Measuring regional public health provision

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Abstract

This paper using Data Envelopment Analysis (DEA) evaluates the performance of public health services of the Greek prefectures. The efficiency levels of the Greek prefectures are compared and analyzed in a regional context. With the use of bootstrap techniques and conditional full frontier applications the paper shows that higher levels of GDP per capita and population density increase the prefectures' performance of public health provision. In addition population density affects more the prefectures' performance compared to the levels of GDP per capita. Finally, it appears that Greek prefectures with GDP per capita levels of 25000 to 30000 € and those with population density levels between 150 and 200 residents per square kilometre have significantly higher efficiency levels of public health provision.

***Keywords*:** Public health; Performance measurement; Conditional DEA; Bootstrap techniques; Kernel density estimation.

JEL classification: I11, I18, C14, C67

1. INTRODUCTION

The health care provision has become a major issue of health economists raising a general scientific and in some respect a political debate. Policy makers have been forced to raise issues regarding hospital costs control and operating efficiency. Scott (1999) raises several issues regarding the effects on operating efficiency and the costs of health care delivery on USA's "universal health coverage".

In that respect numerous of empirical studies have measured hospitals operating efficiency using parametric and non parametric techniques (Hollingsworth and Street, 2006). An analytical literature review of the studies using parametric and non parametric techniques has been well documented and analyzed by Hollingsworth et al. (1999) and Hollingsworth (2003). By reporting only the efficiency levels of different hospitals, health care and medical centers, the majority of the studies have failed to determine reliable evidence for the policy makers in order to be able to use them for policy improvements on health care delivery policies (Hollingsworth, 2008).

Therefore, providing only evidence of efficiency measures using different Data Envelopment Analysis (DEA) formulations (without any sufficient justifications), a situation emerged where an action of 'have software-will analyze' became very popular (Hollingsworth, 2003). In that respect external factors need also to be considered and analyzed in more consistent way when using parametric and non-parametric performance measurement techniques.

When evaluating health expenditure, studies suggest that income variations can explain health care delivery policies (Häkkinen and Luoma, 1995). In addition, Luoma et al. (1996) suggest that structural and economic conditions are also necessary to be taken into account when examining the productive efficiency in primary care.

In that respect our study uses a regional perspective approach rather than hospital or/ and health care center efficiency evaluation approach. The objective of this approach is to use the latest advances on nonparametric techniques in a regional level. From that respect this paper evaluates the performance of all the Greek prefectures in terms of their ability to deliver efficient public health care services. Furthermore, our study uses the latest advances of DEA techniques as has been introduced by Simar and Wilson (1998; 2000; 2002; 2006) and Daraio and Simar (2005a; 2005b; 2007) in order to evaluate the influence of two external factors (GDP per capita and population density) which influence and shape the efficiency of health care provision among the Greek prefectures.

The measurement of efficiency in a regional context is not a new one. MacMillan (1986) was the first to establish the applicability of DEA on regional analysis and planning. In Greek context using DEA techniques Karkazis and Thanassoulis (1998) assess the effectiveness of regional development policies of the Greek Governments. In addition, Athanassopoulos and Karkazis (1997) entering the concept of regional efficiency examined the case of 20 prefectures of Northern Greece and found regional planning inefficiencies. However, none of the papers evaluated so far in the literature have used regional context in order to evaluate the efficiency of health care delivery. Close to those lines Paci and Wagstaff (1993) by describing the Italian health care system emphasize the role of the region and other macroeconomic factors when evaluating the efficiency of the Italian health care system.

As such, our study has as a major objective to provide different indications of what extent Greek citizens in different prefectures of the country have the same chance of obtaining public treatment or care for particular conditions. Furthermore, by using justified conditional measures, this paper aims to provide the current state of the

Greek regional public heath provision. Furthermore, it emphasizes the strengths and weaknesses of the current state of public health delivery planning by concentrating on the effect of GDP per capita and population density of the regions. In that respect it will provide solid evidence for policy evaluation.

The paper is organized a follows. Section 2 presents the various variables used in the formulation of the proposed models. In section 3 the techniques adopted both in theoretical and mathematical formulations are presented. Section 4 discusses the empirical findings of our study. The final section concludes the paper commenting on the derived results and the implied policy implications.

2. DATA

In our paper a number of indicators is used. Each region's indicators differ as one indicator may be high and another may be low. This implies that it is important to weight the various indicators in order to obtain an indicator, which will help us to understand the current conditions of the regional public health service for each prefecture. The main issue is how to weight these indicators in a realistic and representative way and thus to take into consideration the external (environmental) factors influencing them. The National Statistical Service of Greece has recorded the data used here. They refer to the year of 2005 for all the Greek prefectures. The data are provided by All Media Database (2007) (Profile of Greek Regions)[1].

Table I provides descriptive statistics regarding the inputs and the output used in our DEA formulation. As can been realised there are two inputs the number of hospital beds and the number of doctors of both the public hospitals and public health centres across the Greek prefectures. As expected the descriptive statistics indicate

[1] The data can be retrieved from: www.economics.gr

high disparities among the prefectures regarding the number of doctors and hospital beds with a standard deviation of 3291 and 3366 respectively.

In addition the study uses days of in patient care as an output. Again, as table I shows, the standard deviation values are extremely high indicating high variations of days of in patient care among the prefectures. The fact that we have so many variations may be explained upon the different population sizes among the Greek prefectures. However, is this state of in patient care valid for similar (in terms of population size or GDP per capita) prefectures? For that reason two external variables have been also used in our analysis. These are GDP per capita (Z_1) and population density (Z_2). Again in both cases it can be realised that Greek prefectures can be characterised by high dissimilarities both in terms of population size and GDP per capita. These inequalities have a great influence on the regional development strategies adopted by the Greek government and the local/ regional authorities over the years and thus, are expected to have a major impact on the public health provision.

Table 1: Descriptive statistics of variables used

	Inputs		Output	External Variables	
	Hospital beds	Number of doctors	Days of in-patient care	GDP per capita (Z_1)	Population density (residents per sq km) (Z_2)
Average	1021,62	1042,08	267176,24	15534,52	58,87
Minimum	69	60	13232	9753,34	10,31
Maximum	22486	23194	6162318	34289,31	302,16
STD	3291,13	3366,86	894144,32	4557,09	45,05

3. METHODS PROPOSED

3.1 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 Ψ and allowing constant returns to scale (CCR model). The production set Ψ constraints the production process and is the set of physically attainable points (x, y) :

$$\Psi = \left\{ (x, y) \in \Re_{+}^{N+M} \middle| x \quad can \quad produce \quad y \right\} \tag{2},$$

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 $\hat{\psi}_{FDH}$ to estimate Ψ, whereas the BCC model uses the convex hull of $\hat{\psi}_{FDH}$ to estimate Ψ. In this paper we use input oriented models since the decision maker through different governmental and regional policies have greater control over the inputs compared to the output used. Following the notation by Simar and Wilson (2006), the CCR model developed by Charnes et al. (1978) can be calculated as:

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

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

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

Finally the FDH estimator $\hat{\psi}_{FDH}$ which is the free disposal hull of the observed sample X_n and developed by Deprins et al. (1984) can be expressed as:

$$\hat{\Psi}_{FDH} = \left\{ (x,y) \in \Re^{N+M} \left| y \le y_i, x \ge x_i, (x_i, y_i \in X_n \right. \right\}$$

$$= \bigcup_{(x_i,y_i)\in X_n} \left\{ (x,y) \in \Re_+^{p+q} \left| y \le y_i, x \ge x_i \right. \right\} \quad (5).$$

3.2 Bias correction using the bootstrap technique

According to Simar and Wilson (1998, 2000, 2006) 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:

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

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

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

However, according to Simar and Wilson (2006) 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:

$$\hat{\sigma}^2 = B^{-1}\sum_{b=1}^{B}\left[\hat{\theta}^*_{DEA,b}(x,y) - B^{-1}\sum_{b=1}^{B}\hat{\theta}^*_{DEA,b}(x,y)\right]^2 \quad (8).$$

According to Simar and Wilson (2006) we need to avoid the bias correction illustrated in (7) unless:

$$\frac{\left|\hat{BIAS}_B(\hat{\theta}_{DEA}(x,y))\right|}{\hat{\sigma}} > \frac{1}{\sqrt{3}} \qquad (9).$$

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

$$\frac{1}{\hat{\delta}_{DEA}(x,y) - nc^*_{1-a/2}} \le \theta(x,y) \le \frac{1}{\hat{\delta}_{DEA}(x,y) - nc^*_{a/2}} \qquad (10).$$

3.3 Testing for returns to scale and convexity

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:

$$T(X_n) = \frac{1}{n}\sum_{i=1}^{n}\frac{\hat{\theta}_{CRS,n}(X_i,Y_i)}{\hat{\theta}_{VRS,n}(X_i,Y_i)} \qquad (11).$$

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

$$p-value = prob(T(X_n) \le T_{obs} \,|\, H_0 \quad is \quad true) \qquad (12)$$

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:

$$p-value \approx \sum_{b=1}^{B}\frac{\mathrm{I}\left(T^{*b} \le T_{obs}\right)}{B} \qquad (13).$$

A similar statistical test can be created for testing convexity between the DEA and FDH estimators (Daraio and Simar, 2005a). Then the null hypothesis of convexity will be rejected if the test statistic is too small. Bootstrap techniques are the only way to perform these tests when evaluating the appropriate p-values. Therefore, we use for the first time a similar approach as described previously in such a way that $H_0 : \Psi^{\theta}$ is globally DEA (CRS or VRS) against $H_1 : \Psi^{\theta}$ is FDH. The test statistic mean of the ratios of the efficiency scores is then provided by:

$$T(X_n) = \frac{1}{n}\sum_{i=1}^{n} \frac{\hat{\theta}_{DEA,n}(X_i, Y_i)}{\hat{\theta}_{FDH,n}(X_i, Y_i)} \qquad (14).$$

Then the p-value can be calculated following equations (12) and (13). If the p-value is too small then the FDH estimator need to be adopted against the DEA estimator since the convexity hypothesis is not true for the original observed sample X_n.

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

In order to analyse the effect of external variables (population density and GDP per capita) 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:

$$\theta(x, y|z) = \inf\left\{ \theta \middle| F_X(\theta x|y, z) > 0 \right\} \qquad (15),$$

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

$$\hat{F}_{X|Y,Z,n}(x|y,z) = \frac{\sum_{i=1}^{n} I(x_i \leq x, y_i \geq y) K((z - z_i)/h)}{\sum_{i=1}^{n} I(y_i \geq y) K((z - z_i)/h)} \quad (16),$$

where K(.) is the Epanechnikov kernel and h is the bandwidth of appropriate size[2]. Therefore, we obtain a conditional DEA efficiency measurement defined as:

$$\hat{\theta}_{DEA}(x, y|z) = \inf\left\{\theta \middle| \hat{F}_{X|Y,Z,n}(\theta x|y,z) > 0\right\} \quad (17).$$

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 two external factors) and its smoothed nonparametric regression lines would help us to analyse the effect of Z on the efficiency scores. If this regression is increasing it indicates that Z is unfavourable to the efficiency of the prefectures whereas if it is decreasing then it is favourable.

4. RESULTS

This paper tests the model for the existence of returns to scale as analysed previously. In our application we have two inputs and one output and we obtained for this test a p-value of 0,00 < 0,05 (with B=2000) hence, we reject the null hypothesis of CRS (Table II). Therefore, the test adopted indicates that the result needed to be adopted must be based on the BCC model due to the existence of variable returns to scale[3]. Furthermore, as noted previously we obtained a similar statistical test for assuming convexity on the VRS results obtained and thus to choose between the BCC and FDH estimates. In a process analysed previously we obtained a p-value of 0,00 < 0,05 (with B=2000) hence, we reject the null hypothesis of VRS (table II).

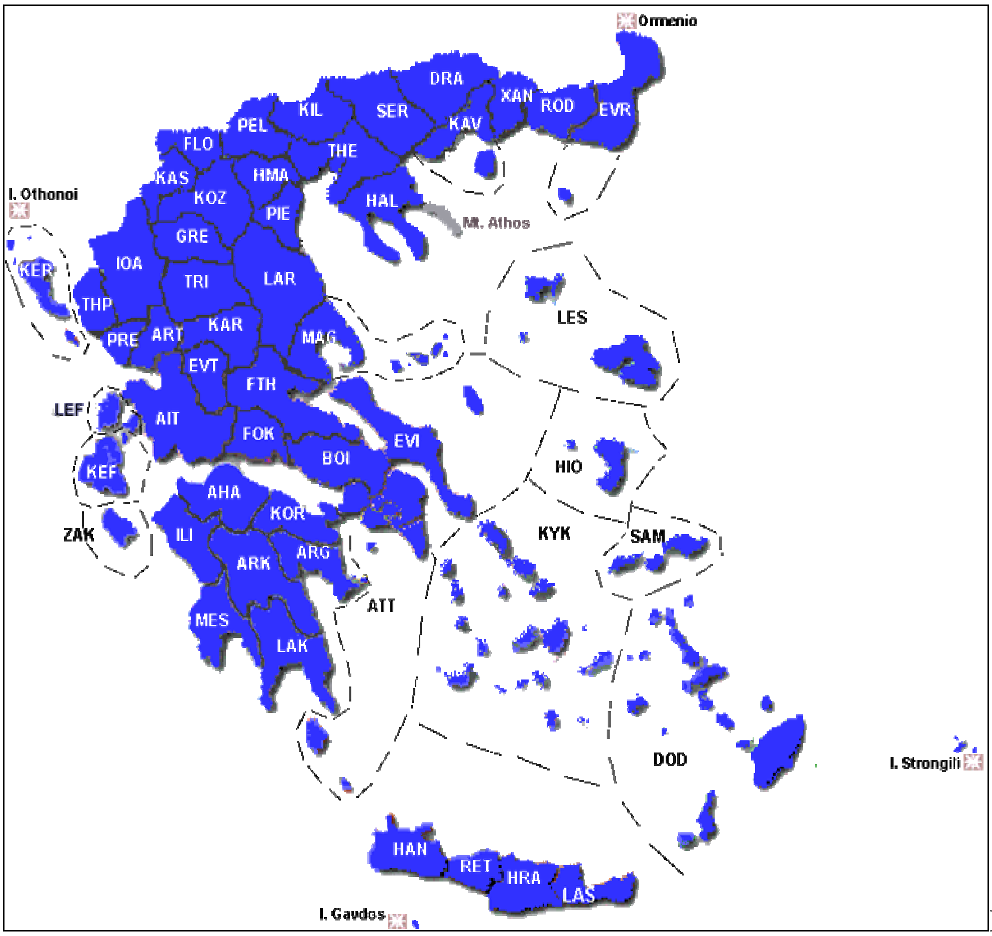
[2] For more discussion on kernel selection and bandwidth choices see Daraio and Simar (2005b, 2007).
[3] All the results obtained from DEA and FDH models are available upon request.

Overall, the two tests taking into account the existence of scales and the assumption of convexity indicate that the proper estimates for measuring the performance of public health services of the Greek prefectures are obtained by the use of FDH model. Nevertheless, the average efficiency results obtained using the three different efficiency measures are presented in Table II. Analytically, table II presents descriptive statistics of the efficiency scores of the 50 prefectures, the biased corrected efficiency scores and the 95-percent confidence internals: lower and upper bound obtained by B=2000 bootstrap replications using the algorithm described previously.

As expected the average efficiency scores of health provision are lower for the CRS (0,43) and the VRS (0,62) case compared to the FDH efficiency scores (0,91). In addition table II provides the values of the average convexity efficiency scores for the CRS (C_{CRS}) and for VRS (C_{VRS}) case. As can be seen the assumption of convexity can not be hold due to the fact that the average convexity efficiency score for VRS case is 0,77 and for the CRS is 0,62. Therefore, the descriptive statistics of the convexity efficiencies complement the results obtained from the convexity test (using the bootstrap technique) indicating that the results of the FDH model need to be adopted.

In addition, Table III reports analytically the efficiency scores under the FDH and VRS case (for comparison reasons). Furthermore, the map of Greece is presented in Figure 1 alongside with the boundaries of the Greek prefectures. Table III provides the map codes and therefore the identification of efficient and inefficient prefectures can be easily obtained. Looking first at the VRS case we realise that only four prefectures are considered as efficient (i.e. efficient score =1). These are the prefectures of Dodekanisou, Euritanias. Kefallonias and the Region of Attiki. However, the prefectures with the lowest performance (i.e. less than 0,5 in a descending order) are reported for Messinias, Irakleiou, Lesvou, Magnisias, Korinthias, Axaias, Aitolokarnanias, Fdiotidas, Evrou, Artas and Larisas.

Figure 1: Map of Greece and Greek prefectures illustrating prefectures' map codes



However, when looking at the values of $\hat{Bias}$ and $\hat{\sigma}$ and by following expression (9) we realise that the biased corrected results need to be evaluated. The prefectures with the higher performance (i.e. more than 0,7 in a descending order) are Euritanias, Kefallonias, Pierias, Thesproteias, Prebezas, Dodekanisou, the Region of Attiki, Kerkiras and Leukadas, whereas the prefectures with the lowest performance (i.e. less/ equal to 0,5 in a descending order) are Xanthis, Kastorias, Ileias, Dramas, Pellas, Argolidas, Rethimnon, Trikalon, Messinias, Xanion, Arkadias, Ioanninon, Lesvou, Kavalas, Korinthias, Aitolokarnanias, Irakleiou, Magnisias, Fdiotidas, Axaias, Evrou, Artas and Larisas.

Table II: Convexity, returns to scale bootstrap results and average efficiency scores of CRS, VRS, FDH models.

CRS	Efficiency	Biased corected	$\hat{Bias}$	$\hat{\sigma}$	Lower	Upper
Average	0,43	0,33	-0,72	0,10	0,29	0,41
Minimum	0,24	0,18	-1,75	0,02	0,16	0,22
Maximum	1,00	0,66	-0,36	0,36	0,60	0,88
Std	0,14	0,10	0,32	0,07	0,09	0,13
VRS	**Efficiency**	**Biased corected**	$\hat{Bias}$	$\hat{\sigma}$	**Lower**	**Upper**
Average	0,62	0,55	-0,21	0,02	0,48	0,61
Minimum	0,31	0,28	-0,46	0,00	0,24	0,31
Maximum	1,00	0,80	-0,08	0,08	0,69	0,97
Std	0,17	0,13	0,10	0,02	0,11	0,17
FDH	**Efficiency**	C_{VRS}	C_{CRS}	**Returns to Scale test**	**Convexity Test**	
Average	0,91	0,77	0,62	*Ho: CRS*	*Ho: VRS*	
Minimum	0,44	0,28	0,24	*H1: VRS*	*H1: FDH*	
Maximum	1,00	2,94	2,26	0,0006125*	0,0000875*	
Std	0,14	0,53	0,44	** p values, significant at 1% level*		

But, when relaxing the assumption of convexity (according to the bootstrap test) the results of the FDH model need to be adopted. As Table III indicates twenty eight prefectures are reported to be efficient. These are the prefectures of Euritanias, Kefallonias, Pierias, Thesproteias, Prebezas, Dodekanisou, Region Attikis, Kerkiras, Halkidikis, Grebenon/ Kozanis, Samou, Thessalonikis, Kikladon, Xiou, Imathias, Florinas, Euvias, Karditsas, Kilkis, Rodopis, Boiotias, Kastorias, Dramas, Pellas, Argolidas, Rethimnon, Xanthis and Ileias. On the other hand, the prefectures with the lowest performance (i.e. less/ equal to 0,7 in a descending order) are reported for Axaias, Irakleiou, Magnisias, Evrou and Larisas. The high number of efficient prefectures (twenty eight out of fifty) under the FDH approach was expected.

In addition Tulkens (1993, p.186) suggests that FDH makes the weakest postulates as to how the reference set is constructed from the statistical data. This is due to the absence of the convexity and therefore, FDH measurement provides better data fit. Moreover, the FDH approach relaxes the convexity assumptions and according to Fried et al. (1996), DEA producer's role models may not dominate the producer being evaluated, whereas in FDH the producer's role models dominate it by construction (p.377).

Table III provides the results of the reference set for dominating and dominated prefectures. For instance, the prefecture of Evrou (10) is being dominated by prefectures of Kerkira (23), Pierias (38) and Serron (43) given its public health provision state. Furthermore, the prefecture of Lesvou (31) is being dominated by the prefecture of Kilkis (25) and Xanthis (35) but also acts as a raw model for the prefecture of Fdiotida (45). The notion of domination which is only provided to that extent by the FDH approach is specifically useful for the evaluation of health provision policies and the establishment of raw models.

As described previously figure 2 illustrates the effect of the two external variables on prefectures' public health services performance. Figure 2a examines the influence of GDP per capita on prefectures' performance. It represents a scatter plot of the ratios $\hat{\theta}_n(x, y|z)/\hat{\theta}_n(x, y)$ against GDP per capita and its smoothed nonparametric regression line in order to define this influence. As the regression is decreasing it specifies that GDP per capita is conducive to the prefectures' public health services performance. Figure 2b presents the same positive influence in a surface context, whereas the figure 2c presents a contour plot of the ratio $\hat{\theta}_n(x, y|z)/\hat{\theta}_n(x, y)$ and the GDP per capita. As can be realised higher performance levels of public health services are reported for prefectures with recorded GDP per capita near the levels of 25000- 30000 €.

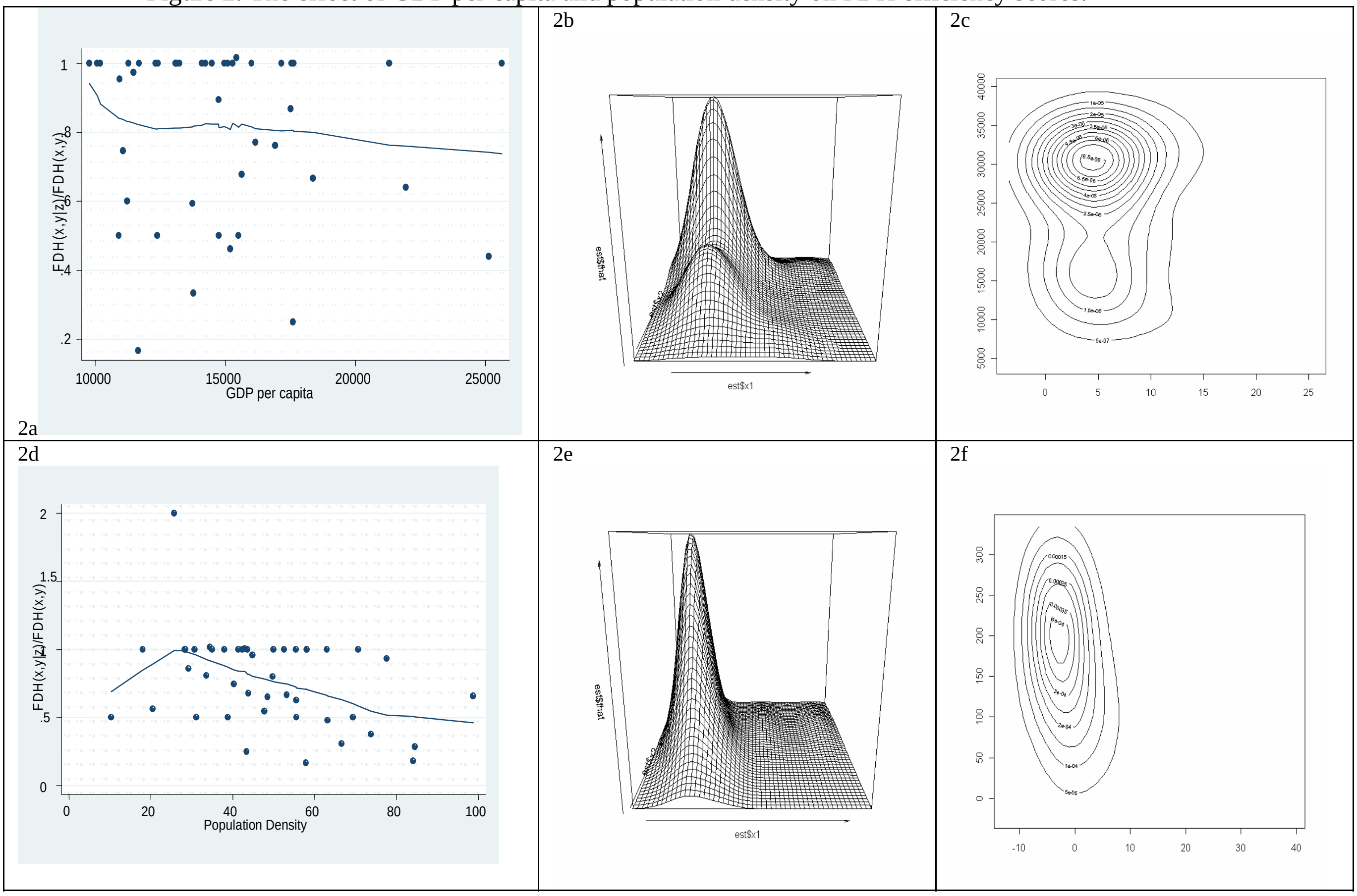
Table III: Map codes and analytical results of public health provision of the Greek prefectures using FDH and VRS formulation.

aa	Map codes	Prefectures	FDH	VRS	Unbiased VRS scores	BIAS	STD	Lower bound	Upper bound	Dominated	Dominating
1	AIT	Aitolokarnanias	0,76	0,42	0,40	-0,13	0,01	0,37	0,42	15 21 34 36 38	-
2	ARG	Argolidas	1,00	0,51	0,48	-0,12	0,01	0,44	0,50	-	-
3	ARK	Arkadias	0,81	0,52	0,45	-0,28	0,02	0,40	0,51	38	
4	ART	Artas	0,75	0,40	0,36	-0,27	0,03	0,32	0,40	6 40 42 48 50	-
5	AHA	Axaias	0,70	0,47	0,39	-0,41	0,06	0,33	0,46	9	-
6	BOI	Boiotias	1,00	0,56	0,51	-0,17	0,01	0,47	0,56	-	4 14 28 40
7	GRE/KOZ	Grebenon/ Kozanis	1,00	0,78	0,66	-0,24	0,02	0,56	0,76	-	29
8	DRA	Dramas	1,00	0,52	0,49	-0,11	0,00	0,45	0,51	-	-
9	DOD	Dodekanisou	1,00	1,00	0,73	-0,38	0,03	0,63	0,97	-	5 16 19 29 33
10	EVR	Evrou	0,57	0,41	0,38	-0,17	0,02	0,34	0,41	23 38 43	-
11	EVI	Euvias	1,00	0,59	0,57	-0,08	0,00	0,52	0,59	-	-
12	EVT	Euritanias	1,00	1,00	0,80	-0,24	0,01	0,69	0,97	-	32 47
13	ZAK	Zakinthou	0,98	0,66	0,58	-0,21	0,02	0,49	0,65	39	-
14	ILI	Ileias	1,00	0,52	0,49	-0,10	0,00	0,46	0,52	6	-
15	HMA	Imathias	1,00	0,63	0,59	-0,09	0,00	0,54	0,62	-	1
16	HRA	Irakleiou	0,67	0,49	0,40	-0,46	0,06	0,34	0,48	9	-
17	THP	Thesproteias	1,00	0,87	0,76	-0,17	0,01	0,65	0,86	-	-
18	THE	Thessalonikis	1,00	0,82	0,63	-0,37	0,03	0,53	0,80	-	-
19	IOA	Ioanninon	0,91	0,52	0,45	-0,29	0,03	0,38	0,51	9	29
20	KAV	Kavalas	0,95	0,51	0,44	-0,31	0,03	0,38	0,50	23	-
21	KAR	Karditsas	1,00	0,61	0,53	-0,23	0,01	0,47	0,59	-	1
22	KAS	Kastorias	1,00	0,60	0,50	-0,34	0,03	0,43	0,58	-	-
23	KER	Kerkiras	1,00	0,87	0,72	-0,24	0,02	0,62	0,86	-	10 20 29 33 49
24	KEF	Kefallonias	1,00	1,00	0,80	-0,25	0,01	0,69	0,97	-	-
25	KIL	Kilkis	1,00	0,57	0,52	-0,17	0,01	0,47	0,56	-	30 31 35 45
26	KOR	Korinthias	0,95	0,47	0,44	-0,12	0,01	0,41	0,47	41	-
27	KYK	Kikladon	1,00	0,70	0,62	-0,19	0,02	0,52	0,69	-	-
28	LAK	Lakonias	0,99	0,55	0,52	-0,10	0,00	0,49	0,55	6	-
29	LAR	Larisas	0,44	0,31	0,28	-0,42	0,08	0,24	0,31	7 9 19 23 33 49	-
30	LAS	Lasithiou	0,98	0,56	0,53	-0,09	0,00	0,49	0,55	25	45
31	LES	Lesvou	0,93	0,48	0,45	-0,12	0,01	0,42	0,47	25 35	45
32	LEF	Leukadas	0,86	0,86	0,70	-0,27	0,02	0,60	0,85	12	47
33	MAG	Magnisias	0,58	0,47	0,40	-0,39	0,05	0,34	0,47	9 23	29
34	MES	Messinias	0,87	0,49	0,47	-0,12	0,01	0,42	0,49	38	1
35	XAN	Xanthis	1,00	0,54	0,50	-0,14	0,01	0,46	0,53	25	31 45
36	PEL	Pellas	1,00	0,56	0,49	-0,25	0,02	0,43	0,54	-	1
37	ATT	Region Attikis	1,00	1,00	0,72	-0,38	0,03	0,62	0,97	-	-
38	PIE	Pierias	1,00	0,86	0,77	-0,14	0,01	0,67	0,85	-	1 3 10 34 43 44
39	PRE	Prebezas	1,00	0,82	0,74	-0,13	0,01	0,64	0,81	-	13
40	RET	Rethimnon	1,00	0,51	0,47	-0,18	0,01	0,42	0,50	6	4
41	ROD	Rodopis	1,00	0,55	0,52	-0,10	0,00	0,48	0,54	-	26
42	SAM	Samou	1,00	0,69	0,65	-0,11	0,01	0,58	0,69	-	4
43	SER	Serron	0,80	0,65	0,60	-0,12	0,01	0,53	0,64	38	10
44	TRI	Trikalon	0,78	0,51	0,47	-0,19	0,01	0,41	0,51	38	-
45	FTH	Fdiotidas	0,84	0,41	0,39	-0,13	0,01	0,36	0,41	25 30 31 35	-
46	FLO	Florinas	1,00	0,67	0,57	-0,24	0,02	0,49	0,66	-	-
47	FOK	Fokidas	0,73	0,73	0,61	-0,27	0,02	0,52	0,73	12 32	-
48	HAL	Halkidikis	1,00	0,73	0,69	-0,09	0,00	0,62	0,73	-	4
49	HAN	Xanion	0,74	0,55	0,47	-0,34	0,04	0,40	0,54	23	29
50	HIO	Xiou	1,00	0,65	0,60	-0,13	0,01	0,54	0,64	-	4

In addition when examining the influence of population density on the prefectures' performance similar results can be derived. Figures 2d - 2e show a similar picture compared to the case of GDP per capita. In that respect we can conclude that prefectures' level of population density has a positive effect on prefectures' performance. Furthermore when looking at the contour plot 2f we may conclude that prefectures which have population density around the levels of 150-200 residents per square kilometre have higher efficiency levels of public health provision compared to the prefectures with significant lower levels of population density.

Thus, our empirical evidence reveals that the prefectures' level of population density has a higher positive impact to the prefectures' performance compared to the effect of prefectures' level of GDP per capita.

Figure 2: The effect of GDP per capita and population density on FDH efficiency scores.



5. CONCLUSIONS

This study uses conditional DEA techniques to examine for the first time the efficiency of public health care delivery in a regional context. In that respect the effect on the efficiency of health care provision of factors such as GDP per capita and population density are examined. Furthermore, several methodological procedures have been applied using the bootstrap technique in order to justify a consistent performance measurement estimator.

Our results reveal that both GDP per capita and population density have a positive impact on the prefectures' ability to deliver highly efficient public health services to the Greek citizens. In addition prefectures with GDP per capita levels of 25000 to 30000 € and those with population density levels between 150 and 200 residents per square kilometre have significantly higher efficiency levels of public health provision.

The study uses the latest advances in DEA techniques trying to overcome the drawbacks of different DEA studies which measure only hospitals' operating efficiency. In that respect it provides solid evidence of different efficiency levels of public health provision in different regions and thus an established way of measuring the state of public health delivery in Greece. As such this paper can be a useful tool for policy makers when evaluating the Greek regional social development plan. However, Hollingsworth (2008), claims that as in any study which uses performance measurement techniques, small differences of inefficiencies between the prefectures may not reflect inefficiency and therefore, need to be treated with caution.

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