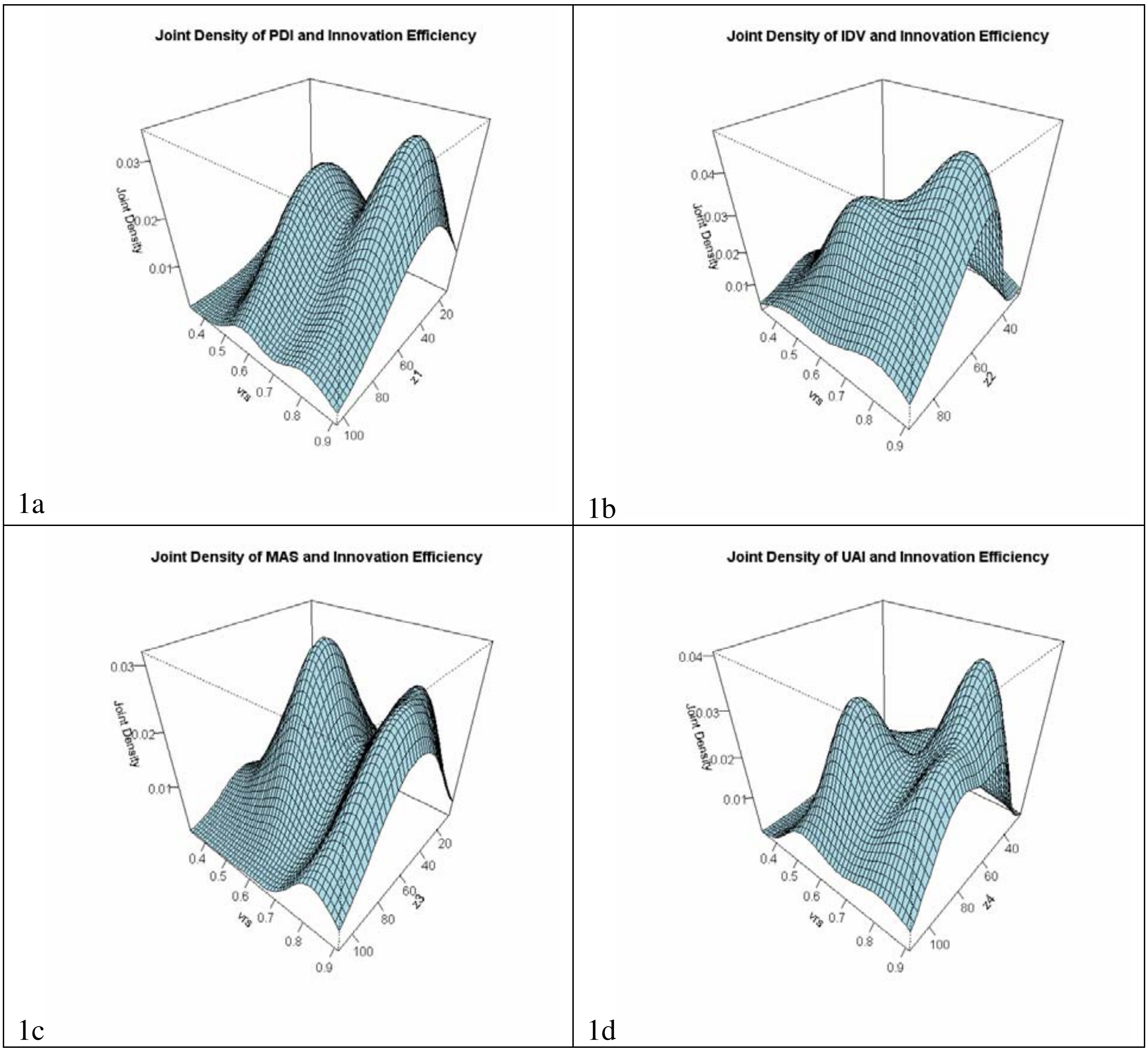
**Table 2:** Efficiency scores of countries' innovation performance

| Countries | VRS | VRS_BC | BIAS | STD | LB | UB |
|---|---|---|---|---|---|---|
| Austria | 1.000 | 0.871 | -0.148 | 0.005 | 0.779 | 0.989 |
| Belgium | 0.686 | 0.633 | -0.123 | 0.004 | 0.585 | 0.678 |
| Bulgaria | 0.641 | 0.579 | -0.166 | 0.006 | 0.531 | 0.634 |
| Czech Republic | 0.815 | 0.744 | -0.117 | 0.005 | 0.665 | 0.806 |
| Denmark | 0.647 | 0.562 | -0.233 | 0.019 | 0.481 | 0.638 |
| Estonia | 1.000 | 0.803 | -0.245 | 0.023 | 0.635 | 0.989 |
| Finland | 1.000 | 0.815 | -0.227 | 0.018 | 0.680 | 0.990 |
| France | 0.992 | 0.899 | -0.105 | 0.002 | 0.830 | 0.977 |
| Germany | 0.670 | 0.582 | -0.224 | 0.020 | 0.496 | 0.662 |
| Greece | 0.571 | 0.528 | -0.145 | 0.005 | 0.486 | 0.566 |
| Hungary | 1.000 | 0.858 | -0.165 | 0.008 | 0.742 | 0.989 |
| Ireland | 0.379 | 0.327 | -0.422 | 0.060 | 0.279 | 0.374 |
| Italy | 0.691 | 0.629 | -0.142 | 0.004 | 0.581 | 0.683 |
| Luxembourg | 0.525 | 0.472 | -0.214 | 0.015 | 0.417 | 0.519 |
| Malta | 1.000 | 0.894 | -0.118 | 0.003 | 0.805 | 0.986 |
| Netherlands | 1.000 | 0.803 | -0.246 | 0.024 | 0.628 | 0.985 |
| Poland | 0.943 | 0.855 | -0.109 | 0.004 | 0.771 | 0.931 |
| Portugal | 0.857 | 0.776 | -0.122 | 0.004 | 0.699 | 0.849 |
| Romania | 0.687 | 0.597 | -0.217 | 0.022 | 0.497 | 0.678 |
| Slovenia | 1.000 | 0.805 | -0.242 | 0.024 | 0.634 | 0.987 |
| Spain | 0.648 | 0.590 | -0.152 | 0.007 | 0.530 | 0.639 |
| Sweden | 0.715 | 0.625 | -0.201 | 0.011 | 0.548 | 0.706 |
| Switzerland | 0.992 | 0.912 | -0.089 | 0.002 | 0.838 | 0.986 |
| United Kingdom | 0.517 | 0.455 | -0.265 | 0.020 | 0.401 | 0.511 |
| United States | 1.000 | 0.804 | -0.243 | 0.025 | 0.625 | 0.989 |
| Mean | 0.799 | 0.697 | -0.187 | 0.014 | 0.606 | 0.790 |
| Min | 0.379 | 0.327 | -0.422 | 0.002 | 0.279 | 0.374 |
| Max | 1.000 | 0.912 | -0.089 | 0.060 | 0.838 | 0.990 |
| STD | 0.198 | 0.162 | 0.073 | 0.013 | 0.143 | 0.195 |

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 (VRS) and the cultural dimensions (PDI/z1, IDV/z2, MAS/z3 and UAI/z4). 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 indicates somewhat "right-angled" distribution having probability mass at medium/high efficiency scores and low power distance vales.

Quite similar results can be obtained when looking at subfigure 1b, which indicates that the joint density between innovation efficiency scores and countries' IDV values having the probability mass at higher efficiency scores and low individualistic values. In subfigure 1c reveals that probability mass of the joint density of innovation efficiency and countries' masculinity values are having the probability mass of higher/medium efficiency scores with medium/lower masculinity values. Finally, in Subfigure 1d we observe two distributions, one having a probability mass low efficiency scores and high UAI values and another of having a higher innovation efficiency scores and lower 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 (VRS) and the cultural dimensions (PDI, IDV, UAI, MAS)




Adopting the methodology proposed by Daraio and Simar (2005, 2007) we created four conditional innovation efficiency estimators (under the VRS hypothesis) taking into account the influence of the four external variables used (i.e. PDI, IDV, MAS, UAI). In addition to Figure 1, Figure 2 provides us with kernel density plots of the conditional innovationl efficiency values[3] (see equations 13-15). Each graph

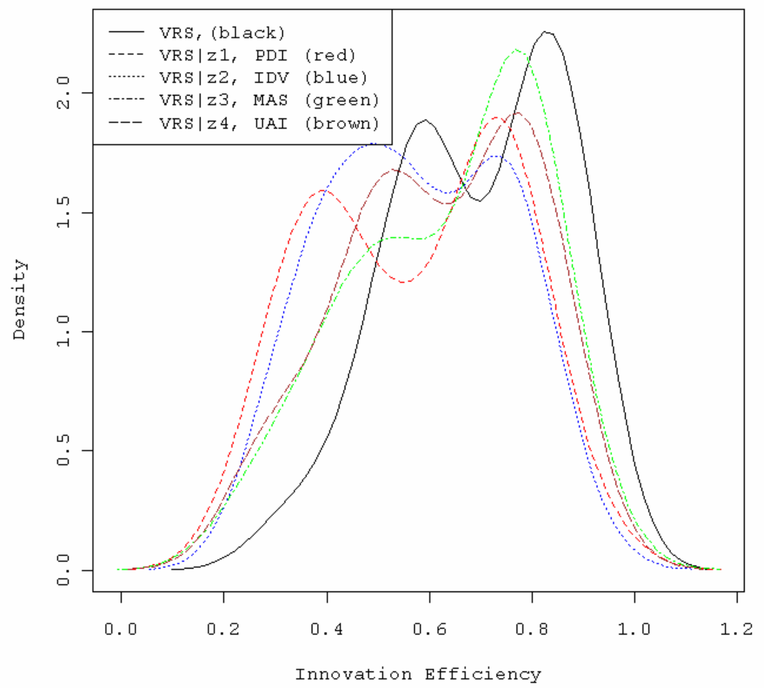
[3] The analytical results of the conditional DEA estimators are available upon request

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 seem to differentiate in contrast with the original innovation efficiency scores (solid black line).

This indicates that countries' cultural characteristics have an effect on their innovation performance. Furthermore, it appears that under the effect of masculine cultures (dashed dot green line) the innovation efficiency scores have a leptokurtic distribution compared to the effect of power distance (thick dotted red line), individualistic (thin dotted blue line) and uncertainty avoidance (long dotted brown line) 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 cultural values in a society influencing more countries' innovation performance.

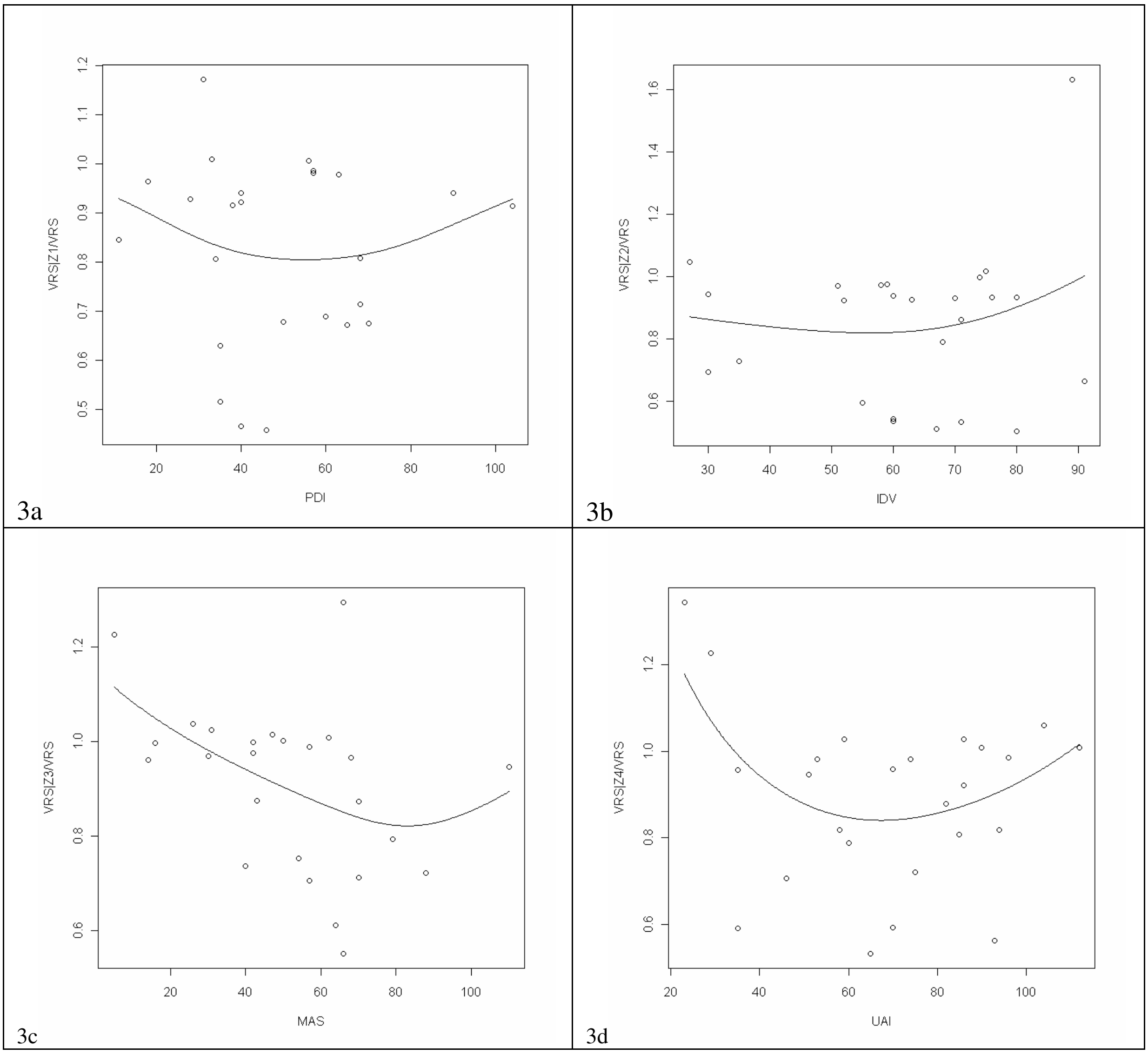
Figure 3 illustrates the effect of the four external variables on countries' innovation efficiency. As can be realised by this figure, PDI and UAI have a positive effect on countries' efficiency performances up to a point which in turn after that point the effect appears to be negative. It appears that lower PDI and UAI have a positive effect on countries' innovation efficiency whereas higher values have a negative effect. The findings for the case of PDI partially confirm the findings by Vaskarelis (2001), indicating that the lower the PDI value of a country the higher it will be its R&D investment intensity.

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




Similarly, the differences between the individualist and the collectivist (IDV) society and the way they perceive innovation can lead to inefficient innovation policies. It appears that lower individualistic values in a society have a rather neutral and slightly positive effect on countries innovation efficiency, whereas higher individualistic values have a negative effect on countries' innovation efficiency. Finally, masculinity values in a society have a positive influence on countries' innovation efficiency. However, higher masculinity values have a negative effect. The results clearly indicate that the effect of national culture on countries innovation efficiency is crucial by determining the way governments shape their innovation policies, their perceptions and the role of innovation on the economy.

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




## 6. Conclusions

According to Baumol (2000) the key for the analysis of capitalistic growth as derived from Schumpeter's theory (Schumpeter, 1934) is the microeconomics of innovation and entrepreneurship. Furthermore, the cultural factors influencing entrepreneurial behaviour must be at the center of the research agenda (Cohran, 1960; Soltow, 1968).

Given the fact that there is a methodological gap in the literature of cross-cultural studies (George and Zahra, 2002; Coviello and Jones, 2004; Engelen et al.

2009), this study by using conditional full frontiers (Daraio and Simar, 2005, 2007) has analysed the effect of national culture on 25 countries' innovation efficiency. By applying the inferential approach introduced by Simar and Wilson (1998, 2000) and bootstrapped procedures introduced by Simar and Wilson (2002, 2008) this paper demonstrates empirically how countries' cultural values influence their innovation performance. Except of contributing to the methodological gap of the literature of relative studies this paper provides solid evidence that countries cultural values have a great influence on the way societies perceive and apply innovation policies.

The results support the result obtained from Vaskarelis (2001) who found a link between lower power distance values and high R&D intensity. Our results indicate that higher PDI, MAS and UAI values have a negative effect on countries' innovation efficiency, whereas masculinity values appear to have a positive effect on countries' innovation performance. The findings suggest that national culture appears to have an impact on countries' innovation efficiency. Since cultural values are not inborn and can be taught (Hofstede 1980) the biggest task of governments and policy makers lays ahead and that is to shape countries' national cultural values towards innovation and entrepreneurial norms and ethics.

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