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Estimating Technical and Scale Efficiency of Meat Products Industry: The Greek Case

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Abstract: The pure technical and scale efficiency of the Greek meat products industry were analyzed over the period of 1994-2007. For this purpose, a bootstrapped data envelopment analysis is applied. The results revealed the presence of inefficiencies in sample firms, as well as a trend of increasing the inefficiencies during the study period. The high rate of growth of prepared meats domestic production and the Greece's integration into European Economic and Monetary Union, since 2001, did not seem to influence the performance of domestic manufacturers of prepared meats. The main sources of inefficiency were related to mismanagement and the excess usage of capital. Furthermore, firm size did not have any effect on the efficiency of our sample firms, as small productive units enjoyed advantages of conductive low costs, through the use of cost low family labour. Some policy applications can be derived from these findings. Knowing the best practices can help managers to apply new methods to decrease the costs and excess inputs usage, following its benchmarks, as well as the implementation of adequate policies by institutions.

Key words: Efficiency, Data Envelopment Analysis (DEA), bootstrapping method, meat products industry

INTRODUCTION

The industry of meat products in Greece has a short history. In the early 20th century, it was a cottage activity and since 1970, it took on the features of a manufacturing industry. Nowadays, it is a sector of the food industry, where the majority of firms are small, private and family owned, which focuses on local markets. The few large production units that exist have automated production processes in place and control a significant part (approximately more than 35%) of the market, through organized distribution networks that cover the whole of Greece (ICAP Hellas, 2008).

The specific sector exhibits high growth rates of production, due to growing demand. The domestic market of prepared meats presented an average annual growth rate of 4.5% over the study period, reaching 47 million tons in 2007, from 29 million tons in 1996 (ICAP Hellas, 2008). Despite the increase in demand, the Greek prepared meat products manufacturers are not threatened by international competitors. The needs of the domestic market in prepared meats are covered almost completely by domestic production, while exports are limited (ICAP Hellas, 2008).

The objective of this study is the estimation of technical and scale efficiency in Greek prepared meats manufacturing firms from 1994 to 2007 and the development of ways of improving efficiency. This research has focused to a single sector, in order to satisfy the requirement for technology homogeneity. The prepared meats sector is chosen due to its increased importance in Greece. It is an industry, which have experienced rapid production growth and seems to have development perspective in future (ICAP Hellas, 2008). The performance investigation in industries with growth perspective is considered as a main issue and the application of adequate efficiency enhancement policies is needed to ensure the increase of the competitiveness and sustainable growth of manufacture in developing economies (Fotinopoulou and Keramidou, 2006). Also, this study examined the relative efficiency of the sample firms in different classes (large, medium and small) categorized by the number of full-time employees.

The analysis covers a time period of fourteen years (1994-2007) and involves changes in institutional settings occurred due to the three stages of integration of Greece into European Economic and Monetary Union (EMU). This started by free movement of capital and abolition of controls of exchange during the 1990', followed by coordinating economic policy (since 1994) and achieving economic convergence (2000), which was accomplished with the assign of Greek state monetary policy decisions

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to European Central Bank in 2001 and the adoption of euro as its currency in 2002. Further, the aim of this study is to examine whether the integration of a developing economy (e.g., the Greece) into EMU has influnced the firms performance operating in this particular sector.

In the current analysis of efficiency, the (Simar and Wilson, 1998, 2000) bootstrapped Data Envelope Analysis (DEA) was applied, which, by combining the non-parametric DEA model with bootstrapping techniques, allows us to provide bias corrected estimates of technical and scale efficiency, as well as confidence intervals. The motivation for employing this method stems from the need to overcome the inherent limitations of the standard DEA model.

The DEA method is used in various studies in industrial economics. Recent examples include studies from the food industry (Basu and Kumar, 2008; Dimara *et al*., 2008; Ismail, 2009) and the meat farms (Yusuf and Malomo, 2007). Also, studies related to the meat manufacturing sector are those of Ali (2007) and Goncharuk (2009). The majority of them use the conventional DEA model. For example Ali (2007) analyzed efficiency and productivity in the Indian meat processing industry, over the period of 1980-2000, by using the standard DEA and estimating the Malmquist TFP index. On the other hand, Goncharuk (2009) estimated the efficiency of Ukrainian and foreign meatpacking companies, by utilizing a DEA model of super-efficiency.

The present study contributes to the empirical analysis of industrial economics by analyzing technical and scale efficiency of meat products industry, where similar studies are limited in comparison to other areas. Moreover, this study improves the accuracy of the standard DEA results, by applying the Simar and Wilson (1998, 2000) method of performance measurement, which, to our knowledge, has not been applied in this context. From a policy perspective, knowing the best practices can facilitate the managers' effort to enhance efficiency, as well as the application of adequate policies by the institutions. This analysis, also, might be useful for shedding light on the relationship between efficiency and accession of a developing economy in EMU, as well as for clarifying the size-efficiency relationship in developing economies.

MATERIALS AND METHODS

In the literature, technical efficiency is defined as the ability of a firm to produce, under certain technological conditions, the maximal output quantities from a given set of inputs, or several output quantities utilizing minimal inputs quantities (Coelli *et al*., 2005). The performance measurement is effectuated by constructing a best practice frontier, which represents the highest possible efficiency that is achievable by employing available technology. Two methodologies have been commonly used to determine the frontier: the nonparametric and parametric approaches. The parametric method, known as the Stochastic Frontier Approach, although it requires the definition a priori of the functional form of the efficient frontier, estimates econometrically the technical efficiency determinants and simultaneously the production function parameters, by introducing two error terms, one for noise and one for inefficiency. The non-parametric approach, known as Data Envelopment Analysis (DEA) developed by Charnes *et al*. (1978), determines the best practice frontier, by using linear programming techniques. Despite the fact that the DEA approach permits the inclusion of a large number of inputs and outputs in the best practice frontier estimation and that it does not require an assumption of a functional form relating inputs to outputs, it has several limitations. One serious disadvantage of DEA is the non-involvement of a random error term in the frontier estimation.

In this study it was adopted a non-parametric linear programming frontier technique compared to parametric statistical methods, because this technique overcomes the problem of incorrect specification of the production function. Additionally, the bootstrapped technique proposed by Simar and Wilson (1998, 2000) permits us to determine statistical properties of non-parametric frontier estimators.

Efficiency measurement using data enveloped analysis: This article uses the DEA approach to estimate the best practice frontier. The latter is the upper boundary of piecewise convex surface derived over data on inputs and outputs for our sample of firms. The efficiency score (TE) of a prepared meats firm is measured as the distance from the point of the input-output combination of this firm, to the best practice frontier. The meat products company, which lies below from this, is characterized as inefficient (Coelli *et al*., 2005), while the firm, which lies on the frontier, is regarded as being efficient. In this study, an input orientation is chosen and the description that follows adopts this selection. If the activity of n production units is characterized by a set of inputs x used to produce given outputs y, the efficiency can be obtained by minimizing the set of inputs x. The assumptions about the returns to scale of the underlying technology, which result into two technical efficiency measurement models, are examined here. Following the (Charnes *et al*., 1978) model (CCR), which is based on the assumption that the technologies are characterized by constant returns to scale (CRS), the technical efficiency (TE), $\hat{\theta}_{CRS}$, of a prepared meats firm for any given point (x, y) is obtained, by solving the following linear program:

$$TE = \min\{\theta > 0 \mid \theta x \geq \sum_{i=1}^{n} \lambda_i x_i, y \leq \sum_{i=1}^{n} \lambda_i y_i, \lambda_i \geq 0, i = 1...n\} \quad (1)$$

Adopting the Banker *et al.* (1984) model (BCC) which is based on the assumption that the technologies exhibit variable returns to scale (VRS), the pure efficiency scores of each firm (PTE), $\hat{\theta}_{VRS}$ is measured, by solving the following linear program:

$$PTE = \min\{\theta > 0 \mid y \leq \sum_{i=1}^{n} \lambda_i y_i, \theta x \geq \sum_{i=1}^{n} \lambda_i x_i, \sum_{i=1}^{n} \lambda_i = 1, \lambda_i \geq 0, i = 1...n\} \quad (2)$$

In Eq. 1 and 2 the efficient level of input is defined by θx, which is the projection of an observed meat products industry (x, y) on to the efficient frontier, while θ is a scalar and λ is a non-negative vector of constants specifying the optimal weights of inputs/outputs. TE (or PET) gives the decrease of inputs, which an observed firm at location (x, y) could undertake, in order to become efficient. If TE = 1 (or PET = 1), the firm is considered fully efficient, while, a value less than one, it reflects inefficiency. According to this theoretical frame, pure technical inefficiency is usually interpreted as a result of inadequate management practices.

Furthermore, the scale efficiency (SE) proposed by Fare and Grosskopf (1985) that measures how close is a prepared meats company, to potentially optimal scale, is estimated, by applying both $\hat{\theta}_{CRS}$ and $\hat{\theta}_{VRS}$ on the same model:

$$SE = \hat{\theta}_{CRS}(x_i, y_i) / \hat{\theta}_{VRS}(x_i, y_i) \quad (3)$$

If SE for the observed firm has a value equal to one, then it is operating under constant returns to scale size and it is characterized as scale efficient. If SE is significantly less than one, the observed firm is scale inefficient, or in others words it is operating under variable returns to scale. In this case, an input savings is possible, through the adjustment of its operational scale. In order to investigate the source of scale inefficiency, it is common practice to use another test that is obtained as:

$$S = \hat{\theta}_{NIRS}(x_i, y_i) / \hat{\theta}_{VRS}(x_i, y_i) \quad (4)$$

where, $\hat{\theta}_{NIRS}$ is the efficiency scores of a sample firm under non-increasing returns to scale. A meat products manufacturer is operating under increasing returns to scale (IRS), when S is significantly less than unity. In the other case, when it is equal to unity, it is operating under decreasing returns to scale (DRS). For more details on DEA, interested readers may refer to Coelli *et al.* (2005) and Cooper *et al.* (2000).

Bootstrap in data enveloped analysis: The standard DEA approach (Charnes *et al.*, 1978) has come under criticism owing to the potential bias of efficiency estimates. The accuracy of the DEA results may be affected by the sampling variation of the estimated frontier. This means that the distances to the frontier are underestimated in the case where the best performers in the population are not included in the sample. Another reason of the potential bias of the DEA efficiency estimators is related to the non-measurement of random error and therefore to the incorrect definition of overall deviation from the frontier as inefficiency. This research project addresses these inherent limitations of DEA, by applying the approach proposed by Simar and Wilson (1998, 2000), which combines the DEA model with bootstrapping methods. By the use of the bootstrap technique (Efron, 1979) we attempt to simulate a true sampling distribution, by imitating a specific Data Generating Process (DGP), using the DEA results. The DGP based on a set of assumptions (namely a specific statistical model) formulated by Simar and Wilson (2000). The new dataset created in this way, is used in turn for re-estimation of efficiency scores. Repeating this process n times ensures a reliable approximation of the true distribution of the sampling. The complete bootstrap algorithm performed in this study is extensively described (Simar and Wilson, 1998). The program FEAR that works in the R software was used for bootstrapping procedure in this study.

The same bootstrap algorithm is adopted in order to test the assumptions about the returns to scale of the underlying technology, which have to be made before employing DEA. By applying the non-parametric test of global returns to scale, proposed by Simar and Wilson (2002), we examine whether the technology indicates global constant or variable returns to scale and therefore choose the resulting formulation. The null hypothesis is tested by examining whether H_0: Ψ_{CRS} is globally constant returns to scale versus H_1: Ψ_{VRS} is globally variable returns. The scale efficiency (SE) proposed by Fare and Grosskopf (1985) is used to facilitate this test. For more technical details on the method applied (Simar and Wilson, 2002).

Data: Data on inputs and output were collected for 40 Greek manufacturers of prepared meats (such as souvlaki, gyros, schnitzel, burgers, chicken rolls) over the period of

1994-2007. Our sample consists of all the large companies of this sector, as well as medium firms with 50 to 249 employees and small firms with less than 49 employees. In this study three inputs and one output was employed. The selection of output and input variables followed previous studies. The output variable is total sales (Ali, 2007; Badunenko, 2010; Kravtsova, 2008). Input variables are the cost of capital, estimated as the sum of depreciation and interest (Ali, 2007; Badunenko, 2010), the cost of raw and auxiliary materials (Ali, 2007; Goncharuk, 2009; Kravtsova, 2008) and the number of full-time employees (Lambert, 1994; Ali, 2007; Goncharuk, 2009). It is worth noting that the DEA convention, stating that the minimum number of DMU should be greater than three times the number of inputs plus outputs, was satisfied, as the use of a great number of inputs and outputs decrease the degrees of freedom, leading to an overestimation of the number of efficient firms.

Our dataset was compiled from several sources, composed of the annual balance sheet of companies published in the Greek Government Gazette and annual industrial bulletin statistics drawn by the Ministry of Development. Also, a questionnaire survey was conducted for prepared meat products manufacturing firms, by Panteion University of Athens, to obtain information that wasn't readily available, such as the cost of raw and auxiliary materials and the number of full-time employees. This process of data collection for prepared meat products manufacturing firms lasted four months, from March to June 2009. During this process, 87 Greek meat products firms, operating in different regions of Greece, were contacted only 36 of them provided us with the relevant information (a response rate of 41.4%). Furthermore, data from 4 firms, that have either been purchased or merged with other firms or have been closed, were included too in the sample. Information for the latter firm category was drawn from the annual industrial bulletin statistics of the Ministry of Development, as well as from the annual balance sheets of companies published in the Greek Government Gazette. Thus the panel data set used here was unbalanced, including 521 observations. This is due to late entries and early exits from the market. The descriptive statistics of database employed, in efficiency scores measure, are presented in Table 1. All the monetary variables were deflated by the producer price index and expressed in thousands of euro at constant 1999 prices. In this study, the R software was used for statistical analysis of our database.

Table 1: Descriptive statistics of the data

Variables	Mean	Min.	Max.	SD
Total sales	12.065	262	126.507	20.412
Capital cost	1.125	11	19.925	2.312
Cost of raw and auxiliary materials	7.589	31	85.826	12.683
No. of full-time employees	0.105	4	1.012	0.176

RESULTS AND DISCUSSION

In order to apply the appropriate DEA model, the above mentioned, non-parametric test concerning the returns to scale was performed for each year in the 14-year study period. In all 14 cases, the null hypothesis, that the technology exhibits constant returns to scale, was rejected. Therefore, the underlying technology for the prepared meats manufacturing firms of the given sample was variable returns to scale. The original and bootstrapped VRS technical efficiency scores are presented in Table 2. These findings revealed that the original DEA average efficiency score for the entire period was equal to 0.87. According to the original DEA results, only few firms (6 out of 40) had produced their outputs on the efficiency frontier and were considered to be efficient during the period of 1997-2007. Table 2 also provides the bootstrapped VRS efficiency estimates. It is important noticing that another statistical test was performed using the approach suggested by Simar and Wilson (2000), which showed that the bias estimation was larger than the standard deviation. Therefore, the bias corrected efficiencies must be preferred compared to the original ones. These results showed that the pure technical efficiency of an average Greek meat products firm ranged from 0.86 to 0.72 from 1994 to 2007. This implies that using-14-28% less than the observed inputs could have produced the same output, for different years of the study,, if the firm was efficient. By analyzing specific years of the study period, a clear trend of decreasing efficiency was observed, when looking at both original and biased corrected estimates. The average efficiency scores diminished during the period of 1994-1998 (except for the year 1997), while between 1999-2005 they tended to remain stable. In 2006, there was another considerable decrease, followed by a slight rise in 2007. This can indicate a managerial failure to fully exploit potential technology. Another crucial observation is that since 2001 the Greece's integration to Economic and Monetary Union of European Union haven't stimulated important changes in efficiency. This result is in agreement with the findings of Vasiliev *et al.* (2008) for grain farms in Estonia during its accession to European Union in the period 2000-2004 of. Significant differences in efficiency were not observed among sample firms. Almost all companies operated at a moderate level of technical efficiency during the study period. In these 14 years, no firm in the sample

Table 2: Original DEA and bias corrected estimates of VRS technical efficiency scores across units and time

Firm	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Mean	UB	LB	DEA
F1	0.89	0.88	0.73	0.80	0.78	0.76	0.87	0.92	0.91	0.90	0.89	0.81	0.77	0.85	0.84	0.91	0.76	0.91
F2	0.81	0.80	0.77	0.76	0.65	0.67	0.72	0.66	0.58	0.63	0.71	0.71	0.73	0.88	0.72	0.76	0.68	0.76
F3	0.92	0.96	0.93	0.88	0.76	0.64	0.75	0.70	0.86	0.67	0.61	-	-	-	0.79	0.84	0.73	0.84
F4	0.71	0.67	0.65	0.76	0.64	0.84	0.75	0.75	0.71	0.88	0.88	0.86	0.89	0.61	0.76	0.82	0.70	0.82
F5	0.87	0.87	0.90	0.77	0.69	0.77	0.78	0.78	0.76	0.79	0.77	0.75	0.89	0.92	0.81	0.86	0.76	0.86
F6	0.90	0.89	0.87	0.88	0.85	0.86	0.89	0.87	0.85	0.86	0.57	0.92	0.49	-	0.82	0.93	0.69	0.93
F7	0.91	0.90	0.89	0.89	0.86	0.87	0.90	0.88	0.86	0.86	0.87	0.86	0.83	0.85	0.87	1.00	0.76	1.00
F8	0.81	0.79	0.78	0.91	0.83	0.68	0.92	0.90	0.87	0.89	0.88	0.87	0.82	0.84	0.84	0.93	0.74	0.93
F9	0.91	0.90	0.87	0.88	0.85	0.86	0.89	0.87	0.86	0.86	0.86	0.86	0.84	0.86	0.87	1.00	0.73	1.00
F10	0.90	0.89	0.87	0.88	0.86	0.86	0.89	0.87	0.86	0.86	0.85	0.86	0.82	0.83	0.86	1.00	0.71	1.00
F11	0.76	0.75	0.81	0.89	0.90	0.63	0.73	0.73	0.78	0.77	0.65	0.59	0.61	0.64	0.73	0.78	0.68	0.78
F12	0.84	0.88	0.87	0.91	0.90	0.86	0.87	0.83	0.72	0.75	0.83	0.73	0.59	0.67	0.80	0.87	0.73	0.87
F13	0.93	0.85	0.83	0.85	0.79	0.76	0.78	0.75	0.69	0.72	0.75	0.71	0.60	0.66	0.76	0.81	0.71	0.81
F14	0.90	0.89	0.87	0.88	0.85	0.86	0.89	0.87	0.86	0.86	0.85	0.85	0.82	0.84	0.86	1.00	0.71	1.00
F15	0.88	0.74	0.64	0.66	0.49	0.50	0.70	0.61	0.55	0.48	0.49	0.48	0.44	0.40	0.58	0.62	0.52	0.62
F16	0.77	0.81	0.74	0.78	0.65	0.68	0.66	0.82	0.71	0.71	0.74	0.68	0.65	0.63	0.72	0.76	0.68	0.76
F17	0.90	0.88	0.88	0.88	0.85	0.86	0.89	0.88	0.86	0.88	0.85	0.85	0.84	0.83	0.87	1.00	0.73	1.00
F18	0.83	0.85	0.85	0.85	0.89	0.84	0.90	0.82	0.91	0.87	0.84	0.87	0.87	0.85	0.86	0.94	0.78	0.94
F19	0.82	0.81	0.70	0.66	0.56	0.54	0.60	0.62	0.60	0.59	0.56	0.55	0.55	0.56	0.62	0.66	0.58	0.66
F20	0.91	0.84	0.60	0.63	0.70	0.77	0.93	0.80	0.55	0.65	0.67	0.67	0.60	0.60	0.71	0.76	0.64	0.76
F21	0.79	0.77	0.63	0.68	0.70	0.75	0.88	0.81	0.73	0.72	0.70	0.73	0.64	0.60	0.72	0.76	0.68	0.76
F22	0.90	0.89	0.90	0.92	0.85	0.86	0.90	0.90	0.86	0.86	0.86	0.86	0.84	0.84	0.87	0.99	0.74	0.99
F23	0.92	0.69	0.67	0.67	0.62	0.84	0.89	0.87	0.86	0.86	0.85	0.87	0.64	0.87	0.79	0.89	0.68	0.89
F24	0.75	0.70	0.66	0.69	0.61	0.62	0.65	0.70	0.61	0.54	0.55	0.53	0.57	0.50	0.62	0.66	0.57	0.66
F25	0.90	0.89	0.87	0.88	0.85	0.87	0.89	0.90	0.86	0.86	0.86	0.85	0.82	0.84	0.87	1.00	0.73	1.00
F26	0.90	0.89	0.87	0.88	0.86	0.87	0.90	0.81	0.84	0.90	0.84	0.88	0.83	0.85	0.87	0.98	0.76	0.83
F27	0.94	0.88	0.81	0.82	0.84	0.93	0.88	0.82	0.72	0.82	0.76	0.78	0.59	0.62	0.80	0.86	0.73	0.98
F28	0.74	0.70	0.69	0.70	0.55	0.64	0.74	0.37	0.86	0.83	0.83	0.87	0.82	0.83	0.73	0.80	0.66	0.86
F29	0.91	0.75	0.76	0.91	0.87	0.87	0.89	0.89	0.87	0.88	0.91	0.86	0.89	0.89	0.87	0.96	0.77	0.80
F30	0.77	0.76	0.75	0.75	0.73	0.76	0.83	0.91	0.87	0.92	0.91	0.90	0.86	0.85	0.83	0.89	0.76	0.96
F31	0.90	0.88	0.88	0.90	0.85	0.86	0.89	0.87	0.75	0.85	0.85	0.85	0.83	0.82	0.86	0.98	0.72	0.89
F32	0.64	0.63	0.85	0.69	0.70	0.64	0.78	0.68	0.64	0.62	0.64	0.71	0.63	0.61	0.68	0.72	0.64	0.98
F33	0.67	0.67	0.63	0.68	0.68	0.81	0.89	0.74	0.65	0.62	0.72	0.61	0.52	0.55	0.67	0.71	0.63	0.72
F34	0.84	0.82	0.73	0.76	0.73	0.89	0.96	0.91	0.76	0.87	0.89	0.91	0.87	0.87	0.84	0.91	0.79	0.71
F35	0.83	0.74	0.83	0.93	0.85	0.86	0.89	0.87	0.65	0.72	0.86	0.61	0.40	0.70	0.77	0.84	0.68	0.91
F36	-	-	-	-	-	-	-	-	-	0.83	0.81	0.80	0.74	0.72	0.78	0.84	0.72	0.84
F37	0.82	0.90	0.79	0.93	0.83	0.89	0.85	-	-	-	-	-	-	-	0.86	0.93	0.77	0.97
F38	'-	'-	'-	'-	'-	0.82	0.81	0.78	0.83	0.75	0.68	0.68	0.74	0.88	0.77	0.83	0.72	0.84
F39	0.90	0.89	0.87	0.88	0.80	0.74	0.92	0.90	0.87	0.87	-	-	-	-	0.86	0.97	0.74	0.91
F40	-	-	-	-	-	-	-	-	-	-	0.89	0.93	0.80	0.74	0.84	0.91	0.78	0.93
Mean	0.86	0.83	0.79	0.81	0.76	0.77	0.82	0.80	0.78	0.78	0.76	0.76	0.72	0.75	0.79	0.86	0.70	0.87
Min.	0.64	0.63	0.60	0.63	0.49	0.50	0.60	0.37	0.55	0.48	0.49	0.48	0.40	0.40	0.58	0.62	0.52	0.62

LB: Lower bound of the confidence interval, UB: Upper bound of the confidence interval, DEA: Original efficiency estimates

operated at the relative maximum efficiency level (i.e., efficiency score = 1), according to the bias corrected measures. Also, none of the firms had a score lower than 0.40. It is noticeable that the three new entry companies that were included in the analysis during the last years were also found to be inefficient. Certainly, two of them seem to perform slightly better to the average level. Nevertheless, the most remarkable result comes from performance analysis of 4 firms that have either been purchased or merged with other firms or have been closed. These firms were inefficient and they did not appear to have important differences in performance compared to others Greek meat product manufacturers, which continue to operate up to date. In other words, they did not perform worse than an average firm in this sector, as it was expected.

Figure 1 shows the average share of sample firms which had input slacks equal to zero or above, over the period 1994-2007. These results have been derived by using original DEA. According to these, a majority of the sample enterprises had inputs slacks greater than zero, during the time under consideration, indicating that in these firms the productive factors were not been fully utilized. The inputs-slacks expressed as a percentage of the input level are shown in Fig. 2. An interesting finding arising from this analysis was that all inputs had to be decreased, in order the Greek prepared meats companies to become pure technically efficient. Capital might be decreased, on average, by 19.2% during the period considered, while labour and raw and auxiliary materials by 11.7 and 9.6%, respectively. The inefficiencies observed in prepared meats companies, therefore, caused

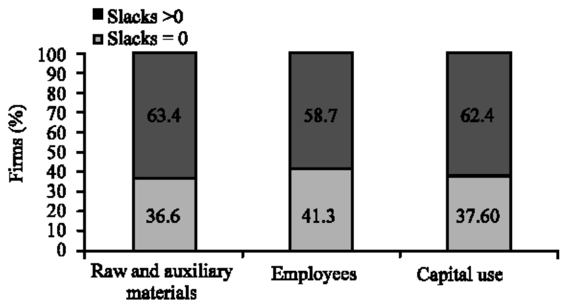

Fig. 1: Distribution of three slack inputs over the period 1994-2007

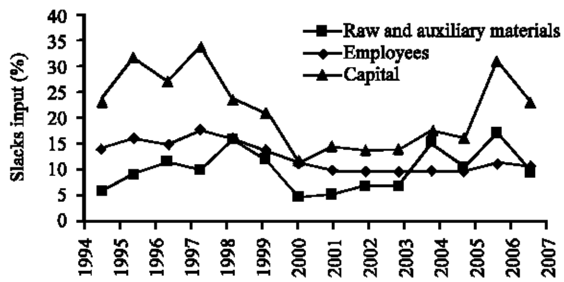

Fig. 2: Ratio between DEA input slacks for VRS technical efficiency and average input level in 2000-2004

mainly by the high capital slack and less by the excessive use of labour. This probably implies that subsidies provided by EU might stimulate purchase of machinery without regard to firm size. The relatively small slack-input for intermediate consumption observed in the sample firms supports the ascertainment about the small inefficiency of this input factor. Another interesting finding is that in period of 1994-2000 all inputs slacks were decreased. During the intergration period to EMU (2001-2007) the former drop of inputs slacks had been replaced by a clear trend towards stabilization of all inputs excesses, from 2001 through 2003, followed in the period 2004-2007 by a great increase of capital and raw and auxiliary materials slacks. There is one possible explanation for the tend of capital excess observed in an average Greek sausage manufacturing firm over the period of study. The explanation may involve a failure of manager to use the subsidies provided by EU for purchase of machinery without taking into consideration the size of the firm. This is supported by the findings of Vasiliev *et al*. (2008) which aim to shed light to the relationship between the Estonia accession to European Union and efficiency of grain farms. Therefore, Greek managers in sausage industry had large space to enhance their competitiveness, by adopting new methods, which decreased the excess inputs usage. Management should pay the most attention to reduction of the input of capital. Moreover, it should promote staff's efficiency, fortifying cooperation and rationalizing the division of work.

Table 3 shows the average level of bias corrected pure technical efficiency scores by size categories. The results indicated that large firms, medium firms and small films, on average, were different in pure technical efficiency. Large, small and medium companies, on average, had the efficiency scores of 0.86, 0.80 and 0.71, respectively in period of 1994-2007, indicating that they had to decrease their inputs by 14, 20 and 29%, respectively without decreasing the amount of output so that they could be efficient. Hence, in most years, relatively larger firms performed better than smaller ones, while the middle firms with 50 to 249 employees performed worse. Smaller firms with less than 49 employees performed similarly to the average level. This result reflects that relatively smaller firms were more efficient than medium firms with 50 to 249 employees. According to these findings, the firm size did not have any influence on the performance of Greek prepared meats manufacturing firms. A similar relationship between size and pure technical efficiency was also revealed in other areas in developing countries (Vasiliev *et al*., 2008; Graner and Isaksson, 2009; Ceyhan and Hazneci, 2010). For example Graner and Isaksson (2009) investigated the link between firm efficiency and exports in Kenyan manufacturing and found that in the food and textiles sectors the mean technical efficiencies are higher for large and small firms than for medium-sized firms. On the contrary, the average efficiency score of Kenyan manufacturing increased with firm size. A negative relationship firm size and technical efficiency was also confirmed by the study of Ceyhan and Hazneci (2010) that focused on the economic efficiency of cattle-fattening farms in Turkey. The above mentioned findings aren't in harmony with results of many previous studies, which found that large firms are more efficient in production. For example, Badunenko (2010) findings pointed out that in German chemical manufacturing firms, the efficiency increased with the size of the firm. These different findings can be exlained by the literature. Larger firms were usually more efficient because they pursued a cost leadership strategy, having the opportunity to enjoy economies of scale due to large production volumes and economies of scope, as they could meet the needs of the mass market, competing, also, on differentiation (quality, brand and customization). On the other hand, smaller companies could be efficient too, because they managed to gain a completive advantage in focused narrow market segments (Fotinopoulou and Keramidou, 2006). Depending on the needs of the selected market segments

Table 3: Averages of efficiency and number of firms by size categories

	Size Firms categorized by the number of employees															
	Pure technical efficiency								Scale efficiency							
	Less than0-49		50-249		More than 250		Total		Less than 0-49		50-249		More than 250		Total	
Year	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean
1994	25	0.84	9	0.86	3	0.9	37	0.85	25	0.93	9	0.96	3	0.93	37	0.94
1995	23	0.83	11	0.79	3	0.89	37	0.79	23	0.94	11	0.98	3	0.91	37	0.94
1996	23	0.8	12	0.76	2	0.88	37	0.81	23	0.92	12	0.98	2	0.81	37	0.9
1997	23	0.81	12	0.79	2	0.9	37	0.81	23	0.91	12	0.99	2	0.75	37	0.88
1998	23	0.79	13	0.71	1	0.85	37	0.76	22	0.9	13	0.99	2	0.86	37	0.92
1999	23	0.81	12	0.75	3	0.8	38	0.78	23	0.91	12	0.99	3	0.95	38	0.95
2000	23	0.83	11	0.83	4	0.9	38	0.84	23	0.93	11	0.98	4	0.83	38	0.91
2001	22	0.8	10	0.77	5	0.89	37	0.8	22	0.96	10	0.98	5	0.89	37	0.94
2002	21	0.79	10	0.68	6	0.87	37	0.78	21	0.96	10	1	6	1	37	0.98
2003	24	0.8	8	0.66	5	0.87	37	0.78	24	0.96	8	1.01	5	1.05	37	1
2004	25	0.8	5	0.6	7	0.82	37	0.78	25	0.96	5	1	7	1.02	37	0.99
2005	23	0.79	7	0.58	7	0.86	37	0.78	23	0.91	7	0.97	7	0.95	37	0.95
2006	22	0.75	9	0.54	6	0.79	37	0.72	22	0.94	9	0.98	6	1.04	37	0.99
2007	22	0.76	8	0.62	6	0.85	36	0.75	22	0.93	8	0.99	6	1	35	0.97
Mean		0.8		0.71		0.86		0.79		0.93		0.99		0.93		0.95

N: No. of firms, Mean: Average of efficiency score

Table 4: Frequency of scale efficient and scale inefficient firms with inefficiency due to decreasing or increasing returns to scale (1994-2007)

	Scale efficient		Scale Inefficient				Total			
Year	N of SE	%	N of SI due to DRS	%	N of SI due to IRS	%	N of SI	%	N	%
1994	6	16.2	0	0.00	31	83.8	31	83.8	37	100
1995	6	16.2	4	10.8	27	73.0	31	83.8	37	100
1996	8	21.6	1	2.70	28	75.7	29	78.4	37	100
1997	6	16.2	0	0.00	31	83.8	31	83.8	37	100
1998	9	24.3	0	0.00	28	75.7	28	75.7	37	100
1999	11	28.9	0	0.00	27	71.1	27	71.1	38	100
2000	7	18.4	2	5.30	29	76.3	31	81.6	38	100
2001	9	24.3	1	2.70	27	73.0	28	75.7	37	100
2002	15	40.5	0	0.00	22	59.5	22	59.5	37	100
2003	15	39.5	0	0.00	23	60.5	23	60.5	38	100
2004	13	34.2	0	0.00	25	65.8	25	65.8	38	100
2005	11	29.7	0	0.00	26	70.3	26	70.3	37	100
2006	13	35.1	0	0.00	24	64.9	24	64.9	37	100
2007	11	30.6	0	0.00	25	69.4	25	69.4	36	100
Mean	10	26.9	1	1.50	27	71.6	27	73.1	37	100

SE: Scale efficient, SI: Scale inefficient, DRS: Decreasing returns to scale, IRS: Increasing returns to scale, N: Number of firms

and the resources and capabilities of each firm, several small firms gained a competitive advantage, offering differentiated products, through product innovation, or the superior product quality compared to those ones of their counterparts. However, in developing countries, several smaller firms could offer low prices, enjoyed advantages of conductive low costs, through the use of cost low family labour, the productive flexibility, or other cost economies, attained often in illegal ways (paying less than the minimum wage, or not paying over time pay for hours working in excess of 40 h per weeks, or even tax evasion). These are some of the reasons, which could explain why in developing economies it is possible small firm to have better performance than middle ones.

Information on scale efficiency scores of the analyzed Greek firms is reported in Table 4. The most striking result was that in fourteen years under consideration an average firm of the sample displayed high scale efficiency. The average scale efficiency score for the entire period was equal to 0.95. The low pure technical efficiency in comparison to scale efficiency suggests that inefficiencies were mostly due to inadequate management practices (pure technical inefficiency), than to inappropriate size of firms (scale inefficiencies). In term of size, large firms, medium and small films, on average, were slightly different in scale efficiency, as they had the average scale efficiency scores of 0.93, of 0.99 and of 0.93 respectively in period of 1994-2007 (Table 3). Thus, medium firms were close to be operating at optimal scale, while large and small companies could obtain input savings, through the adjustment of their operational scale.

The nature of return to scale (RTS) is presented in Table 4. From these results, in period of 1994-2007 approximately 26.9% of the sample firms achieved constant returns to scale (CRS). Thus a considerable portion of firms was scale inefficient. Nearly 71.6% of the sample firms were operating at Increasing Returns to Scale (IRS). So these firms should consider further expanding, because an increase in input causes an output increase at a larger proportion. Only the 1.5% of the firms considered was operating at Decreasing Returns to Scale (DRS), which indicates that in these firms the percentage of the increase of outputs was behind the one in inputs. The relatively small-scale production of the research area and in Greece in general, was the main reason why a minor number of firms had DRS. Moreover the increasing trend in the share of scale efficient firms was present. During the period under inspection, the number of scale efficient firms had been growing in relative terms-from 16.2% of all firms in 1994 to 30.6% in 2007. As a result the share of scale inefficient firms due to IRS was decreased (from 83.8% in 1994 to 69.4% in 2007). This means that the majority of the firms had to expand their size to be scale efficient and this was exactly the case in the study period. Vasiliev *et al*. (2008) and Ceyhan and Hazneci (2010) reported similar results, in oposition to others research projects conducted in developped economies which reported a downsizing behavior (Badunenko, 2010).

CONCLUSIONS

This article provides an application of the DEA bootstrapping procedure in the meat products industry, in order to estimate efficiency scores. This approach combines the advantages of both parametric and non-parametric methods, avoiding the problems of mis-specification of the production function and sample variation bias. The study starts with the estimation of the pure technical efficiency scores (PTE) during period of 1994-2007. Overall, the analysis leads to the conclusion that the average level of pure technical inefficiency was rather high, about 21%, during these fourteen years. It presented a clear increase trend of inefficiencies, regardless of the high growth trend of prepared meats domestic production and the Greece's participation in European Economic and Monetary Union since 2001. From the results of slacks inputs it is clear the inefficiencies observed in prepared meats companies caused mainly by the high capital slack and less by the excessive use of labour. The inefficiencies observed in prepared meats companies, therefore, caused mainly by the high capital slack and less by the excessive use of labour. he subsidies provided by EU might stimulate purchase of machinery without regard to firm size. Furthermore, the findings revealed that firm size did not have any effect on the efficiency of our sample firms, as small firms enjoyed advantages of conductive low costs, through mostly the use of low cost family labour. The most remarkable result, however, came from analysis of scale efficiency. Almost all sample firms displayed high scale efficiency during the study period, indicating that the overall inefficiencies were basically due to pure technical inefficiencies, namely to the inefficient implementation of the production plan in converting inputs to outputs. Moreover, the share of scale efficient firms has been progressively increasing from 16.2% in 1994 to 30.6 % in 2007. Among scale inefficient firms 87 to 100% of firms in different years were inefficient due to increasing returns to scale; they had to enlarge their size in order to be more scale efficient.

Some policy implication enables to be derived from these findings. Managers have large space to enhance their competitiveness by decreasing the waste of productive factors. This can be done by adopting similar practices, to those of best performers in the sample. It is also worth paying attention to the size of the firm. More specifically, it is necessary to investigate the technology conditions under which the firm operates as well as its impact in the decision of the size of the firm. Last but not least, decision-makers should implement the sectoral policies to ensure an adequate institutional setting and an efficient use of subsiaries of EU that improve sectors' efficiency.

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