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Abstract

This paper analyses how European football clubs' current value and debt levels influence their performance. The Simar and Wilson (J Econometrics, 136: 31–64, 2007) procedure is used to bootstrap the data envelopment analysis DEA scores in order to establish the influence of football clubs' current value and debt levels on their obtained efficiency performances. The results reveal that football clubs' current value levels have a negative influence on their performances, indicating that football clubs' high value doesn't ensure higher performance. At the same time, the empirical evidence suggests that there is no influence associated of football clubs' debt to their efficiency levels.

Keywords: European football clubs; Data Envelopment Analysis; Truncated regression; Bootstrapping.

JEL classification: C14**,** C69**,** L83

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I. INTRODUCTION

Several studies have applied efficiency analysis on sport teams' performances[1]. However the economic framework of professional sporting activity it is based on the works of Rottenberg (1956), Neale (1964), Jones (1969) and Sloane (1969, 1971, 1976). In addition the first empirical evidence in a average production function framework was found in the work of Scully (1974) who investigated the performance of baseball players. By using the percentage of matches won in order to model teams' output and management, capital and team spirit as inputs Scully's empirical work was the first to apply a production function in order to provide empirical evidence. However, the sporting production process has been modeled by several others in a similar way (among others Zech, 1981; Atkinson et al., 1988; Schofield, 1988).

The application of frontier production function in order to measure teams' performance has been dated back on the works of Zak et al. (1979), Porter and Scully (1982) and Fizel and D'Itri (1996, 1997). In addition over the last two decades several scholars have been applying parametric and nonparametric frontier analysis in order to establish football teams' performance and their determinants. Dawson et al. (2000), applying stochastic frontier approach (SFA), measure managers' efficiency for a panel of managers in English soccer's Premier league using as output the percentage of matches won and as inputs several player quality variables, for the time period of 1992 to 1998.

Haas (2003a) applied a data envelopment analysis (DEA) measuring team efficiency of the USA Major League Soccer (MLS). In a DEA setting and for the year 2000, Haas used head coaches' and players' wages as inputs; and revenues, points

[1] For a literature review on the subject matter see Barros and Garcia-del-Barrio (2008).

awarded and number of spectators as outputs. In addition Haas (2003b) in a similar DEA setting has performed an efficiency analysis for twenty English Premier League clubs for the year 2000-2001. Barros and Leach (2006a, 2006b, 2007) applying a stochastic Cobb-Douglas production frontier and DEA measured the performance of football clubs in the English F.A. Premier League for the time periods 1989-1990 to 2002-2003. They applied a combination of sport and financial data in order to measure football clubs' efficiency levels. Frick and Simmons (2008) by applying SFA on data for German premier soccer league (Bundesliga) showed that managerial compensation impact positively on team success.

Similar to our study, Barros et al. (2010) by applying Simar and Wilson's (2007) DEA bootstrap procedure analyzed the performance of the Brazilian first league football clubs. More recently Barros and Garcia-del-Barrio (2011) measured the efficiency of the Spanish football clubs for the seasons 1996–1997 and 2003–2004 by applying the two-stage procedure (Simar and Wilson 2007). In their DEA setting they have used operating cost, total assets and team payroll as inputs, whereas, attendance and other receipts as outputs. In the second stage of their analysis they regressed the obtained team efficiency levels on several factors using truncated regression and tobit model (for comparison reasons) in order to explain Spanish clubs' efficiency variations.

Our study, similarly to the ones already presented, by applying a two-stage DEA bootstrap procedure investigates how clubs' value and debt levels influence their performances. In contrast to the main research stream, instead of using data of a specific national football league, our study uses a sample of the top 25 richest European football clubs and proposes for the first time a composite index for measuring output.

II. DATA AND METHODOLOGY

II.1 Description of variables

In our analysis we use a sample of the top European football clubs[2] based on their current values. All the data are extracted from Forbes database (2011) and concern data recorded for the year 2009. In our DEA formulation we use one input and one composite output. The input used is football clubs' revenues (measured in millions $) and one composite output which measures football clubs European and domestic trophies. The composite output contains the sum of the number of European champions cups (weighted by 5), UEFA cups/ Euroleague cups (weighted by 4), European cup winners cups (weighted by 3), Intercontinental cups (weighted by 3) and FIFA Club World cups (weighted by 3).

In addition the composite output contains also the sum of the number of domestic championships (weighted by 2) and domestic cups (weighted by 1). Both the number of the weighted domestic champions and domestic cups (includes all domestic cups, i.e. supercups, league cups, national cups... etc) are again weighted by FIFA world ranking score (FIFA, 2010). This extra weight has been added in order to reflect the different difficulty levels of obtaining a domestic cup and/ or championship among the different European leagues[3]. We also assume that club revenues are used from the clubs in order to buy the best (in term of football quality) possible managers

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[2] Nine football clubs are from the English Premier League, six from German league, four from Italian league, two from Spanish league, two from French league and two from Scottish league.The 25 European football club in a descending order based on their current value are: *Manchester United FC, Real Madrid FC, Arsenal FC, Bayern Munich FC, Liverpool FC, AC Milan FC, Barcelona FC, Chelsea FC, Juventus FC, Schalke 04 FC, Tottenham Hotspur FC, Olympique Lyonnais FC, AS Roma FC, Internazionale Milan FC, Hamburg SV FC, Borussia Dortmund FC, Manchester City FC, Werder Bremen FC, Newcastle United FC, VfB Stuttgart FC, Aston Villa FC, Olympique Marseille FC Celtic FC, Everton FC* and *Glasgow Rangers FC.*

[3] We assume that it is not of the same difficulty to obtain a domestic championship or cup between the English, the Scottish, the Spanish, the German and the Italian football league. All the weights used in order to for the composite output to be constructed are subjective and can be subject to criticism.

and players which can lead to team success (based on world, European and domestic championships and cups).

Similarly, a recent study for the English Premier League suggests that revenues are related to clubs' success (Carmichael *et al.*, 2010). Then by applying a second-stage analysis we examine in what way European football clubs' current value and debt levels (measured in millions of $) affect their obtained efficiency levels. Table 1 presents the descriptive statistics of the variables used in our study. As can be realized table 1 reports several variations of the variables used indicated by the high standard deviation values. Finally, in our DEA setting we assume an output orientation suggesting by how much football clubs can increase their outputs while keeping the level of inputs fixed.

Table 1: Descriptive statistics of the variables used

	External Variables		**Input**
	Current Value($mil)	*Debt($mil)*	*Revenue ($mil)*
Mean	597.080	218.238	274.720
Std	443.374	338.197	128.008
Min	194.000	0.002	128.000
Max	1870.000	1284.000	576.000
		Output components	
	Intercontinental Cup	*FIFA Club World Cup*	*Domestic Championships*
Mean	0.56	0.08	13.80
Std	1.00	0.28	12.70
Min	0.00	0.00	2.00
Max	3.00	1.00	51.00
		Output components	
	European Champions Cups	*Uefa Cups/Euroleague Cups*	*European Cup Winners Cup*
Mean	1.600	0.840	0.800
Std	2.432	1.143	0.913
Min	0.000	0.000	0.000
Max	9.000	3.000	4.000
		Output components	
	Domestic Cups	*FiFA country Ranking*	*Composite Output*
Mean	13.48	7.04	27.29
Std	13.04	8.88	33.82
Min	2.00	1.00	1.46
Max	57.00	35.00	142.00

II.2 Efficiency measurement

Based on the work by Koopmans (1951) and Debreu (1951) the production set Ψ constraints the production process and is the set of physically attainable points (x, y) :

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

where $x \in \Re_{+}^{N}$ is the input vector and $y \in \Re_{+}^{M}$ is the output vector.

Then the output oriented efficiency boundary $\partial Y(x)$ is defined for a given $x \in \Re_{+}^{N}$ as:

$$\partial Y(x) = \left\{ y \middle| y \in Y(x), \lambda y \notin Y(x), \forall \lambda > 1 \right\}, \quad (2)$$

and the Debreu-Farrell output measure of efficiency for a production unit can be defined as:

$$\lambda(x, y) = \sup \left\{ \lambda \middle| (x, \lambda y) \in \Psi \right\} \quad (3).$$

In equation (3) by construction $\lambda(x, y) \geq 1$ and technical efficiency is achieved when $\lambda(x, y) = 1$. As suggested by several authors (Førsund and Sarafoglou, 2002; 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, 1971) 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)[4].

Following Zelenyuk and Zheka (2006, p.149) we apply the assumption of CRS due to the fact that it enables to obtain greater discriminative power, which in turn would result in larger variation of the regressand. In addition, since we examine the 25 European football clubs with the highest values, we are not expecting great differences among their sizes. This formulation can be expressed as:

$$\hat{\Psi}_{CRS} = \left\{ (x, y) \in \Re^{N+M} \,\middle|\, y \le \sum_{i=1}^{n} \gamma_i y_i ; x \ge \sum_{i=1}^{n} \gamma_i x_i \text{ for } (\gamma_1, ..., \gamma_n) \right. \\ \left. \text{such that } \gamma_i \ge 0, i = 1, ..., n \right\} \tag{4}$$

which then can be computed by solving the following linear program:

$$\hat{\lambda}_{CRS} = \sup \left\{ \lambda \,\middle|\, \lambda y \le \sum_{i=1}^{n} \gamma_i y_i ; x \ge \sum_{i=1}^{n} \gamma_i x_i \text{ for } (\gamma_1, ..., \gamma_n) \right. \\ \left. \text{such that } \gamma_i \ge 0, i = 1, ..., n \right\} \tag{5}$$

II.3 A bootstrap approach for bias correction of the efficiency estimator

Simar and Wilson (1998, 2000, 2008) suggest that DEA estimators were shown to be biased by construction. They introduced an approach based on bootstrap techniques (Efron, 1979) to correct and estimate the bias of the DEA efficiency indicators[5]. The bootstrap bias estimate for the original DEA estimator $\hat{\lambda}_{CRS}(x, y)$ can be calculated as:

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[4] Later Banker *et al.* (1984) used convex hull of $\hat{\Psi}_{FDH}$ (Derpins *et al.*, 1984) to estimate Ψ and thus to allow for variable returns to scale (VRS) adding the constraint $\sum_{i=1}^{n} \gamma_i = 1$ in equations (4) and (5).

[5] The essence of bootstrapping efficiency scores has been highlighted by several authors. For further applications of the bootstrap technique on DEA efficiency scores see also Simar and Wilson (2002), Zelenyuk and Zheka (2006), Simar and Zelenyuk (2007) and Halkos and Tzeremes (2010).

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

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

$$\begin{aligned}\hat{\hat{\lambda}}_{CRS}(x,y) &= \hat{\lambda}_{CRS}(x,y) - \hat{BIAS}_B\left(\hat{\lambda}_{CRS}(x,y)\right) \\ &= 2\hat{\lambda}_{CRS}(x,y) - B^{-1}\sum_{b=1}^{B}\hat{\lambda}^*_{CRS,b}(x,y)\end{aligned} \quad (7).$$

II.4 A two-stage analysis using a double bootstrap procedure

Following Simar and Wilson (2007) in order to account for environmental variables (z_i) on efficiency scores (λ_i) a double bootstrap procedure must be used in a second stage regression analysis in order to produce valid estimates. Let us consider the following model:

$$\hat{\lambda}_i = z_i\beta + \varepsilon_i \quad (8),$$

where β is a vector of parameters an ε_i is the statistical noise. According to Simar and Wilson (2007) when using a conventional method of analysis like the Ordinarily Least Squares (OLS) method two are the main problems that lead to invalid estimates. Firstly, when using small samples the basic assumption that z_i is independent from ε_i is violated due to the high correlation of inputs/outputs used and the explanatory variables. Secondly, the DEA efficiency scores are expected to be correlated due to the fact that the efficiency levels of one football club is a product of the data of the other clubs of the same data set. Therefore Simar and Wilson (2007, p.42-43) proposed a double bootstrap procedure (Algorithm #2) in order to avoid the dependency problems and produce valid estimates of the second-stage regression analysis. Synoptically the algorithm contains the following seven steps:

1. Using the original data, we compute $\hat{\lambda}_i = \hat{\lambda}(x_i, y_i), i = 1,...,n,$ by applying equation (5).

2. Then the maximum likelihood estimates $\hat{\beta}$ and $\hat{\sigma}_\varepsilon$ from the left normal truncated regression of $\hat{\lambda}_i$ on z_i (by using only $\hat{\lambda}_i > 1$) are applied.

3. For each football club $i = 1,...n,$ we repeat the next four steps (a-d) L_1 times in order to obtain $\left\{\hat{\lambda}^*_{ib}\right\}_{b=1}^{L_1}, i = 1,...,n:$

   a. For $i = 1,...n,$ we draw ε_i^* from $N\left(0, \hat{\sigma}_\varepsilon\right)$ with left truncation at $\left(1 - \hat{\beta}' z_i\right)$.

   b. Then we compute $\lambda_i^* = \hat{\beta}' z_i + \varepsilon_i^*, i = 1,...,n.$

   c. We set $x_i^* = x_i, y_i^* = y_i \hat{\lambda}_i / \lambda_i^*$ for all $i = 1,...,n.$

   d. Then we compute $\hat{\lambda}^*_i = \lambda\left(x_i, y_i \middle| \hat{\Psi}^*\right), i = 1,...,n,$ where $\hat{\Psi}^*$ is obtained by replacing (x_i, y_i) by $\left(x_i^*, y_i^*\right)$.

4. We compute the bias corrected estimator $\hat{\hat{\lambda}}_i$ using the bootstrap estimates in step 3 and the original estimate $\hat{\lambda}_i$.

5. Then we estimate by maximum likelihood the truncated regression of $\hat{\hat{\lambda}}_i$ on z_i in order to get the $\left(\hat{\hat{\beta}}, \hat{\hat{\sigma}}\right)$.

6. For each football club $i = 1, \ldots n,$ we repeat the next three steps (a-c) L_2 times in order to obtain $\left\{\left(\hat{\beta}^*, \hat{\sigma}_\varepsilon^*\right)_b\right\}_{b=1}^{L_2}$:

   a. For $i = 1, \ldots n,$ we draw ε_i^{**} from $N\left(0, \hat{\hat{\sigma}}\right)$ with left truncation at $\left(1 - \hat{\hat{\beta}}' z_i\right)$.

   b. Then we compute $\lambda_i^{**} = \hat{\hat{\beta}}' z_i + \varepsilon_i^{**}, i = 1, \ldots, n.$

   c. Then we estimate by maximum likelihood the truncated regression of λ_i^{**} on z_i in order to get the $\left(\hat{\hat{\beta}}*, \hat{\hat{\sigma}}*\right)$.

7. Finally using the bootstrap values from step 6 and the original estimates of $\hat{\hat{\beta}}, \hat{\hat{\sigma}}$ we construct confidence intervals for β.

III. EMPIRICAL RESULTS AND CONCLUSIONS

Table 2 presents the results obtained from the efficiency analysis assuming the CRS assumption. Looking at the descriptive statistics we realize that there is a consistency with previous research on European football leagues (Barros and Leach 2006a, 2006b, 2007; Barros et al. 2010; Barros and Garcia-del-Barrio 2011) indicated with significant differences of the original (DEA) and the biased corrected (BC) efficiency scores obtained. The standard deviation values are 0.34 for the original estimates (DEA) and 0.35 for the biased corrected (BC). The results indicate two football clubs (*Glasgow Rangers FC* and *Real Madrid FC*) that are reported to be efficient (i.e. with efficiency score equal to 1) under the original efficiency estimates.

In addition when looking at the biased corrected results the five European clubs with the highest efficiency scores are reported to be: *Glasgow Rangers FC*, *Juventus FC*, *AC Milan FC*, *Celtic FC* and *Aston Villa FC*. Whereas the five European clubs with the lowest efficiency levels are reported to be *Manchester United FC*, *Arsenal FC*, *AS Roma FC*, *Olympique Lyonnais FC* and *Chelsea FC*. In addition the largest bound differences of the biased corrected efficiency scores are reported for *Real Madrid FC*, *Barcelona FC*, *Olympique Lyonnais FC*, *Bayern Munich FC* and for *Manchester United FC*.

Table 2: Efficiency scores under the CRS assumption

a/a	Football Clubs	DEA	BC	BIAS	STD	LB	UB	Bound difference
1	*Manchester United FC*	1.681	1.773	-0.091	0.005	1.950	1.688	0.262
2	*Real Madrid FC*	1.000	1.209	-0.209	0.016	1.466	1.013	0.454
3	*Arsenal FC*	1.752	1.814	-0.062	0.002	1.923	1.760	0.163
4	*Bayern Munich FC*	1.350	1.449	-0.099	0.005	1.621	1.358	0.263
5	*Liverpool FC*	1.141	1.198	-0.057	0.002	1.315	1.145	0.171
6	*AC Milan FC*	1.051	1.112	-0.061	0.002	1.227	1.055	0.171
7	*Barcelona FC*	1.051	1.186	-0.135	0.010	1.415	1.056	0.359
8	*Chelsea FC*	2.380	2.457	-0.077	0.003	2.586	2.388	0.198
9	*Juventus FC*	1.053	1.096	-0.044	0.001	1.185	1.057	0.129
10	*Schalke 04 FC*	1.511	1.560	-0.049	0.001	1.644	1.516	0.128
11	*Tottenham Hotspur FC*	1.342	1.384	-0.042	0.001	1.455	1.347	0.108
12	*Olympique Lyonnais FC*	1.914	2.040	-0.126	0.007	2.212	1.919	0.293
13	*AS Roma FC*	1.902	1.971	-0.069	0.002	2.093	1.909	0.184
14	*Internazionale Milan FC*	1.097	1.142	-0.045	0.001	1.234	1.101	0.133
15	*Hamburg SV FC*	1.269	1.309	-0.040	0.001	1.379	1.273	0.106
16	*Borussia Dortmund FC*	1.130	1.166	-0.036	0.001	1.226	1.134	0.092
17	*Manchester City FC*	1.281	1.374	-0.092	0.003	1.483	1.289	0.195
18	*Werder Bremen FC*	1.279	1.331	-0.052	0.002	1.422	1.282	0.140
19	*Newcastle United FC*	1.429	1.486	-0.058	0.002	1.588	1.432	0.156
20	*VfB Stuttgart FC*	1.375	1.471	-0.096	0.003	1.591	1.381	0.210
21	*Aston Villa FC*	1.092	1.137	-0.046	0.001	1.216	1.095	0.121
22	*Olympique Marseille FC*	1.461	1.523	-0.063	0.002	1.629	1.465	0.164
23	*Celtic FC*	1.079	1.133	-0.054	0.001	1.214	1.085	0.130
24	*Everton FC*	1.115	1.168	-0.052	0.001	1.251	1.120	0.131
25	*Glasgow Rangers FC*	1.000	1.075	-0.075	0.002	1.158	1.011	0.147

Mean	1.349	1.423	-0.073	0.003	1.539	1.355	0.184
Std	0.346	0.350	0.039	0.003	0.364	0.347	0.085
Min	1.000	1.075	-0.209	0.001	1.158	1.011	0.092
Max	2.380	2.457	-0.036	0.016	2.586	2.388	0.454

Furthermore, as explained earlier we apply the approach of Simar and Wilson (2007) in an estimated specification for the regression taken the form of:

$$\lambda_i = \beta_0 + \beta_1 \cdot \text{Current Value}_i + \beta_2 \cdot \text{Debt} + \varepsilon_i \qquad (9)$$

where λ represents the DEA model efficiency scores presented in table 2. In addition "Current Value" refers to the football clubs' current value levels measured in millions of dollars, whereas "Dept" refers to football clubs' debt levels measured also in millions of dollars. Following Simar and Wilson (2007) we employed a bootstrap algorithm of 2000 replications in order to construct 95% confidence intervals. The results of the truncated bootstrapped second-stage regression are presented in table 3. It can been seen that the constant term and the football clubs' "Current Value" levels are statistically significant, while football clubs' "Debt" levels does not seem to explain their efficiency variations. In addition we can observe a negative sign on the "Current Value" coefficient indicating that the higher football clubs value doesn't necessary results on higher efficiency levels.

Table 3: Truncated bootstrapped second-stage regression results

Bias-adjusted coefficients (2000 bootstrap replications)				
Variables	**Coefficient**	**Std. Err.**	**95% Bootstrap confidence interval**	
			Lower	*Upper*
Constant	1.62892*	0.08723	1.45795	1.79989
Current Value	-0.00052**	0.00020	-0.00091	-0.00012
Debt	-0.00031	0.00029	-0.00088	0.00026
Variance	0.19362*	0.03670	1.45795	1.79989

Statistically significant at *: 1% , **: 5%

Finally, in terms of policy implications it appears that when comparing the top European football clubs, their determinants of higher efficiency (in terms of the number of domestic and European club trophies) are not based on their higher revenue and value levels. The deterministic nature of DEA methodology proved to be a vital tool for showing that money alone does not ensure football clubs' success. Other factors like managerial efficiency (Fizel and D'Itri 1996, 1997; Dawson et al. 2000) and team spirit (Scully 1974) may be more important when comparing the top European football clubs with the highest value. In addition referring back to our primary DEA formulation it appears that the characteristics of the football clubs' presidents are also crucial determinants of the clubs' success. Most of the times the president of a club is the primary decision maker who is responsible for the allocation of resources (i.e. revenues) and responsible for the "right" investments (i.e. on the "right" players and managers) which in turn can result on football clubs' success.

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