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Abstract

This paper applies a probabilistic approach in order to develop conditional and unconditional Data Envelopment Analysis (DEA) models for the measurement of sectors' input oriented technical and scale efficiency levels for a sample of 23 Greek manufacturing sectors. In order to capture the Averch and Johnson effect (A-J effect), we measure sectors' efficiency levels conditioned on the number of companies competing within the sectors. Particularly, various DEA models have been applied alongside with bootstrap techniques in order to determine the effect of competition conditions on sectors' inefficiency levels. Additionally, this study illustrates how the recent developments in efficiency analysis and statistical inference can be applied when evaluating the effect of regulations in an industry. The results reveal that sectors with fewer numbers of companies appear to have greater scale and technical inefficiencies due to the existence of the A-J effect.

Keywords: Averch-Johnson effect; Industry regulations; Manufacturing sectors; Nonparametric analysis.

JEL Codes: C14; L10; L25; L59.

1. Introduction

Regulatory actions on monopoly firms and deregulatory actions towards competitive markets are two interrelated issues which have been addressed extensively by the literature in the scope of capital utilization (Kim 1999). The most frequently used regulations are the rate-of-return and the price-cap (Blank and Mayo 2009). The regulations are imposed by a regulatory agency often prompted by a court (Sherman 1985). In theory, a regulatory agency targets to improve general welfare by imposing regulations in order to correct market anomalies but this may not always be the case (Klevorick 1966). Joskow (2005) provides different results derived from regulation and deregulation cases. Sectors like airlines, railroads, electric power, gas and oil were imposed with some sort of regulation. The process of deregulation has been completed in a number of cases while in other cases the deregulation process is on-going.

In their seminal work, Averch and Johnson (1962) study a monopoly firm which seeks to maximize its profits under rate-of-return regulation. The monopoly firm employs capital and labor to produce one output. The availability of capital and labor is assumed to be unlimited and the price per unit fixed. The regulatory agency imposes a "fair rate of return" on the firm through the rate-of-return regulation. If the firm's unrestricted rate of return is smaller than the "fair rate of return" then the firm is allowed to act as if there was no regulation and for example raise the price. Otherwise if the firm's unrestricted rate of return is bigger than the "fair rate of return" then the firm will be compelled to lower the price. After that, according to the Averch-Johnson effect (A-J effect) and under the assumption of no regulatory lags (Johnson, 1973), if the cost of "fair rate of return" is greater than the cost of capital but less than the unrestricted rate of return, the firm is expected to produce at a point where the capital-labor ratio is not optimum. Although the firm will not minimize the cost of production, the excessive use of capital will allow the firm to achieve greater profits through a bigger "fair rate of return".

Our paper applies for the first time conditional full frontiers, based on the probabilistic approach of efficiency measurement developed by Daraio and Simar (2005, 2007a, 2007b) and in order to investigate the A-J effect for the Greek manufacturing sectors. Furthermore it applies the statistical inference framework developed by Simar and Wilson (1998, 2000a, 2000b) on the conditional efficiency measures obtained in order to create biased free estimates. The structure of the paper is the following. Section 2 presents the literature review, while section 3 discusses the data used and the proposed methodology. Section 4 comments on the empirical results derived while the last section concludes the paper.

2. A brief review of the literature

Takayama (1969) following the study by Averch and Johnson (1962) presented an alternative mathematical formulation of the problem and obtained similar results about the overcapitalization of a regulated monopolistic firm. In addition, Westfield (1965) examined the possibility of conspiracies among buyers and sellers of plant, machinery and electrical equipments. He demonstrated that a private power generating company which is under regulation is willing to pay more for the capital equipment. This capital waste can lead the monopoly firm to achieve greater profits. Klevorick (1966) suggested an inverse relation among the "fair rate of return" and amount of capital employed in order to deal with the A-J effect. Thus, if the firm raises its capital, the "fair rate of return" will be reduced.

Furthermore, Stigler and Friedland (1962) are the first to investigate A-J effect among firms from different states and compare the results from states with and without regulations. In addition, Spann (1974) applied a translog production function in order to study the regulated electric utilities. He relied on Stigler and Friedland (1962) study where the effect of regulation is assumed to be uniform across the states, and allows the effect to vary. The results appeared to verify the A-J effect. Additionally, the A-J effect is validated by Petersen (1975) who marks that a more tightened regulation leads to an increase of the firm's unit costs.

Moreover, Sherman (1972) notes that rate-of return regulation will drive the firm to continue behaving as a monopoly for every input except capital, but it will make choices about capital as if it was in a competitive market. The rate-of-return regulation has additional negative effects which in fact may be more significant than input distortions, like the absence of motivation for innovative actions and efficient operation. Another negative effect of rate-of-return regulation is the technological advancement and R&D (Frank 2003a).

Rumbos (1999) introduced the variable utilization rate of capital stock in the profit maximization problem of the monopolistic firm and proposed the measurement of the inefficiency of the production of total services of capital instead of the ratio of capital and labor. On the other hand, Maloney (2001) employed a variable cost function in order to measure electricity generation industry. In addition, Kolpin (2001) introduces a dynamic model, which incorporates among others, multiple inputs and outputs, periods of production and uncertainty, in order to test and verify the A-J effect. Finally, Caputo and Partovi (2002) defined four conditions under which the A-J effect is present.

A number of authors challenge the traditional assumptions and results of the A-J effect. Baumol and Klevorick (1970) argued that in practice regulatory lags exist. Thus, the monopolistic firm can achieve greater returns from the "fair" for a short time period. Also, the authors note that every tax leads to input distortion and rate-of-return regulation has not an additional effect in practice. Zajac (1970) exhibited the geometrical presentation of the A-J effect and questioned some of the original model's assumptions. Among others, the author came in line with Baumol and Klevorick (1970) about regulatory lags and he has found no solid evidence about the regulated monopolistic firms' optimum strategy between the minimization of the cost or the overcapitalization.

One of the most famous cases of a regulated monopolistic firm is in the US telephone industry, the American Telephone and Telegraph Company (AT&T). Irwin (1997) presented the internal story of the investigation about the firm. The author provided evidence that the AT&T was purchasing the equipment from Western Electric in a very high price, confirming the A-J effect in practice. The natural monopoly of AT&T was ended in 1984 when the company was divested from the Bell operating companies, a move which is now considered as a pro-competitive change (Ying and Shin 1993). Oum and Zhang (1995) investigated the US telephone industry after the transformation towards competition. The authors find evidence that introduction of competition has increased productive efficiency and reduced A-J effect.

They also demonstrated that introducing competition in a previously regulated monopolistic industry may result in multiple benefits like innovations and improved quality. In general, competition appears to be the solution in order to reduce inefficiencies from monopoly and especially regulated monopoly. Dixon and Easaw (2001) studied the UK gas industry for the period 1986-1996 including the privatization period. The authors argue that competition is necessary in order to benefit from the privatization. Similarly, Christopoulos and Tsionas (2001) using heteroscedastic stochastic frontier models for the Greek bank sector found evidences that increased competition after the privatization period reduced the allocative and technical inefficiencies associated with the previous regulated industry conditions.

Frank (2003b) investigated the electric utilities in Texas for the period 1965-1985, ten years before and ten years after the rate-of-return regulation. He has found that before 1975 technological progress results in decreasing costs while after 1975 the negative effect of regulation on technological progress results in greater costs.

Finally, in contrast to the previous mentioned studies examining separate sectors and different industries' competitive conditions, our study for the first time applies a different approach analysing twenty three manufacturing sectors based on the new advances of efficiency analysis as has been introduced by several authors (Daraio and Simar 2005, 2007a, 2007b; Bădin et al. 2010; Jeong et al. 2010) and in order to investigate the A-J effect.

3. Data and Methodology

3.1 Data description

Our analysis uses data of the Greek manufacturing sector as has been provided from ICAP (2007). The data are based on the balance sheets of income statements of 2006. More analytically, consolidated income statements of every Greek manufacturing sector have been used for the companies which are listed in Athens Stock Exchange. In addition table 1 provides a description of the manufacturing sector alongside with information regarding the number of companies competing in each of them. In our analysis and in order to model in a nonparametric context the A-J effect the number of companies in a sector are used as a proxy of the competitive structure of each sector (Oum and Zhang 1995). From table 1 it can be seen that the sectors of ‘tobacco products’, ‘office machinery, computers’ and ‘recycling’ are the sectors with the lowest competition and oligopoly conditions where as the sectors of ‘food and beverages’, ‘non-metallic mineral products’ and ‘Publishing-printing’ appear to have increased competition.

In terms of the Data Envelopment Analysis (DEA) context the measurement of each sector’s efficiency levels must be measured after defining the proper inputs/outputs. Since the A-J effect describes that monopoly firms tend to use more capital than the economic efficient level in order to produce their outputs (Averch and Johnson, 1962), this study uses total assets and inventories (measured in thousands of €) as the two inputs. In addition the outputs used are sales and gross profit levels (also measured in thousands of €).

Table 2 provides the descriptive statistics of the variables used. As it is revealed from the high standard deviation values there are several dissimilarities among the sectors indicating the different nature and structure of the sectors under examination. Since the efficient input utilisation is the subject of the A-J effect, our DEA formulation uses input orientation due to the fact that that input quantities appear to be the primary decision variables (Coelli et al. 2005). In our DEA context the input-oriented technical efficiency is used enabling us to model the ability of the sectors to use minimum input quantities given their level of output quantities.

Finally, by applying the methodology introduced by Daraio and Simar (2005, 2007a, 2007b) we conditioned in a second stage analysis the effect of competition on sectors’ input–oriented technical efficiency levels. As explained earlier the number of companies competing in every sector has been used as an external variable in our analysis.

Table 1: Number of companies listed in the Athens Stock Exchange Market per manufacturing sector

Manufacturing Sectors	Number of Companies
Food-beverages	1,214
Tobacco products	4
Textile	301
Clothing	369
Leather	73
Wood	125
Paper	127
Publishing-printing	459
Oil refining	31
Chemicals	286
Rubber-plastic products	316
Non-metallic mineral products	500
Basic metals	94
Metal products	457
Machinery, equipment	278
Office machinery, computers	9
Electrical machinery	120
Radio, television and communication equipment	36
Precision instruments	54
Vehicles	31
Other transport equipment	63
Furniture and other products	336
Recycling	10

Table 2: Descriptive statistics of the variables used

	Number of Companies	Total Assets (1000 €)	Inventories (1000 €)	Sales (1000 €)	Gross Profits (1000 €)
Mean	230.130	2481699.174	415794.826	2002898.130	432042.304
Std	269.213	3068654.956	472310.005	2769825.576	643519.695
Max	1214.000	14150226.000	1919614.000	10061793.000	2839887.000
Min	4.000	15605.000	1946.000	10921.000	2661.000

3.2 DEA models and bias correction

Following the notation from Daraio and Simar (2007a), Koopmans (1951) and Debreau (1951) definition of production technology can be characterized as a set of $x \in R_{+}^{p}$ inputs which are used to produce $y \in R_{+}^{q}$ outputs. Then the feasible combinations of (x, y) can be defined as:

$$\Psi = \left\{ (x, y) \in R_{+}^{p+q} \middle| x \quad can \quad produce \quad y \right\} \tag{1}$$

By assuming free disposability of inputs and outputs then $(x, y) \in \Psi$ and at the same time $(x^{'}, y^{'}) \in \Psi$ when $x^{'} \geq x$ and $y^{'} \geq y$. As suggested by several authors (Førsund and Sarafoglou 2002; Førsund and Sarafoglou 2005; Førsund et al. 2009), Hoffman's (1957) discussion regarding Farrell's (1957) paper was the first to indicate that linear programming can be used in order to find the frontier and estimate efficiency scores, but only for the single output case. Later, Boles (1967) developed the formal linear programming problem with multiple outputs identical to the constant returns to scale (CRS) model in Charnes et al. (1978) who named the technique as Data Envelopment Analysis (DEA). Later, Banker et al. (1984) introduced a DEA estimator allowing for variable returns to scale (VRS model)[1].

As such, based on the Farrell (1957) measure for a unit operating at the level (x, y) the input oriented efficiency score can be defined as:

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

[1] For information regarding the history of the origins of efficiency measurements see Cooper and Lovell (2011).

Then the efficiency measurement of a given country (x_i, y_i) defines an individual production possibilities set $\psi(x_i, y_i)$, which under the assumption of free disposability of inputs and output can be expressed as:

$$\psi(x_i, y_i) = \left\{(x, y) \in \Re_{+}^{p+q} \middle| x \geq x_i, y \leq y_i\right\} \quad (3).$$

As such the union of these individual production possibilities sets provides the Free Disposal Hull (FDH) estimator (introduced by Derpins et al. 1984) of the production set Ψ which can be written as:

$$\hat{\Psi}_{FDH} = \bigcup_{i=1}^{n} \psi(x_i, y_i) = \left\{(x, y) \in \Re_{+}^{p+q} \middle| x \geq x_i, y \leq y_i, i = 1, ..., n\right\} \quad (4)$$

It follows that the DEA estimator[2] $\hat{\Psi}_{DEA}$ is obtained by the convex hull (CH) of $\hat{\Psi}_{FDH}$ and can be calculated as:

$$\begin{aligned} \hat{\Psi}_{DEA} &= CH\left(\bigcup_{i=1}^{n} \psi(x_i, y_i)\right) \\ &= \left\{ \begin{array}{l} (x, y) \in \Re_{+}^{p+q} \middle| y \leq \sum_{i=1}^{n} \gamma_i y_i; x \geq \sum_{i=1}^{n} \gamma_i x_i \\ for(\gamma_1, ..., \gamma_n) \quad s.t. \sum_{i=1}^{n} \gamma_i = 1; \gamma_i \geq 0, i = 1, ..., n \end{array} \right\} \end{aligned} \quad (5)$$

Next and in order to obtain the corresponding input oriented DEA estimators of efficiency scores we need to incorporate $\hat{\Psi}_{DEA}$ in equation (2). In addition by applying the methodology introduced by Simar and Wilson (1998, 2000a, 2000b) we perform the bootstrap procedure for DEA estimators in order to obtain biased corrected results (see the Appendix for details). The main applications of bootstrap are: the DEA estimator bias correction and the construction of confidence intervals

(Simar and Wilson 1998; 2000a; 2000b), test procedures to assess returns to scale (Simar and Wilson 2002), the criterion for bandwidth selection (Simar and Wilson 2002; 2008), statistical procedures for comparing the efficiency means of several groups (Simar and Wilson 2008), statistical procedures for testing the equality of distribution of the efficiency scores (Simar and Zelenyuk 2006) and for statistical inference for aggregate efficiency measures (Simar and Zelenyuk 2007)[3].

Thus, following Simar and Wilson (1998, 2000a, 2000b) procedure the bias corrected efficiency score is given by:

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

After that and 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:

$$\left[\hat{\delta}_{DEA}(x,y) - \hat{\alpha}_{1-a/2}, \hat{\delta}_{DEA}(x,y) - \hat{\alpha}_{a/2}\right] \quad (7).$$

Furthermore, following the bootstrap test developed by Simar and Wilson (2002) we test whether the CRS or VRS formulation is appropriate in our analysis. The null hypothesis of the test can be developed as

$H_0 : \Psi^{\theta}$ is globally CRS against $H_1 : \Psi^{\theta}$ is VRS.

Subsequently the test statistic mean of the ratios of the efficiency scores is provided by:

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[2] We consider here only the VRS case; however CRS can be obtain by dropping the constraint in (5) requiring γs to sum to one.

$$T(X_n) = \frac{1}{n}\sum_{i=1}^{n}\frac{\hat{\theta}_{CRS,n}(X_i,Y_i)}{\hat{\theta}_{VRS,n}(X_i,Y_i)} \quad (8).$$

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

$$p - value = prob(T(X_n) \leq T_{obs} | H_0 \quad is \quad true) \quad (9)$$

where T_{obs} is the value of T computes on the original observed sample X_n. It follows that 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:

$$p - value \approx \sum_{b=1}^{B}\frac{\Im\left(T^{*b} \leq T_{obs}\right)}{B} \quad (10).$$

3.3 Calculating the conditional measures of efficiency

Daraio and Simar (2005, 2007a, 2007b) by extending the ideas developed by Cazals et al. (2002) developed a probabilistic formulation of the production process. This probabilistic approach allowed the introduction of external-environmental factors (Z) directly in the production process[4]. In contrast to the traditional two-stage approaches, the probabilistic approach introduced by Daraio and Simar (2005, 2007a, 2007b) does not impose a reparability assumption between Z values and the input-output space (De White and Verschelde 2010)[5]. By denoting $Z \in \Re^r$ as the external

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[3] For an empirical application of bootstrapped DEA investigating firms' and sectors' efficiency levels see Halkos and Tzeremes (2010, 2011)

[4] For the theoretical background of the statistical properties of the conditional estimators see Jeong et al. (2010).

[5] For a critique of two-stage approaches when using DEA and FDH estimators see Simar and Wilson (2007, 2011).

factors, the joint distribution of (X,Y) conditional on $Z=z$ defines the production process if $Z=z$. In this way the attainable production set Ψ^z is defined by:

$$H_{X,Y|Z}(x,y|z) = \text{Prob}(X \leq x, Y \geq y | Z = z) \quad (11).$$

Then the input oriented conditional efficiency measure can be defined as:

$$H_{X,Y|Z}(x,y|z) = \text{F}_{X,Y|Z}(x,y|z) S_{Y|Z}(y|z) \quad (12).$$

In addition the input oriented efficiency score can be obtained from:

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

It follows that a kernel estimator can be calculated as:

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

where K(.) is the Epanechnikov kernel[6] and h is the bandwidth of appropriate size.

Following, Bădin et al. (2010) we use a fully automatic data-driven approach for bandwidth selection based on the work of Hall et al. (2004) and Li and Racine (2004; 2007) least-squares cross-validation criterion (LSCV) which leads to bandwidths of optimal size for the relevant components of Z. This method is based on the principle of selecting a bandwidth that minimizes the integrated squared error of the resulting estimate[7]. Li and Racine (2007) suggest that we have also to correct the resulting h by an appropriate scaling factor, which equals to $n^{-\frac{q}{(4+q+r)(4+r)}}$ where

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[6] Other kernels from the family of continuous kernels with compact support can also be used.

[7] See Bădin et al. (2010) for a Matlab routine that computes the bandwidth based on the LSCV criterion.

q is the dimension of Y and r is the dimension of Z [8]. Therefore, we can 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 visualize the influence of an environmental variable on the efficiency scores obtained, a scatter of the ratios $Q_z = \frac{\hat{\theta}_n(x,y|z)}{\hat{\theta}_n(x,y)}$ against z (the number of companies competing in a sector) and the smoothed nonparametric regression lines would help us to analyze the effect of Z on the sectors' efficiency scores obtained. Similarly, the effect of competition on sectors' scale efficiency can be visualized if we use a scatter of the ratios $Q_{Scale,z} = \frac{\frac{\hat{\theta}_{CRS,n}(x,y|z)}{\hat{\theta}_{VRS,n}(x,y|z)}}{\frac{\hat{\theta}_{CRS,n}(x,y)}{\hat{\theta}_{VRS,n}(x,y)}}$ against z. For this purpose we use the nonparametric regression estimator introduced by Nadaraya (1965) and Watson (1964) as:

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

If this regression line is increasing it indicates that Z is unfavorable to the sectors' efficiency levels whereas if it is decreasing then it is favorable. When Z is unfavorable then the number of companies acts like an extra undesired output to be produced demanding the use of more inputs in the production activity. In the opposite case the external factor plays a role of a substitutive input in the production process

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[8] For more information regarding LSCV criterion and its properties see Silverman (1986), Hall et al. (2004) and Li and Racine (2004, 2007).

giving the opportunity to save inputs in the production activity. This of course is very crucial when investigating the A-J effect.

An increasing regression line in our case will indicate that competition has a negative effect on sectors utilization of capital, whereas a decreasing line will indicate that sectors use their inputs in an economical efficient way. Even though the visualization framework of the effect of the environmental variable Z (Daraio and Simar 2005, 2007a, 2007b) provides us with useful information, it does not give us any indication of the significance of the observed effect. For that reason our study adopts a significance test for nonparametric regression as has been introduced by several authors (Racine 1997; Racine et al. 2006; Li and Racine 2007) in order to compute a significance level of the observed effect of the external variable on sectors' input oriented technical efficiency levels.

If the conditional mean $E\left(Q_z|z\right)$ is independent from z then the vector of partial derivatives of $E\left(Q_z|z\right)$ with respect to z will be equal to zero. Thus:

$$E\left(Q_z|z\right) \perp z \Leftrightarrow \frac{\partial E\left(Q_z|z\right)}{\partial z} = 0 \tag{17}$$

From equation (17) we can derive the null hypothesis as:

$$H_0 = \frac{\partial E\left(Q_z|z\right)}{\partial z} = g\left(z\right) = 0 \tag{18}$$

In this way the test statistic the estimator of $I = E\left\{g\left(z\right)^2\right\}$ and can be obtained by forming a sample of average of I replacing the unknown derivatives with $\hat{g}\left(z_i\right)$ as:

$$I_n = \frac{1}{n}\sum_{i=1}^{n} \hat{g}(z_i)^2 \qquad (19).$$

Finally, the distribution of the statistic can be obtained by applying the bootstrap procedure described in Racine (1997).

4. Empirical results

Following the methodology proposed by Simar and Wilson (2002) our paper tests the model for the existence of constant or variable returns to scale. In our application we have two inputs and two outputs and we obtained for this test a p-value of $0.028 < 0.05$ (with B=2000) implying rejection of the null hypothesis of CRS. Therefore, the results adopted in our study are based on the BCC model (Banker et al. 1984) assuming variable returns to scale[9].

Table 3 provides the results of VRS analysis[10] adopting the bias correction method using the methodology proposed by Simar and Wilson (1998, 2000a, 2000b). For the sample of 23 manufacturing sectors under the VRS assumption seven sectors appear to be efficient (efficiency score = 1). These are the sector of 'Food', 'Publishing-printing', 'Oil refining', 'Chemicals', 'Office machinery, computers', 'Precision instruments' and the 'Recycling' sector. The last seven performers are reported to be the sectors of 'Metal products', 'Vehicles', 'Machinery and equipment', 'Textile', 'Radio, television and communication equipment', 'Wood' and 'Other transport equipment'.

However, when looking at the bias corrected efficiency results (VRS_{BC}), we realize that the efficiency scores are in many cases considerably lower. For instance in

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[9] Due to size inequalities among the Greek manufacturing sectors the most appropriate assumption for efficiency measurement is the variable returns to scale (Halkos and Tzeremes 2011)
[10] The results obtained under the hypothesis of CRS are also available upon request.

the case of the 'Food' sector the biased corrected (BC) efficiency score is 0.736 (original VRS score equals to 1) with lower bound (LB) of 0.566 and upper bound (UB) of 0.977 in a confidence interval of 95%. Almost identical results are reported in the case of 'Office machinery, computers' where the biased corrected (BC) efficiency score is 0.735 with a lower bound (LB) of 0.581 and an upper bound (UB) of 0.974 in a confidence interval of 95%. Daraio and Simar (2007) suggest that when the bias (BIAS) is larger than the standard deviation (STD) then the bias corrected efficiencies (BC) must be preferred compared to the original estimates.

Table 3: Results of the conditional and unconditional measures of the original and the biased corrected efficiency scores.

Sectors	VRS	VRS_{BC}	BIAS	STD	LB	UB	VRS$\mid$Z	$VRS_{BC}\mid Z$	BIAS	STD	LB	UB	SE	SE$\mid$Z
Textile	0.384	0.331	-0.413	0.038	0.293	0.376	0.894	0.781	-0.161	0.009	0.672	0.880	0.913	0.551
Vehicles	0.478	0.412	-0.338	0.024	0.364	0.468	0.795	0.700	-0.171	0.010	0.614	0.785	0.997	0.998
Food	1.000	0.736	-0.359	0.039	0.566	0.977	1.000	0.766	-0.305	0.042	0.550	0.982	0.633	0.338
Tobacco products	0.703	0.593	-0.264	0.021	0.511	0.690	1.000	0.831	-0.203	0.009	0.737	0.985	0.960	0.899
Clothing	0.730	0.615	-0.256	0.016	0.538	0.717	1.000	0.791	-0.264	0.023	0.650	0.987	0.999	0.903
Electrical machinery	0.663	0.567	-0.255	0.013	0.502	0.646	1.000	0.802	-0.247	0.017	0.683	0.983	0.958	1.000
Publishing-printing	1.000	0.760	-0.316	0.023	0.637	0.980	1.000	0.784	-0.275	0.025	0.643	0.981	0.773	0.477
Oil refining	1.000	0.735	-0.361	0.038	0.575	0.975	1.000	0.768	-0.301	0.037	0.584	0.982	1.000	0.349
Chemicals	1.000	0.744	-0.344	0.031	0.609	0.982	0.173	0.151	-0.848	0.165	0.134	0.170	1.000	0.935
Rubber, plastic products	0.696	0.592	-0.253	0.013	0.521	0.680	1.000	0.816	-0.226	0.013	0.699	0.982	0.847	0.598
Non, metallic mineral products	0.821	0.664	-0.289	0.017	0.565	0.798	0.526	0.446	-0.342	0.048	0.367	0.519	0.708	0.458
Basic metals	0.576	0.471	-0.388	0.040	0.396	0.564	0.386	0.339	-0.363	0.040	0.295	0.381	0.791	0.509
Metal products	0.561	0.470	-0.343	0.025	0.409	0.550	0.626	0.544	-0.239	0.014	0.481	0.615	0.900	0.647
Machinery, equipment	0.441	0.378	-0.379	0.033	0.333	0.431	0.735	0.620	-0.252	0.024	0.517	0.724	0.999	0.851
Office machinery, computers	1.000	0.735	-0.361	0.037	0.581	0.974	1.000	0.776	-0.289	0.035	0.596	0.983	0.567	0.692
Radio, television and communication equipment	0.379	0.328	-0.407	0.034	0.291	0.371	0.562	0.503	-0.208	0.011	0.454	0.552	0.996	0.989
Precision instruments	1.000	0.734	-0.363	0.040	0.565	0.973	1.000	0.772	-0.296	0.038	0.551	0.982	1.000	1.000
Other transport equipment	0.216	0.189	-0.666	0.112	0.167	0.212	0.371	0.325	-0.383	0.073	0.269	0.367	0.885	0.833
Furniture and other products	0.599	0.498	-0.339	0.030	0.432	0.589	1.000	0.857	-0.166	0.007	0.750	0.983	1.000	0.817
Recycling	1.000	0.739	-0.353	0.034	0.600	0.977	1.000	0.776	-0.288	0.033	0.603	0.985	1.000	1.000
Leather	0.592	0.514	-0.256	0.013	0.456	0.579	0.824	0.736	-0.146	0.004	0.671	0.808	0.995	0.964
Wood	0.359	0.309	-0.458	0.042	0.273	0.350	0.597	0.517	-0.259	0.021	0.452	0.589	0.964	0.995
Paper	0.671	0.584	-0.222	0.009	0.524	0.654	1.000	0.822	-0.216	0.012	0.703	0.984	0.901	0.904
Mean	0.690	0.552	-0.347	0.031	0.466	0.674	0.804	0.662	-0.280	0.031	0.551	0.791	0.913	0.551
Std	0.250	0.169	0.092	0.020	0.128	0.244	0.256	0.195	0.139	0.034	0.161	0.252	0.997	0.998
Max	1.000	0.760	-0.222	0.112	0.637	0.982	1.000	0.857	-0.146	0.165	0.750	0.987	0.633	0.338
Min	0.216	0.189	-0.666	0.009	0.167	0.212	0.173	0.151	-0.848	0.004	0.134	0.170	0.960	0.899

In addition table 3 provides the analytical results obtained following the conditional measurement approach by Daraio and Simar (2005, 2007a, 2007b) and the statistical inference framework by Simar and Wilson (1998, 2000a, 2000b) in order to measure sectors' efficiency when accounting for the effect of the number of companies competing within a sector. According to De White and Marques (2007, p. 25) integrating these two frameworks can help us to avoid main drawbacks of efficiency analysis and have some attractive features such as

1) The absence of separability condition,
2) The avoidance of the need for priory assumptions on the functional form of the model and
3) The allowance of the exploration of the effect of environmental variables.

Furthermore, table 3 presents the results estimated from the conditional measures under the VRS assumption taking into account the effect of the number of companies competing within a sector (VRS|Z). The results indicate that twelve sectors appear to be efficient. These are 'Food', 'Publishing-printing', 'Oil refining', 'Office machinery, computers', 'Precision instruments', 'Recycling', 'Clothing', 'Tobacco products', 'Rubber, plastic products', 'Paper', 'Electrical machinery' and 'Furniture and other products'.

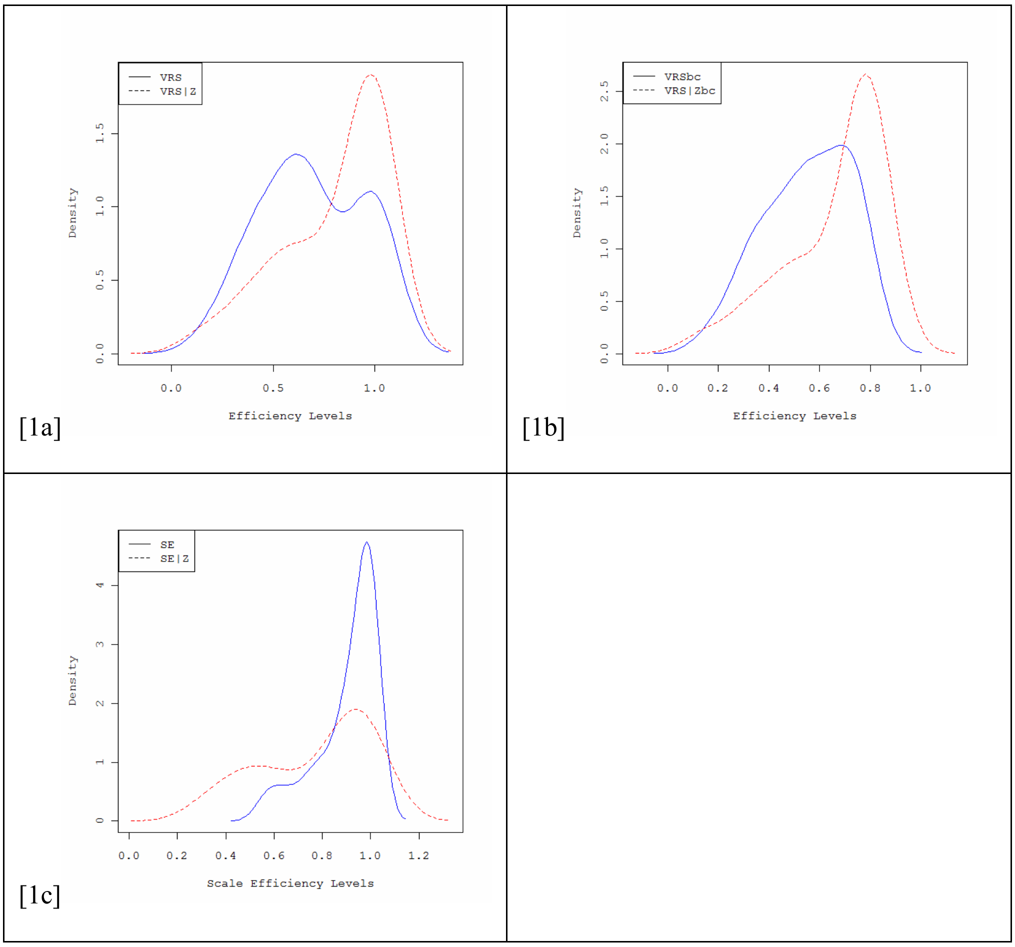
However as previously stated the biased corrected results need to be adopted ($VRS_{BC}|Z$) since the bias is larger than the standard deviation (Daraio and Simar 2007a). Again great differences are reported between the biased corrected and the original conditional efficiencies. Taking into consideration these biased corrected conditional efficiency scores the highest five performers in a descending order are reported to be 'Furniture and other products', 'Tobacco products', 'Paper', 'Rubber, plastic products' and 'Electrical machinery'. Similarly, the five sectors with the lowest biased corrected conditional efficiency scores are reported to be ‘Radio, television and communication equipment’, ‘Non metallic mineral products’, ‘Basic metals’, ‘Other transport equipment’ and ‘Chemicals’.

Finally, the last two columns of table 3 report the original and the conditional scale efficiency scores. The top five performers of scale efficiencies are ‘Chemicals’, ‘Clothing’, ‘Oil refining’, ‘Furniture and other products’ and ‘Machinery, equipment’. Under the conditional measures the top five performers of scale efficiencies are ‘Electrical machinery’, ‘Clothing’, ‘Vehicles’, ‘Radio, television and communication equipment’ and ‘Wood’. According to Balk (2001, p.168) increased scale efficiency means that the sector has moved to a position with a better input-output quantity ratio at the frontier.

In addition, Figure 1 presents the density estimates using the “normal reference rule-of-thumb” approach for bandwidth selection (Silverman 1986) and a second order Gaussian kernel. Subfigure 1a, indicates the differences between sectors’ input oriented technical efficiency scores against the conditional input oriented technical efficiency scores (VRS|Z). It appears that the original estimates under the VRS assumption (solid line) are platykurtic compared to the original VRS conditional estimates (dotted line) which appear to be leptokurtic. 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. In addition subfigure 1b indicates high differences between the densities of the biased corrected efficiency scores (VRSbc-solid line) and the biased corrected conditional efficiency scores (VRS|Zbc-dotted line). As can be realised the conditional estimates (original and biased corrected) are reported to show higher efficiency estimates compared to the unconditioned efficiencies (original and biased corrected). This in turn indicates that when we account for the effect of competition on sectors’ efficiency scores, this results on increasing sectors’ efficiency levels. Moreover, subfigure 1c indicates the differences between sectors’ original and conditional scale efficiencies. As can be realized the unconditional scale efficiencies are leptokurtic, whereas the conditional scale efficiencies are platykurtic. Finally, it appears that the original scale efficiencies are higher compared to the conditional ones.

Figure 1: Kernel density functions of sectors’ efficiencies derived from unconditional and conditional VRS and biased corrected VRS DEA models using Gaussian Kernel and the appropriate bandwidth



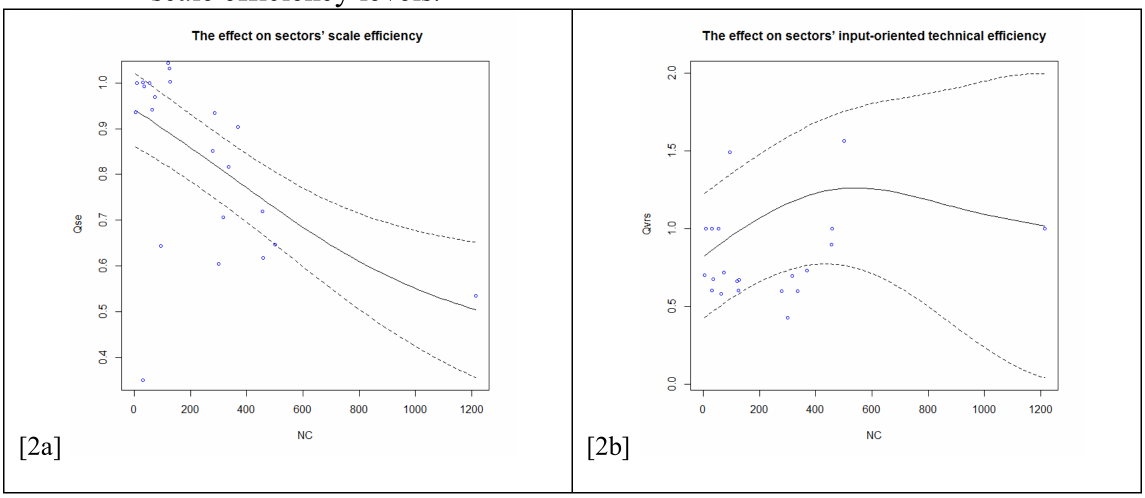
In these lines, Figure 2 provides a graphical representation of the effect of the number of companies on sectors' input oriented technical and scale efficiency. For this task we use the 'Nadaraya-Watson' estimator, which is the most popular method for nonparametric kernel regression proposed by Nadaraya (1965) and Watson (1964). For both the cases the significance of the effect of Z (number of companies –NC) in the nonparametric regression setting was based on the procedure described previously (Racine 1997; Racine et al. 2006; Li and Racine 2007). For the scale efficiencies a p-value of 0.029 was attained, while for the input orientated technical efficiencies a p-value of 0.032 was obtained, indicating significance at 5% level.

As such subfigure 2a illustrates the nonparametric estimate of the regression function using the conditional and unconditional biased corrected scale efficiency estimates. Moreover it presents their variability bounds of point wise error bars using asymptotic standard error formulas (Hayfield and Racine 2008). When the regression is decreasing, it indicates that 'Z' factor (i.e. the number of companies competing within a sector) is favorable to sector's scale efficiency levels. In our case subfigure 2a illustrates a decreasing nonparametric regression line indicating that the high number of companies competing within a sector increase sector's scale efficiency levels. Therefore, the number of companies acts as a substitutive input in the production process of sectors' scale efficiency providing the opportunity to "save" inputs in the activity of production.

In addition when we looking at subfigure 2b the regression line has a steeper and increasing shape for a lower number of firms competing within a sector, indicating a highly negative effect on sectors' input oriented technical efficiency levels. However, for higher number of companies the regression line has a decreasing shape indicating a positive effect. Our results comply with the empirical results found by Christopoulos and Tsionas (2001) indicating that during the deregulation period the Greek banking sector decreased its allocative and technical inefficiencies. In addition they have reported that through the intensification of cross-country competition the efficiency has been increased.

Finally, our results confirm the findings of Oum and Zhang (1995) indicating that increased competition affects positively firms to use efficiently their capital inputs and therefore to reduce the allocative inefficiency caused by the A-J effect. Therefore it appears that Greek manufacturing sectors with higher competition tend to have higher scale and input oriented technical efficiency levels compared with the sectors with monopolized/oligopolized conditions which induce an economically inefficient use of capital.

Figure 2: The global effect of competition on sectors' input-oriented technical and scale efficiency levels.



5. Conclusions

This paper applies the probabilistic approach in a sample of 23 Greek manufacturing sectors and in order to construct conditional efficiency measures taking into account the effect of competitive conditions within the sectors. Then by applying an inferential approach on DEA efficiency scores it measures the bias corrected sectors' input oriented technical efficiency levels. Furthermore, the biased corrected results and 95% confidence intervals have been produced indicating major inefficiencies among the sectors.

At a second stage of the analysis our paper uses nonparametric regressions in order to quantify the effect of competitive conditions on sectors' scale and input oriented technical efficiency levels by calculating their conditional measures. In addition and in order to establish if the effect is statistical significant, our paper applies a nonparametric statistical test. The results reveal that the increased competition has a positive effect on sectors' scale and input oriented technical efficiency levels reducing the inefficiencies caused by the A-J effect.

Finally our contribution to the existing literature with respect to the methodology used is that we provide evidence of how the new advances and recent developments in efficiency analysis and statistical inference can be applied and directed towards an effective evaluation of industrial policies, providing in such a way a vital tool to industrial policy makers for analyzing the effects of their policies on industry regulation problems.

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APPENDIX

This appendix synoptically illustrates the bootstrapped based algorithm introduced by Simar and Wilson (1998, 2000a, 2000b). Specifically, the following steps are followed:

Step 1: Transform the input-output vectors using the original efficiency estimates $\left\{\hat{\theta}_{in,}\ i=1,\ldots,n\right\}$ as $\left(\hat{x}_i^{\,l}, y_i\right)=\left(x_i\cdot\hat{\theta}_{in}, y_i\right)$

Step 2: Generate smoothed resampled pseudo-efficiencies γ_i^* as follows:

2.1 Given a set of estimated efficiencies $\left\{\hat{\theta}_{in}\right\}$, use the "rule of thump" (Silverman, 1986, p.47-48) to obtain the bandwidth parameter h as $h=0.9n^{1/5}\min\left\{\hat{\sigma}_{\hat{\theta}}, R_{13}/1.34\right\}$, where $\hat{\sigma}_{\hat{\theta}}$ = the standard deviation of $\left\{\hat{\theta}_{in}\right\}$ and R_{13} is the interquartile range of the empirical distribution of $\left\{\hat{\theta}_{in}\right\}$.

2.2 Generate $\{\delta_i^*\}$ by replacing, with replacement, from the empirical distribution of $\left\{\hat{\theta}_{in}\right\}$ of the estimated efficiencies.

2.3 Generate the sequence $\left\{\tilde{\delta}_i^*\right\}$ using:

$$\tilde{\delta}_i^* = \begin{cases} \delta_i^* + h\varepsilon_i^* & \text{if} \quad \delta_i^* + h\varepsilon_i^* \le 1 \\ 2-(\delta_i^* + h\varepsilon_i^*) & \text{otherwise} \end{cases}$$

where ε_i^* is drawn i.i.d. from a standard normal distribution.

2.4 Generate the smoothed pseudo-efficiencies $\{\gamma_i^*\}$ using the following formula:

$\gamma_i^* = \bar{\delta}_i^* (\tilde{\delta}_i^* - \bar{\delta}_i^*) / \sqrt{1 + h^2 / \hat{\sigma}_{\hat{\theta}}^2}$, where $\bar{\delta}_i^* = \sum_{i=1}^n \delta_i^* / n$ which is the average of the resampled original efficiencies.

Step 3: Let the pseudo-data be given by

$$\left(x_i^*, y_i^*\right) = \left(\hat{x}_i^l / \gamma_i^*, y_i \right)$$

Step 4: Estimate the bootstrap efficiencies using the pseudo-data as:

$$\hat{\theta}_{in}^{SW*} = \min_{\theta, z} \left\{ \theta : y_i \leq Yz, \theta x_i \geq X^* z, \sum_{i=1}^n z_i = 1, z \in R_+^n \right\}$$

Step 5: Repeat steps (2)-(4) $\mathbf{B}$ times to create a set of $\mathbf{B}$ bank specific bootstrapped efficiency estimates $\hat{\theta}_{in}^{SW*b}$ $, i = 1, \ldots, n, b = 1, \ldots, B$, According to Simar and Wilson (1998, 2000) a proper B = 2000 replications.

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