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Research article

Social Media and Sports Management: a Data Envelopment Analysis of the English Premier League

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Abstract:

Purpose: The aim of this paper is to contribute to communication, sports, and operational research literature proposing the incorporation of social media indicators into data envelopment analysis (DEA) methodology by analyzing which teams are more efficient in English football from three perspectives of sports, financial, and social media management. To achieve this, an input-oriented DEA model will be employed. The motivation and scope of this paper respond to the fact that social media management is becoming an essential aspect to incorporate into sports management.

Methodology: For that end, Data Envelopment Analysis (DEA) has been extensively employed to assess sports productivity. In this particular case, selected inputs are total assets, wages & salaries, and number of Facebook posts. As outputs, season points, number of Facebook followers, and profits before taxes are considered.

Findings/Contribution: This paper makes a theoretical contribution by proposing a new model to assess efficiency of sport institutions. It proposes a new array of inputs and outputs that combines sports, financial, and social media indicators in both sides. Furthermore, it has found a direct relationship between table position, efficiency, profits before taxes and social media use. Teams capable of better integrating these 3.0 technologies in their marketing plans obtained the largest efficiency gains.

Keywords: Social Media; Sports Efficiency; Football; Soccer; Data Envelopment Analysis.

1. Introduction

Sports organizations need to interact with their fans in a mutually beneficial way (Bühler, Chadwick, & Nufer, 2009). Accordingly, sports managers must understand fan motivations and how these are uniquely identified within the context (Beverland, Farrelly, & Quester, 2010). Promoting

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audience engagement throughout media platforms has proven to be an essential strategy for that end (Chan-Olmsted & Wolter, 2018), given that many people even watch sports while using a second screen (Weimann-Saks, Ariel, & Elishar-Malka, 2020). In addition, sports fans tend to identify themselves more with successful institutions (Fan, Billings, & Zhu, 2020).

Efficiency in the internal management of institutions is determined by the costs and benefits of their activities (Farrell, 1957). In order to reach efficiency, institutions need to find the optimal combination of costs and benefits that meets any of the following requirements: a) generates the highest benefit from the combinations that have the same cost; b) incurs in fewer costs for activities producing identical benefits; and c) presents the best proportional relationship between incurred costs and gained benefits.

As social media use has developed, sport companies have adapted their practices to communicate with consumers, as other media organizations have been doing extensively in the last decade (Martín, Fernández, & Segado, 2019). That have led to a distinctive role for social media, different from that of conventional media. Among other features, social media embrace interactivity; integrates communication and distribution channels; and enable greater speed in the delivery of information and feedback (Shilbury et al., 2014). Moreover, social media has got direct and indirect effects on brand equity, though active audience response generates more marketing value than passive interaction (Shay & Van Der Horst, 2019). Particularly in sports, fan's needs for brand love, empowerment, and information drive their consumption, contribution and content creation on social media (Vale & Fernandes, 2018).

During the last few decades, professional football (known as soccer in the USA) has become a major sport business in Europe (Andreff & Staudohar, 2000; Dima, 2015; Jones et al., 2008). The English Premier League (EPL) is the leading European football competition in terms of generated income (Deloitte Sports Business Group, 2014, 2015; Jones, Rawnsley, & Switzer, 2013). Its economic structure is a strong reason to select this league over others. A portion of income distribution among clubs is based on table ranks and also the number of matches shown on television. That is a reason why more equality is given at the EPL in comparison with for instance the Spanish league, where stronger teams have their income more secure regardless of their results.

The aim of this paper is to contribute to communication, sports, and operational research literature proposing the incorporation of social media indicators into data envelopment analysis (DEA) methodology by analyzing which teams are more efficient in English football from three perspectives: sports, financial, and social media management. To achieve this, an input-oriented DEA model will be employed. The motivation and scope of this paper respond to the fact that social media management is becoming an essential aspect to incorporate into sports management.

The rest of the paper is organized as follows. Next subheadings offer a brief literature review. Section 3 describes the materials and methods used in this study. Section 4 presents the results for overall performance as well as variables' correlations. Finally, Section 5 gives results' discussion and conclusion.

2. Literature Review

2.1. Efficiency of Sports Institutions

According to the resource-based theory (Barney, 1991; Barney, 2001; Rumelt, 1991; Wernerfelt, 1984; Taymaz, 2005), heterogeneity of resources and capabilities on which organizations base their management are the origin of their different efficiency levels. In the literature, many pieces of research can be found that assess efficiency of sports industry (Barros & Santos, 2007; Collier, Johnson, & Ruggiero, 2010; Dawson, Dobson, & Gerrard, 2000; Debnath & Malhotra, 2015; Glass, Kenjegalieva, & Taylor, 2015; Hausch, & Ziemba, 1995; Meza, Valério, & Mello, 2015; Moreno, & Lozano, 2014; Reddy, Stam, & Agrell, 2015). Empirical studies have investigated the efficiency of production management in several kind of organizations (Liu et al., 2013). Within sports institutions, research has assessed different issues, such as the efficiency of players (Hofler & Payne, 1997; Hadley et al., 2000; Espitia-Escuer & García-Cebrián, 2004; Torgler & Schmidt, 2007), trainers (Dawson et al. 2000a) or financial performance (Barros & García del Barrio, 2008b).

2.2. Social Media and Sports Management

Nowadays, social media have transformed the way in which people live and conduct business (Qualman, 2012). In sports, organizations and brands invest a significant amount of time and resources in engaging with their virtual audience (Filo, Lock, & Karg, 2014; Parganas et al., 2017; Scelles et al., 2017). In a dynamic and changing environment, understanding the influence of social networks on organizations competitiveness is vital (Garrigos-Simon, Alcamí, & Ribera, 2012). Social media versus traditional media provides new information approaches and opportunities for organizational management and decision making, providing new features that are able to describe the functioning and position of a team in the market.

A specific review of sports and social media research (Filo et al., 2015) has revealed that this new information and communication technology has caused a profound impact on sports’ delivery and consumption. The main logic in using these tools is service-dominant. Social networks contribute to strengthen relationships among and between sports brands and individuals. To do so, interaction and engagement are the most important functions played by social media regarding the management of sports institutions. Apart from general considerations, not all social media serve the same ends regarding sports fan engagement. In the USA, for instance, Facebook obtains better results than Twitter in motivational measures; while in China, WeChat has proven better to maintain relationships and for habitual use, while Weibo is more convenient for arousal (Billings, Broussard, & Xu, 2019).

2.3. DEA applications in English Premier League (EPL)

Efficiency analysis can be applied using parametric and non-parametric methodologies. Among the non-parametric methods, based on linear programming techniques, DEA is used to measure and analyze the efficiency of a given institution by comparing it with other homogeneous organizations. More specifically in football, research activities relating to DEA have grown in the last few years. Previous studies have evaluated performance in football through different approaches, as it is reviewed in the next sentences. Some papers have studied the specific efficiency of sports variables, like players or trainers (Espitia-Escuer & García-Cebrián, 2004; Torgler & Schmidt, 2007, Terrien et al. 2017). Other studies have analyzed efficiency taking into account other clubs’ characteristics, such as wages or coach salary (Barros, Garcia-del-Barrio, & Leach, 2009; Dawson et al., 2000; Fizel, & D’Itri, 1997). Some have included variables such as stadium facilities, stadium utilization rate, or home town population (Barros & Leach, 2006; Haas, 2003; Kocher, & Sutter, 2004). Additionally, several researchers have assessed the EPL efficiency (Barros and Leach, 2006; Haas, 2003) by using different measurement input and output variables in different periods.

Haas (2003a) measured the efficiency of 12 soccer clubs in 2000 by use of DEA method. This study considered as inputs: players wages, coach wages, and the stadium utilization rate. Outputs were understood as: points awarded, attendance, and total revenue. Results showed that efficiency scores are highly correlated with performance in sports competition. Later on, Haas (2003b) used DEA method to analyze the efficiency of 20 EPL clubs as observed in the 2000-2001 season. Inputs considered were: total wages, coach salary and town population; while outputs were: points achieved, attendance, and total revenue. Results showed greater variation in efficiency scores according to different model specifications and variable combinations. Finally, Barros and Leach

(2006) measured the EPL efficiency from seasons 1998-1999 to 2002-2003. This study uses sport and financial variables to conduct DEA method. Players, wages, net assets and stadium facilities are considered inputs. On the other hand, points achieved, attendance, and turnover were outputs. The study concluded that several inputs play an important role in football efficiency and that efficiency scores are mixed. As shown, there are three good examples of how DEA was applied to football efficiency.

3. Materials and Methods

3.1. Data envelopment analysis (DEA)

DEA can be defined roughly as a non-parametric method of measuring the efficiency of a Decision Making Unit (DMU) with multiple inputs and/or multiple outputs. DEA is used to measure the relative productivity of a DMU by comparing it with other homogeneous units, transforming the same group of measurable positive inputs into the same types of measurable positive outputs. Charnes, Cooper and Rhodes (1978, 1981) introduced the DEA method to address the problem of efficiency measurement for DMUs with multiple inputs and multiple outputs in the absence of market prices. DEA is appropriate for this piece of research given that it works especially well in highly competitive environments, such as sports competition, where usually 20 or more clubs participate. More DMUs implies more relevant findings than when players are very few. They coined the expression “decision making units” (DMU) in order to include non-market agencies such as schools, hospitals and courts, which produce identifiable and measurable outputs from measurable inputs but generally lack market prices for outputs (and often for some inputs as well). Supposing that there are N firms each producing m outputs from n inputs, firm t uses the input bundle $x^t = (X_{1t}, X_{2t}, \dots, X_{nt})$ to produce the output bundle $y^t = (y_{1t}, y_{2t} .., y_{mt})$. As noted above, average productivity measurement requires inputs and outputs aggregation. To solve efficiency scores, Charnes, Cooper, & Rhodes (1978) proposed to obtain the efficiency score assuming constant returns to scale (CRS), which represents the global technical efficiency of a DMU, called the CCR (Charnes-Cooper-Rhodes) model:

$$
\begin{gathered}
\min \theta \\
\text{s.t.} \sum_{j=1}^{N} \lambda_j y^j \geq y^t : \\
\sum_{j=1}^{N} \lambda_j x^j \leq \theta \; x^t ; \\
\lambda_j \geq 0 \,(j = 1, 2, .., N); \theta \text{ free}. \qquad (1)
\end{gathered}
$$

Where N is the number of DMU and; x_{io} and y_{ro} are, respectively, the ith input and rth output for DMU0 under evaluation.

If an additional convexity constraint of $\sum_{j=1}^{n} \lambda j = 1$ is imposed on the CCR model (1), the resulting frontier exhibits variable returns to scale (VRS). It is called here the VRS or BCC (Banker-Charnes-Cooper) model (Banker, Charnes, & Cooper, 1984):

$$\min \theta$$
$$\text{s.t.} \quad \sum_{j=1}^{N} \lambda_j x^j \leq \theta \, x^t;$$
$$\sum_{j=1}^{N} \lambda_j y^j \geq y^t;$$
$$\sum_{j=1}^{N} \lambda_j = 1;$$
$$\lambda_j \geq 0 \, (j = 1, 2, \ldots, N). \quad (2)$$

The BCC model assumes the convex combination of the observed DMU as the production possibility set, where in the VRS the score is called local pure technical efficiency (PTE). The problem is to solve PTE θ and lambda value λ_j for an observed DMU: PTE = 1 means that the DMU is technically efficient; PTE < 1 means that the DMU is technically inefficient.

For an observed DMU, the solution of lambda value λ_j indicates whether DMU j works as a role model (peer) for the observed DMU k. If $\lambda_{ik} = 0$, DMU j is not a role model. If $\lambda_{jk} > 0$, DMU j is a role model of the observed DMU k. λ_{ij} represents the weight with which that the observed DMU k references DMU j, to reach target efficiency.

The CCR model assumption implies that the radial expansion and reduction of all the observed DMU (and their non-negative combinations) are possible, the CRS score being called global technical efficiency (TE). Comparing the CCR and BCC scores, a deeper insight is obtained into those sources of inefficiency that a DMU might provide.

θ^0_{CRS} and θ^0_{VRS} denote, respectively, the CCR and BCC scores of a DMU, and the scale efficiency is defined by $SE = \frac{\theta CRS}{\theta BRS} = \frac{TE}{PTE}$ (3). Using (3), the (global) technical efficiency of a DMU is decomposed as $TE = PTE \times SE$ (4). Thus, the global or overall inefficiency of a DMU is explained by inefficient operation (PTE), by the scale effect (SE), or by both.

The characterization of the CCR model as constant returns-to-scale is technically correct, but somewhat misleading, as the model can also be used to determine whether the returns to scale are increasing or decreasing. This is achieved using the following theorem (Theorem 1) proved by Banker and Thrall (1992):

i) If $\sum_{j=1}^{n} \lambda j = 1$ in any alternate optimum, then CRS prevails;

ii) If $\sum_{j=1}^{n} \lambda j > 1$for all alternate optima, then decreasing returns-to-scale prevail; or

iii) If $\sum_{j=1}^{n} \lambda j < 1$for all alternate optima, then increasing returns-to-scale prevail.

The relationship between the BCC and the CCR model is described by the following theorem, from Ahn, Charnes and Cooper (1989): a DMU0 found to be efficient with a CCR model will also be found to be efficient with the corresponding BCC model, and CRS prevails for DMU_0.

3.2. Bootstrapping DEA technique

Bootstrap procedure has been used to obtain the biased corrected results for the DEA estimators following Simar, and Wilson (1998, 2000). It is defined as a data-based simulation technique for statistical inference (Daraio, & Simar, 2007). The correction for the bias and the construction of confidence intervals of the efficiency estimators are two of the main applications of this procedure (Simar, & Wilson, 1998, 2000).

The resampling from an original data sample to replicate datasets from which statistical inference can be made is the basis of the bootstrapping technique, introduced by Efron (1979). This work uses the "smoothed bootstrap" approach proposed by Simar, & Wilson (1998). The extensive work of Simar and Wilson (1998, 1999, 2000a, 2000b) gathered the theoretical underpinnings. The bootstrap process will, therefore, generate values that imitate the distributions, which would be generated from the unobserved and unknown data generating process (Simar, & Wilson, 2000a, 2000b). Bootstrapping process used can be summarized as follows:

1. Calculate the DEA efficiency score $\left\{\hat{\theta}_i; i = 1,2, \dots, n\right\}$ with the original data (x_i, y_i) by solving model (1).

2. Use Kernel density estimation and the reflection method to generate a random sample $\{\theta_i^*; i = 1,2, \dots, n\}$ with replacement from the original DEA efficiency score $\hat{\theta}_i$.

3. Generate the $\hat{\theta}_i$ using

$\tilde{\theta}_i^* = \theta_i^* + h\varepsilon_i^*, i = 1,2, \dots, n$

Where ε_i^* is a random drawn from a standard normal distribution and h is a control parameter.

4. Obtain the θ_i^{**} through

$$\theta_i^{**} = \bar{\theta}^* + \frac{\tilde{\theta}_i^* - \bar{\theta}^*}{\sqrt{1 + \frac{h^2}{s^{*2}}}}, i = 1,2, \dots, n$$

Where $\bar{\theta}^*$and $s^{*2}$are the empirical mean and values' variance θ_i^* .

5. Generate resampled pseudo-efficiencies γ_i^*using

$$\gamma_i^* = \begin{cases} 2 - \theta_i^{**}, if \theta_i^{**} < 1 \\ \theta_i^{**}, i.o.c. \end{cases}$$

6. Obtain a new data sample using $(x_i^*, y_i) = \left(\frac{\gamma_i^*}{\hat{\theta}_i} x_i, y_i\right)$

7. Calculate the DEA efficiency score $\left\{\hat{\theta}_i^*; i = 1,2, \dots, n\right\}$with data, (x_i^*, y_i)

8. Repeat steps 2 to 7 B times to create a set with B efficiency estimates for each unit

$$\hat{\theta}_{i,b}^*; i = 1,2, \dots, n; b = 1,2, \dots, B$$

The bootstrap estimate of the DEA bias is obtained through

$$bias_i = \frac{1}{B} \sum_{b=1}^{B} \hat{\theta}_{i,b}^* - \hat{\theta}_i , i = 1,2, \dots, n$$

A bias corrected efficiency estimator is then obtained by defining

$$\tilde{\theta}_i = 2\hat{\theta}_i - \frac{1}{B}\sum_{b=1}^{B}\hat{\theta}^*_{i,b}, i = 1,2,\ldots,n$$

3.3. Data, input and output indicators

Data from 20 English Premier League (EPL) clubs are used as an illustrative example to demonstrate how DEA can be employed to measure efficiency in a multidimensional construct, and to provide additional information regarding EPL teams' competitiveness. The first and probably most difficult step in an efficiency evaluation is to decide which input and output data should be included. Regarding inputs, in this study a combination of sports, financial and social media measures was collected, selecting the following variables:

a) Assets: the total assets on the balance sheet in 2013. This input was used in previous works by Barros and Leach (2006), Martínez-Núñez and Pérez-Aguiar (2014) and Zhu (1998) among others, to analyze the performance of best-practice frontier in companies. The logic behind is that total wealth of clubs drives their results, as shown in the cited literature.

b) Wages and salaries: they include the values of any social benefits, income taxes, and so on payable by the employee for the year 2013 (Haas et al., 2004; Haas, 2003). The reason here is that in theory better players get higher salaries, so that it is a good proxy to represent competitive potential.

c) Number of each club's posts on Facebook during season 2013-2014: it measures activity level in social networks (Groza, & Pronschinske, 2012; Martínez-Núñez, & Pérez-Aguiar, 2014; Stavros et al., 2014). The data source was FanPage Karma (http://www.fanpagekarma.com). Previous research identifies posts' number as a good indicator of social media activity of each club.

On the other hand, the selected outputs measure the performance of EPL clubs:

a) Season points: following the recommendations of previous works (Dawson et al., 2000; Haas et al., 2004). It is numerically better than table position, for instance.

b) Profit before taxes: a profitability measure also well supported in the literature (Martínez-Núñez, & Pérez-Aguiar, 2014; Zhu, 1998). It also excludes possible tax differences among clubs.

c) Number of Facebook fans: some studies have explored the motivations of sports fans in using Facebook (Groza, & Pronschinske, 2012; Sanderson, 2013). They concluded the importance of these networks to create value for sports consumers. This output was also used by Martínez-Núñez, & Pérez-Aguiar (2014). The data source was again FanPage Karma. Followers have been proved too as a good proxy of social media success.

To summarize, three inputs and three outputs have been considered in this piece of research, as shown in Figure 1. Finally, table 1 reports all the quantitative variables used for the 20 EPL teams in season 2013-2014, according to their financial statements and Facebook accounts.

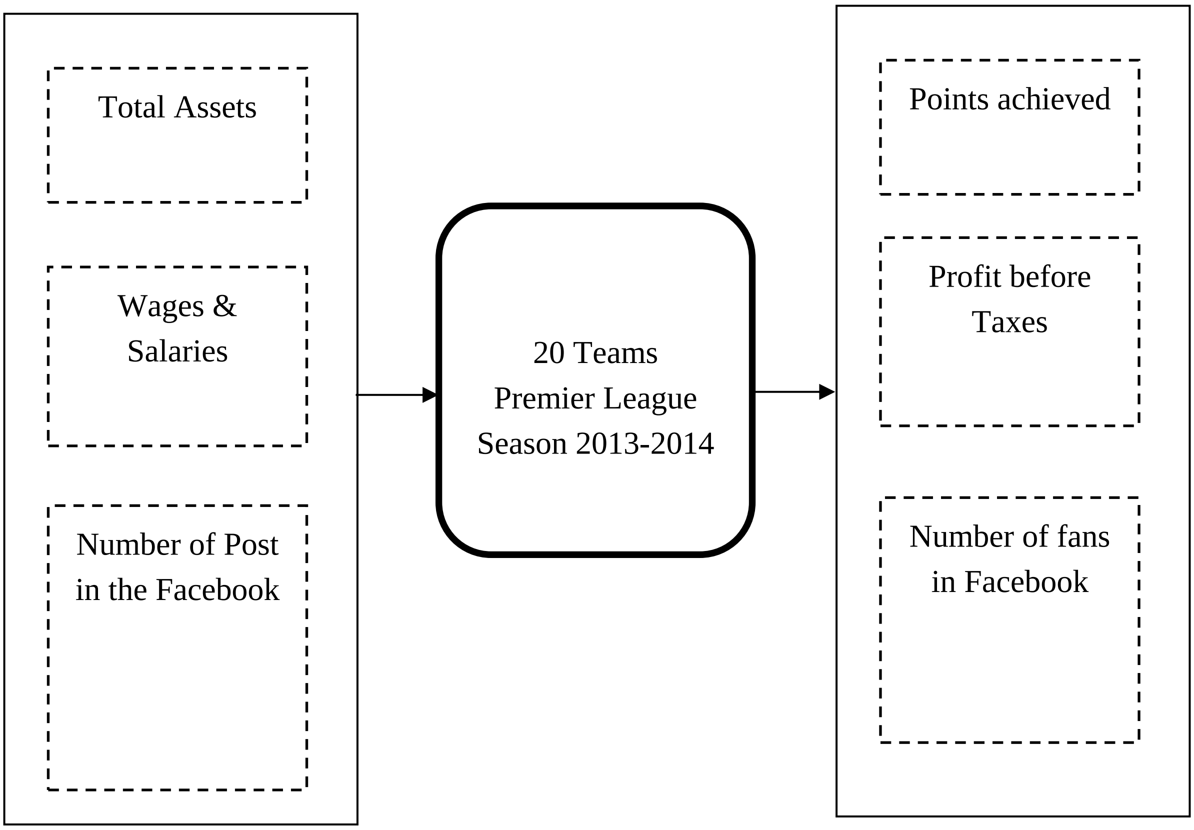

Figure 1. Efficiency model employed

Table 1. Descriptive Data for Premier League Season 2013/2014.

DMU	Ranking position	Assets	Wages and salaries	Number of team's posts on Facebook	Season points	Profit before taxes	Number of Facebook fans
Arsenal	4	651,711	132,838	1,660	79	220,246	24,976,186
Aston Villa	13	90,924	9,051	2,909	38	81,684	1,910,001
Cardiff City	20	71,717	29,965	1,998	30	20,120	348,589
Chelsea	3	566,291	151,649	1,501	82	255,772	30,573,458
Crystal Palace	11	21,194	15,980	929	45	13,019	282,170
Manchester City	1	759,109	204,701	4,844	86	271,000	13,047,563
Manchester United	7	504,092	165,350	2,258	64	194,442	129,833,386
Everton	5	56,658	55,320	2,726	72	86,397	1,172,814
Fulham	19	57,880	58,551	2,780	32	73,015	595,969
Hull City	15	29,226	43,323	1,441	37	8,777	710,398
Liverpool	2	269,420	116,092	939	84	206,115	20,212,610
Newcastle	10	178,392	54,040	1,649	49	95,879	1,163,003
Norwich City	18	81,513	45,877	1,101	33	74,733	363,168
Southampton	8	32,757	43,500	2,741	56	69,413	426,465

Stoke City	9	68,383	52,479	322	50	66,516	281,399
Sunderland	14	88,341	49,848	1,356	38	72,026	394,884
Swansea City	12	62,591	42,920	1,447	42	67,113	605,521
Tottenham	6	160,610	84,727	1,803	69	147,392	5,075,361
West Bromwich	16	63,864	47,962	1,720	36	69,734	302,712
West Ham	16	104,207	49,278	2,309	36	89,815	776,232

4. Results

4.1. DEA results

As explained, it has been estimated the relative efficiency for two input-oriented DEA models, namely, CCR with CRS, and BCC with VRS using bootstrapping techniques. DEA inputs represent negative evaluation items (smaller values are better and more desirable) and DEA outputs represent positive evaluation items (greater values are preferred) (Hashimoto, & Ishikawa, 1993). An input oriented measure quantifies the necessary input reduction to become efficient, holding outputs constant. Symmetrically, an output-oriented measure quantifies the necessary output expansion holding inputs constant. An input oriented model is used here. To obtain meaningful results, instance dimensions should follow the rule of thumb (Charnes, & Cooper, 1990): Number of DMUs > 3 * (inputs + outputs) (5). Table 2 reports the results for both constant returns to scale (CCR model) and variable returns to scale (BCC model).

Table 2. Results for CCR and BCC models

DMU No.	DMU	Global Technical Efficiency CCR model	Purely Technical Efficiency BCC model	Scale Efficiency	Returns to Scale
1	Arsenal	0.90	0.94	0.96	Decreasing
2	Aston Villa	1.00	1.00	1.00	Constant
3	Cardiff City	0.41	0.54	0.75	Increasing
4	Chelsea	0.95	1.00	0.95	Decreasing
5	Crystal Palace	1.00	1.00	1.00	Constant
6	Manchester City	0.62	1.00	0.62	Decreasing
7	Manchester United	1.00	1.00	1.00	Constant
8	Everton	1.00	1.00	1.00	Constant
9	Fulham	0.80	0.80	1.00	Increasing
10	Hull City	0.66	0.78	0.84	Increasing
11	Liverpool	1.00	1.00	1.00	Constant
12	Newcastle	0.83	0.86	0.97	Increasing
13	Norwich City	0.95	0.96	0.99	Increasing
14	Southampton	1.00	1.00	1.00	Constant
15	Stoke City	1.00	1.00	1.00	Constant
16	Sunderland	0.83	0.84	0.99	Increasing
17	Swansea City	0.95	0.97	0.98	Increasing
18	Tottenham	1.00	1.00	1.00	Constant
19	West Bromwich	0.91	0.91	0.99	Increasing
20	West Ham	0.86	0.86	0.99	Increasing

CCR and BCC indicate respectively efficiency scores of a given club with constant and variable returns to scale. Teams on the efficiency frontier have an efficiency score of 1. Lower scores indicate inefficiency.

Eight teams achieve technical efficiency (CCR model): Aston Villa, Crystal Palace, Manchester United, Everton, Liverpool, Southampton, Stoke City, and Tottenham. The technical efficiency scores for inefficient units under CRS range from 0.41 to 0.95. DMUs number 2, 5, 7, 8, 11 14, 15 and 18 are the only efficient ones in the CCR model, are also efficient in the BCC model (as predicted by Theorem 2), and have the most productive scale size (MPSS).

VRS efficiency scores measure pure technical efficiency (PTE), excluding the effects of scale operations. They are greater than the corresponding CRS efficiency scores. Pure efficiency scores for inefficient units under VRS range from 0.54 to 0.97. In the BCC model, DMUs number 6 (Manchester City), and 4 (Chelsea) are locally technically efficient, but not globally efficient.

Apart from the inefficiencies that could arise in the conversion process, another reason for inefficiencies in units could be attributed to the operational scale. DMUs that do not operate at the most efficient (or productive) size cannot be fully efficient. Inefficiency may arise because a unit is operating under Decreasing Returns to Scale (DRS) or Increasing Returns to Scale (IRS).

The significance of scale inefficiencies induces that this is an activity that gives rise to variable returns to scale and, consequently, each club's size is an aspect to consider when evaluating its efficiency. As the number of DMU studied is not enough to generate a great results' consistency, the model incorporates a bootstrapping estimation to make it stronger.

After 2,500 replications, the mean bias is 1.2, an estimated mean variance of 0.11 (Table 4). The bias and mean variance of the estimates are quite low after 2,500 replications, so that results can be considered to be generally robust (Von Hirschhausen, & Cullmann, 2010).

Following Simar, and Wilson (1999), table 3 includes the bootstrap results for the 20 EPL clubs. An adequate coverage of the confidence intervals should be provided. The first column presents the DEA VRS technical efficiency scores, the second column shows the DEA bootstrapped efficient scores of the 20 EPL clubs, and the third and fourth columns present the lower and upper bound of the DEA confidence intervals. It can be observed that the bias-corrected estimate is within relatively narrow confidence intervals, i.e. the lower and upper bounds of the intervals are relatively close. This provides statistical confidence for the bias-corrected estimate, as explained in Fried et al. (2008).

According to results (Table 3), 10 out of the 20 teams are efficient. This is the case of Aston Vila, Chelsea, Crystal Palace, Manchester City, Manchester United, Everton, Liverpool, Southampton, Stoke City, and Tottenham. However, 10 teams are inefficient: Arsenal, Cardiff City, Fulham, Hull City, Newcastle, Norwich City, Sunderland, Swansea City, West Bromwich, and West Ham. In addition, the average efficiency level of all 20 teams is 0.91. That means that, as an average, a football team could reduce 9% of its inputs level in order to obtain the output level. Cardiff City (DMU 3) obtains the lowest efficiency and its interval bounds are not coincident with other DMU intervals. It is for sure the lowest efficient club within the EPL. Table 4 summarizes efficiency values obtained for the 20 EPL teams.

Table 3. Original and bias-corrected efficiency score

DMU No.	DMU	Original eff. Score	Bias-corrected eff.	Lower bound	Upper bound
1	Arsenal	0.94	0.92	0.89	0.94
2	Aston Villa	1	1	1	1
3	Cardiff City	0.54	0.52	0.43	0.54
4	Chelsea	1	1	1	1
5	Crystal Palace	1	1	1	1
6	Manchester City	1	1	1	1
7	Manchester United	1	1	1	1
8	Everton	1	1	1	1
9	Fulham	0.8	0.78	0.7	0.81
10	Hull City	0.78	0.75	0.61	0.78
11	Liverpool	1	1	1	1
12	Newcastle	0.86	0.83	0.75	0.86
13	Norwich City	0.96	0.94	0.92	0.96
14	Southampton	1	1	1	1
15	Stoke City	1	1	1	1
16	Sunderland	0.84	0.81	0.75	0.84
17	Swansea City	0.97	0.94	0.93	0.97
18	Tottenham	1	1	1	1
19	West Bromwich	0.91	0.89	0.85	0.91
20	West Ham	0.86	0.84	0.78	0.86

Table 4. Efficiency and bootstrapped performance estimates summary

Indicator	Estimate
Nº DMUs	20
Original average efficiency score	0.92
Average bias-corrected efficiency score	0.91
Bias	-1.26
Average efficiency score of inefficient DMUs corrected	0.82
St Dev	0.113
Bootstrap Median	0.91
Lower bound	0.88
Upper bound	0.92
Nº efficient DMU	10
% DMU efficient rate	50%
Maximum value	1
Maximum value	0.54

4.2. Benchmarks

The optimal values of λ j in the benchmarks columns of Table 5 (for BCC models) demonstrate that linear combination of clubs on the efficiency frontier is closer to the team whose efficiency is being evaluated (its projection into the frontier, in fact). As already explained, the members of this combination (i.e. those clubs for which λ j >0) constitute the peer group of the team concerned; i.e. a set of other clubs, all of them located on the efficiency frontier, relative to which it is inefficient.

Table 5. Results of BCC models and benchmarks

Number	DMU Name	Original eff. Score	Bias-corrected eff.	Benchmarks
1	Arsenal	0.94	0.92	λ 2= 0.08, λ 4= 0.49, λ 7= 0.01, λ 11= 0.41
2	Aston Villa	1	1	λ 2=1
3	Cardiff City	0.54	0.52	λ 2=0.09, λ 5= 0.89 , λ 15= 0.02
4	Chelsea	1	1	λ 4=1
5	Crystal Palace	1	1	λ 5=1
6	Manchester City	1	1	λ 6=1
7	Manchester United	1	1	λ 7=1
8	Everton	1	1	λ 8=1
9	Fulham	0.8	0.78	λ 2= 0.01, λ 14=0.75, λ 15= 0.19, λ 18=0.05
10	Hull City	0.78	0.75	λ 5=1
11	Liverpool	1	1	λ 11=1
12	Newcastle	0.86	0.83	λ 2=0.38, λ 11=0.17, λ 15=0.097
13	Norwich City	0.96	0.94	λ 5=0.632, λ 7=0.001, λ 15=0.45
14	Southampton	1	1	λ 14=1
15	Stoke City	1	1	λ 15=1
16	Sunderland	0.84	0.81	λ 2=0.25, λ 14=0.05, λ 15=0.67, λ 18=0.02
17	Swansea City	0.97	0.94	λ 2=0.16, λ 5=0.05, λ 14 = 0.26, λ 15=0.53
18	Tottenham	1	1	λ 18=1
19	West Bromwich	0.91	0.89	λ 2= 0.13, λ 14=0.38, λ 15=0.49
20	West Ham	0.86	0.84	λ 2= 0.35, λ 14=0.18, λ 15=0.25 , λ 18=0.22

Table 6 summarizes the frequency in which a team is listed as reference club for inefficient ones. The first column lists the teams detected as efficient. The second column shows the frequency in which inefficient ones are referenced.

Table 6. Frequency of appearance of efficient unit as reference team

Number	DMU Name	Frequency
2	Aston Villa	9
4	Chelsea	1
5	Crystal Palace	3
6	Manchester City	0
7	Manchester United	3
8	Everton	0
11	Liverpool	2
14	Southampton	6
15	Stoke City	8
18	Tottenham	5

DMU 2 (Aston Villa), mainly, and secondly DMU 15 (Stoke City) and DMU 14 (Southampton), are those that appear more frequently as reference efficient teams.

4.3. Correlations

Table 7 shows simple correlations between the table position obtained, global technical efficiency (CCR model), purely technical efficiency (BCC), scale efficiency, bias corrected efficiency, profit before taxes (output 2) and number of Facebook fans (output 3). The correlation between EPL ranking and pure technical efficiency is positive and significant. In addition, table position and profits before taxes, and number of Facebook fans are positively correlated.

Table 7. Correlation between ranking and other variables

		CCR	BCC	Scale Eff	Biascorrectedeff.	Output 2	Output 3
Ranking	2013-14	0.412	0.738**	0.072	0.728*	0.665*	0.672*

*p<0.01

5. Discussion

This piece of research intends to measure the efficiency of English Premier League (EPL) soccer clubs, especially with regard to their use of social media, so as to show hoy social networks can contribute to sports management. The efficiency scores for 20 EPL clubs are found using a DEA model. To clearly illustrate the approach, bubble charts are employed to visualize the data. They combine bias-corrected efficiency (x axis) and the social-media-index ad-value (y axis, in Euros). Social-media-index ad-value shows how much an institution would have to spend so as to reach as many people through common online ads as did on Facebook. The bubbles' size is determined by profit before taxes (Figure 2).

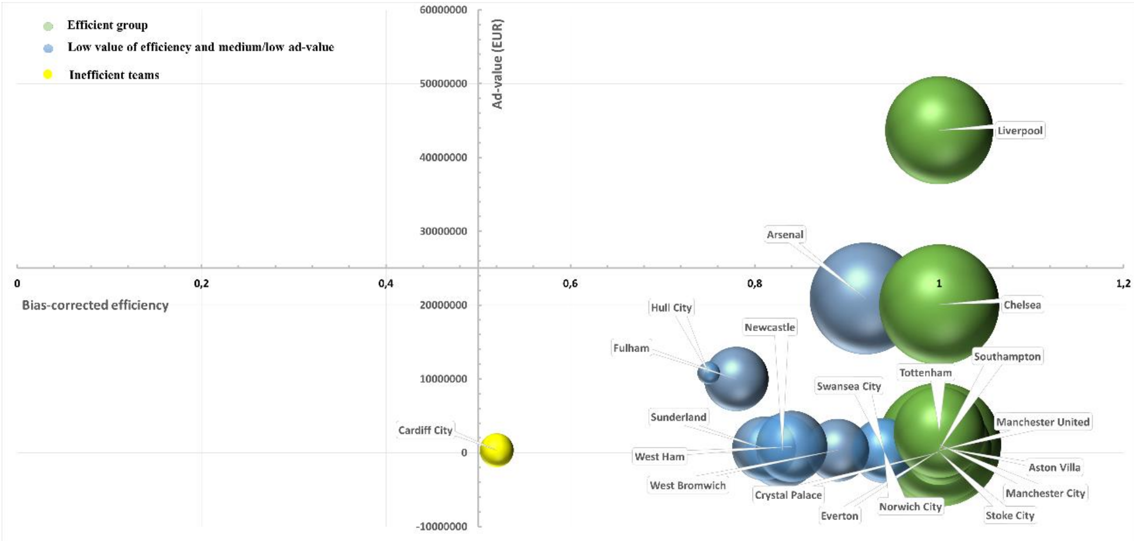

Figure 2. Efficiency, social media and profit

The graph is divided into four quadrants. The first quadrant is the upper right-hand corner of the graph; it shows teams with efficiency close to 1 and ad-value between Euros 25,000,000 and 60,000,000 (Liverpool). The second quadrant, in the lower right-hand corner, includes a range of efficiency between 0.5 and 1 and medium and low ad-value, and corresponds to the vast majority of the analyzed clubs. The third quadrant, the lower left-hand corner, includes low values of both x and y. Finally, the fourth quadrant, the upper left-hand corner, includes high ad-value and low efficiency value. There is no team in the third and fourth quadrants, which is consistent with the benchmark's definition.

From a quality perspective, three groups of teams can be found. The first group (green bubbles) corresponds to the efficient group. This group include clubs with a historical trajectory of sporting success, such as Liverpool, Arsenal, and Manchester United, and the highest ad-value. The second group (blue bubbles) cover teams with low efficiency value and medium ad-value (such as Chelsea or Hull City). Their own management model and singular features, such as foreign investment in the case of Chelsea, make them a singular group. The third group (yellow bubbles) includes inefficient teams with low ad-value, such as Cardiff City.

6. Conclusion

This article shows a parallelism between EPL ranking and Facebook fans. According to the findings, managing the number of fans and posts on Facebook may increase income from sponsors and advertisers. In this sense, the greater social-media-index ad-value the clubs have, the more income they will obtain. Sport managers could use this study to understand how social networks influence the business of football. In this sense, it helps to deepen the knowledge of social networks and their relationship and interaction with a club's followers. This analysis relates sports management from three performance levels: sports, financial, and social.

This paper also makes a theoretical contribution by proposing a new model to assess efficiency of sport institutions. It proposes a new array of inputs and outputs that combines sports, financial, and social media indicators in both sides. Furthermore, it has found a direct relationship between table position, efficiency, profits before taxes and social media use. Teams capable of better integrating these 3.0 technologies in their marketing plans obtained the largest efficiency gains.

This study shows that there is a significant advantage to take from social media as a technological resource among the EPL teams analyzed. All sport businesses are stressed to superior performance in sports, financial, and social terms. Results in all three areas support each other so as to become more efficient, though some endogeneity should be taken into account. But an intensive use of social networks can contribute to the enlargement of the social base of a sports institution, which can also improve its financial resources to be employed in the proper sports potential of the club.

6.1. Research Limitation

Of course this piece of research includes some limitations. The main one has to do with endogeneity. It cannot be excluded that interaction among variables might be so intimate that some drives the others naturally. For instance, sports success is expected to raise fans' numbers, profits and social media followers. Even though, DEA is a methodology that works well for DMUs of all sizes in the same competitive environment.

6.2. Suggestions for future researches

Future research can reply the model or try to find a different operationalization of inputs and/or outputs so as to better identify relevant findings. However, DEA limitations also restricts the total number of variables to 6 with a similar number of DMUs. Regardless of that, refinement of the model might be possible with more empirical testing, applied to other leagues and seasons.

References

Andreff, W., & Staudohar, P. D. (2000). The evolving European model of professional sports finance. *Journal of Sports Economics*, 1, 257–276. DOI: 10.1177/152700250000100304

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17, 99-120. DOI: 10.1177/014920639101700108

Barney, J. (2001). Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view. *Journal of Management*, 27, 643-650. DOI: 10.1016/S0149-2063(01)00115-5

Barros, C., & Santos, A. (2007). Productivity in sports organisational training activities: a DEA study. *European Sport Management Quarterly*, 3, 46-65. DOI: 10.1080/16184740308721939

Barros, C., Garcia-del-Barrio, P., & Leach, S. (2009). Analysing the technical efficiency of the Spanish Football League First Division with a random frontier model. *Applied Economics*, 41, 3239-3247. DOI: 10.1080/00036840701765379

Barros, C., & Leach, S. (2006). Analyzing the performance of the English Premier League with an econometric frontier model. *Journal of Sports Economics*, 7, 391-407. DOI: 10.1177/1527002505276715

Beverland, M. B., Farrelly, F., & Quester, P. G. (2010). Authentic subcultural membership: Antecedents and consequences of authenticating acts and authoritative performances. *Psychology and Marketing*, 27, 698–716. DOI: 10.1002/mar.20352

Billings, A. C., Broussard, R. M., Xu, Q. (2019). Untangling International Sport Social Media Use: Contrasting U. S. and Chinese Uses and Gratifications Across Four Platforms. *Communication & Sport*, 5 (7), 630-652. DOI: 10.1177/2167479518790014

Bühler, A., Chadwick, S., & Nufer, G. (2009). *Relationship marketing in sports–the fan perspective*. New York: Butterworth-Heinemann.

Chan-Olmsted, S., & Wolter, L. (2018). Perceptions and practices of media engagement: A global perspective. *International Journal on Media Management*, 20 (1), 1-24. DOI: 10.1080/14241277.2017.1402183

Collier, T., Johnson, A., & Ruggiero, J. (2010). Measuring technical efficiency in sports. *Journal of Sports Economics*, 12, 579-598. DOI: 10.1177/1527002510391582

Daraio, C., & Simar, L. (2007). *Advanced robust and nonparametric methods in efficiency analysis: Methodology and applications.* New York: Springer Science & Business Media.

Dawson, P., Dobson, S., & Gerrard, B. (2000). Estimating coaching efficiency in professional team sports: Evidence from English association football. *Scottish Journal of Political*, 47, 399-421. DOI: 10.1111/1467-9485.00170

Debnath, R., & Malhotra, A. (2015). Measuring efficiency of nations in multisport events: A case of Commonwealth Games XIX. *Naše gospodarstvo/Our Economy*, 61, 25-36. DOI: 10.1515/ngoe-2015-0003

Deloitte Sports Business Group. (2014). A premium blend: Annual review of football finance. Manchester, United Kingdom: Deloitte. Retrieved from https://www2.deloitte.com/uk/en/pages/sports-business-group/articles/annual-review-of-football-finance-2014.html

Deloitte Sports Business Group. (2015). Commercial breaks: Football money league Manchester, United Kingdom: Deloitte. Retrieved from deloitte.com/content/dam/Deloitte/global/Documents/Audit/gx-football-money-league-2015.pdf

Dima, T. (2015). The business model of european football club competitions. *Procedia Economics and Finance*, 23, 1245-1252. DOI: 10.1016/S2212-5671(15)00562-6

Efron, B. (1979). Computers and the theory of statistics: thinking the unthinkable. *SIAM Review*, 21, 460-480. DOI: 10.1137/1021092

Espitia-Escuer, M., & García-Cebrián, L. (2004). Measuring the efficiency of spanish First-Division soccer teams. *Journal of Sports Economics*, 5, 329–346. DOI: 10.1177/1527002503258047

Fan, M., Billings, A., & Zhu, X. (2020). Twitter-Based BIRGing: Big Data Analysis of English National Team Fans during the 2019 FIFA World Cup. *Communication & Sport*, 8 (3), 317-345. DOI: 10.1177/2167479519834348

Farrell, M. (1957). The measurement of productive efficiency. Journal of the Royal Statistical Society, 120, 253-290. DOI: 10.2307/2343100

Filo, K., Lock, D., & Karg, A. (2015). Sport and social media research: A review. *Sport Management Review*, 18, 166–181. DOI:10.1016/j.smr.2014.11.001

Fizel, J., & D'Itri, M. (1997). Managerial efficiency, managerial succession and organizational performance. *Managerial and Decision Economics*, 18, 295-308. DOI: 10.1002/(SICI)1099-1468

Fried, H. O., Lovell, C. K., & Schmidt, S. S. (2008). *The measurement of productive efficiency and productivity growth*. New York: Oxford University Press.

Garrigos-Simon, F. J., Alcamí, R. L., & Ribera, T. B. (2012). Social networks and web 3.0: their impact on the management and marketing of organizations. *Management Decision*, 50, 1880–1890. DOI: 10.1108/00251741211279657

Glass, A., Kenjegalieva, K., & Taylor, J. (2015). Game, set and match: evaluating the efficiency of male professional tennis players. *Journal of Productivity Analysis*, 43, 119-131. DOI: 10.1007/s11123-014-0401-3

Groza, M. D., & Pronschinske, M. (2012). Attracting facebook "fans": the importance of authenticity and engagement as a social networking strategy for professional sport teams. *Sport Marketing Quarterly*, 21, 221–231. Retrieved from -importance-authenticity-and-engagement-social-networking-strategy

Haas, D. (2003). Productive efficiency of english football teams—a data envelopment analysis approach. *Managerial and Decision Economics*, 24, 403-410. DOI: 10.1002/mde.1105

Haas, D., Kocher, M., & Sutter, M. (2004). Measuring efficiency of german football teams by Data Envelopment Analysis. *Central European Journal of Operations Research*, 12, 251-268. DOI:10.17559/TV-20140306134047

Hausch, D. B., & Ziemba, W. T. (1995). Efficiency of sports and lottery betting markets. *handbooks in Operations research and Management Science*, *9*, 545-580. DOI: 10.1016/S0927-0507(05)80062-3

Jones, D. (2014). Deloitte Football Money League. Manchester, United Kingdom: Deloitte Consulting, Sports Business Group. Retrieved from deloitte.com/content/dam/Deloitte/global/Documents/Audit/gx-deloitte-football-money-league-2014.pdf

Jones, D., Parkes, R., Houlihan, A., & Ingles, G. (2008). Deloitte Football Money League. United Kingdom: Deloitte Consulting, Sports Business Group. Retrieved from deloitte.com/content/dam/Deloitte/global/Documents/Audit/gx-deloitte-football-money-league-2008.pdf

Jones, D., Rawnsley, P., & Switzer, A. (2013). Annual review of football finance. Highlights Deloitte Annual Review of Football Finance. Manchester, United Kingdom: Deloitte. Retrieved from deloitte.com/content/dam/Deloitte/uk/Documents/sports-business-group/deloitte-uk-sbg-arff-2013-highlights-download.pdf

Liu, J., Lu, L., Lu, W., & Lin, B. (2013). A survey of DEA applications. *Omega*, 41, 893-202. DOI: 10.1016/j.omega.2012.11.004

Martínez-Núñez, M., & Pérez-Aguiar, W. S. (2014). Efficiency analysis of information technology and online social networks management: An integrated DEA-model assessment. *Information & Management*, 51, 712–725. DOI: 10.1016/j.im.2014.05.009

Martín-Quevedo, J., Fernández-Gómez, E., & Segado-Boj, Francisco (2019). How to Engage with Youngster Users on Instagram: A Comparative Analysis of HBO and Netflix in the Spanish and US Market. International *Journal on Media Management*, 21 (2), 67-87. DOI: 10.1080/14241277.2019.1585355

Meza, L., Valério, R., & Mello, J. de. (2015). Assessing the efficiency of sports in using financial resources with DEA Models. *Procedia Computer Science*, 55, 1151-1159. DOI: 10.1016/j.procs.2015.07.086

Moreno, P., & Lozano, S. (2014). A network DEA assessment of team efficiency in the NBA. *Annals of Operations Research*, 214, 99-124. DOI: 10.1007/s10479-012-1074-9

Parganas, P., Liasko, R., & Anagnostopoulos, C. (2017). Scoring goals in multiple fields: Social media presence, on-field performance and commercial success in European professional football. *Sport, Business and Management: An International Journal*, 7(2), 197-215. DOI: 10.1108/SBM-11-2016-0072

Qualman, E. (2012). Socialnomics: *How social media transforms the way we live and do business*. California: Wiley.

Reddy, S., Stam, A., & Agrell, P. (2015). Brand equity, efficiency and valuation of professional sports franchises: The case of major League Baseball. *International Journal of Business and Social Research*, 5, 63-89. DOI: 10.18533/ijbsr.v5il.666

Rumelt, R. P. (1991). How much does industry matter?. *Strategic Management Journal*, 12, 167–185. Retrieved from www.jstor.org/stable/2486591

Sanderson, J. (2013). From loving the hero to despising the villain: Sports fans, Facebook, and social identity threats. *Mass Communication and Society*, 16, 487-509. DOI: 10.1080/15205436.2012.730650

Scelles, N., Helleu, B., Durand, C., Bonnal, L., & Morrow, S. H. (2017). Explaining the number of social media fans for North American and European professional clubs with determinants of their financial value. *International Journal of Financial Studies*, 5(4), 25. DOI: 10.3390/ijfs5040025

Shay, R., & Van der Horst, M. (2019). Using Brand Equity to Model ROI for Social Media Marketing. International *Journal on Media Management*, 2 (1), 24-44. DOI: 10.1080/14241277.2019.1590838

Shilbury, D., Westerbeek, H., Quick, S., Funk, D. C. (2014). *Strategic sport marketing*. New York: A&U Academic.

Simar, L., & Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models. Management Science, 44, 49-61. Retrieved from http://pubsonline.informs.org/doi/abs/10.1287/mnsc.44.1.49?journalCode=mnsc

Simar, L., & Wilson, P. W. (1999). Of course we can bootstrap DEA scores! But does it mean anything? Logic trumps wishful thinking. *Journal of Productivity Analysis*, 11, 93-97. DOI: 10.1023/A:1007739507007

Simar, L., & Wilson, P. W. (2000a). Statistical inference in nonparametric frontier models: The state of the art. *Journal of Productivity Analysis*, 13, 49-78. DOI: 10.1023/A:1007864806704

Simar, L., & Wilson, P. W. (2000b). A general methodology for bootstrapping in non-parametric frontier models. *Journal of Applied Statistics*, 27, 779-802. DOI: 10.1080/02664760050081951

Stavros, C., Meng, M. D., Westberg, K., & Farrelly, F. (2014). Understanding fan motivation for interacting on social media. Sport Management Review, 17, 455–469. DOI: 10.1016/j.smr.2013.11.004

Taymaz, E. (2005). Are Small Firms Really Less Productive?. *Small Business Economics*, 25, 429–445. DOI: 10.1007/s11187-004-6492-x

Terrien, M., Scelles, N., Morrow, S., Maltese, L., & Durand, C. (2017). The win/profit maximization debate: Strategic adaptations as the answer?. *Sport, Business and Management: An International Journal*, 7(2), 121-140. DOI: 10.1108/SBM-10-2016-0064

Torgler, B., & Schmidt, S. (2007). What shapes player performance in soccer? Empirical findings from a panel analysis. *Applied Economics*, 39, 2355-2369. DOI: 10.1080/00036840600660739

Vale, L., & Fernandes, T. (2018). Social media and sports: driving fan engagement with football clubs on Facebook. *Journal of Strategic Marketing*, 26(1), 37-55. DOI: 10.1080/0965254X.2017.1359655

Von Hirschhausen, C., & Cullmann, A. (2010). A nonparametric efficiency analysis of German public transport companies. *Transportation Research Part E: Logistics and Transportation Review*, 46(3), 436-445. DOI: 10.1016/j.tre.2009.11.005

Wernerfelt, B. (1984). A resource based view of the firm. *Strategic Management Journal*, 5, 171-180. DOI: 10.1002/smj.4250050207

Weimann-Saks, D., Ariel, Y., & Elishar-Malka, V. (2020). Social Second Screen: WhatsApp and Watching the World Cup. *Communication & Sport*, 8 (1), 123-141. DOI: 10.1177/2167479518821913

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