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Industry performance evaluation with the use of financial ratios: An application of bootstrapped DEA

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ABSTRACT

In data envelopment analysis (DEA) context financial data/ratios have been used in order to produce a unified measure of performance metric. However, several scholars have indicated that the inclusion of financial ratios create biased efficiency estimates with implications on firms' and industries' performance evaluation. By applying bootstrap techniques the paper provides an application of evaluating the performance of 23 Greek manufacturing sectors with the use of financial data. The results reveal that in the first stage of our sensitivity analysis the efficiencies obtained are biased. However, after applying the bootstrap techniques the sensitivity analysis reveals that the efficiency scores have been significantly improved.

1. Introduction

According to Nanni, Dixon, and Vollman (1992) in a business changing environment the key element for business to maintain competitive advantage is business strategy. In that respect performance measurement issues are vital for designing and implementing their strategies. Melnyk, Stewart, and Swink (2004) suggest that metrics and performance measurements are receiving more attention over the last years but according to Evans (2004) practitioners need better approaches in order to analyse performance results under the perspective of competitive comparisons and benchmarks among the organizations. On the other hand traditional, financial-based metrics are reported to have deficiencies when employed in a dynamic environment for business and industry performance evaluation (Atkinson, Waterhouse, & Wells, 1997).

Management accounting theorists assert the need for the account of non-financial performance measures which drive success in achieving strategic goals (Abernethy, Horne, Lillis, Malina, & Selto, 2005; Ittner & Larcker, 1998; Malina & Selto, 2004). In that respect advanced manufacturing practices have been employed to capture the use and performance consequences of non-financial measures in organisations (Fisher, 1992; Hertenstein & Platt, 1998).

However, the problem arises because financial measures are usually more objective and less subject to managerial discretion, however, non-financial measures are usually related to key strategic factors. In that respect, the choice of performance measures is one of the most critical issues in the design of management control systems (Banker & Datar, 1989; Barkema & Gomez-Mejia, 1998; Chen & Chen, 2011; Core, Holthausen, & Larcker, 1999; De Andrés, Landajo, & Lorca, 2009; Feltham & Xie, 1994; Lee & Pai, 2010).

Given the debate of whether only traditional financial ratios remain appropriate for monitoring organizations' performance (Atkinson et al., 1997; Bushman, Indjejikian, & Smith, 1995; Fisher, 1992; Kaplan & Norton, 1996). Data envelopment analysis (DEA) has been used to solve this problem. DEA techniques by accommodating non-financial and financial measures as inputs/outputs variables provide a metric for industry and firm performance measurement. More specifically several studies have used DEA techniques in order to measure industry performance (Destefanis & Sena, 2007; Majumdar & Chang, 1996; Sun, 2011). According to Siriopoulos and Tziogkidis (2009) emphasise the fact that when researchers and practitioners employ financial ratio analysis (especially ROE, ROA and the cost/income ratio) fail in practise to provide a general efficiency score when multiple inputs or outputs are used. Then the so-called global DEA-model (GDM) that includes all these selected variables provide a unified performance metric (Gonzalez-Bravo, 2007).

However, the weaknesses of the methodology have been stated by several authors in different applications (Deville, 2009; Gietzmann, 1990; Halkos & Salamouris, 2004; Rouse, Putterill, & Ryan, 2002). In addition, this method is subject to biased results and overestimated efficiency scores, units could be erroneously classified as efficient or inefficient, and a proper ranking or classification cannot be obtained (Daraio & Simar, 2007; Jenkins & Anderson, 2003; Simar & Wilson, 1998; Smith, 1997; Zhang & Bartels, 1998).

To avoid these problems several methods have been used such as: sensitivity analysis (Valdmanis, 1992); Prior-Ratio-Analysis (PRA), allowing the identification of typical behaviours while

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providing insights into the factors that determine the unit efficiency (Gonzalez-Bravo, 2007); and DEA/output–input ratio analysis displaying the differences and the similarities of both previous approaches to assess efficiency and to rank units (Fernandez-Castro & Smith, 1994; Smith, 1990; Thanassoulis, Boussofiane, & Dyson, 1996; Zhu, 2000).

In contrast to these approaches this paper for the first time uses several DEA models combining multiple financial measures in a single measure with the use of bootstrap techniques as has been introduced by Simar and Wilson (1998, 2000, 2007). In such a way we provide an illustrative way of how financial (non-financial) measures can be combined into a single measure producing unbiased results. Using financial data the paper measures the performance of twenty three Greek manufacturing sectors providing empirical evidences of the influence of performance evaluation when different financial ratios in different sectors are adopted. Moreover, it raises issues regarding the influence of non-financial factors which interrelate with the choice of the financial metrics adopted and how errors in efficiency estimation can be avoided with the use of bootstrap techniques.

The structure of the paper is the following. Section 2 presents the techniques adopted both in theoretical and mathematical formulations. In Section 3 the various variables used in the formulation of the proposed models are presented while in Section 4 the empirical results derived are discussed. The final section concludes the paper discussing our findings and the implied methodological implications.

2. Methods proposed

2.1. 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, Cooper, and Rhodes (1978) to estimate Ψ and allowing constant returns to scale (CCR model). This involves the measurement of efficiency for a given unit (x,y) relative to the boundary of the convex hull of $X = \{(X_i, Y_i), i = 1,\ldots,n\}$. The production set Ψ constraints the production process and is the set of physically attainable points (x,y):

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

where $x \in \Re_+^N$ is the input vector and $y \in \Re_+^M$ is the output vector. Later, Banker, Charnes, and Cooper (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.

Following the notation by Daraio and Simar (2007) $\hat{\Psi}_{\text{DEA}}$ is given by

$$\hat{\Psi}_{\text{DEA}} = \left\{ \begin{array}{l} (x,y) \in \Re_+^{p+q} | y \leqslant \sum_{i=1}^{n} \gamma_i Y_i; \quad x \geqslant \sum_{i=1}^{n} \gamma_i X_i \quad \text{for } (\gamma_1,\ldots,\gamma_n) \\ \text{s.t.} \quad \sum_{i=1}^{n} \gamma_i = 1; \quad \gamma_i \geqslant 0, \quad i = 1,\ldots,n \end{array} \right\}. \tag{2}$$

Formula (2) represents the BCC model introduced by Banker et al. (1984) allowing for variable returns to scale (hereafter, VRS). This study uses VRS specification following Hollingsworth and Smith (2003) suggesting that when using ratios in DEA specifications VRS formulation must be adopted otherwise perverse and technically incorrect results will be produced. In addition we use an output orientation formulation since we want to expand proportionally the outputs quantities without altering the input quantities used (Coelli, Rao, & Battese, 1998, p. 54).

Therefore, the estimator of the output efficiency score for a given (x_0,y_0) can been obtained solving the linear program illustrated below:

$$\hat{\lambda}_{\text{DEA}}(x_0,y_0) = \sup\left\{\lambda | (x_0, \lambda y_0) \in \hat{\Psi}_{\text{DEA}}\right\}, \tag{3}$$

$$\hat{\lambda}_{\text{DEA}}(x_0,y_0) = \max\left\{ \begin{array}{l} \lambda | \lambda y_0 \leqslant \sum_{i=1}^{n} \gamma_i Y_i; \quad x_0 \geqslant \sum_{i=1}^{n} \gamma_i X_i; \\ \sum_{i=1}^{n} \gamma_i = 1; \quad \gamma_i \geqslant 0; \quad i = 1,\ldots,n. \end{array} \right\}. \tag{4}$$

2.2. Bias correction using the bootstrap technique

Several authors have point out the essence of bootstrap techniques as an alternative method of conducting inference where the sample size is not large or sampling distributions are analytically intractable, due to nonlinearity or pretesting, etc. (Alonso, Pena, & Romo, 2006; Assaf, Barros, & Matousek, 2010; Halkos & Tzeremes, 2010; Tu & Zhang, 1992). Simar and Wilson (1998, 2000, 2007) based on bootstrap techniques (Efron, 1979) introduced an approach in order to correct and estimate the bias of the DEA efficiency indicators.

More analytically and in order to build a bootstrap sample of the original DEA scores we follow the following steps[1]:

In order to implement the homogenous bootstrap algorithm for a set of bootstrap estimates $\{\hat{\lambda}_b^*(x,y) | b = 1,\ldots,B\}$ for a given fixed point (x,y) the following eight steps must be carried out:

(1) From the original data set we compute to $\hat{\lambda}_{VRS}$.
(2) Then we apply the "rule of thump" (Silverman, 1986, p. 47–48) to obtain the bandwidth parameter h.
(3) We generate $\beta_1^*,\ldots,\beta_n^*$ by drawing with replacement from the set $\{\hat{\lambda}_1,\ldots,\hat{\lambda}_n,(2-\hat{\lambda}_1),\ldots,(2-\hat{\lambda}_n)\}$.
(4) Then we draw $\varepsilon_i^*, i = 1,\ldots,n$ independently from the kernel function $K(.)$ and compute $\beta_i^{**} = \beta_i^* + h\varepsilon_i^*$ for each $i = 1,\ldots,n$.
(5) For each $i = 1,\ldots,n$ we compute β_i^{***} as: $\beta_i^{***} = \bar{\beta}^* + \frac{\beta_i^{**}-\bar{\beta}}{(1+h^2\sigma_k^2\sigma_\beta^2)^{1/2}}$, where $\bar{\beta}^* = \sum_{i=1}^n \beta_i^*/n, \sigma_\beta^2 = \sum_{i=1}^n (\beta_i^* - \bar{\beta}^*)/n$ and σ_k^2 is the variance of the probability density function used for the kernel function. In addition λ_i^* can then be computed as: $\lambda_i^* = \begin{cases} 2-\beta_i^{***} \ \forall\ \beta_i^{***} < 1 \\ \beta_i^{***} \text{ otherwise} \end{cases}$.
(6) The bootstrap sample is created as: $X_n^* = \{(x_i^*, y_i) | i = 1,\ldots,n\}$ where $x_i^* = \lambda_i^* \hat{x}^\partial(y_i) = \lambda_i^* \hat{\lambda}_i^{-1} x_i$.
(7) We compute the DEA efficiency estimates $\hat{\lambda}_i^*(x_i,y_i)$ for each of the original sample observations using the reference set X_n^* in order to obtain a set of bootstrap estimates.
(8) Finally, we repeat steps 3–7 B times (at least 2000 times) to obtain a set of bootstrap estimates $\{\hat{\lambda}_b^*(x,y) | b = 1,\ldots,B\}$.

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

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

Furthermore, $\hat{\lambda}_{DEA}^*(x,y)$ are the bootstrap values and B is the number of bootstrap replications (2000 replications in our case). Then a biased corrected estimator of $\lambda(x,y)$ can be calculated as:

[1] For greater discussion regarding the bootstrap techniques see Simar and Wilson (1998, 2000, 2007, 2008).

$$\hat{\hat{\lambda}}_{DEA}(x,y) = \hat{\lambda}_{DEA}(x,y) - B\hat{I}AS_B\left(\hat{\lambda}_{DEA}(x,y)\right) = 2\hat{\lambda}_{DEA}(x,y) - B^{-1}\sum_{b=1}^{B}\hat{\lambda}^*_{DEA,b}(x,y). \quad (6)$$

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

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

In addition it is needed to avoid the bias correction illustrated in (7) unless:

$$\frac{\left|B\hat{I}AS_B\left(\hat{\lambda}_{DEA}(x,y)\right)\right|}{\hat{\sigma}} > \frac{1}{\sqrt{3}}. \quad (8)$$

Finally a straight forward rule according to Daraio and Simar (2007) when the Bias is larger than the standard deviation (σ), the bias-corrected estimates have to be preferred to the original values (p. 153).

3. Data used for the empirical application

The choice of the inputs and outputs is very crucial for the relative efficiencies to be useful in arriving at meaningful conclusions. The data used have been provided by ICAP. (2007) and present a panorama of the Greek manufacturing sector based on the balance sheets and income statements of 2005. The data were collected and processed by ICAP's Business Information Division and include all financial statements, which were published within the time limits set by the Greek law that is until 10th of June. The year 2005 marks the beginning of the introduction of the International Financial Reporting Standards in Greece.

However, these apply mostly to companies listed in the Athens Stock Exchange and their subsidiaries, which are the only ones included in our study. According to statistics of ICAP Greek manufacturing reported satisfactory growth rates in assets and turnover. However, the increase in sales was mostly due to rise in oil prices. Exclusive of the oil-refining sector manufacturing turnover remained flat. Overall manufacturing gross profits increased more slowly than turnover and gross margins were trimmed from 22.4% to 21.6%. Pre-tax income increased by a mere of 1.5% and net margins was down to 5.1%, while return on equity dropped to 9.5%.

The industry data used in our analysis are derived from consolidated income statements of each manufacturing sector. Furthermore, Table 1 provides the number of companies listed in Athens Stock Exchange for every sector. It appears that the sector of 'food and beverages' has the highest number of companies (1214 companies listed in Athens Stock Exchange), whereas the sector of 'non-metallic mineral products' with 500 companies has the second higher number of companies. However, as expected due to oligopolistic economic conditions the sector of 'tobacco products' with 4 companies has the lowest number. Furthermore 'office machinery, computers' and 'recycling' have second and third lowest number of companies with 9 and 10 companies, respectively.

Table 2 provides descriptive statistics regarding the inputs/outputs used in DEA methodology. Following Marie, Rao, and Kashani (2009) this paper follows the financial intermediation approach for the selection of variables to represent inputs and outputs. The inputs represent resources that a decision-making unit employs in order to conduct its operations. The outputs reflect the results that are desired from the inputs utilized. This interpretation of inputs being facilitating quantities and outputs being desired outcomes or objectives of the decision-making entity provides a useful perspective for industry evaluation. More analytically three industry inputs have been used in our analysis, namely total assets, equity[2] and administrative, distribution and selling expenses. Moreover, three industry financial ratios (profitability ratios) have been used as outputs in order to capture the performance of the industries. These are the net profit margin (pre tax profits/turnover%), 2) the return on equity (Pre tax profits/Average equity%)[3] and the return on assets (Pre tax profits + interest charges/Average assets%)[4].

Looking at the descriptive statistics among the seven variables we can observe considerable high values of standard deviations indicating the effect of size and differentiations among the examined sectors. This is also a first indication of the inability to use ratios in order to compare different sectors with different sizes.

Table 1
Number of companies listed in Athens Stock Exchange per manufacturing sector.

Manufacturing sectors	Number of companies
Food-beverages	1214
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 financial data used in the analysis.

Variables	Mean	Standard deviation	Minimum	Maximum
Total assets (€ '000) (input)	2481699,00	3068655,00	15605,00	14150226,00
Equity (€ '000) (input)	1100546,00	1473140,00	5223,00	6674184,00
Administrative, distribution and selling expenses (€ '000) (input)	327579,00	504288,00	2566,00	2261652,00
Net profit margin% (output)	5.95	8.88	0.01	43.09
Return on equity% (output)	10.08	11.49	0.01	50.49
Return on assets% (output)	6.54	7.05	0.85	35.41

[2] The term's meaning depends very much on the context. In general, equity may be considered as ownership in any asset after all debts associated with that asset are paid off.

[3] A measure of an organization's profitability that reveals how much profit a company generates with the money shareholders have invested.

[4] An indicator of how profitable a company is relative to its total assets. ROA gives an idea as to how efficient management is at using its assets to generate earnings.

Table 3
Comparing the performances of different sectors using financial data/ratios.

Rankings	Total assets (€ '000) (input)	Equity (€ '000) (input)	Administrative, distribution and selling expenses (€ '000) (input)
1	Food-beverages	Food-beverages	Food-beverages
2	Basic metals	Basic metals	Chemicals
3	Non-metallic mineral products	Non-metallic mineral products	Publishing–printing
4	Oil refining	Oil refining	Non-metallic mineral products
5	Chemicals	Chemicals	Basic metals
6	Metal products	Metal products	Clothing
7	Publishing–printing	Publishing–printing	Oil refining
8	Other transport equipment	Textile	Machinery, equipment
9	Textile	Rubber–plastic products	Furniture and other products
10	Rubber–plastic products	Other transport equipment	Metal products
11	Machinery, equipment	Furniture and other products	Rubber–plastic products
12	Clothing	Machinery, equipment	Textile
13	Furniture and other products	Clothing	Paper
14	Paper	Wood	Tobacco products
15	Electrical machinery	Electrical machinery	Electrical machinery
16	Wood	Paper	Other transport equipment
17	Tobacco products	Tobacco products	Wood
18	Vehicles	Vehicles	Vehicles
19	Radio, television and communication equipment	Radio, television and communication equipment	Leather
20	Leather	Precision instruments	Radio, television and communication equipment
21	Precision instruments	Leather	Precision instruments
22	Recycling	Recycling	Recycling
23	Office machinery, computers	Office machinery, computers	Office machinery, computers

Rankings	Net profit margin% (output)	Return on equity% (output)	Return on assets% (output)
1	Recycling	Recycling	Recycling
2	Non-metallic mineral products	Oil refining	Oil refining
3	Tobacco products	Tobacco products	Non-metallic mineral products
4	Radio, television and communication equipment	Radio, television and communication equipment	Radio, television and communication equipment
5	Oil refining	Chemicals	Tobacco products
6	Furniture and other products	Non-metallic mineral products	Chemicals
7	Metal products	Rubber–plastic products	Rubber–plastic products
8	Chemicals	Metal products	Furniture and other products
9	Food-beverages	Food-beverages	Food-beverages
10	Rubber–plastic products	Furniture and other products	Metal products
11	Basic metals	Vehicles	Leather
12	Vehicles	Leather	Electrical machinery
13	Publishing–printing	Electrical machinery	Basic metals
14	Leather	Basic metals	Vehicles
15	Electrical machinery	Publishing–printing	Publishing–printing
16	Precision instruments	Precision instruments	Precision instruments
17	Clothing	Clothing	Paper
18	Paper	Paper	Clothing
19	Wood	Wood	Wood
20	Office machinery, computers	Office machinery, computers	Office machinery, computers
21	Machinery, equipment	Machinery, equipment	Machinery, equipment
22	Textile	Textile	Textile
23	Other transport equipment	Other transport equipment	Other transport equipment

Table 4
Specification of inputs/outputs used in the construction of the eight DEA models.

Variables	Models' specifications						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Total assets (€ '000) (input)	*	*	*	*	*	*	*
Equity (€ '000) (input)	*	*	*	*	*	*	*
Administrative, distribution and selling expenses (€ '000) (input)	*	*	*	*	*	*	*
Net profit margin% (output)	*			*	*		*
Return on equity% (output)		*		*		*	*
Return on assets% (output)			*		*	*	*

4. Empirical results

Table 3 provides the rankings of the performance of every sector taking into account every time a different measure of performance. For instance in order to evaluate the performance of sectors according to their total assets, we can observe that companies from 'food-beverages' sector have the highest levels (expressed in €'000) of total assets whereas the lowest are being reported for companies in the 'office machinery, computers' sector. Similarly, when we would like to use as a measure of performance the profitability ratios (for instance return on assets) we realise the best performance has been reported for organisations operating in 'recycling' sector whereas the lowest performance has been reported for organisations operating in the 'other transport equipment' sector.

Table 5
Estimated efficiency scores, estimated bias and estimated bias' standard deviations.

Sectors	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Food-beverages	0.000	0.000	0.000	0.000	0.024	0.024	0.024
Tobacco products	0.080	0.157	0.157	0.157	0.127	0.157	0.157
Textile	0.131	0.174	0.174	0.174	0.163	0.174	0.174
Clothing	0.271	0.380	0.380	0.380	0.271	0.380	0.380
Leather	0.070	0.133	0.133	0.133	0.167	0.167	0.167
Wood	0.070	0.134	0.134	0.134	0.131	0.134	0.134
Paper	0.079	0.110	0.110	0.110	0.115	0.115	0.115
Publishing–printing	0.155	0.571	0.571	0.571	0.438	0.571	0.571
Oil refining	0.133	0.356	0.356	0.356	0.210	0.356	0.356
Chemicals	0.126	0.186	0.186	0.186	0.164	0.186	0.186
Rubber–plastic products	0.275	0.290	0.290	0.290	0.275	0.290	0.290
Non-metallic mineral products	0.103	0.126	0.126	0.126	0.129	0.129	0.129
Basic metals	0.136	0.178	0.178	0.178	0.161	0.178	0.178
Metal products	0.000	0.000	0.000	0.000	0.027	0.027	0.027
Machinery, equipment	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Office machinery, computers	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Electrical machinery	0.056	0.092	0.092	0.092	0.109	0.109	0.109
Radio, television and communication equipment	0.000	0.000	0.000	0.000	0.166	0.166	0.166
Precision instruments	0.273	0.286	0.286	0.286	0.313	0.313	0.313
Vehicles	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Other transport equipment	0.078	0.143	0.143	0.143	0.143	0.143	0.143
Furniture and other products	0.004	0.004	0.004	0.004	0.057	0.057	0.057
Recycling	0.109	0.159	0.159	0.159	0.381	0.381	0.381
Average	0.224	0.282	0.282	0.282	0.286	0.307	0.307
Std	0.318	0.315	0.315	0.315	0.300	0.303	0.303
Min	0.000	0.000	0.000	0.000	0.024	0.024	0.024
Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	$\widehat{Bias}$						
Food-beverages	−0.001	−0.001	−0.001	−0.001	−0.069	−0.067	−0.067
Tobacco products	−0.132	−0.319	−0.320	−0.319	−0.234	−0.302	−0.306
Textile	−0.291	−0.528	−0.523	−0.447	−0.356	−0.439	−0.387
Clothing	−0.496	−0.899	−0.891	−0.806	−0.452	−0.823	−0.738
Leather	−0.115	−0.264	−0.265	−0.258	−0.318	−0.322	−0.326
Wood	−0.110	−0.255	−0.255	−0.254	−0.235	−0.239	−0.242
Paper	−0.158	−0.290	−0.287	−0.253	−0.246	−0.258	−0.239
Publishing–printing	−0.380	−2.005	−1.956	−1.949	−1.303	−1.675	−1.642
Oil refining	−0.304	−1.131	−1.114	−1.111	−0.528	−0.974	−0.975
Chemicals	−0.282	−0.573	−0.562	−0.506	−0.352	−0.464	−0.423
Rubber–plastic products	−0.603	−0.873	−0.858	−0.629	−0.516	−0.722	−0.548
Non-metallic mineral products	−0.252	−0.440	−0.430	−0.335	−0.301	−0.338	−0.286
Basic metals	−0.308	−0.553	−0.545	−0.455	−0.334	−0.445	−0.383
Metal products	0.000	−0.001	−0.001	0.000	−0.068	−0.067	−0.068
Machinery, equipment	−1.200	−1.279	−1.297	−1.312	−1.312	−1.334	−1.336
Office machinery, computers	−1.204	−1.298	−1.309	−1.303	−1.307	−1.332	−1.336
Electrical machinery	−0.080	−0.155	−0.156	−0.157	−0.182	−0.183	−0.184
Radio, television and communication equipment	−0.001	−0.001	−0.001	−0.001	−0.335	−0.347	−0.350
Precision instruments	−0.453	−0.566	−0.568	−0.482	−0.510	−0.577	−0.523
Vehicles	−1.197	−1.300	−1.297	−1.303	−1.318	−1.323	−1.339
Other transport equipment	−0.114	−0.244	−0.245	−0.248	−0.241	−0.236	−0.239
Furniture and other products	−0.008	−0.010	−0.010	−0.008	−0.130	−0.128	−0.130
Recycling	−0.147	−0.245	−0.245	−0.244	−0.580	−0.593	−0.598
	$\hat{\sigma}$						
Food-beverages	0.000	0.000	0.000	0.000	0.018	0.019	0.019
Tobacco products	0.148	0.556	0.572	0.565	0.421	0.614	0.607
Textile	0.428	0.992	0.983	1.075	0.913	0.934	0.985
Clothing	1.665	3.617	3.755	4.394	2.130	3.699	4.240
Leather	0.156	0.659	0.631	0.660	0.965	0.924	0.899
Wood	0.145	0.542	0.550	0.529	0.483	0.526	0.502
Paper	0.162	0.383	0.384	0.449	0.431	0.406	0.458
Publishing–printing	0.583	11.262	10.900	11.400	6.203	10.666	10.946
Oil refining	0.422	4.106	3.985	4.203	1.404	3.974	3.897
Chemicals	0.384	1.145	1.104	1.259	0.933	1.101	1.230
Rubber–plastic products	1.932	2.758	2.765	2.922	2.619	2.671	2.892
Non-metallic mineral products	0.255	0.534	0.523	0.551	0.548	0.545	0.564
Basic metals	0.449	1.020	0.998	1.110	0.932	1.031	1.107
Metal products	0.000	0.000	0.000	0.000	0.021	0.021	0.022
Machinery, equipment	30.067	24.718	21.913	20.563	27.038	24.139	24.138
Office machinery, computers	28.352	21.792	20.476	21.289	25.825	24.553	23.536
Electrical machinery	0.080	0.186	0.184	0.182	0.266	0.288	0.273
Radio, television and communication equipment	0.000	0.000	0.000	0.000	0.819	0.823	0.836
Precision instruments	2.297	2.807	2.672	3.003	3.330	3.456	3.325

Table 5 (*continued*)

Sectors	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Vehicles	32.196	21.864	21.139	21.586	24.918	26.028	23.271
Other transport equipment	0.153	0.448	0.442	0.436	0.472	0.526	0.480
Furniture and other products	0.000	0.000	0.000	0.001	0.082	0.088	0.088
Recycling	0.283	0.495	0.483	0.500	3.336	3.107	3.099

Table 6
Biased corrected efficiency scores.

Sectors	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Food-beverages	0.001	0.001	0.001	0.001	0.069	0.067	0.067
Tobacco products	0.130	0.157	0.157	0.157	0.127	0.157	0.157
Textile	0.280	0.174	0.174	0.174	0.163	0.174	0.174
Clothing	0.271	0.380	0.380	0.380	0.271	0.380	0.380
Leather	0.114	0.133	0.133	0.133	0.167	0.167	0.167
Wood	0.110	0.134	0.134	0.134	0.131	0.134	0.134
Paper	0.156	0.281	0.278	0.110	0.115	0.250	0.115
Publishing–printing	0.359	0.571	0.571	0.571	0.438	0.571	0.571
Oil refining	0.292	0.356	0.356	0.356	0.210	0.356	0.356
Chemicals	0.272	0.186	0.186	0.186	0.164	0.186	0.186
Rubber–plastic products	0.275	0.290	0.290	0.290	0.275	0.290	0.290
Non-metallic mineral products	0.246	0.417	0.126	0.321	0.129	0.324	0.129
Basic metals	0.296	0.178	0.178	0.178	0.161	0.178	0.178
Metal products	0.000	0.001	0.001	0.000	0.068	0.067	0.068
Machinery, equipment	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Office machinery, computers	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Electrical machinery	0.080	0.153	0.154	0.154	0.179	0.179	0.180
Radio, television and communication equipment	0.001	0.001	0.001	0.001	0.166	0.166	0.166
Precision instruments	0.273	0.286	0.286	0.286	0.313	0.313	0.313
Vehicles	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Other transport equipment	0.113	0.143	0.143	0.143	0.143	0.143	0.143
Furniture and other products	0.008	0.010	0.010	0.008	0.129	0.127	0.129
Recycling	0.109	0.159	0.159	0.159	0.381	0.381	0.381
Average	0.278	0.305	0.292	0.293	0.295	0.331	0.317
Std	0.306	0.309	0.311	0.311	0.294	0.290	0.295
Min	0.000	0.001	0.001	0.000	0.068	0.067	0.067
Max	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Table 7
Mann–Whitney tests of efficiency scores.

Models	m2	m3	m4	m5	m6	m7
Efficiency scores						
m1	469.5	469.5	466.5	449**	438**	438**
m2		540.5	537.5	527	509.5	509.5
m3			537.5	527	509.5	509.5
m4				527	509.5	509.5
m5					519	519
m6						540.5
Biased corrected efficiency scores						
m1	506	518.5	519.5	512.5	480.5	493.5
m2		556.5	554	552	509.5	530
m3			540	536	492.5	514
m4				536	494.5	515
m5					494	517.5
m6						560

** Significance at 5% level.

In general, when looking at the results in Table 3 we observe that we get different performances according to the financial data/ratios used. The results indicate the problem described from different studies (Halkos & Salamouris, 2004; McLeay & Fieldsend, 1987) which is focused on the fact that financial ratios/data provide multiple view of performance measurement and are being affected by the different sectors and size of firms. Therefore, for the decision maker is a priority the usage of these important measures to a unified performance index. As has previously indicated, factor analysis (Chen & Shimerda, 1981; Ezzamel, Brodie, & Mar-Molinero, 1987) is a partial solution of the problem as the multiple criteria of performance are still remaining.

In order to overcome those problems and create a unified measure of performance this paper uses DEA methodology. In order to test the sensitivity of the efficiency scores relative to the financial data used eight different DEA models have been created. Moreover, Table 4 indicates the variables (inputs/outputs) used for these different DEA formulations. The idea behind every model is to test whether the efficiency scores are sensitive to the financial data/ratios used in our analysis. For instance model 5 uses three inputs (total assets, equity, administrative, distribution and selling expenses) and two outputs (net profit margin and return on assets) in order to 'grasp' any efficiency changes when excluding the 'return on equity' relative to the other DEA models. In addition model 6 uses three inputs and two outputs (in order to test the effect on performance measurement of 'net profit margin') and so on.

In addition Table 4 illustrates the specifications of the 7 models used in our sensitivity analysis. As can be realised due to the fact that our models are output oriented the sensitivity analysis is based on the outputs (i.e. the financial ratios).

Furthermore, Table 5 presents the results obtained from Eqs. (4), (5), and (7). The results represent the efficiency scores obtained from the VRS output oriented DEA models. As can be observed for all the models three are the sectors with the highest performance. These are: vehicles, office-machinery/computers and machinery/equipment. The sectors with the lowest performances are reported to be: Food-beverages, Metal products and Furniture/other products. As can be realised in some cases the different models'

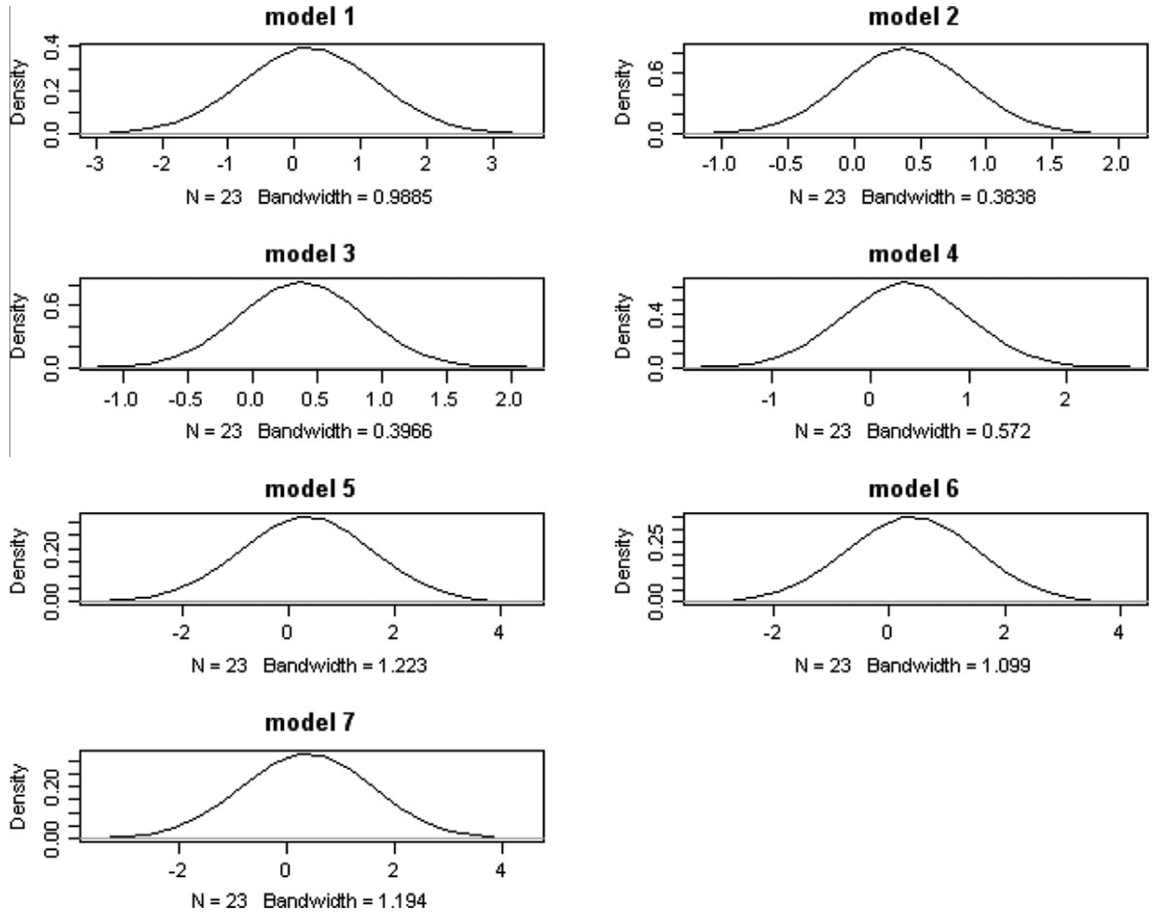

Fig. 1. Kernel density functions of VRS efficiency estimates using Gaussian Kernel and the appropriate bandwidth (using two-stage plug-in method).

specifications have major effect on the efficiencies obtained. More specifically, the sector of Radio, television and communication equipment is reported to have approximately zero efficiency score for models 1, 2, 3 and 4. However for the models 5, 6 and 7 is reported to have an efficiency level of 0.166. Similarly, for the performance of the sector of Recycling is reported to have different efficiency scores between the seven models. These fluctuations on the efficiency scores obtained can be analytically observed when looking at the estimated bias ($\widehat{Bias}$) and the sample variance of the bootstrap values ($\hat{\sigma}$).

In addition Table 6 illustrates the biased corrected efficiency scores obtained by Eq. (6). However, the biased corrected efficiency scores have been replaced the original efficiency estimates following the rule obtained from Eq. (8). As can be observed the rankings haven't changed with the sectors of vehicles, office-machinery/computers and Machinery/equipment reported as efficient. However, the fluctuations of efficiency scores have been minimised (see Table 7).

In order to observe the improvement of the efficiency scores following Daraio and Simar (2007) and Simar and Wilson (2008) we used kernel density estimates of the efficiency scores obtained that rely on the reflection method. In such a way we are able to avoid problems of bias and inconsistency at the boundary of support. The results of Fig. 1[5] illustrate the problems highlighted from several authors when using financial ratios in DEA formulation such as: biased results, overestimated/underestimated efficiency scores, (Daraio & Simar, 2007; Gonzalez-Bravo, 2007; Jenkins & Anderson, 2003; Simar & Wilson, 1998; Smith, 1997; Zhang & Bartels, 1998). More analytically, the density functions reveal the heterogeneities model 1, 2, and 4. These results indicate that biased efficiency scores are obtained from the inclusion/exclusion of net profit margin and return on equity as outputs in our models. In addition, Fig. 2 represents the results obtained after the biased correction obtained from Eqs. (6) and (8). The kernel density functions indicate that the efficiency scores among the seven models are similar with minor changes and fewer fluctuations.

In order to test more thoroughly the efficiency scores before and after the biased correction between the seven models we use the Mann–Whitney non-parametric test. Due to the fact that DEA is a non-parametric technique this paper uses the Mann–Whitney test similar to Grosskopf and Valdmanis (1987) and Brockett and Golany (1996) in order to observe if there are any differences on the efficiency scores between the models before and after the biased correction and thus to determine whether or not the biased correction helped us to improve our results obtained. The results obtained from the Mann–Whitney tests among the seven models support the findings of the two figures illustrated previously. In the first case the results reveal that model 1 produces different results compared to other models indicating the existence of bias among the models used. In contrast the results obtained after the correction of bias reveal that the models between them have not got major differences (in terms of their median efficiency equalities). As such it appears that after applying bootstrap techniques (Simar & Wilson, 1998, 2000) along side with sensitivity analysis (Valdmanis, 1992) and DEA/output–input ratio analysis assessing

[5] The bandwidths for Figs. 1 and 2 rely on the reflection method in order to avoid problems of bias and inconsistency at the boundary of support. In addition for the kernel density functions the Gaussian Kernel has been used (Scott, 1992; Sheather & Jones, 1991).

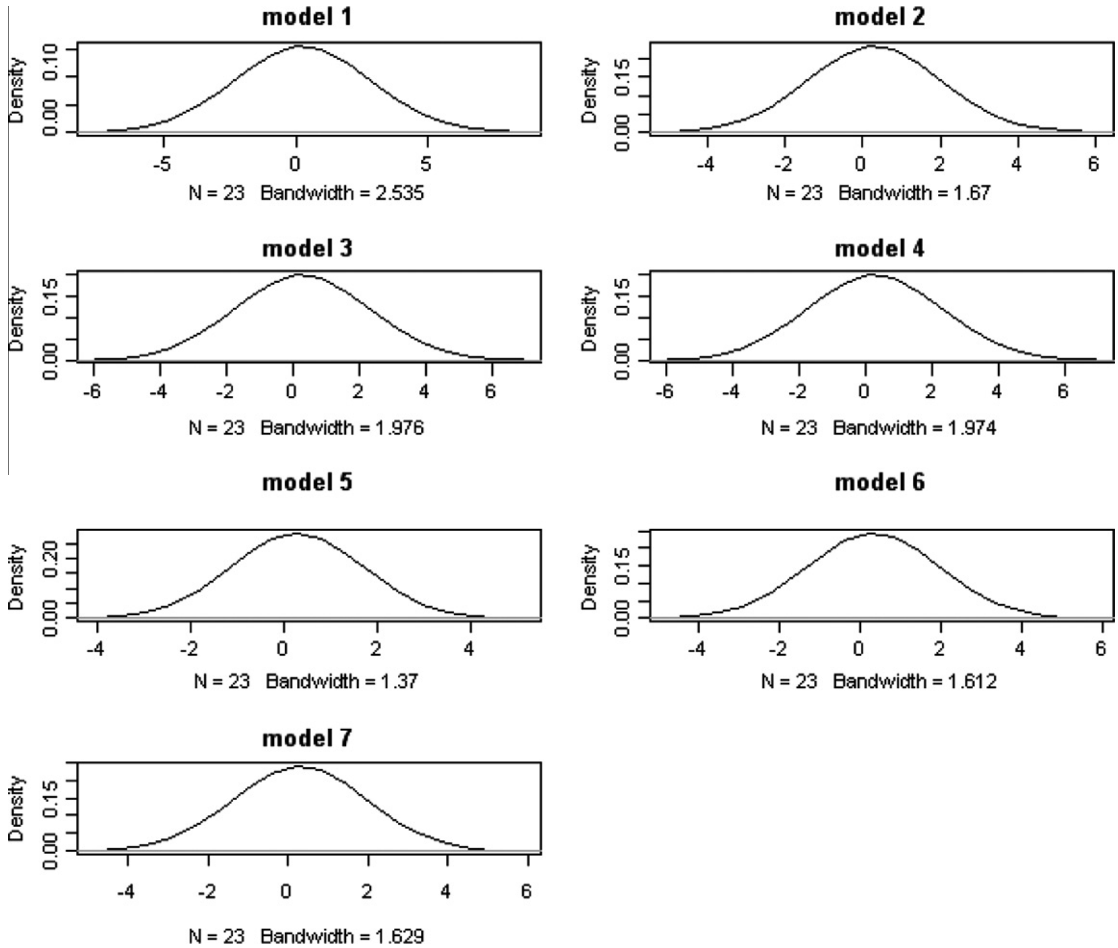

Fig. 2. Kernel density functions of biased corrected VRS efficiency estimates using Gaussian Kernel and the appropriate bandwidth (using two-stage plug-in method).

the efficiency and the rank of the examined units (Fernandez-Castro & Smith, 1994; Smith, 1990; Thanassoulis et al. 1996; Zhu, 2000) the results appear to be less sensitive to inclusion/exclusion of financial ratios providing more reliable estimations.

5. Conclusions and methodological discussion

In the analysis of performance measurement there is a practical limitation to the number of ratios which can be included. Increasing the number of ratios for predictive purposes introduces redundancies in the analysis and makes the interpretation of the results increasingly difficult. In normative studies it is always desired to limit the choice of dimensional measures, particularly if the results are aimed at setting targets or policies for the company. This is a further shortcoming of the univariate ratio approach, since it requires the specification of a small set of financial indicators and provides no means of resolving possible conflicting signals emerging from competing ratios (Fernandez-Castro & Smith, 1994). This approach also ignores the interdependencies between ratios (Lev, 1974).

In addition with the use of multivariate ratio analysis for predictive purposes, it is not only essential to select the ratios which are deemed to be the most indicative of future events, but one must combine them into a single indicator which represents the probability of occurrence of the event. In order to achieve this accurately, the relative importance of each ratio to the prediction must be examined. Regression based techniques can be used to come up with a predictive score, but the statistical assumptions underlying parametric analysis are often violated during the analysis.

The most common assumption, the one that is required for discriminant analysis, is that of multivariate normality. Several studies support the fact that many financial ratios are not normally distributed (Bird & McHugh, 1977; Bougen & Drury, 1980; Deakin, 1972; Ezzamel et al., 1987; Mecimore, 1987), but in fact often have a skewed distribution. Many of the ratios cannot be normally distributed from the fact alone that they are bounded on one side. Taffler (1983) argues that there is a definite advantage in exploring techniques like DEA, which do not rely on such restrictive assumptions.

However, when combining financial ratios in DEA models it is more likely to have problems of biased results and overestimated/underestimated efficiency scores (Daraio & Simar, 2007; Gonzalez-Bravo, 2007; Jenkins & Anderson, 2003; Simar & Wilson, 1998; Smith, 1990, 1997; Thanassoulis et al., 1996; Zhang & Bartels, 1998; Zhu, 2000). This paper provides empirical evidences which demonstrate with the application of bootstrap techniques those traditional biased related problems can be avoided. The empirical application reveals that the efficiency results obtained after applying the techniques have been significantly improved. However, the specification of the models used is still an on going methodological and computational issue in terms of the exclusion/inclusion of variables used.

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