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DOCTORAL THESIS

Performance Evaluation of European Football

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PODEROSO CABALLERO ES DON DINERO

(Francisco de Quevedo y Villegas, 1906)

*Madre, yo al oro me humillo,
Él es mi amante y mi amado,
Pues de puro enamorado
Anda continuo amarillo.
Que pues doblón o sencillo
Hace todo cuanto quiero,
Poderoso caballero
Es don Dinero.*

*Nace en las Indias bonrado,
Donde el mundo le acompaña;
Viene a morir en España,
Y es en Génova enterrado.
Y pues quien le trae al lado
Es hermoso, aunque sea fiero,
Poderoso caballero
Es don Dinero.*

*Son sus padres principales,
Y es de nobles descendiente,
Porque en las venas de Oriente
Todas las sangres son Reales.
Y pues es quien hace iguales
Al rico y al pordiosero,
Poderoso caballero
Es don Dinero.*

*¿A quién no le maravilla
Ver en su gloria, sin tasa,
Que es lo más ruin de su casa
Doña Blanca de Castilla?
Mas pues que su fuerza humilla
Al cobarde y al guerrero,
Poderoso caballero
Es don Dinero.*

*Es tanta su majestad,
Aunque son sus duelos hartos,
Que aun con estar becho cuartos
No pierde su calidad.
Pero pues da autoridad
Al gañán y al jornalero,
Poderoso caballero
Es don Dinero.*

*Más valen en cualquier tierra
(Mirad si es harto sagaz)
Sus escudos en la paz
Que rodelas en la guerra.
Pues al natural destierra
Y hace propio al forastero,
Poderoso caballero
Es don Dinero.*

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Chapter 1:

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Introduction

Sport is a cultural phenomenon of indisputable social, political, and economic impact, and football (soccer, in North America) is the world's most popular sport (Palacios-Huerta, 2004). This game has unrivalled worldwide appeal, and is the Roman circus of the present (Richter, 2016). Today the *Fédération Internationale de Football Association* (FIFA), the football world's governing body, has more national members than the United Nations (UN) (Szymanski, 2014).

The game's nature is basically eleven against eleven kicking the ball. It seems to be simple, but football performance analysis (PA) has inherent problems, being a multifaceted and often uncontrollable phenomenon. There is a huge difference between football and other team sports. Handball, baseball, basketball, and volleyball are more predictable than football (Anderson and Sally, 2013). There are a lot of factors that contribute to its unpredictability: the number of players involved, the tactical possibilities, the low number of actions that count towards the final score, etc. In more predictable sports the probability of the strongest team defeating the weakest is higher (Anderson & Sally, 2013). Perhaps the possibility of small clubs defeating the big ones could explain why football moves crowds.

Football is practised and followed around the world. Europe and then Latin America were the first places where it became very popular; however, powerful leagues are growing in Asia, many star players come from Africa, and in North America there are more teenagers kicking footballs than hitting baseballs nowadays. Besides local consumers, television, media, and social networks feed the unstoppable growth of fans' interest in a global market. The Union of European Football Associations (UEFA) Champions League (UCL) and the FIFA World Cup are among the world's top-watched sporting events. Not surprisingly, star players are often more famous than religious and political leaders; thus, football has become an important medium to secure brand visibility and many corporations consider it key to gaining a

global market share for their products. Indeed, football is often considered one of the most important social phenomena of the 20th century (Palacios-Huerta, 2004).

As the game has become a business, sports economics was born as a research area. Seminal papers such as Rottenberg's (1956) on baseball player's labour market, Neale (1964) about the peculiar economics of professional sports, Sloane (1971) about the football club as a utility maximizer, and Scully (1974) on pay and performance in Major Baseball League shaped the early direction of the field.

Almost three decades later, Szymanski and Kuypers (1999) have deepened understanding of fundamental issues of sports teams' economic performance that were previously studied by Sloane (1971) and Scully (1974). The strong relationships between wages and sports results, and between sports results and revenue of sports teams, were discussed. These relationships are the basis of clubs' survival and success. In this cycle, a strong squad achieved good performance on-field that helped clubs to increase their revenue, which in turn, will enable clubs to hire or maintain the best players, and so on. This basic relationship is the basis of management and the financial-economic structure of football clubs (Szymanski & Kuypers, 1999; and Carmichael et al., 2011).

Football clubs' first objective, like that of any organization, is survival. This will depend on the sports system and the rules that the club is subject to. In Europe, the promotion and relegation system enables the clubs with the best performance on-field to stay on top; however, clubs with low sports performance are relegated to a lower category. So, until recently, European clubs had to win to survive. Garcia-del-barrio and Szymanski (2009) have found that Spanish and English clubs' choices are more closely approximated a by win maximization objective than by profit maximization. In this sense, the small clubs' purposes are different from those of big clubs. In regular leagues, the smalls clubs' aim used to be to maintain their category, medium clubs aimed to qualify for European competitions (UCL and UEFA Europa League), and the big clubs' objective was to win the league. In the case of European competitions, with a knockout structure, weaker clubs have more chances to defeat the favorites in one or two matches than in round-robin (league) competitions, where regularity is rewarded and usually the strongest teams are favored.

In 2006, it was rumoured that there was a general financial crisis in European football, the main highlighted causes being the imbalance between income and expenditures and the clubs' rising debt (Lago

et al., 2006). The fact that European football clubs are win maximizers make them more aggressive when competing for talented players than professional teams on other continents. This competition for the best players, leads European clubs to spend more resources than they can afford (Solberg & Haugen, 2010).

The first measures to solve the financial problems of European football began in 1999, and the Financial Fair Play (FFP) regulations were approved by the UEFA Executive Committee in May 2010 and in May 2012 to protect the long-term viability and sustainability of European football. The first full implementation of the FFP rules, with clubs being assessed against the break-even requirement for the first time, was in 2013; in 2015 the first club was not admitted to a UEFA club competition due to non-fulfilment of the break-even requirement (Barajas & Rodriguez, 2014; and UEFA, 2015).

This restrictive scenario forced clubs to reconsider the prices they had been paying for players (transfer fees, salaries, and wages), and how they manage their resources. Based on that, the general objective of this doctoral thesis is to evaluate the performance of European football clubs. The performance evaluation measures how an organization (decision-making unit, DMU, or a club in this case and henceforth) develops its activity, attempts to compare its performances with others, and also tries to identify which actions are working or not. So, to know and understand how to interpret this evaluation, it will be imperative to improve the clubs' performance. In order to carry out this main purpose, efficiency analysis and benchmarking will be the main tools for assessing clubs' management and performance. In the experiential process of this thesis, I will attempt to answer the questions that emerge from the successive analyses. A better understanding of the peculiarities of football clubs' production process and the issues that remain contentious in this field could be helpful for clubs, leagues and governing bodies.

I will analyse European football clubs in three different scenarios and employ different methodologies, which will allow me obtain a more detailed and accurate view of their performance. This thesis is structure into three blocks, and five self-contained chapters. The first block analyses the efficiency of clubs that participate in the UCL and consists of chapter 1 and 2. The second block is dedicated to a comprehensive analysis of English Premier League (EPL) clubs and is developed in chapter 3 and 4. Finally the third block analysed the determinants of sport performance of the football clubs playing in the "Big Five" European leagues (the English *Premier League*, the German *Bundesliga*, the Spanish *Liga*, *Serie A* Italian *Calcio*, and the French *Ligue 1*).

The most prestigious competition at the club level is the UCL, however it has received minor attention in the PA literature. **Chapter 1**, entitled **performance evaluation in the UEFA Champions League**, aims to evaluate sports performance of teams that have participated in the UCL during the 10 seasons (2004/05 to 2013/14). Technical efficiency is estimated using well-known data envelopment analysis (DEA) approaches and in order to test the robustness of our results a bootstrapped DEA model has also been employed. To solve the problem of measuring sporting results as output in knockout competitions, the use of the coefficients applied by the UEFA from UCL revenue distribution is proposed. In **Chapter 2**, which examines the **calculation of efficiency in European football teams using Window DEA**, the best practises and evolution of the sports efficiency of football clubs playing in the UCL in the 2004/05-2012/13 period are analysed. As the sample is panel data, we propose a research procedure to find the most accurate methodology to analyse its efficiency. The S statistic was employed to check for temporal trends and the Kruskal-Wallis statistic was run to analyse stability in relative ranks. We detected a temporal trend, and teams did not maintain their relative rankings over time. According to these results, Window Data Envelopment Analysis (WDEA) emerges as the most appropriate method to estimate the efficiency of UCL teams. The WDEA efficiency score estimates could be used to evaluate teams' robustness and analyse the evolution of their efficiency more rigorously.

After analysing the performance of the UCL clubs following the approaches used in the literature, a ground-breaking approach was proposed. Currently, professional football clubs exist thanks to their fans, who through live attendance and viewing online or on television impact on revenue and sport results. So, in order to enable an analysis of the clubs' performance as a whole, we included two measures of fans' impact in our model. To this end, the EPL was chosen because it is one of the world' most important regular football leagues and because of the availability of reliable and quality data.

The second block of the thesis starts with **Chapter 3**, entitled "**And if the ball does not cross the line? A comprehensive analysis of football clubs' performance.**" This comprehensive approach is proposed because the football clubs' market is changing fast in the social media era. In this global market, clubs must maintain or improve fans' attendance at the stadium; simultaneously, they need, more than ever, to take care of social media. The aim of this study is to test and discuss a comprehensive approach to analysing the performance of football clubs regarding their multiplicity of objectives. We analyse the

efficiency of EPL clubs during three seasons (2012/13–2014/15). The methodologies employed are data envelopment analysis (DEA) and a bootstrapped DEA model. **Chapter 4** is entitled **Performance analysis with ex-ante and ex-post inputs in the Premier League**, and discusses whether **managers are as efficient as coaches**. The existing controversy in the sport performance literature about what type of inputs might explain more deeply the performance of sports clubs (inputs specification controversy) is analysed and discussed in this chapter. On one hand, several papers have analysed sports teams' performance using match-related statistics or wages as inputs (so-called ex-post inputs). On the other hand, some authors have criticized the use of these ex-post inputs, and recommend the use of ex-ante inputs, such as the market value of the players. To shed some light on this open discussion we have analysed the performance of football teams, estimating technical efficiency with three different input specifications (one ex-ante and two ex-post inputs). The methodologies employed were data envelopment analysis (DEA) and a bootstrapped DEA. Our sample is composed of EPL football clubs, whose performance over the course of three seasons (2012/13-2014/15) was examined.

There is not a secret successful formula hidden in numbers, nor a recipe to win, but there is a way to ensure if we are asking the right questions (Anderson & Sally, 2013). In this regard, a question that already existed since the first chapter has returned to intrigue, and become the focus of the last study of this thesis: Is there a combination of specific actions that relate to statistically significant differences between successful and unsuccessful teams? The multifaceted and complex nature of football highlighted before motivated **Chapter 5**, which is entitled **“Determinants of sport performance in European Football: What can we learn from the data?”** Today, game-related statistics are demanded by coaches, players, managers, journalists, supporters, fans and academics. Furthermore, we can't forget the “fantasy games” or video games sector and the sports betting market, where nobody plays with the importance of these data. This chapter analyses the importance of a large number of possible determinants of sport performance in the “Big Five” European football leagues during the period 2012/13-2014/15.

Instead of restricting our study to a single regression model estimation, we perform inference based on a Bayesian model averaging (BMA) econometric analysis; this eliminates the need to consider all possible models by constructing a sampler that explores relevant parts of the larger model space. The BMA approach has the advantage of minimising the likelihood of producing biased estimates and

artificially low confidence intervals (Moral-Benito, 2015). This analysis is complemented with relative importance metrics. Regression analysis is one of the most used statistical methods to analyse determinants of sport performance. Often, part of the research questions is the identification of the most important regressors. Most regression models are not specifically suited for answering the variable importance question, and although the topic is quite old, advances in computational capabilities have led to increased applications of computer-intensive methods like averaging over orderings that enable a reasonable decomposition of the model variance. Therefore, we have applied estimators of relative importance in linear regression based on variance decomposition proposed by Grömping (2007, 2015). This methodology will enable the assignment of shares of relative importance to each or to a set of regressors that is one of the key goals of applied studies.

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1. Performance evaluation in the UEFA Champions League

Abstract

This paper aims to evaluate the sports performance of teams that have participated in the UEFA Champions League (UCL) during the last 10 seasons (2004/05 to 2013/14). Technical efficiency is estimated using well-known data envelopment analysis (DEA) approaches and a bootstrapped DEA model. To solve the problem of measuring sporting results as output in knockout competitions, we propose the use of the coefficients applied by the UEFA from UCL revenue distribution. The results obtained show first that there is a high level of inefficiency in UCL over the period studied: only 10% of the teams seem to be efficient. Also, the teams have many problems in maintaining their efficiency during the seasons. Second, the champion is always efficient. Third, we identify two sources of inefficiency: waste of sports resources and the selection of sporting tactics. Finally, from a methodological perspective, the output measure proposed seems to be suitable to represent reliably the sports results achieved by clubs in this qualifying competition type; furthermore, our results are robust when applying alternative estimation methods. Regarding the results, some management implications are discussed and suggestions are made to boost efficiency in inefficient clubs.

Keywords: Efficiency; DEA; Football; UEFA Champions League; Sports results.

1.1. Introduction

In the 20th century, sport was established as a cultural phenomenon of evident social, political and economic impact. Today, football is one of the most important means of expression in sport, as well as being a business of undoubted economic importance. Born in Europe, today football is a global phenomenon, but is still dominated by European clubs. The UEFA² Champions League (UCL) is the most important competition at club level.

The football industry has changed significantly over the last two decades and economic survival has become increasingly important in recent years. In 2013/14, the aggregate revenue of the top 20 clubs was €6.2 billion, 14% more than in the previous season (Deloitte Football Money League, 2015). Nevertheless, high rates of growth cannot continue indefinitely. In 2012, the indebtedness of clubs was around €1 billion (UEFA Benchmarking Report, 2013/14).

A more restrictive future will force clubs to reconsider the prices they have been paying for players, their wages, and how they manage their resources. Based on this scenario, technical efficiency analysis and benchmarking emerge as potent tools for assessing clubs' management and sports performance; they could also be helpful to football clubs in making better use of sports and economic resources. The marked increase in academic research on sports efficiency confirms the relevance of this approach.

There is extensive literature on football efficiency, particularly for the most important national leagues in Europe (Barros & Douvis, 2009; Barros & Garcia-del-Barrio, 2008; Boscá, Liern, Martínez, & Sala, 2009; Espitia-Escuer & García-Cebrián, 2004, 2006; Haas, 2003; Gerrard, 2010; Ribeiro & Lima, 2012). However, studies on European competitions are sparse and not conclusive (Espitia-Escuer & García-Cebrián, 2010; Papahristodoulou, 2007).

² The Union of European Football Associations (UEFA) represents the national football associations of Europe, runs national and club competitions, including the UEFA European Championship, the UEFA Champions League, the UEFA Europa League, and the UEFA Super Cup, and controls the prize money, regulations, and media rights to those competitions.

Papahristodoulou (2007) observed only the 2005/06 UCL season with a limited sample of 32 clubs. Espitia-Escuer and García-Cebrián (2010), on the other hand, evaluated four seasons of UCL (2003/04–2006/07). Nevertheless, both studies use questionable variables to measure sports performance results. Papahristodoulou (2007) considered mainly the variables of goals scored and points won as outputs. Espitia-Escuer and García-Cebrián (2010) selected the number of games played as the output measure. However, in knockout competitions, these variables have some limitations in measuring sports results. For example, in terms of the number of games played, the champion and the runner-up would have the same result.

This paper tries to overcome these limitations by considering a wider sample of seasons and clubs, as well as new performance variables. In particular, the main objective of this paper is to determine the technical efficiency of the sport through the analysis of a wide time horizon (10 seasons), and tries to provide useful information on the sources of the clubs' inefficiency. This more robust analysis provides accurate, objective and relevant information, which can help in the decision making of coaches and managers, and thus lead to the improvement of football clubs' efficiency.

This work contributes to previous research in several ways. First, our study considers a sample of teams that have participated in UCL over 10 seasons (2004/05 to 2013/14). This is the first time that such long-term data have been used in this context, allowing us to examine the changes in efficiency among the clubs and seasons. Second, we use a new measure of sports output, which gives us more representative and more reliable efficiency rankings and overcomes some problems detected in previous evidence. The output measure proposed is the revenue obtained, according to the coefficients applied by UEFA for UCL revenue distribution regarding sports performance. Third, we have estimated the technical efficiency using traditional data envelopment analysis (DEA) models and a DEA bootstrapping approach, which allows us to test the robustness of our results.

The remainder of this article is structured as follows. The next section introduces the football teams' production process through a review of empirical studies, thus providing a framework for the research. The third section briefly describes the methodology and explains the output and input variables used. The results are presented in the fourth section. The last section discusses the results and concludes the paper.

1.2. Empirical Review and Study Framework

The most common way of assessing sports performance is simple observation of the outcome. When we evaluate performance considering the sports result as the outcome, this evaluation is undertaken from the perspective of effectiveness. The concept of effectiveness is related to the achievement of objectives, independently of the resources employed. For sport teams, as for most organizations, the assessment of the efficiency perspective is really important.

In general terms, efficiency can be understood as the lack of waste. This definition is rather too general, but some types of efficiency can be distinguished. Technical efficiency in a production unit refers to the achievement of the maximum potential output from given amounts of factor inputs, or the minimum input required to obtain a given level of output. It is important to note that this concept involves physical quantities and technical relationships (Coelli, Rao, O'Donnell, & Battese, 2005). On the other hand, the concept of allocative efficiency involves issues such as costs. In this paper, our interest is in the little known or studied technical efficiency of the clubs that play at the highest level of European football. Through technical efficiency analysis, evaluating the performance of a club in relation to other clubs that compete in the same context could help in decision making concerning which tactics to employ, the use of sports resources, and the signing of players with characteristics that the team specifically needs.

From an economic perspective, the transformation of inputs into outputs is a production process described by a production function. The estimation of the production function to measure the relationship between teams'/players' success and game-related statistical inputs has

been undertaken by many researchers (e.g., Boscá et al., 2009; Tiedemann, Francksen, & Latacz-Lohmann, 2011; Zak, Huang, & Siegfried, 1979; amongst others). The performance on the field is the core of football clubs' production function. As we can observe in Figure 1.1, in the first stage, a squad and coaching staff with their given skills and characteristics, will train through their pre-match work (technical, tactical, and physical workouts) to produce attack and defense plays. In the second stage, during the match, the combination of these plays will generate an outcome, which could be goals, wins, points, etc., depending on the context to be analyzed. Works such as those of Schofield (1988) in cricket, Carmichael and Thomas (1995) in rugby, and Carmichael, Thomas, and Ward (2000) in football, have followed this framework in which the production function in sports is composed of two different stages. Here, we propose to analyze the efficiency of the second stage of the production process of clubs participating in the UCL. Recent papers have also followed this framework (Espitia-Escuer & García-Cebrián 2004, 2006, 2010; Torres-Dávila & García-Cebrián, 2012).

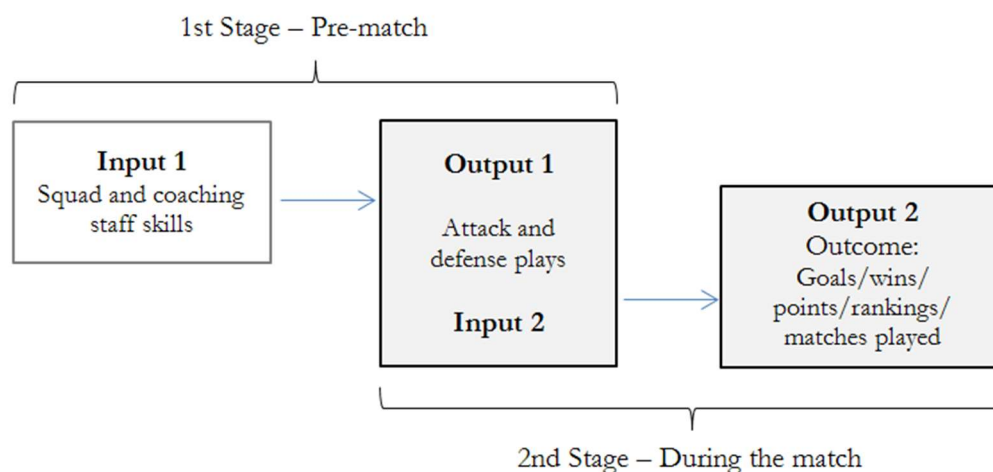


Figure 1.1: Football Production Process (own elaboration adapted from Espitia-Escuer & García-Cebrián, 2004).

A systematic review of the literature allows us to observe that there is an extensive body of work that assesses the performance of European national leagues (Barros & Douvis, 2009; Barros & Garcia-del-Barrio, 2008; Boscá et al., 2009; Espitia-Escuer & García-Cebrián, 2004, 2006; Gerrard, 2010; Haas, 2003; Ribeiro & Lima, 2012). Boscá et al. (2009) conclude that to obtain a

better classification in the Italian league, it is more important to improve defensive efficiency than attack positions; on the other hand, they found that to improve the ranking in the Spanish league, the most rewarding strategy consists of improving offensive efficiency. Espitia-Escuer and García-Cebrián (2004) analyzed the efficiency of the Spanish first division teams in converting attack moves during the match into sporting success. They concluded that the efficient teams are not always those that finish highest in the league at the end of the season.

Outside Europe, there are also studies on national leagues. Torres-Dávila and García-Cebrián (2012) analyzed the technical efficiency of the Mexican league, a tournament with a similar format to that of the UCL. They found a high level of inefficiency, caused for the most part by the wrong tactical choices rather than wasted resources. For all the seasons and tournament phases analyzed, the correlation between the efficiency scores estimated and the sports results obtained were significant.

As far as we know, only Papahristodoulou (2007) and Espitia-Escuer and García-Cebrián (2010) have estimated the efficiency of UCL teams. The particular aspects of eliminating competitions, such as the high level of uncertainty concerning the outcome and the diversity of the teams participating each year (which characterize unbalanced panel data), could be the main reasons for the lack of studies in this context.

Papahristodoulou (2007) estimated efficiency with different sets of inputs, and found that for the season analyzed (2005/06) only three teams were efficient in all sets of estimations made; two of these were the finalists (the winner and the runner-up). Espitia-Escuer and García-Cebrián (2010) concluded that in the UCL there were no different dominating tactics in the period observed (2003/04–2006/07), but there was a general wasting of resources.

1.3. Methodology and Data

1.3.1. Methodology

The concept of relative efficiency proposed by Farrell (1957) measures the efficiency of an organization or decision-making unit (DMU), comparing its performance to that of the best companies observed, which defines the efficient frontier. From the empirical review, we have identified two main different approaches to analyzing efficiency: the parametric or econometric approach, and the non-parametric approach. In the parametric approach, the stochastic frontier is the most popular methodology (Barros & García-del-Barrio, 2008; Barros & Leach, 2006b; Hofer & Payne, 2006; Zak et al., 1979, amongst others). In a non-parametric approach, DEA is most commonly applied (Barros & Leach, 2006a; Bosca et al., 2009; Espitia-Escuer & García-Cebrián, 2004; Hass, 2003, amongst others).

Charnes, Cooper and Rhodes (1978) were the first to use the term DEA, applying linear programming methods to construct a non-parametric frontier for the data. Their basic model, known as the Charnes–Cooper–Rhodes (CCR) model, assumes constant returns to scale (CRS) to estimate the technical efficiency (TE) scores of the DMUs. This model may be oriented toward input minimization or output maximization. Given the characteristics of our output variable, which cannot grow indefinitely and is regulated, we have assumed an input-oriented model in this paper. Therefore, assuming CRS and input minimization, the technical efficiency of each DMU of the sample can be obtained by solving the following linear programming problem:

$$\begin{aligned} & \text{Min}_{\lambda, z} \lambda_{1i} \\ \text{s.a.} \quad & u_i \leq z_i U \\ & \lambda_{1i} x_i \geq z_i X \\ & z \in R_+^k \end{aligned} \tag{1.1}$$

where λ_{1i} is the technical efficiency index considering an input orientation; u_i is the vector that represents the quantities of m products produced by organization i ; U is the matrix of the range

$k \times m$, which represents the quantities of m products for the k organizations in the sample; x_i are the quantities of the n production factors used by the organization the efficiency of which is being measured; X is the matrix of the range $k \times n$ for the quantities of n production factors used by the companies in the sample; z_i is a vector of intensity parameters that determines the combinations of factors and products observed. When $\lambda_{1i} = 1$, the organization analyzed is on the efficient frontier and it is impossible to obtain its production vector with a radial reduction of all its resources, that is to say, it is technically efficient. The technical efficiency value indicates the radial reduction that could be implemented in the consumption of production factors by the unit studied to be efficient. If $\lambda_{1i} < 1$, it indicates the proportion by which the quantity of all inputs used could be reduced radially to achieve the actual output quantity, but in an efficient manner, i.e., without wasting resources.

Banker, Charnes and Cooper (1984) proposed an adjustment to the CRS model in which variable returns to scale (VRS) are assumed. Their model, known as the Banker–Charnes–Cooper (BCC) model, allows the calculation of pure technical efficiency (PTE). The use of the VRS specification is indicated for the efficiency calculation when not all DMUs are operating at the optimal scale. The linear programming problem to be solved in this case constructs the reference unit from units of a similar size/technology³, which leads to the following formula:

$$\begin{aligned}
 & \text{Min}_{\lambda, z} \lambda_{2i} \\
 \text{s.a.} \quad & u_i \leq z_i U \\
 & \lambda_{2i} x \geq z_i X \\
 & \sum z_i = 1 \\
 & z_i \in R_+^k
 \end{aligned} \tag{1.2}$$

³ Usually in the DEA literature, the size of a unit is related to the different technologies that may exist to make a product. In this specific case, analyzing football clubs through the use of true variables, such as sports variables, technology refers to the different types of play, namely the tactics employed. When the term “size” is employed in this paper, it refers to the tradition and the “financial-economic” size of the football clubs, as with regular companies.

where λ_{2i} is the PTE of the unit studied. The PTE value indicates the radial reduction that could be implemented in the consumption of production factors by the unit studied to be efficient compared to those of units with similar technology (or, in this specific case, tactics). Thus, if we have $\lambda_{1i} < 1$ and $\lambda_{2i} = 1$, it indicates an appropriate use of the resources without waste, and any inefficiency is due to the choice of the wrong tactics. The scale efficiency (SE) is given by the ratio between the TE score and the PTE score. Generally, if $SE = 1$, this means that the DMU operates at the optimal scale. Otherwise, if $SE < 1$, the DMU is not operating on the most productive scale size (technology).

Non-parametric models, such as DEA, have significant advantages. DEA has greater discriminatory power than other models, and has proved especially valuable when non-marked inputs or outputs are being considered and the correct weighting of inputs and outputs cannot be defined. Also, compared to the stochastic frontier, it is not necessary to prespecify the functional form in the estimation of the production frontier, nor does it require large sample sizes. Nevertheless, DEA also suffers from some limitations; it has been labelled deterministic because it does not allow for statistical inference, and this could result in DEA overestimating efficiency scores.

The inability to allow for random errors in efficiency measurements has also been considered one of its main drawbacks (Simar & Wilson, 2013). One way to overcome this limitation is by using bootstrapping methodology, introduced in this context by Simar and Wilson (1998). In this way, it is possible to estimate bias-corrected DEA scores and obtain confidence intervals. The method relies on applying DEA with a pseudo dataset, resampling the original DEA efficiency scores and repeating it many times.

To test the sensitivity of the measured efficiency scores to the sampling variation, we also estimated the bias-corrected DEA and present the correlation between the two methodologies. In the sports context, the use of DEA bootstrapping methodology is relatively new. As far as we

know, only Barros et al. (2010), Barros and Garcia-del-Barrio (2011) and Halkos and Tzeremes (2013) have employed it to analyze the efficiency of football clubs. However, none of these studies measured the technical efficiency of on field performance.

1.3.2. Data and Variables

The UCL is Europe's top international football competition at club level. Initially contested by the national league's champions, it now has several qualifiers. The UEFA coefficient system⁴ provides the criteria to access the group stage directly or to go through to the qualifier rounds. The competition itself starts with the group stage, consisting of eight groups with four teams each. All teams meet with the others in their group twice, in matches as host and visitor. The two highest ranked teams in each group advance to the next stage. With sixteen teams qualifying for the second round, the knockout stage comprises double matches, home and away, with the winner advancing to the next phase; this continues in the same way until the semi-final. The final, exceptionally, is played as a single match at a field chosen a year earlier.

The sample consists of the 32 clubs qualifying for the UCL group stage in each of the 10 sports seasons between 2004/05 and 2013/14, totaling 320 units of observation. Some of these 320 DMUs are the same club in different seasons. Many clubs participated only once in the competition during the study period; however, a select group, consisting of Arsenal, Barcelona, Chelsea, Manchester United, and Real Madrid, participated in all 10 seasons analyzed. Therefore, there are 97 different clubs in the sample.

The actions taken by teams during the match are the core of football clubs' production process. As we can see from the study framework, the attack and defense plays are the input in the second stage, and produce an outcome that will lead to advancement in the next phase of the UCL in our case. The inputs selected are the attempts on target, ball possession, total passes, and ball recoveries; the descriptive statistics of the variables are presented in Table 1.1.

⁴ More information on the competition format and the UEFA coefficient system is available from <http://www.uefa.com/memberassociations/uefarankings/index.html> (accessed 7 November 2014).

Table 1.1. Descriptive Statistics of the Data Used

Season	Inputs				Output	
	Attempts on target	Ball recoveries	Ball possession	Passes	Sports results	
2004/05	Max	69	690	375	5,684	17.374
	Min	16	210	119	1,717	3.57
	Average	36.75	373.59	209.63	3,217.34	6.49
	SD	16.08	135.31	69.77	1,202.08	3.26
2005/06	Max	90	748	390	7,358	18.14
	Min	12	234	132	2,037	3.9
	Average	36.72	404.81	200.47	3,411.47	6.78
	SD	18.59	136.12	66.73	1,314.26	3.31
2006/07	Max	81	750	352	6,826	22.2
	Min	15	274	129	2,222	5.4
	Average	37.97	427.19	197.34	3,489.41	9.64
	SD	16.50	137.53	62.70	1,248.03	4.02
2007/08	Max	82	813	401	7,791	23.4
	Min	15	278	128	2,206	5.4
	Average	37.22	436.69	204.41	3,622.34	9.64
	SD	18.00	138.08	71.67	1,388.51	4.19
2008/09	Max	92	769	428	8,305	22.8
	Min	12	298	117	1,971	5.7
	Average	37.72	435.72	199.84	3,579.66	9.64
	SD	19.33	136.20	78.58	1,509.37	4.09
2009/10	Max	83	695	445	8,798	29.5
	Min	10	243	118	1,798	7.2
	Average	36.78	408.47	195.94	3,432.56	12.91
	SD	18.04	135.92	80.45	1,558.50	5.47
2010/11	Max	97	984	504	9,916	30.7
	Min	13	364	119	2,093	7.2
	Average	39.91	540.41	205.44	3,938.50	12.91
	SD	20.25	164.32	84.70	1,701.69	5.74
2011/12	Max	106	994	472	9,932	29.9
	Min	15	340	121	2,161	7.2
	Average	40.75	546.59	206.97	4,037.72	12.91
	SD	23.72	172.35	83.84	1,737.92	5.58
2012/13	Max	90	960	472	9,852	35.9
	Min	12	344	99	1,888	9.1
	Average	39.97	534.53	208.13	4,076.38	15.47
	SD	20.36	163.86	77.57	1,616.82	6.64
2013/14	Max	99	974	444.22	9,247	36.9
	Min	13	352	116.37	2,153	8.6
	Average	37.25	538.06	205.64	4,107.66	15.47
	SD	20.22	168.71	80.88	1,782.73	6.82

Notes: Max: maximum; Min: minimum; SD: standard deviation

The attempts on target, both shots and halts, are the completion of the offensive plays of a team. Lago-Peñas, Lago-Ballesteros, and Rey (2011) analyzed the group stage matches of three UCL seasons (2007/08–2009/10), showing that winning teams have significantly higher average values for shots on goal than losing teams. Similarly, Delgado-Bordonau, Domenech-Monforte, Guzmán, and Mendez-Villanueva (2013) studied matches played by teams playing in the 2010 Soccer World Cup and Lago-Peñas, Lago-Ballesteros, Dellal, and Gómez (2010) analyzed those in the Spanish soccer league (2008/09 season), finding that winning teams have significantly higher average values for attempts on target than losing teams.

The minutes of ball possession and total passes represent the volume of play of a team, providing valuable information on which team dominates the match, or shows more initiative and intent to have control of the ball. Lago-Peñas et al. (2011) conclude that ball possession is an indicator of success in the UCL. Other papers that have used these indicators as input measures are Carmichael et al. (2000), Espitia-Escuer and García-Cebrián (2006, 2010) Papahristodoulou (2007), Bosca et al. (2009), Carmichael, McHale, and Thomas (2011), and Tiedemann et al. (2011).

Ball possession could have potential limitations as a measure in assessing the development of tactics in opposition sports. A team that plays a counter-attack may not take the initiative to gain possession of the ball, instead counting on its players' speed and capacity to counter attack. A team following this tactic could be fairly efficient, if it manages to turn counter-attacks into goals. Thus, to overcome this limitation, ball recovery is an important indicator of an active attitude in relation to controlling the match. Furthermore, this variable can be a substitutive input for ball possession, because if a team has possession of the ball for much of the game, it will therefore have fewer opportunities to recover the ball, and vice versa. Therefore, ball recovery, which could be considered a defensive play or the first step in an attack play (Barreira, Garganta, Guimarães, MacHado, & Anguera, 2014), is the fourth input measure used in our model.

If there is a point on which there is a consensus in the literature, it is that the output variable must be sporting performance, or one of them in the case of more than one output. In national regular leagues, the most common way to measure this outcome is through the points achieved. When it is a mixed tournament, consisting of a group stage and a knockout phase, the selection of the variable is more complicated. González-Gómez and Picazo-Tadeo (2010) observed three tournaments played by Spanish clubs, taking as the output the points achieved, the number of rounds played for the cup, and the number of games played in European competitions (UCL and UEFA Europa League). Torres-Dávila and García-Cebrián (2012) used the points for the group stage and the games played in the knockout phase to study separately Mexican national league phases. Finally, Espitia-Escuer and García-Cebrián (2010) used the number of games played to evaluate the technical efficiency of clubs in the UCL. This number represents teams' progress in the competition, which is the main objective in this competition type. A team that reaches round 16, for example, has an output of eight games, six in the group stage and two in the second round.

In the UCL case, using the number of games played results in all the clubs involved in the group stage having the same output, regardless of whether they won, tied or lost in the respective matches. The same is true for the finalists, the winning team and the runners-up, as they play the same number of matches. Thus, using the number of games played would introduce bias in the performance evaluation. To solve the problem of measuring sporting results in knockout competitions, we propose the use of the coefficients applied by UEFA from UCL revenue distribution. These coefficients will thus be the output variable used in our paper. This output measure fully preserves the order of the final ranking in the competition, overcoming some limitations shown by previous studies.

The distribution of UCL revenues is as follows. A fixed part of the amount of revenue⁵ from media rights and commercial contracts is allocated to clubs, and corresponds to the sports results achieved. The group stage participation and performance are rewarded, adding a bonus for wins or draws. At the knockout stage, they are rewarded with a pass to the next phase. The other part concerning revenue is variable, depending on the market pool, and is not related to sports performance, and therefore does not matter in this work. For all analyzed periods, the prizes assigned respect the same criteria (as can be seen in Appendix A, a summarized table of the evolution of prize values). Participation in each phase and the performance in the group stage are rewarded. As the contracts with sponsors and television companies are negotiated by the UEFA in three-year cycles, the prize values also change in the same cycles.

The data employed to estimate the calculations in this study come from different sources. The data related to the quantity of inputs used by the teams, which refer to the plays performed, have been supplied by OPTA Sports, a company with one of the largest sports databases on European football. For previous works using OPTA Sports data, see Carmichael et al. (2000), Boscá, et al. (2009), Espitia-Escuer and García-Cebrián (2010), and Carmichael et al. (2011). On the other hand, the output variables, for which the sports results are taken and related to the respective prize distributed by UEFA, were obtained directly from the official UEFA website (www.uefa.com) and [UEFADirect](#), UEFA's official magazine.

1.4. Results

The results of the DEA for TE, PTE, and SE are detailed in section 1.4.1. To test the sensitivity of the efficiency scores to sampling variation, we have also estimated the bias-corrected DEA. In section 1.4.2, we present the correlations between the two methodologies.

⁵ UEFA negotiates agreements with sponsors and television companies in 3-year cycles. Some 75–82% of the total revenue from media rights and commercial contracts concluded by UEFA goes to the clubs, while the remaining 25–18% is reserved for European football and remains with UEFA to cover organizational and administrative costs, and solidarity payments to associations, clubs, and leagues. What defines the exact value of these figures is the revenue of each period; for the 2012/13 season, for example, up to a maximum of €530 million, 75% was earmarked for the clubs, and any revenue in excess of this value raised the clubs' proportion to 82%.

1.4.1. Results of TE, PTE, and SE

The results for each season are depicted sorted by sporting performance in Table 1.2. For ease of comparison, the lines separating clubs in the results table represent the final stage in which clubs are ranked in each season. From top to bottom these are: final (champion and runner-up), semi-finals, quarterfinals, knockout round, and group stage. Following the methodology described in the previous section, we introduce the results using a similar approach. First, the TE results are presented, stressing the more efficient seasons and the efficient DMUs. Second, the inefficient cases ($TE < 1$) are decomposed. On the one side, cases characterized by $PTE = 1$ and $SE < 1$ identify those DMUs that did not waste resources. On the other side, cases for which $SE = 1$ and $PTE < 1$ represent good tactical choices, but wasted resources. Finally, cases that are inefficient in both estimates ($PTE < 1$ and $SE < 1$) are also described and decomposed.

In terms of TE, an analysis of the results along the seasons studied in this paper reveals that there is a high degree of inefficiency in the UCL. Only 33 DMUs – 27 clubs as some appear more than once – have a TE ratio equal to one in a season (less than 10% of all DMUs observed, highlighted gray in Table 2). The 2010/11 season is the most efficient of all those observed. This season has the best TE average (0.87) and is the one with the highest number of efficient clubs: six in total. The 2008/09 season also shows six efficient clubs, with an average of 0.86; in 2013/14 the clubs attain the same average, but with fewer efficient observations (four). In 2004/05, only one club has a TE ratio equal to one and the average TE is the lowest (0.70) in the sample.

Table 1.2. Efficiency Scores for Teams Playing in UEFA Champions League

UCL 2004-05				UCL 2005-06				UCL 2006-07				UCL 2007-08				UCL 2008-09			
DMU	TE	PTE	SE	DMU	TE	PTE	SE	DMU	TE	PTE	SE	DMU	TE	PTE	SE	DMU	TE	PTE	SE
Liverpool	1.00	1.00	1.00	Barcelona	1.00	1.00	1.00	Milan	1.00	1.00	1.00	Man. United	1.00	1.00	1.00	Barcelona	1.00	1.00	1.00
Milan	0.87	0.88	<u>0.99</u>	Arsenal	1.00	1.00	1.00	Liverpool	1.00	1.00	1.00	Chelsea	0.83	0.85	<u>0.98</u>	Man. United	0.92	0.97	0.95
Chelsea	0.81	0.85	<u>0.95</u>	Villarreal	0.91	1.00	0.91	Chelsea	0.87	0.90	<u>0.96</u>	Barcelona	0.78	0.83	<u>0.95</u>	Chelsea	0.88	0.91	0.97
PSV Eindhoven	0.66	0.71	<u>0.94</u>	Milan	0.79	0.83	<u>0.95</u>	Man. United	0.77	0.80	<u>0.96</u>	Liverpool	0.72	0.77	<u>0.93</u>	Arsenal	0.83	0.90	0.92
Juventus	0.64	0.73	0.88	Lyon	0.80	0.88	0.91	Valencia	0.85	0.87	<u>0.98</u>	Arsenal	0.70	0.78	<u>0.91</u>	Liverpool	0.89	0.89	<u>0.99</u>
Internazionale	0.68	0.75	0.90	Juventus	0.77	0.79	<u>0.98</u>	Bayern Munich	0.78	0.81	<u>0.96</u>	Roma	0.75	0.84	0.90	Bayern Munich	0.87	0.88	<u>0.99</u>
Lyon	0.71	0.78	<u>0.91</u>	Internazionale	0.83	0.85	<u>0.98</u>	PSV Eindhoven	0.89	1.00	0.89	Fenerbahçe	0.75	0.81	<u>0.92</u>	Porto	0.91	0.94	0.97
Bayern Munich	0.75	0.83	0.91	Benfica	0.81	0.90	0.90	Roma	0.85	0.86	<u>0.99</u>	Schalke	0.74	0.83	0.90	Villarreal	0.80	0.82	<u>0.98</u>
Werder Bremen	0.70	0.80	0.87	Liverpool	0.79	0.89	0.89	Lyon	0.84	0.91	0.92	Internazionale	1.00	1.00	1.00	Juventus	1.00	1.00	1.00
Monaco	0.72	0.84	0.85	Bayern Munich	0.72	0.86	0.84	Porto	0.84	0.92	0.92	Sevilla	0.75	0.86	0.87	Atlético Madrid	0.97	0.99	0.98
Man. United	0.71	0.86	0.83	Chelsea	0.78	0.85	0.91	Real Madrid	0.79	0.87	0.91	Milan	0.71	0.83	0.86	Sporting Lisboa	1.00	1.00	1.00
Arsenal	0.67	0.79	0.85	Ajax	0.72	0.82	0.87	Arsenal	0.77	0.82	<u>0.94</u>	Olympiacos	0.86	0.97	0.89	Roma	0.96	0.99	0.97
Real Madrid	0.60	0.70	0.86	PSV Eindhoven	0.95	0.98	0.97	Barcelona	0.75	0.81	<u>0.92</u>	Porto	0.77	0.87	0.88	Lyon	0.94	0.95	1.00
Bayer Leverkusen	0.60	0.70	0.85	Real Madrid	0.65	0.77	0.85	Internazionale	0.84	0.89	0.94	Real Madrid	0.66	0.77	0.86	Real Madrid	0.76	0.79	<u>0.96</u>
Barcelona	0.67	0.78	0.86	Rangers	0.87	0.93	0.94	Lille	0.81	0.91	0.89	Lyon	0.72	0.85	0.85	Panathinaikos	0.89	0.93	0.96
Porto	0.71	0.83	0.85	Werder Bremen	0.70	0.85	0.83	Celtic	0.87	0.88	<u>0.99</u>	Celtic	0.82	0.92	0.89	Internazionale	0.80	0.83	<u>0.96</u>
Dynamo Kyiv	0.80	1.00	0.80	Schalke	0.78	0.98	0.80	Werder Bremen	0.87	0.97	0.89	PSV Eindhoven	0.91	1.00	0.91	Dynamo Kyiv	1.00	1.00	1.00
Olympiacos	0.75	0.99	0.76	Club Brugge	1.00	1.00	1.00	CSKA Moscow	1.00	1.00	1.00	Rangers	0.91	1.00	0.91	Shakhtar Donetsk	0.90	0.96	0.95
Panathinaikos	0.68	0.91	0.75	Udinese	0.82	1.00	0.82	AEK	0.89	1.00	0.89	Rosenborg	0.80	0.93	0.85	Werder Bremen	0.75	0.91	0.82
Fenerbahçe	0.71	0.90	0.79	Betis	0.67	0.84	0.80	Copenhaguen	0.92	1.00	0.92	Sporting Lisboa	0.73	0.94	0.78	Anorthosis	1.00	1.00	1.00
Valencia	0.78	0.99	0.79	Lille	0.95	0.97	0.98	Bordeaux	0.90	0.95	0.95	Marseille	0.73	0.88	0.83	Aalborg	0.89	0.95	0.93
CSKA Moscow	0.71	0.90	0.78	Artmedia	0.86	1.00	0.86	Benfica	0.89	0.99	0.90	Benfica	0.68	0.90	0.76	Fiorentina	0.88	0.92	0.95
Shakhtar Donetsk	0.70	0.90	0.77	Man. United	0.83	0.86	<u>0.97</u>	Shakhtar Donetsk	0.74	0.87	0.84	Besiktas	0.88	1.00	0.88	Bordeaux	0.85	0.99	0.86
PSG	0.68	0.97	0.70	Porto	0.80	1.00	0.80	Anderlecht	0.78	0.97	0.80	Shakhtar Donetsk	0.65	0.85	0.77	Celtic	0.86	1.00	0.86
Celtic	0.60	0.94	0.64	Rosenborg	0.91	1.00	0.91	Steaua Bucuresti	0.97	1.00	0.97	Werder Bremen	0.64	0.85	0.76	Zenit	0.72	0.87	0.82
Maccabi Tel Aviv	0.76	1.00	0.76	Thun	0.86	1.00	0.86	Sporting Lisboa	0.86	0.91	0.95	Slavia Praue	0.86	1.00	0.86	BATE Borisov	1.00	1.00	1.00
Ajax	0.62	0.81	0.76	Panathinaikos	0.81	0.94	0.86	Spartak Moscow	0.76	0.95	0.80	Valencia	0.82	0.94	0.87	CFR Cluj	0.82	0.93	0.89
Deportivo Coruña	0.78	1.00	0.78	Fenerbahçe	0.72	0.89	0.82	Olympiacos	0.70	0.91	0.77	Lazio	0.72	0.95	0.75	Marseille	0.70	0.86	0.81
Rosenborg	0.70	0.91	0.77	Olympiacos	0.67	0.91	0.73	Galatasaray	0.79	0.89	0.89	Stuttgart	0.57	0.84	0.67	Fenerbahçe	0.68	0.90	0.76
Roma	0.75	1.00	0.75	Sparta Prague	0.89	1.00	0.89	Dynamo Kyiv	0.69	0.93	0.74	Steaua Bucuresti	0.75	1.00	0.75	PSV Eindhoven	0.66	0.85	0.78
Sparta Prague	0.50	0.83	0.61	Anderlecht	0.77	0.99	0.77	Hamburg	0.66	0.90	0.74	CSKA Moscow	0.61	0.91	0.67	Basel	0.81	1.00	0.81
Anderlecht	0.49	0.76	0.65	Rapid Wien	0.64	0.93	0.69	Levski	0.73	0.96	0.75	Dynamo Kyiv	0.57	0.93	0.61	Steaua Bucuresti	0.71	0.93	0.77

Notes: DMU: Decision Making Unit; TE: Technical Efficiency; PTE: Pure Technical Efficiency; SE: Scale Efficiency. Highlighted values (TE=1); rectangle box values (TE<1 and PTE=1); underlined values (TE<1, PTE<1, and SE<1; very high TE value and low PTE value).

Table 1.2. (continued)

UCL 2009-10				UCL 2010-11				UCL 2011-12				UCL 2012-13				UCL 2013-14			
DMU	TE	PTE	SE	DMU	TE	PTE	SE	DMU	TE	PTE	SE	DMU	TE	PTE	SE	DMU	TE	PTE	SE
Internazionale	1.00	1.00	1.00	Barcelona	1.00	1.00	1.00	Chelsea	1.00	1.00	1.00	Bayern Munich	1.00	1.00	1.00	Real Madrid	1.00	1.00	1.00
Bayern Munich	0.90	0.92	0.99	Man. United	1.00	1.00	1.00	Bayern Munich	0.83	0.84	<u>0.99</u>	Bor. Dortmund	0.98	1.00	0.98	Atlético Madrid	1.00	1.00	1.00
Lyon	0.83	0.84	<u>0.99</u>	Real Madrid	0.93	0.94	0.99	Real Madrid	0.81	0.83	<u>0.97</u>	Barcelona	0.93	0.95	0.98	Bayern Munich	0.82	0.82	<u>1.00</u>
Barcelona	0.72	0.75	<u>0.96</u>	Schalke	1.00	1.00	1.00	Barcelona	0.84	0.87	<u>0.96</u>	Real Madrid	0.77	0.77	<u>0.99</u>	Chelsea	0.86	0.87	<u>1.00</u>
Bordeaux	0.92	0.95	0.97	Shakhtar Donetsk	0.94	0.96	0.99	Benfica	0.76	0.82	0.93	PSG	0.82	0.84	<u>0.98</u>	Man. United	0.91	0.94	0.97
Man. United	0.70	0.75	<u>0.93</u>	Chelsea	0.89	0.91	0.99	APOEL	1.00	1.00	1.00	Malaga	0.82	0.88	0.93	Barcelona	0.83	0.83	<u>1.00</u>
Arsenal	0.69	0.73	<u>0.93</u>	Tottenham	0.91	0.91	<u>1.00</u>	Milan	0.85	0.90	0.95	Juventus	0.79	0.79	<u>1.00</u>	PSG	0.83	0.86	0.96
CSKA Moscow	0.76	0.78	<u>0.97</u>	Internazionale	0.84	0.85	<u>0.98</u>	Marseille	0.82	0.82	<u>1.00</u>	Galatasaray	0.78	0.79	<u>0.98</u>	Bor. Dortmund	0.73	0.79	0.93
Chelsea	0.81	0.88	0.92	Bayern Munich	0.81	0.90	0.90	Napoli	0.95	0.99	0.96	Valencia	0.96	1.00	0.97	Man. City	0.87	1.00	0.87
Fiorentina	0.83	0.93	0.89	Valencia	0.78	0.81	<u>0.96</u>	Basel	0.86	0.94	0.92	Porto	0.80	0.81	<u>0.99</u>	Arsenal	0.98	0.99	0.99
Sevilla	0.78	0.87	0.90	Marseille	0.84	0.85	<u>0.98</u>	Arsenal	0.79	0.86	0.92	Schalke	0.75	0.76	<u>0.99</u>	Milan	0.96	0.99	0.97
Real Madrid	0.68	0.75	<u>0.90</u>	Arsenal	0.78	0.80	<u>0.98</u>	Bayer Leverkusen	0.82	0.87	0.94	Man. United	0.82	0.90	0.91	Olympiacos	0.96	1.00	0.96
Porto	0.75	0.84	0.90	Copenhaguen	0.98	1.00	0.98	Internazionale	0.77	0.90	0.86	Arsenal	0.90	1.00	0.90	Schalke	0.88	0.88	<u>1.00</u>
Olympiacos	0.79	0.89	0.89	Roma	0.91	0.93	0.97	Zenit	0.75	0.81	<u>0.93</u>	Celtic	0.87	0.87	<u>0.99</u>	Bayer Leverkusen	0.81	0.89	0.91
Milan	0.85	0.91	0.94	Lyon	0.76	0.78	0.98	CSKA Moscow	0.77	0.84	0.92	Shakhtar Donetsk	0.80	0.85	0.94	Galatasaray	0.83	0.85	<u>0.98</u>
Stuttgart	0.75	0.85	0.89	Milan	0.91	0.92	0.99	Lyon	0.70	0.79	0.89	Milan	0.81	0.89	0.92	Zenit	0.76	0.78	<u>0.97</u>
Unirea Urziceni	0.90	1.00	0.90	Sporting Braga	1.00	1.00	1.00	Man. City	0.83	1.00	0.83	CFR Cluj	1.00	1.00	1.00	Napoli	0.92	1.00	0.92
Juventus	0.83	1.00	0.83	Spartak Moscow	0.81	0.90	0.91	Man. United	0.76	0.91	0.83	Chelsea	0.84	1.00	0.84	Benfica	0.88	1.00	0.88
Liverpool	0.78	0.96	0.81	Ajax	0.86	0.95	0.90	Olympiacos	0.90	1.00	0.90	Benfica	0.83	0.94	0.89	Basel	0.98	1.00	0.98
Marseille	0.70	0.87	0.80	Rangers	1.00	1.00	1.00	Ajax	0.75	0.94	0.80	Olympiacos	0.80	0.85	0.94	Shakhtar Donetsk	0.89	0.97	0.92
Wolfsburgo	0.67	0.86	0.78	Rubin Kazan	0.96	0.97	0.99	Valencia	0.70	0.89	0.78	Zenit	0.78	0.85	0.92	Ajax	0.80	0.96	0.83
Rubin Kazan	0.93	1.00	0.93	Twente	0.85	0.87	<u>0.98</u>	Porto	0.66	0.87	0.76	Anderlecht	0.89	0.93	0.96	Juventus	0.70	0.92	0.76
Dynamo Kyiv	0.89	1.00	0.89	Benfica	0.86	0.97	0.89	Trabzonpor	1.00	1.00	1.00	BATE Borisov	0.75	0.86	0.87	Austria Wien	1.00	1.00	1.00
Standard Liège	0.86	1.00	0.86	Hapoel Tel-Aviv	0.83	0.95	0.87	Lille	0.72	0.90	0.80	Dynamo Kyiv	0.71	0.84	0.85	Porto	0.71	0.78	<u>0.91</u>
AZ Alkmaar	0.82	0.91	0.91	Werder Bremen	0.78	0.89	0.87	Viktoria Plzen	0.90	1.00	0.90	Ajax	0.73	0.88	0.83	Copenhaguen	1.00	1.00	1.00
APOEL	1.00	1.00	1.00	Basel	0.73	0.88	0.83	Shakhtar Donetsk	0.66	0.87	0.76	Man. City	0.68	0.87	0.78	Steaua Bucuresti	0.78	0.86	0.91
Zürich	0.91	1.00	0.91	CFR Cluj	0.96	1.00	0.96	KRC GenK	0.80	0.97	0.82	Spartak Moscow	0.73	0.93	0.78	Celtic	0.96	1.00	0.96
Besiktas	0.73	0.86	0.86	Panathinaikos	1.00	1.00	1.00	Bor. Dortmund	0.64	0.79	0.81	Lille	0.70	0.91	0.77	Viktoria Plzen	0.96	1.00	0.96
Atlético Madrid	0.65	0.85	0.77	AJ Auxerre	0.81	0.94	0.87	BATE Borisov	0.80	1.00	0.80	Sporting Braga	0.67	0.94	0.72	CSKA Moscow	0.65	0.88	0.74
Rangers	0.81	0.94	0.86	Bursaspor	0.75	0.93	0.80	Dinamo Zagreb	0.77	1.00	0.77	Montpellier	0.65	0.80	0.82	Anderlecht	0.90	1.00	0.90
Debreceni VSC	0.70	1.00	0.70	MŠK Žilina	0.79	1.00	0.79	Villarreal	0.74	1.00	0.74	Dinamo Zagreb	1.00	1.00	1.00	Real Sociedad	0.72	0.87	0.83
Maccabi Haifa	0.65	0.96	0.68	Partizan	0.64	0.81	0.79	Otelul Galati	0.69	1.00	0.69	Nordsjaelland	0.79	1.00	0.79	Marseille	0.72	0.87	0.83

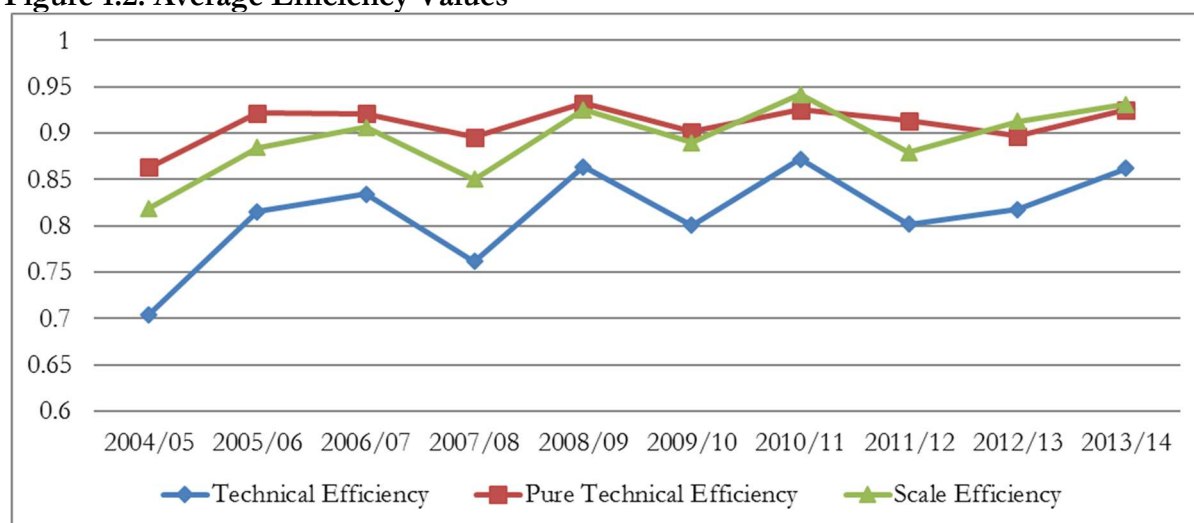
Notes: DMU: Decision Making Unit; TE: Technical Efficiency; PTE: Pure Technical Efficiency; SE: Scale Efficiency. Highlighted values (TE=1); rectangle box values (TE<1 and PTE=1); underlined values (TE<1, PTE<1, and SE<1; very high TE value and low PTE value).

Barcelona is highlighted, being efficient three times over the studied period. These results contrast with those obtained in other seasons, in which the club has rates below the average efficiency of the respective season. Furthermore, APOEL, Internazionale, Liverpool, and Manchester United also show good results for efficiency, with two episodes of TE. The analysis of the PTE results shows that the inefficiency of some teams is exclusively due to the incorrect choice of technology, especially the wrong choice of game tactics ($TE < 1$ and $PTE = 1$). The performance of these DMUs (edge highlighted in Table 2), compared to those that employed the same technology, is characterized by the appropriate use of their resources, i.e., without waste. In terms of PTE, 16% of the entire sample can be considered efficient.

Decomposing inefficiency, we find that the second main source of inefficiency is related to good tactical choice, but wasted resources ($TE < 1$, $PTE < 1$, and $SE = 1$). There is no exclusive case of this source of inefficiency in our sample.

The greater part of the sample (74%) is not efficient and the sources of inefficiency could be both the main causes described above: wasting of resources and the wrong tactical choices ($TE < 1$, $PTE < 1$, and $SE < 1$). In Table 1.2, the underlined cases stand out predominantly for the mix of a very high SE value, which indicates an appropriate choice of tactics, and a low PTE value, characterizing the waste of resources. Barcelona, Bayern Munich, and Real Madrid feature here as being inefficient by wasting resources four times in 10 seasons. Clubs such as Arsenal, Chelsea, Internazionale, Lyon, and Manchester United obtain similar results (three times), all large clubs that belong to the Big Five (the five most important domestic/national European leagues: English, Spanish, German, Italian, and French).

Figure 1.2. Average Efficiency Values



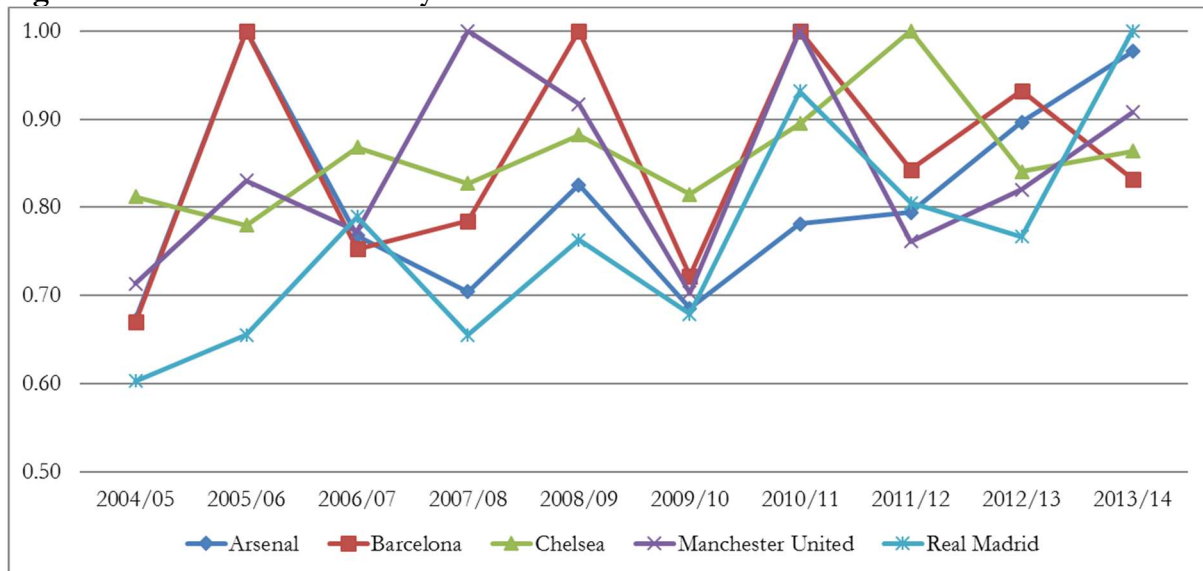
From a longitudinal perspective, we can study the evolution of efficiency across the 10 seasons. In Figure 1.2, we can observe the average efficiency values of TE (under the CRS assumption), PTE (under the VRS assumption), and SE. These figures show that the efficiency (or inefficiency) levels are not constant over the time. A more detailed analysis shows that TE and SE are clearly unstable from 2004/05 to 2013/14. Only the PTE shows relatively stable behavior on average.

From this longitudinal perspective, we analyze the efficiency behavior exhibited by the five clubs that played in the UCL for all the 10 seasons under review: Barcelona, Madrid, Arsenal, Chelsea, and Manchester United. As can be seen from Figure 1.3, TE is not maintained over time. Looking at the performance of these five clubs together, we can observe that 2004/05, 2006/07, and 2009/10 were the worst seasons in terms of TE.

A separate analysis by club reveals interesting results. Chelsea in particular is highlighted, having the best TE average (0.86 , $SD \pm 0.6$) among these selected clubs. In decreasing order, the TE average and standard deviations for the other clubs are: Barcelona (0.85 ± 0.12), Manchester United (0.84 ± 0.10), Arsenal (0.81 ± 0.11), and Real Madrid (0.76 ± 0.12). In terms of stability, looking at the standard deviation, Chelsea stands out as having the most stable performance over the 10 seasons. In contrast, Barcelona, in spite of having high efficiency in three seasons shows

very poor stability in performance. Nevertheless, the worst performance is shown by Real Madrid. With the exception of 2010/11, 2011/12, and 2013/14, the club's TE is below the average values in each season. The results also show that this phenomenon is explained for the most part by a waste of resources.

Figure 1.3. Technical Efficiency



Other clubs showing a high average TE did not participate in the UCL in all the 10 seasons considered. The best example is APOEL, with an average TE of 1. This club has the best *average* of the sample and shows efficiency in all the seasons in which it participated in the competition. Nevertheless, it should be borne in mind that it participated in only two seasons. More regular participants, Milan and Internazionale also had good results in nine and eight seasons respectively over the 10 evaluated.

From a national perspective, we can see that among the 25 DMUs with a TE value of one, the majority are those that play in the Big Five. English DMUs show efficiency six times, with four different clubs appearing: Liverpool and Manchester United twice; Arsenal and Chelsea once. Spain is the second country, with five efficient DMUs; Barcelona three times, and Real Madrid and Valencia once. In Italy, the three efficient clubs are Internazionale (twice), Juventus and Milan. Schalke and Bayern Munich represent the German Bundesliga on the efficient

frontier. France has no efficient DMUs. Surprisingly, the Cypriot league contributes three efficient DMUs: Anorthosis once and APOEL twice, highlighting the performance of APOEL, which reached the quarterfinals in the UCL in the 2011/12 season.

1.4.2. Bias-Corrected DEA and Robustness

To determine how robust our results are and how sensitive they are to other methodology, we have estimated a bootstrap DEA. We use the algorithm developed by Simar and Wilson (1998, 2000), implemented in the FEAR software library provided by Wilson (2008), in combination with the R statistical package. Our bias-corrected scores are derived from 2 000 bootstrap iterations. Table 1.3 shows the correlations between the standard DEA and bootstrap DEA. To compare the efficiency scores estimated, we use Pearson correlations, and to compare the rankings generated, we use Rho Spearman correlations.

Table 1.3. Correlations (No of Observations 320)

	Pearson (Scores)				Rho Spearman (Rankings)			
	TE	TE_BC	PTE	PTE_BC	TE	TE_BC	PTE	PTE_BC
TE	1	.972**	.661**	.610**	1	.980**	.683**	.549**
		.000	.000	.000		.000	.000	.000
TE_BC		1	.619**	.610**		1	.670**	.555**
			.000	.000			.000	.000
PTE			1	.972**			1	.926**
				.000				.000
PTE_BC				1				1

** . Correlation is significant at the 0.01 level (2-tailed).

Note: TE, Technical Efficiency; TE_BC, Technical Efficiency Bias-Corrected; PTE, Pure Technical Efficiency; PTE_BC, Pure Technical Efficiency Bias-Corrected.

The Pearson correlations between the efficiency scores estimated by the standard DEAs and the bootstrap bias-corrected DEA are positive and very significant. The correlations of the efficiency scores for each season were 0.972 ($p=0.00$) between TE and TE with bias correction (TE_BC), and 0.972 ($p=0.00$) between PTE and PTE with bias correction (PTE_BC).

As expected from the high correlation between the scores estimated, the Spearman correlations between the efficiency rankings for the standard DEAs and the bootstrap bias-corrected DEA were also very strong, positive, and significant. The correlation between the efficiency rankings of each season was 0.980 ($p=0.00$) between TE and TE_BC, and 0.926 ($p=0.00$) between PTE and PTE_BC. These results show that the estimations of TE are robust using the standard DEA model or DEA bootstrapping for the years observed.⁶

Interesting results have been observed in the relation between the efficiency scores and rankings with sports results. Only positive and significant correlations are found between TE and SE and sports results: values of 0.412, 0.430, and 0.598 respectively for the correlations of TE, TE_BC, and SE scores with sports results, and values for TE, TE_BC, and SE rankings of 0.340, 0.340, and 0.693 respectively. These values lead us to argue that in some cases clubs might achieve good sports results but nonetheless waste resources.

1.5. Discussion and Conclusions

Considering the current economic and financial situation of football clubs, the need for knowledge on how efficiently a club uses its resources is increasing. Furthermore, this analysis also is important to evaluate clubs' sports performance. Among the different tools widely applied in the literature for measuring efficiency, we have opted DEA methodology. Cooper, Seiford and Tone (2007) highlight its ability to identify efficient and inefficient units, as well the sources (and amounts) of inefficiency. To test the consistency of our results, we have applied a DEA bootstrapping technique, which makes it possible to draw statistical inferences from the estimations.

⁶ As scale efficiency is a ratio, there is no sense in calculating it for the bootstrap interactions. The 2000 interactions undertaken for technical efficiency were not the same for pure technical efficiency.

In this paper, we have estimated the technical efficiency of the best clubs in Europe, considering 97 different clubs that played in the Champions League over 10 seasons (2004/05–2013/14). The use of a greater number of seasons than in previous studies allows us to draw interesting conclusions for each season, as well as for the overall period.

For our first conclusion, in the period analyzed, the UCL champion is always efficient, but not all efficient clubs will win the UCL. This means that being efficient is a necessary condition but not sufficient to be the UCL champion. This result is detected in all the 10 seasons analyzed and confirms previous empirical evidence (Espitia-Escuer & García-Cebrián, 2010; Papahristodoulou, 2007). Nevertheless, some differences from previous studies can be highlighted. In previous empirical evidence, the champion and the runner-up have been considered efficient. However, our results show that all the champions were efficient, but only 4 of the 10 runners-up were efficient. This difference is due to the use of different performance variables. The use of the UEFA coefficient of revenue distribution allows us to make a clearer distinction between efficient and inefficient clubs in the UCL. If we consider only the same seasons analyzed by Espitia-Escuer and García-Cebrián (2010), we can see that all the DMUs found to be efficient in our paper were also efficient in theirs. However, the reverse is not true, as many more DMUs were considered efficient in their paper. Rather, the results of the correlations between the efficiency scores and rankings lead us to argue that in some cases clubs might achieve good sports results but nonetheless waste resources.

The analysis of the technically efficient DMUs that did not take the UCL championship (23 cases) lets us suggest some ways of improving their results. These clubs employed their sports resources adequately, but they must increase the amount of inputs employed if they want to improve their results. In general, these clubs are of medium and small size, and their main characteristic is that they were efficient in the use of their scarce resources.

A second conclusion can be derived from the large number of seasons included in our study. As we can see from the 10 seasons analyzed, no club managed to maintain technical efficiency, indicating that this is a very difficult task in the most competitive European football tournament. Furthermore, it is important to note that the clubs and the resources employed change from one season to other, as do the opponent teams; thus, a club that is efficient in one season, employing the same resources (in the same way), might not be efficient in another season.

The low level of DMUs considered efficient in our study leads us to the third highlighted conclusion: there is a high degree of inefficiency in the UCL. Observing the results of the per season analysis as a whole, we have found 10% of units to be efficient on average, compared to 29% in Espitia-Escuer and García-Cebrián (2010). As is known, DEA is a methodology that is very sensitive to change, and this is not without basis in fact. If we consider a new output, in this case the UEFA coefficients, we should expect some changes. For example, among teams eliminated in the same phase, for any that employed few inputs and had fewer victories or ties in the group stage, or a worst goal average in the knockout stage, their efficiency could be greater than others that were eliminated in the same stage of the competition. As the output measure applied in this paper is closely related to performance, we have found that many of the runners-up and teams not classified in the knockout phase are no longer efficient. These clubs represent over half of the sample and now performance is differentiated by the output measure. Nevertheless, at the global level by season, our results are very similar to previous evidence. For example, in the study developed by Espitia-Escuer and García-Cebrián (2010), the season with the highest level of inefficiency was 2004/05. The same result is obtained in our research.

As a fourth conclusion, we have detected different sources of inefficiency. The first source of inefficiency is observed through the pure technical efficiency analysis and is related to a clear waste of resources. Clubs in this situation can employ their resources better, improving their

sports technique. Also, when forming a new squad for future years, such clubs must seek out and sign players with specific characteristics to address these shortcomings.

The second source of inefficiency can be observed through the calculation of scale efficiency and is associated with the choice of inappropriate sports tactics. Here, the implications primarily involve the head coach. The problem may lie in how the club applies its resources, and whether it is employing too few or too many inputs. These clubs should develop a medium and long-term strategy to develop new and different tactics with the resources that they have or could have in the future. If the existing coach is not capable of doing so, it will be necessary to appoint a new coach. In the same way, and associated with the coach's choices, the hiring of players should also be analyzed in the context of the development of these new sport tactics. All these guidelines lead to inferences in the first stage of the production process, suggesting potential only if the performance evaluation is continuous.

We have also found some clubs that suffer both types of inefficiency. In this case, these clubs might be encouraged to look carefully at their reference unit, in particular in terms of size, to discover how efficient clubs develop efficient sport tactics and use their sport resources adequately. Benchmarking could be considered in terms of sport management, this being an essential tool for the sporting and economic survival of football clubs.

To check the robustness of our results, we applied bias-corrected DEA. The scores and rankings estimated are significant, positive, and highly correlated with the standard DEA results. Thus, we can conclude that the results are robust using alternative estimation methods.

Finally, the new output measure proposed seems to be suitable for representing the sports results achieved by the football clubs that play in the UCL in a reliable manner. This new measure is able to allocate more realistic values to the sports results. The use of the coefficients applied by the UEFA from UCL revenue distribution will be helpful in further research.

In this context, the coefficients of revenue distribution from the UCL might be also used to analyze all the seasons as a whole. This procedure has as its main advantage the number of units considered under analysis, helping to overcome one of the limitations of DEA. As the values of revenue distribution applied by the UEFA change in a 3-year cycle, the monetary values should be homogenized. Taking the values of the coefficients for the last season analyzed as the reference, these could be applied to the other seasons of the sample. In the same way, this methodology and output measure could be applied to other competitions with a similar format to the UCL, such as the FIFA World Cup, national cups, or the South American club tournament (known as the *Copa Libertadores de America*, an important market sector, still poorly studied).

Appendix

Table 1.4. UEFA Prizes

Prize for participation, matches played and performance (values in millions of Euros)										
	2013/2 014	2012/2 013	2011/2 012	2010/2 011	2009/2 010	2008/2 009	2007/2 008	2006/2 007	2005/2 006	2004/2 005
Participation	8.6	8.6	7.2	7.2	7.1	5.4	5.4	5.4	3.9	3.9
Win	1	1	0.8	0.8	0.8	0.6	0.6	0.6	0.32	0.32
Draw	0.5	0.5	0.4	0.4	0.4	0.3	0.3	0.3	0.16	0.16
Play rond of sixteen	3.5	3.5	3	3	3	2.2	2.2	2.2	1.6	1.6
Play quarterfinal	3.9	3.9	3.3	3.3	3.3	2.5	2.5	2.5	1.92	1.92
Play semifinal	4.9	4.9	4.2	4.2	4.2	3	3	3	2.56	2.56
Runner-up	6.5	6.5	5.6	5.6	5.6	4	4	4	3.84	3.84
Champion	10.5	10.5	9	9	9	7	7	7	6.4	6.4
Mimumum	8.6	8.6	7.2	7.2	7.1	5.4	5.4	5.4	3.9	3.9
Maximum	37.4	37.4	31.5	31.5	31.4	23.7	23.7	23.7	18.3	18.3

Source: Adapted from UEFA.com and UEFADirect.

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2. Calculation of efficiency in European football teams using Window DEA. Analysis of best practices and evolution

Abstract

This paper analyzes the evolution of the sports efficiency of football clubs playing in the UEFA Champions League (UCL) in the 2004/05–2012/13 period. As the sample is panel data, we propose a research procedure to find the most accurate methodology to analyze its efficiency. The S statistic was employed to check for temporal trend and the Kruskal-Wallis statistic was run to analyze stability in relative ranks. We detected a temporal trend and teams do not maintain their relative rankings over time. According to these results, Window Data Envelopment Analysis (WDEA) emerges as the most appropriate method to estimate the efficiency of UCL teams. WDEA-estimated efficiency scores can be used to evaluate teams' robustness and analyze the evolution of their efficiency more rigorously. The WDEA results in this paper indicate that there is a low efficiency level (6%) in the nine seasons observed. There is a strong correlation (72%) between sports results and the efficiency of semifinalists. From the analysis, we conclude that improvement in a club's efficiency could enhance its sports results. Finally, as practical implications, we highlight benchmark teams and alternative sports tactics to help clubs become more efficient and achieve better sports results.

Keywords: DEA; panel data; UEFA Champions league; sports economics.

2.1. Introduction

The UEFA Champions League (UCL) is one of the most prestigious tournaments in the world and the most important club competition in European football. Nowadays, football, and specially the UCL, has a strong social impact. The Berlin final of the 2014/15 tournament attained extraordinarily high television audience ratings as it aired in more than 200 countries to 400 million viewers. Its social media presence has also exploded. The number of Twitter followers grew 51% during the 2014/15 season, the UCL Facebook page is the world's most popular league or association page on the platform, and during that season, overall page likes increased by 30%, reaching 45.6 million likes ([UEFA](#)).

In the sports field, football is a very competitive sector. As with other organizations, professional football clubs must seek the best use of their resources. The financial-economic restrictions implemented by the FIFA FFP (Financial Fair Play) have made the significance of the optimal use of available resources more apparent. Efficiency is even more essential in the UCL context, because clubs in small leagues must compete with Europe's largest. Consequently, estimating efficiency as a means of analyzing clubs' sports performance is an important approach if they need to consider the resources employed, not just the final sporting result. The assessment of sports performance can also provide useful information to help team managers decide whether to hire players or make more investment on its own reserve of young players, help coaches design playing strategy or tactics, and also help players train and improve their individual technical shortcomings.

Therefore, the main aim of this paper is to estimate and analyze the efficiency and evolution of clubs playing in the UCL using Data Envelopment Analysis (DEA). DEA methodology does not need the specification of a production function and allows efficiency calculations in multi-input and multi-output organizations. The period under study covers 2004/05 to 2012/13, in other words, nine seasons forming a panel data set. Our aim is to present a research procedure

for determining the most accurate DEA methodology to estimate and compare the efficiency of panel data.

In the literature, we can find four alternative methodologies of efficiency using DEA from panel data: contemporaneous, sequential, intertemporal and window analysis. Each is adequate depending on the temporal evolution of technology and, as a consequence, of benchmarks in efficiency. The first step in our research procedure is to test if there is a temporal trend and the stability of rankings before choosing the DEA methodology to be used. The final selection of DEA methodology in this paper is based on the characteristics of the sample under study and not on the literature or research innovation bias. When testing for the existence of a temporal trend in our sample, window analysis emerged as the accurate methodology to analyze efficiency in this paper.

One of the advantages of window analysis is that it enables us to evaluate the robustness of the efficiency ratios. If the results are robust, efficient units are the benchmark for improving club efficiency. We could provide some guidelines on changes in sport tactics or technical skills based on individual and personalized observation of those efficient units. To the best of our knowledge, only Sala-Garrido, Liern Carrión, Martínez Esteve, and Boscá (2009) have applied window analysis to estimate the efficiency of football clubs and no paper has applied this methodology to a competition with the characteristics of the UCL.

The remainder of the paper is as follows. Section 2.2 contains a review of the empirical evidence on efficiency in football. Section 2.3 describes the sample and variables we analyzed. Section 2.4 explains the research procedure we followed to discover the most accurate methodology and the methodology we applied. The results of the analysis of the temporal trend, the calculation of efficiency in DEA by means of window analysis and the results of efficiency are exposed in section 2.5. In section 2.6 we discuss our results and present our concluding thoughts.

2.2. Literature review

There is an extensive academic research on efficiency and its implications in the sports field. The efficiency analysis in football leagues is a well-established research line (Barros & Garcia-del-Barrio, 2011). Dawson, Dobson and Gerrard (2000) and Kulikova and Goshunova (2013) provide a comprehensive review of this literature.

From a methodological perspective, two main approaches have been used to measure the efficiency of sports: the econometric or parametric (stochastic frontier analysis, SFA) and the non-parametric frontier methodology (DEA). As Kulikova and Goshunova (2013) observed, DEA is the most popular and it measures technical efficiency. Technical efficiency refers to the ability of an organization or a decision-making unit (DMU in DEA literature) to obtain the maximum potential output from given amounts of factor inputs, or the minimum input required to obtain a given level of output. This concept involves physical quantities and technical relationships (Coelli, Rao, O'Donnell, & Battese, 2005).

Studies analyzing football efficiency include papers that observed regular national championships and eliminatory competitions. The main difference between them is that the outcome of eliminatory competitions is more uncertain when compared with regular leagues. The regular national football leagues reward the most stable performance and last longer, because teams usually play two rounds against all the others in the league. In contrast, eliminatory competitions require less time and random results are more likely. Regular competitions are normally leagues played in countries and eliminatory competitions involve nations or clubs in a large territory (i.e. the FIFA World Cup or the UEFA Champions League).

There is more comprehensive empirical literature on regular leagues. The English Premier League (Haas, 2003; Barros & Leach, 2006; etc.) and the Spanish *Liga* (Espitia-Escuer & García-Cebrián, 2004; González-Gómez & Picazo-Tadeo, 2010; etc.) are the most analyzed. Hass (2003), with a small sample size of 20 clubs (2000/01 season), investigated how close the English

Premier League clubs play to their potential. Barros and Leach (2006), combining financial and sports variables, applied DEA to measure the efficiency of the teams playing in the Premier League for five seasons (1998/99 to 2002/03) for the 12 clubs that participated in the competition in all the seasons studied. The authors made important recommendations at a managerial level, but, as a limitation, they highlighted the need for a more extensive panel data set to generalize the conclusions. Espitia-Escuer and García-Cebrián (2004) analyzed the efficiency of Spanish clubs playing in the national league for three seasons (1998/99 to 2000/01) and González-Gómez and Picazo-Tadeo (2010) compare the performance between the Spanish league, the Spanish cup and European competitions for six seasons (2001/02 to 2006/07). Other national leagues have also been analyzed, such as the Italian (Boscá Liern, Martínez, & Sala, 2009); German (Tiedemann, Francksen, & Latacz-Lohmann, 2011); Portuguese (Ribeiro & Lima, 2012); Greek (Barros & Douvis, 2009); Brazilian (Barros, Assaf, & Sá-Earp, 2010); and Mexican (Torres-Dávila & García-Cebrián, 2012).

We would highlight the work by Tiedemann et al. (2011), which analyzed the football players in the German league for seven seasons (2002/03 to 2008/09), due to its different perspective. They found a clear positive relationship between a team's average player efficiency score and its rank in the league table at the end of the season. Their results are corroborated by those of Sala-Garrido et al. (2009) which highlight the very nature of football: the performance of the whole team is more important than that of its constituent parts.

The relation between estimated efficiency rankings and sports results is one of the most mentioned in the literature. Barros and Leach (2006) and Torres-Dávila and García-Cebrián (2012) found a statistical correlation between awarded points and estimated efficiency scores. Espitia-Escuer and García-Cebrián (2004) and Haas (2003), however, did not find a significant correlation between efficiency and sports results.

Concerning supranational competitions, the UEFA Champions League is the world's top competition at football club level, and efficiency studies are really scarce in this area (as examples we can find Espitia-Escuer & García-Cebrián, 2010, and Zambom-Ferraresi, García-Cebrián, Lera-López, & Iráizoz, 2017). The fact that the sample comprises an unbalanced panel data set and the limited availability of data could be some reasons for this shortage.

Espitia-Escuer and García-Cebrián (2010) evaluated the efficiency of teams that played in the UCL for four seasons (2003/04 to 2006/07). First, they observed clubs' efficiency season by season, and, in a second analysis, they estimated a frontier for the sample as a whole. The results indicated that in the four analyzed seasons there were no different dominating tactics, which means that there was no technological change in this period. In this case, inefficiency results from wasting resources. Zambom-Ferraresi et al. (2017) analyzed the sports performance of the same competition for ten seasons (2004/05 to 2013/14). They estimated season-by-season efficiency and found high inefficiency levels in the analyzed period, in contrast to the results of Espitia-Escuer and García-Cebrián (2010).

As we have a panel of data in the present paper, our literature revision also focuses on the treatment found in former studies proposing DEA as a method for measuring the efficiency of football teams. Some of them have estimated its efficiency season by season (Tiedemann et al., 2011; Torres-Dávila & García-Cebrián, 2012; Zambom-Ferraresi et al., 2017) and/or have looked at the sample as a whole (Barros & Lech, 2006; Espitia-Escuer & García-Cebrián, 2010; González-Gómez & Picazo-Tadeo, 2010). To the best of our knowledge, only Sala-Garrido et al. (2009) have applied window analysis at a football league scope.

2.3. Data and variables

Considering existing literature, we propose estimating the efficiency of nine UCL seasons. This analysis will be based on DEA, because specifying a production function is unnecessary and it provides easily interpretable results. Our main interest is to know how efficiently teams use their

sports resources, turning play styles and tactics into victories. Hence, the input measures are the sports statistics of the main actions on the field and the output measure is the sport result clubs achieve at the end of the competition.

Our sample comprises teams that played nine UCL seasons, from 2004/05 to 2012/13. As the clubs participating in the competition change from one year to the next, there are 32 clubs per season. Some clubs participated in more than one season and some of them participated in all the analyzed seasons. This leads us to have an unbalanced panel data set comprising 288 observations relating to 94 clubs.

In the present paper, we have taken the following variables as representatives of actions on the field: ball recoveries, crosses (open play), corners and total shots. All these inputs have been used in previous works (Sala-Garrido et al., 2009; Espitia-Escuer & García-Cebrián, 2010; Torres-Dávila & García-Cebrián, 2012; Carmichael & Thomas, 2014) and they are the main resources employed by teams to try to score goals and win matches. The aggregated values of the playing statistics over the whole competition are provided by Opta Sports data. Table 2.1 shows the descriptive statistics of these variables.

The use of ball recovery as an indicator of actions on the field is relatively new. The number of ball recoveries a team performs during a match provides a large quantity of information on a team's intention to dominate the game. Even when a team does not have much ball possession, if it tries to get the ball, this variable will measure the purpose of playing actively. Ball recovery could be considered the outcome of defensive plays or the first step in attack plays (Carmichael & Thomas, 2014; Zambom-Ferraresi et al., 2017).

Crosses and corners are common plays and an important way to get close to the penalty area, where a major part of the plays turns into goals. Carmichael and Thomas (2014) included them in their model. Both inputs are indicators of one characteristic tactic. Crosses can be a quick way to go to the penalty area or a tactic variation that allows opening spaces in the central

area. If a team mainly used these plays (crosses and corners), it could be characterized as a tactic style. On the other hand, if a team used them a great deal, but in the same amount as other plays, this could only indicate a variation in the type of play, which is very important to surprise opponent teams.

Table 2.1. Descriptive statistics

Variable	Means	SD	Min	Max	N
Total shots (I)	104.5	45.1	34	255	288
Crosses (I)	187.1	72.1	57	444	288
Corners (I)	38.8	16.5	12	108	288
Ball recoveries (I)	456.4	159.9	210	994	288
Sports results (O)	15.5	6.6	8.6	36.9	288

Note: (I)= Input; (O)= Output

Total shots are one of the most important indicators of actions on the field in football. The main reasonable option to score a goal is shooting. Sala-Garrido et al. (2009), Espitia-Escuer and García-Cebrián, (2010), Torres-Dávila and García-Cebrián (2012) and Carmichael and Thomas (2014) used this input variable to estimate football teams' efficiency.

The output used in this paper is a variable representing sports results during the Championship: the amount of the UCL financial retribution related to sports performance. They are the prizes clubs receive for advancing in the UCL phases. The ranking provided by this variable is the same as the ranking provided by points and played stages, but this output measure will allow us to differentiate between clubs that were eliminated in the same stage but have a different number of victories (Zambom-Ferraresi et al., 2017). For example, in the 2012/13 season clubs received an €8.6 million prize just for participating in the group stage, plus €1 million for each victory and €0.5 million for each draw. The clubs that passed into the round of 16 received €3.5 million more; €3.9 million for playing the quarterfinals, and €4.9 million for playing the semifinals. The runner-up earned an extra prize of €6.5 million and the champion earned €10.5 million. Consequently, the minimum that a club could receive was €8.6 million and if a club won all the matches in the group stage and won the competition, it could receive a prize

of €37.4 million for its sports performance. As prizes change every three years and our sample covers nine seasons, we have taken the values of last season's prize as the reference year.

2.4. Calculation of efficiency using DEA with panel data

Several methodologies have been proposed in the literature to calculate efficiency. One approach is frontier methods, which consider the estimation of isoquant as the sample data envelope. Among frontier methods, deterministic non-parametric and stochastic methods have also been most often used in empirical papers. Deterministic non-parametric or DEA does not specify a functional form for production processes and this is its main advantage. Nevertheless, all deviations from the frontier are classified as inefficient.

Under the assumption of constant returns to scale, DEA proposes the solution to the following linear programming problem for every unit in the sample:

$$\begin{aligned}
 & \text{Min. } \lambda_i \\
 & \text{s.t. } \lambda_i x \geq zX \\
 & \quad y \leq zY \\
 & \quad z \in \mathbb{R}^+
 \end{aligned} \tag{2.1}$$

where x is the vector of consumed inputs by unit i under analysis, X is the matrix of consumed inputs for all units in the sample, y is the vector of obtained output by unit i , Y is the matrix of obtained outputs for all units in the sample, z is a vector of parameters whose values are obtained in the resolution of the problem and λ_i is the ratio of efficiency for unit i . In the orientation to input presented in this problem, λ_i represents the radial reduction to be applied to every input in unit i to become efficient.

In the original DEA formulation, efficient units present a ratio equal to 1 and their ratio for inefficient units is less than one. This supposes that efficient units in a sample show the same value of efficiency and it is impossible to discriminate among them. To solve this inconvenience, Andersen and Petersen (1993) proposed the calculation of super-efficiency, which consists of

calculating efficiency ratios on the basis of the aforementioned problem, but taking the whole sample except the unit under analysis as a comparison sample. Consequently, inefficient units present the same ratio of efficiency as solving the original DEA problem, but efficient units do not have their efficiency ratio limited by 1, so they can present ratios above this value and we can order them by the criteria of the highest value. Therefore, the efficiency ratios calculated for football clubs in the sample under study have been calculated using super-efficiency.

In empirical work aiming to discover the efficiency of units forming a sample, the availability of information in the form of panel data is an improvement to be taken into consideration. Of course, calculations can be repeated in every single period in the time horizon, but the treatment of pooled data can be taken advantage of as a whole. If a researcher has panel data, several analysis possibilities exist. Tulkens and Vanden Eeckaut (1995), Asmild, Paradi, Aggarwall, and Schaffnit (2004) and Cullinane and Wang (2006) propose four different calculations of efficiency using DEA from a panel data set:

- Contemporaneous approach: efficiency is calculated for every DMU taking only the input and output data of DMUs in the same period as a reference set. As many efficiency ratios as periods in the whole sample are calculated for each DMU, each of them with a different frontier.
- Sequential: efficiency is calculated for every DMU in one period taking input and output data of DMUs in the same period and all the precedents as a reference set.
- Intertemporal: efficiency is calculated for every DMU in one period taking input and output data of DMUs in the whole time of the sample as a reference set. Efficiency is calculated taking all the data from the panel in a pooled manner. As many efficiency ratios as periods in the whole sample are calculated for each DMU, all of them with the same frontier.

- Window analysis: efficiency is calculated for every DMU in one period taking input and output data of DMUs in the periods forming the window length as a reference set. Researchers should decide on window length depending on the characteristics of each empirical work. DMUs forming each window vary because the first period is suppressed to add the following one to form the next window.

The choice of methodology requires taking their characteristics into account. Following Tulkens and Vanden Eeckaut (1995) concerning changes in production technology, it could be argued that if the contemporaneous method is chosen, the efficient frontier is considered to change from period to period. Concerning the technology available at each moment, it is assumed that, with the sequential method, the way of producing in the past will be also available in the future; therefore, only shifts in the frontier reflecting technical progress are assumed. If the intertemporal frontier is chosen, it is assumed that no shift occurs.

If there is no temporal trend, the efficiency calculated year by year only considers DMU data in the same period as a reference sample and some organizations could be qualified as efficient, even though they could be qualified as inefficient if they were compared with the same units' performance in different periods. In this case of no temporal trend, the best way of exploiting information provided by panel data is to estimate an intertemporal frontier and calculate efficiency by taking it as a reference set. In fact, Brockett, Golany and Li (1998) establish that the use of a single efficiency frontier assumes that no technological changes affecting productive efficiency have occurred over the time periods. Wang, Wang, Huang, Wu, and Liu (2014) explain that, in the presence of technical change, evaluating efficiency using an intertemporal frontier formed by many periods can deem that DMUs observed in the technical improvement periods are efficient. Therefore, DMUs of periods with no technical improvement and considered inefficient would be recommended to become a benchmark impossible to reach given their technological context.

Where a temporal trend is detected, the year-by-year calculation of efficiency can lose information: it is difficult to analyze improvements in efficiency because the sample changes every year. In this case, two different situations can be applied. If the temporal trend is in fact the realization of an event at a single and recognizable moment that drastically changes technological conditions, efficiency could be calculated with two intertemporal frontiers, one before that event and the other afterwards. Brockett et al. (1998) propose a procedure in the event of no drastic changes. These authors quoted that these trends can develop slowly, only in a few DMUs (they are not generalized), and can go unnoticed by managers. Brockett et al. (1998) also remarked that efficiency results calculated across time in contrast to year-by-year results are more useful to managers as they avoid the influence of extraordinary events in a single period.

Proposing recommendations that fit with the technological evolution in the sample under study require verification of this evolution before starting the efficiency calculation. Consequently, Brockett et al. (1998) suggested an intertemporal calculation of efficiency and the running of several tests on the obtained efficiency ratios. For the study of the eventual existence of trends in performance over time, following Brockett et al. (1998) and Ross and Droge (2002), we have used the S statistic proposed by Brockett and Kemperman (1980). For the analysis of stability in relative ranks, we have used the Kruskal-Wallis statistic, proposed by Brockett et al. (1998) and Sueyoshi and Aoki (2001). All these previous processes have enabled us to choose the most accurate methodology considering the characteristics of our sample.

2.5. Results

2.5.1. Analysis of the existence of temporal trend

We are going to verify the two aspects proposed in Brockett and Golany (1996) and Brockett et al. (1998): analysis of the existence of a temporal trend in the whole sample and of stability in relative ranks.

Concerning the analysis of a temporal trend in the whole sample, Brockett et al. (1998) and Ross and Droge (2002) use the S statistic proposed by Brockett and Kemperman (1980). These authors have a complete panel in their analysis. In our case, we have unbalanced panel data because not all the teams in the sample have played in the UCL throughout the entire period under analysis. Nevertheless, it is possible to apply the S statistic because observations are accumulated by period and 32 teams play in the UCL every season. As we have previously obtained super-efficiency in our calculations, we have avoided ties in the application of the test. As we obtained a statistic value equal to 3830, we found that we can reject the null hypothesis of no temporal trend with a significance level of 5%.

To analyze the stability in relative ranks, Brockett et al. (1998) and Sueyoshi and Aoki (2001) propose the use of the Kruskal-Wallis statistic. Brockett and Golany (1996) also quote this method. Brockett et al. (1998) and Sueyoshi and Aoki (2001) have a complete panel again, but the original paper of Kruskal and Wallis (1952) considers the possibility of a different number of observations for each individual in the statistic calculation. We have calculated this statistic for our sample using super-efficiency ratios, again to avoid ties, and we have obtained a value for the statistic equal to 101.66; therefore, we have accepted the null hypothesis of equivalent distribution of efficiency ranking with a level of significance of 5%.

To sum up, we have detected a temporal trend and teams have not maintained their relative positions over time. Therefore, intertemporal analysis cannot be conducted with our data to determine which teams are efficient because a temporal trend exists. The contemporaneous approach is also incomplete because the technical changes in football (players and coaches) are usually gradual and it is possible to find similar contexts in two consecutive periods. Although Brockett et al. (1998) do not use window analysis, they quote this method in their paper referring to it as a way of introducing new temporal data in the DEA calculation. These authors mention that studies applying WDEA do not use statistical tests, an issue that we try to solve in our

paper. Furthermore, window analysis provides knowledge of robustness in efficiency ratios. This helps to identify really reliable results and, as a consequence, to identify which DMUs can be used as an efficiency benchmark. Due to statistically equivalent distribution of efficiency positions, we would not expect efficient teams to be the same throughout the period studied in this paper.

2.5.2. Calculation of efficiency in DEA using window analysis

Window analysis consists of calculating efficiency rates using DEA but forming the sample with data collected from a number of consecutive periods. This sample extracted from the whole panel is called a window, and the number of periods in a window is called the width of the window. Calculations are repeated by eliminating the data corresponding to the first period in the window and adding data for the following period (season in our case) after the last in the window. This process is repeated as many times as the length of panel provides data. Window analysis enables us to assess the robustness of the efficiency ratios and to come to more reliable conclusions on the evolution of efficiency.

As we have previously highlighted, only Sala-Garrido et al. (2009) have applied window analysis methodology to the sports field. Traditionally, apart for a methodological approach (Tulkens & Vanden Eeckaut, 1995; Sueyoshi & Aoki, 2001), studies considering window analysis have been applied to various economic sectors: banking (Yue, 1992; Asmild et al., 2004); air forces (Charnes, Clark, Cooper, & Golany, 1985); brewing industry (Day, Lewin & Salazar, 1994); carbonated beverage industry (Charnes, Cooper, Golany, Learner, Phillips, & Rousseau, 1994a); container port (Cullinane & Wang, 2006); semiconductor manufacturer (Chung, Lee, Kang, & Lai, 2008); telecommunications firms (Yang & Chang, 2009); science park (Sun & Lin, 2009); and coffee sector (Suárez & Mejía, 2010), for instance. Recent works have also applied window analysis to calculate efficiency. For example, Detotto, Pulina and Brida (2014) analyzed

the productivity of the hospitality sector in Italian regions; Wang et al. (2014) and Epure and Lafuente (2015) study efficiency in banking. Mariano, Sobreiro and do Nascimento Rebelatto (2015) present a revision of the literature on the application of DEA to analyze efficiency in human development processes and window analysis appears as one of the extensions of DEA if panel data is available.

When applying window analysis, one important decision is to establish the width of windows, which depends on assumptions about changes in the frontier (Tulkens & Vanden Eeckaut, 1995). Several approaches have been proposed in the literature. Papers by Boussofiane, Dyson, and Thanassoulis (1991), Day et al. (1994), Ross and Droge (2002), Sala-Garrido et al. (2009), and Suárez and Mejía (2010) state that it is a decision taken by an analyst. Nevertheless, to provide some criteria, Paradi, Vela and Yand (2004), Asmild et al. (2004), Charnes et al. (1994a) and Yang and Chang (2009) suggest that windows should be wide enough to have the necessary degrees of freedom and narrow enough to maintain the same context. Finally, more formal suggestions are those by Cooper, Seiford and Zhu (2004), Charnes, Cooper, Lewin and Seiford (1994b, 60), who propose the trial and error method, and Cooper, Seiford and Tone (2000), who propose a formula.

Following the formulae provided by Cooper et al. (2000), we should have used a width of five seasons in the present paper. Nevertheless, Sala-Garrido et al. (2009) suggest that most teams change either players or their coaches from one season to another, which means there is no sense analyzing windows of more than three seasons for football clubs. Regarding this consideration, we have also employed a width of three seasons, as this period is consistent with the average time coaches, players and teams remain in the championship.

Before exposing the efficiency results, it is important to remember that we do not have a complete panel of data. In this paper, efficiency for each team in each window is calculated with

the sample formed by teams playing in some of the three seasons forming the window, although some of them did not participate in all three seasons.

The overall results of efficiency (WDEA) are presented in table 2.2. Due to a shortage of space, table 2.2 is organized by season. For seasons that belong to more than one window, we present the efficiency scores for all the respective windows (two or three). The differences between the efficiency scores for the same season in different windows give us an idea of the robustness of the results. The coefficient of variation (CV) between efficiency scores is added to help observe robustness whenever there is more than one window. The results are sorted by the clubs' sporting performance. The lines separating clubs in the results table represent the final stage in which clubs are ranked in each season. From top to bottom, these are final (champion and runner-up), semifinals, quarterfinals, knockout round and group stage. The results highlighted in gray are efficient observations and results underlined are not considered robust.

To interpret the results, it is important to remember that observations with an efficiency score of less than one are inefficient and of one or more are efficient. For general results, a coefficient of variation above 10% was considered to mean substantial differences in efficiency values and not robust. On the other hand, all those observations that present a $CV < 10\%$ had estimated robust efficiency scores. As we have used super-efficiency in our calculations, efficient units present ratios above one, independent of the exact ratio value. We will, therefore, consider efficient teams robust if the ratios in all the seasons in the same window are above one, even if their CV is above 10%. Consequently, efficient teams at least once with CV less than 10% or with CV above 10%, but efficient in all seasons in a window, will be considered robust efficient clubs and will be used as reference units and benchmarking for the inefficient clubs in the sample.

Table 2.2. Efficiency scores for teams playing UEFA Champions League.

	Season 2004/05		Season 2005/06			Season 2006/07				Season 2007/08				Season 2008/09								
	Clubs/Windows	1	Clubs/Windows	1	2	CV	Clubs/Windows	1	2	3	CV	Clubs/Windows	2	3	4	CV	Clubs/Windows	3	4	5	CV	
Champion	Liverpool05	1.16	Barcelona06	0.99	1.06	0.05	Milan07	0.92	0.94	0.98	0.03	Man. United08	1.04	1.10	0.99	0.05	Barcelona09	0.99	0.97	0.97	0.01	
Runner-up	Milan05	0.91	Arsenal06	1.06	1.06	0.00	Liverpool07	0.93	0.96	1.07	0.08	Chelsea08	0.83	0.87	0.78	0.06	Man. United09	0.83	0.81	0.81	0.01	
Semifinalist	Chelsea05	0.92	Villarreal06	0.92	0.92	0.00	Chelsea07	0.72	0.75	0.79	0.05	Barcelona08	0.80	0.80	0.80	0.00	Chelsea09	0.83	0.75	0.75	0.06	
	PSV05	0.75	Milan06	0.79	0.81	0.02	Man. United07	0.73	0.74	0.84	0.08	Liverpool08	0.74	0.75	0.72	0.02	Arsenal09	0.79	0.74	0.74	0.03	
Quarter-finalists	Juventus05	0.77	Lyon06	0.81	0.83	0.02	Valencia07	0.75	0.78	0.88	0.09	Arsenal08	0.76	0.81	0.74	0.05	Liverpool09	0.84	0.77	0.77	0.05	
	Internazionale05	0.82	Juventus06	0.74	0.79	0.05	Bayern Munich07	0.73	0.74	0.83	0.07	Roma08	0.77	0.77	0.76	0.01	Bayern Munich09	0.79	0.72	0.72	0.05	
	Lyon05	0.85	Internazionale06	0.82	0.83	0.01	PSV Eindhoven07	0.75	0.79	0.89	0.09	Fenerbahçe08	0.76	0.82	0.72	0.07	Porto09	0.78	0.71	0.71	0.05	
	Bayern Munich05	0.88	Benfica06	0.77	0.77	0.00	Roma07	0.75	0.78	0.85	0.07	Schalke08	0.64	0.69	0.62	0.05	Villarreal09	0.82	0.70	0.70	0.10	
knockout stages	Werder Bremen05	0.87	Liverpool06	0.70	0.72	0.02	Lyon07	0.77	0.79	0.88	0.07	Internazionale08	0.92	0.96	0.88	0.04	Juventus09	0.84	0.76	0.76	0.06	
	Monaco05	0.88	Bayern Munich06	0.77	0.79	0.02	Porto07	0.71	0.76	0.79	0.05	Sevilla08	0.69	0.75	0.65	0.07	Atlético Madrid09	0.94	0.86	0.86	0.05	
	Man. United05	0.89	Chelsea06	0.86	0.88	0.02	Real Madrid07	0.74	0.76	0.84	0.07	Milan08	0.75	0.82	0.71	0.07	Sporting Lisboa09	0.94	0.84	0.84	0.06	
	Arsenal05	0.92	Ajax06	0.82	0.87	0.04	Arsenal07	0.66	0.69	0.75	0.07	Olympiacos08	0.86	0.95	0.85	0.06	Roma09	0.93	0.84	0.84	0.06	
	Real Madrid05	0.76	PSV Eindhoven06	1.02	1.13	0.08	Barcelona07	0.78	0.78	0.91	0.10	Porto08	0.73	0.75	0.73	0.01	Lyon09	0.77	0.68	0.68	0.07	
	Bayer Leverkusen05	0.75	Real Madrid06	0.72	0.74	0.01	Internazionale07	0.95	1.15	1.12	0.10	Real Madrid08	0.68	0.75	0.67	0.06	Real Madrid09	0.66	0.65	0.65	0.01	
	Barcelona05	0.82	Rangers06	0.91	0.94	0.02	Lille07	0.66	0.70	0.75	0.06	Lyon08	0.76	0.89	0.71	0.12	Panathinaikos09	0.79	0.76	0.76	0.02	
	Porto05	0.87	Werder Bremen06	0.66	0.68	0.02	Celtic07	0.88	0.90	0.96	0.04	Celtic08	0.95	1.00	0.93	0.04	Internazionale09	0.71	0.68	0.68	0.02	
	Dynamo Kyiv05	0.92	Schalke06	0.87	0.89	0.01	Werder Bremen07	0.71	0.73	0.82	0.08	PSV Eindhoven08	0.84	0.86	0.76	0.07	Dynamo Kyiv09	1.11	0.81	0.81	0.19	
	Olympiacos05	1.03	Club Brugge06	0.84	0.96	0.10	CSKA Moscow07	0.89	0.99	1.00	0.06	Rangers08	0.99	1.01	0.95	0.03	Shakhtar Donetsk09	0.84	0.78	0.78	0.05	
Group stage	Panathinaikos05	1.16	Udinese06	0.75	0.79	0.04	AEK07	0.83	0.85	0.86	0.02	Rosenborg08	0.76	0.83	0.76	0.05	Werder Bremen09	0.71	0.68	0.68	0.02	
	Fenerbahçe05	0.90	Betis06	0.70	0.71	0.02	Copenhaguen07	0.82	0.85	0.91	0.06	Sporting Lisboa08	0.72	0.73	0.71	0.01	Anorthosis09	1.04	0.99	1.01	0.03	
	Valencia05	0.84	Lille06	0.72	0.78	0.06	Bordeaux07	0.70	0.74	0.82	0.09	Marseille08	0.70	0.73	0.69	0.03	Aalborg09	0.87	0.80	0.80	0.05	
	CSKA Moscow05	0.89	Artmedia06	0.84	0.90	0.06	Benfica07	0.79	0.83	0.91	0.07	Benfica08	0.67	0.70	0.66	0.04	Fiorentina09	0.65	0.64	0.64	0.01	
	Shakhtar Donetsk05	0.87	Man. United06	0.65	0.75	0.10	Shakhtar Donetsk07	0.69	0.70	0.77	0.06	Besiktas08	0.89	0.94	0.88	0.03	Bordeaux09	0.94	0.72	0.72	0.16	
	PSG05	0.84	Porto06	0.89	0.91	0.01	Anderlecht07	0.66	0.67	0.75	0.07	Shakhtar Donetsk08	0.63	0.63	0.62	0.00	Celtic09	0.84	0.79	0.79	0.04	
	Celtic05	0.71	Rosenborg06	0.67	0.73	0.06	Steaua Bucurest07	0.78	0.83	0.90	0.07	Werder Bremen08	0.58	0.60	0.57	0.03	Zenit09	0.68	0.64	0.64	0.03	
	Maccabi Tel Aviv05	0.95	Thun06	0.75	0.80	0.05	Sporting Lisboa07	0.64	0.66	0.68	0.03	Slavia Praga08	1.07	1.06	1.03	0.02	BATE Borisov09	0.81	0.76	0.76	0.04	
	Ajax05	0.77	Panathinaikos06	0.61	0.70	0.10	Spartak Moscow07	0.69	0.70	0.71	0.02	Valencia08	0.84	0.83	0.79	0.04	CFR Cluj09	0.82	0.65	0.65	0.13	
	Deportivo Coruña05	0.66	Fenerbahçe06	0.68	0.70	0.02	Olympiacos07	0.63	0.65	0.74	0.09	Lazio08	0.72	0.82	0.72	0.08	Marseille09	0.61	0.57	0.57	0.04	
	Rosenborg05	0.67	Olympiacos06	0.74	0.75	0.01	Galatasaray07	0.65	0.75	0.79	0.10	Stuttgart08	0.62	0.65	0.57	0.07	Fenerbahçe09	0.76	0.66	0.66	0.09	
	Roma05	0.83	Sparta Prague06	0.65	0.68	0.04	Dynamo Kyiv07	0.59	0.62	0.68	0.07	Steaua Bucurest08	0.75	0.75	0.70	0.04	PSV Eindhoven09	0.65	0.58	0.58	0.07	
	Sparta Prague05	0.60	Anderlecht06	0.76	0.79	0.03	Hamburg07	0.59	0.60	0.63	0.03	CSKA Moscow08	0.57	0.63	0.56	0.06	Basel09	0.73	0.69	0.69	0.04	
	Anderlecht05	0.59	Rapid Wien06	0.55	0.59	0.05	Levski07	0.59	0.66	0.68	0.07	Dynamo Kyiv08	0.58	0.59	0.57	0.01	Steaua Bucurest09	0.76	0.71	0.73	0.03	
	AV		0.84		0.78	0.82			0.74	0.78	0.84			0.77	0.81	0.74			0.81	0.74	0.74	
	SD		0.13		0.12	0.12			0.10	0.11	0.11			0.13	0.13	0.12			0.11	0.09	0.10	

Note: CV = coefficient of variation; values highlighted in gray = efficient; underlined values = non robusts results.

Table 2.2. Cotinued

	Season 2009/10					Season 2010/11					Season 2011/12					Season 2012/13					
	Clubs/Windows	4	5	6	CV	Clubs/Windows	5	6	7	CV	Clubs/Windows	6	7	8	CV	Clubs/Windows	7	8	9	CV	
Champion	Internazionale10	1.35	1.22	1.22	0.06	Barcelona11	1.18	1.05	1.17	0.06	Chelsea12	0.88	1.04	1.17	<u>0.14</u>	Bayern Munich13	0.95	1.04	1.11	0.08	
Runner-up	Bayern Munich10	0.90	0.90	0.90	0.00	Man. United11	0.91	0.84	0.92	0.05	Bayern Munich12	0.69	0.75	0.83	0.09	Bor. Dortmund13	0.89	0.91	1.06	0.10	
Semifinalist	Lyon10	0.79	0.79	0.79	0.00	Real Madrid11	0.71	0.71	0.72	0.01	Real Madrid12	0.72	0.72	0.82	0.07	Barcelona13	0.85	0.93	1.02	0.09	
	Barcelona10	0.73	0.73	0.73	0.00	Schalke11	0.78	0.75	0.83	0.05	Barcelona12	0.79	0.79	0.90	0.08	Real Madrid13	0.67	0.75	0.81	0.10	
Quarter-finalists	Bordeaux10	0.88	0.88	0.88	0.00	Shakhtar Donetsk11	0.87	0.80	0.88	0.05	Benfica12	0.61	0.72	0.74	0.10	PSG13	0.81	0.84	0.97	0.10	
	Man. United10	0.71	0.71	0.71	0.00	Chelsea11	0.60	0.60	0.69	0.08	Apoel12	1.46	1.43	1.43	0.01	Malaga13	0.82	0.83	0.94	0.08	
	Arsenal10	0.73	0.73	0.73	0.00	Tottenham11	0.81	0.76	0.82	0.04	Milan12	0.71	0.82	0.82	0.08	Juventus13	0.70	0.74	0.81	0.07	
	CSKA Moscow10	0.79	0.79	0.76	0.02	Internazionale11	0.72	0.71	0.71	0.01	Marseille12	0.68	0.72	0.73	0.04	Galatasaray13	0.73	0.75	0.85	0.08	
knockout stages	Chelsea10	0.80	0.80	0.80	0.00	Bayern Munich11	0.64	0.64	0.74	0.08	NapolesC12	0.71	0.78	0.79	0.06	Valencia13	0.93	0.95	1.02	0.05	
	Fiorentina10	0.84	0.84	0.84	0.00	Valencia11	0.58	0.58	0.69	0.10	Basel12	0.76	0.84	0.85	0.06	Porto13	0.73	0.75	0.82	0.06	
	Sevilla10	0.78	0.78	0.78	0.00	Marseille11	0.55	0.55	0.66	0.10	Arsenal12	0.80	0.83	0.84	0.02	Schalke13	0.65	0.68	0.75	0.08	
	Real Madrid10	0.69	0.69	0.69	0.00	Arsenal11	0.87	0.80	0.83	0.04	Bayer Leverkusen12	0.70	0.75	0.76	0.05	Man. United13	0.77	0.80	0.82	0.03	
	Porto10	0.66	0.66	0.66	0.00	Copenhaguen11	0.85	0.77	0.83	0.05	Internazionale12	0.69	0.78	0.80	0.08	Arsenal13	0.89	0.89	1.16	<u>0.16</u>	
	Olympiacos10	0.80	0.80	0.80	0.00	Roma11	0.65	0.65	0.75	0.08	Zenit12	0.58	0.66	0.68	0.08	Celtic13	0.83	0.84	0.89	0.04	
	Milan10	0.80	0.80	0.80	0.00	Lyon11	0.55	0.55	0.64	0.09	CSKA Moscow12	0.68	0.74	0.75	0.05	Shakhtar Donetsk13	0.73	0.76	0.85	0.08	
	Stuttgart10	0.76	0.76	0.76	0.00	Milan11	0.80	0.71	0.78	0.06	Lyon12	0.51	0.61	0.65	<u>0.12</u>	Milan13	0.70	0.72	0.80	0.07	
	Unirea Urziceni10	0.92	0.92	0.90	0.01	Sporting Braga11	0.95	0.95	0.97	0.01	Man. City12	0.66	0.77	0.84	<u>0.12</u>	CFR Cluj13	0.91	0.92	1.02	0.06	
	Juventus10	0.85	0.85	0.85	0.00	Spartak Moscow11	0.68	0.66	0.74	0.06	Man. United12	0.64	0.73	0.75	<u>0.09</u>	Chelsea13	0.78	0.84	0.85	0.05	
Group stage	Liverpool10	0.80	0.80	0.80	0.00	Ajax11	0.67	0.63	0.73	0.07	Olympiacos12	0.64	0.72	0.74	0.07	Benfica13	0.68	0.74	0.74	0.05	
	Marseille10	0.69	0.69	0.69	0.00	Rangers11	1.01	0.99	1.02	0.01	Ajax12	0.59	0.70	0.75	<u>0.12</u>	Olympiacos13	0.75	0.76	0.86	0.08	
	Wolfsburgo10	0.69	0.69	0.69	0.00	Rubin Kazan11	0.81	0.70	0.75	0.07	Valencia12	0.56	0.67	0.70	<u>0.11</u>	Zenit13	0.69	0.71	0.79	0.07	
	Rubin Kazan10	0.95	0.95	0.90	0.03	Twente11	0.56	0.56	0.65	0.09	Porto12	0.51	0.59	0.66	<u>0.12</u>	Anderlecht13	0.73	0.74	0.79	0.04	
	Dynamo Kyiv10	0.72	0.72	0.72	0.00	Benfica11	0.55	0.55	0.66	0.10	Trabzonpor12	0.74	0.79	0.80	0.04	BATE Borisov13	1.17	1.22	1.69	<u>0.21</u>	
	Standard Liège10	0.79	0.79	0.79	0.00	Hapoel Tel-Aviv11	0.92	0.81	0.85	0.06	Lille12	0.55	0.66	0.69	<u>0.11</u>	Dynamo Kyiv13	0.72	0.73	0.83	0.08	
	AZ Alkmaar10	0.75	0.75	0.75	0.00	Werder Bremen11	0.52	0.52	0.62	0.10	Viktoria Plzen12	0.67	0.76	0.78	0.08	Ajax13	0.67	0.69	0.76	0.07	
	Apoel10	1.23	1.26	1.00	<u>0.12</u>	Basel11	0.56	0.56	0.65	0.09	Shakhtar Donetsk12	0.54	0.63	0.65	0.10	Man. City13	0.68	0.70	0.73	0.03	
	Zürich10	0.93	0.93	0.91	0.02	CFR Cluj11	0.70	0.67	0.75	0.05	KRC GenK12	0.69	0.75	0.76	0.05	Spartak Moscow13	0.70	0.71	0.80	0.08	
	Besiktas10	0.67	0.67	0.67	0.00	Panathinaikos11	0.92	0.80	0.82	0.08	Bor. Dortmund12	0.52	0.57	0.59	0.07	Lille13	0.62	0.64	0.67	0.05	
	Atlético Madrid10	0.66	0.66	0.66	0.00	AJ Auxerre11	0.61	0.57	0.62	0.05	BATE Borisov12	0.70	0.71	0.76	0.05	Sporting Braga13	0.60	0.66	0.75	<u>0.11</u>	
	Rangers10	0.72	0.72	0.72	0.00	Bursaspor11	0.61	0.59	0.65	0.05	Dinamo Zagreb12	0.66	0.71	0.72	0.05	Montpellier13	0.55	0.57	0.63	0.07	
	Maccabi Haifa10	0.69	0.69	0.69	0.00	MŠK Žilina11	0.52	0.52	0.59	0.07	Villareal12	0.61	0.65	0.66	0.04	Dinamo Zagreb13	0.68	0.68	0.75	0.06	
	Debreceni VSC10	0.70	0.70	0.70	0.00	Partizan11	0.57	0.49	0.53	0.07	OtelulGalati12	0.62	0.65	0.66	0.03	Nordsjaelland13	0.80	0.81	0.96	<u>0.11</u>	
	AV		0.81	0.80	0.79			0.73	0.69	0.76			0.68	0.75	0.78			0.76	0.79	0.73	
	SD		0.15	0.14	0.11			0.16	0.14	0.13			0.16	0.15	0.15			0.12	0.13	0.16	

Note: CV = coefficient of variation; values highlighted in gray = efficient; underlined values = non robust results.

The first highlighted result concerns the low efficiency level of the UCL for the 2004/05 to 2012/13 seasons. This result agrees with those found by Zambom-Ferraresi et al. (2017). Our sample comprises 288 observations and, due to the repetition in calculating efficiency in Window DEA, we have 768 different ratios and only 6% of the entire sample is efficient. Looking at windows separately, these results are similar. On the one hand, the window with more efficient observations is window 3, with nine efficient observations. On the other, window 4 had only three efficient observations.

Clubs that had robust efficient scores in their respective windows will be a reference for the rest of the sample. Internazionale 2009/10 and Barcelona 2010/11 are the best benchmarking observations. Both clubs were champions and had relative technically efficient scores when compared with other teams that played in window 4, 5 and 6 and 5, 6 and 7, respectively. Apoel's 2011/12 performance is an example and must be a reference for all the small and medium clubs in the sample. This club reached the quarterfinals of the UCL by being efficient when compared with the performance of the other clubs in the two periods before and after. The performance of Slavia Prague 2007/08, Apoel 2009/10 and BATE Borisov 2012/13 is also worthy of note. These clubs did not advance past the knockout round, but as they did not waste their sports resources, they can be qualified as efficient. These robust efficient clubs achieved good sports results on the basis of the inputs they employed.

If we also take into account teams with at least one ratio above 1 in one window and with CV below 10%, robust efficient units are found in all the stages and over the entire time horizon studied in the present paper. After eliminating observations only present in one or two windows, these cases are: Liverpool 2006/07, Internazionale 2006/07, CSKA Moscow 2006/07, Manchester United 2007/08, Celtic 2007/08, Anorthosis 2008/09, Ranges 2010/11, Bayern Munich 2012/13, Borussia Dortmund 2012/13, Barcelona 2012/13, Valencia 2012/13 and CFR Cluj 2012/13.

Finally, efficient teams are not the same throughout the entire time horizon in this paper, as expected after the statistical acceptance of null hypothesis of the equivalent distribution in efficiency ranking. This lack of continuity in efficient teams is not only due to the existence of teams not playing in all the seasons under study, as some of the efficient teams have a continuous presence in the UEFA Champions League.

2.5.3. Evolution of efficiency and sports results

Given that WDEA was employed, we can draw more accurate conclusions about the evolution of efficiency. By observing the relation between DMU efficiency in the first season of a window and the variation in its efficiency during the window period we can observe interesting issues. The following figures (2.1.A to 2.1.G) are easy to interpret and help us to analyze the evolution of efficiency. The clubs on the right side of the horizontal axis have showed positive efficiency changes, and the clubs on the left side have had negative changes during the window cycle. Clubs in the top left quadrant are efficient in the first season of the windows, but cannot maintain this efficiency in the next two seasons. We find nine observations with this performance and four of them are the champions of the competition in the first season of the respective window (w): Barcelona 2005/06 (w 2) and 2010/11 (w 7), Internazionale 2009/10 (w 7) and Liverpool 2004/05 (w 1).

In the seven windows we studied, no case was found in the top right quadrant, which means that no clubs were capable of maintaining efficiency for three seasons. These results corroborate those found by Zambom-Ferraresi et al. (2017), where teams had many problems maintaining their efficiency during the seasons.

Figure 2.1.A. Relationship of efficiency evolution and the efficiency of the first season of window 1 (seasons 2004/05-2006/07, n=15)

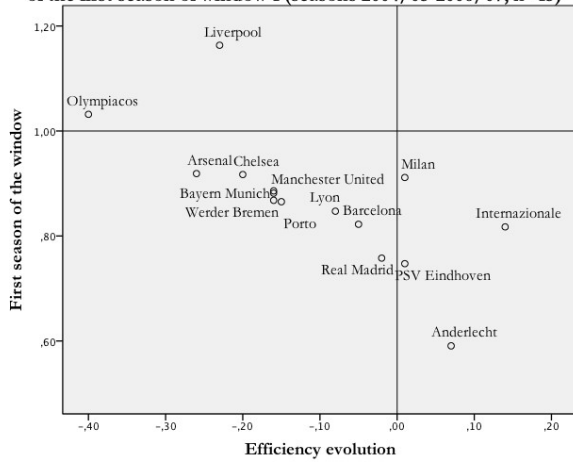


Figure 2.1.B. Relationship of efficiency evolution and the efficiency of the first season of window 2 (seasons 2005/06-2007/08, n=14)

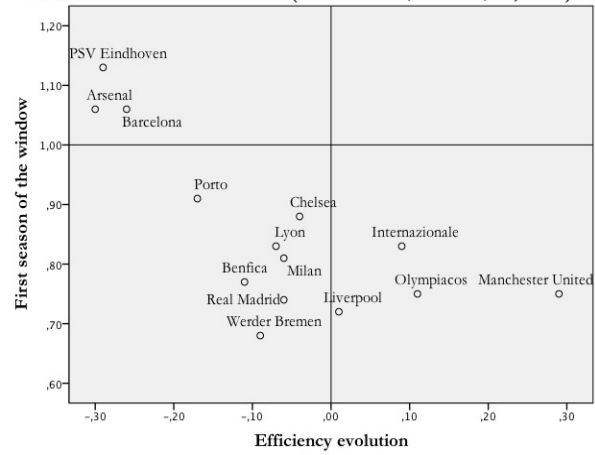


Figure 2.1.C. Relationship of efficiency evolution and the efficiency of the first season of window 3 (seasons 2006/07-2008/09, n=17)

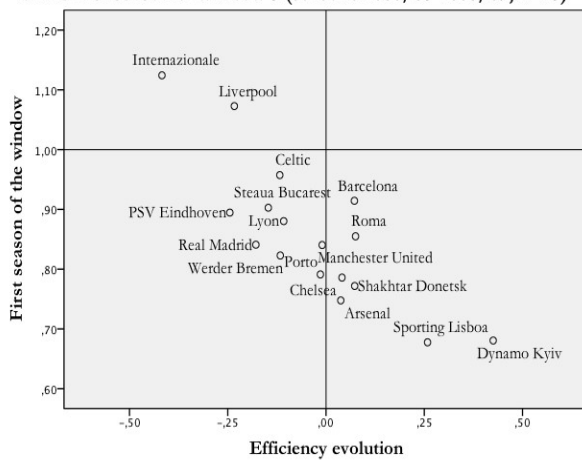


Figure 2.1.D. Relationship of efficiency evolution and the efficiency of the first season of window 4 (seasons 2007/08-2009/10, n=11)

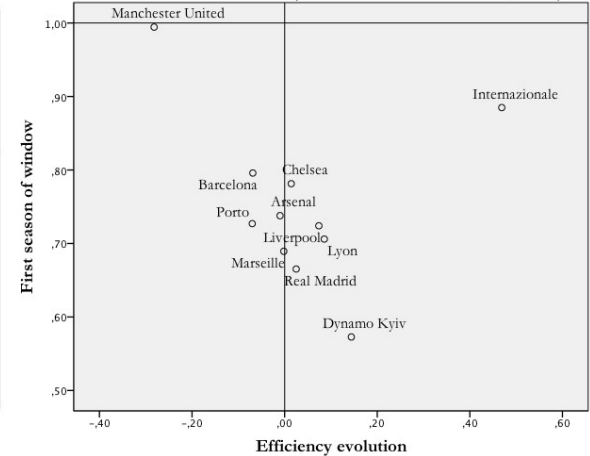


Figure 2.1.E. Relationship of efficiency evolution and the efficiency of the first season of the window 5 (seasons 2008/09-2010/11, n=9)

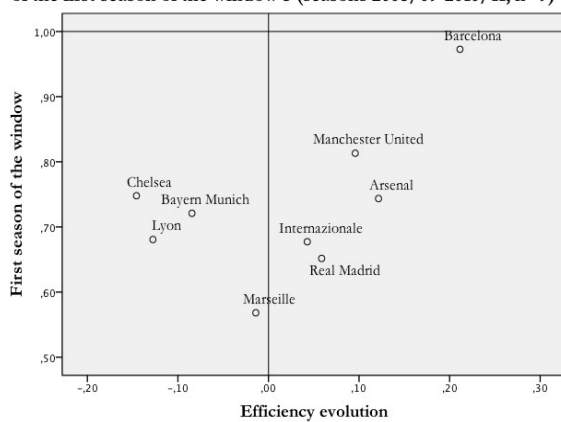


Figure 2.1.F. Relationship of efficiency evolution and the efficiency of the first season of the window 6 (seasons 2009/10-2011/12, n=10)

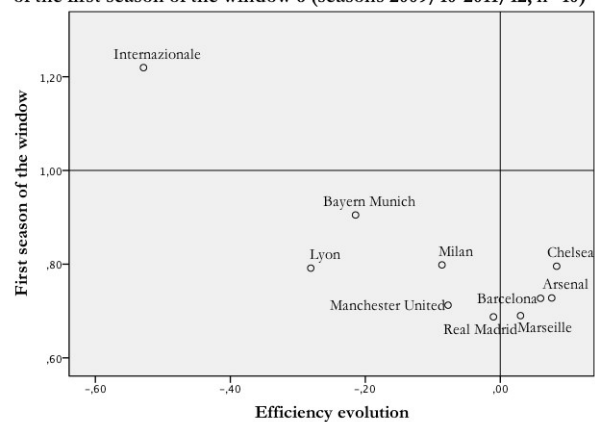
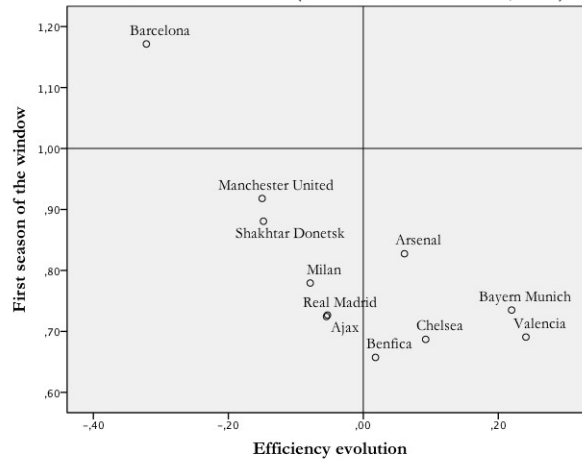


Figure 2.1.G. Relationship of efficiency evolution and the efficiency of the first season of window 7 (seasons 2010/11-2012/13, n=11)



In the bottom left quadrant, we can see those clubs that were inefficient in the first season of the window and cannot improve on this inefficiency during the window cycle. The most highlighted cases are Lyon and Manchester United, which are inefficient and do not change in five out of seven analyzed windows. Real Madrid was found in the same case in four out of seven of the observed windows and this team is present in all of them. In contrast, Porto participated in the UCL in four out of these seven windows and was inefficient in all the seasons in which they played.

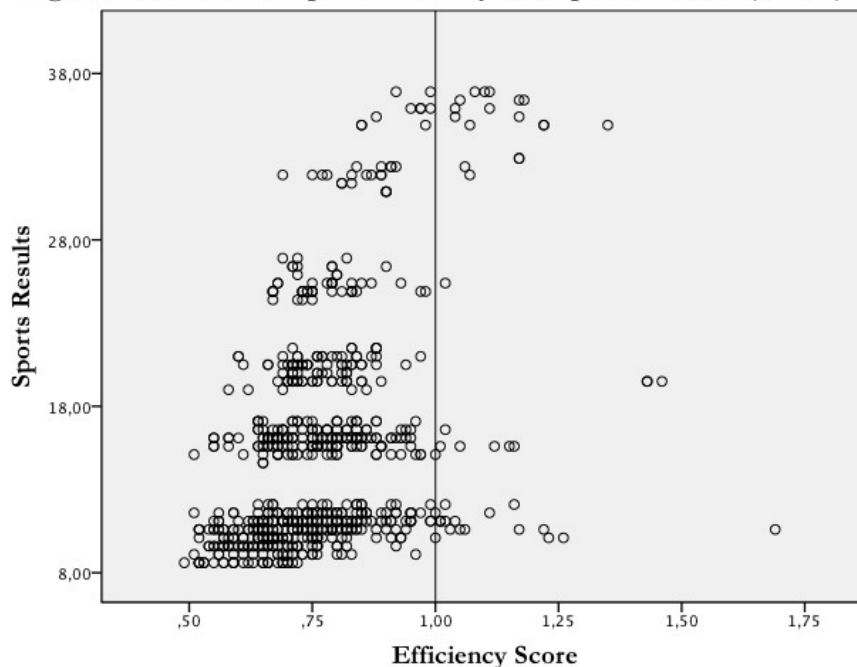
Porto's situation captures our attention. In the last decade, exactly the period analyzed here, Porto was known as one of the best clubs at the time for hiring (mainly) and training young, talented and unknown players. This means that, when hiring players, Porto (Yahoo Sports UK, 2016) presents a satisfactory performance, but its resources on the field were used inefficiently. Pursuing efficiency in all areas is essential for medium clubs like Porto, which is competing on the field with the largest clubs in Europe.

Finally, the bottom right quadrant includes clubs that improved their efficiency scores during the window cycle, but their improvement did not suffice to be efficient when their performance is compared with all the clubs in the window. The clubs in this situation are Arsenal, Chelsea and Internazionale, four times out of the seven possible. Barcelona and Real

Madrid also improved their efficiency three times during the seven observed windows. We could see that these are major clubs that participated in the UCL in all or almost all the analyzed windows. In some performances they had good sports results, but they wasted their resources, e.g. Arsenal reached the 2008/09 semifinal and Chelsea was the 2011/12 champion. Sometimes clubs present very poor sports results considering the number of inputs they employed and, in these cases, their inefficiency is evident. This is the case of Real Madrid in windows 4, 5, and 6.

The relation between sports results and efficiency can be observed in figure 2.2. Most observations are inefficient, which explains the few observations on the right side of the axis of the efficiency score. The observations of the first two competition stages (group and knockout) are very crowded, as was expected, because both concentrate the largest part of the sample. The highest sports prizes for these two groups could be 14.6 and 18.1 (million euros), respectively. A growing trend in figure 2.2 can only be observed in the final stages of the competition.

Figure 2.2. Relationship of Efficiency and Sports Results (n=768)



After analyzing the correlation between sports results and the efficiency score of all the 768 ratios in the sample in table 2.3, we have found a positive and significant correlation of almost

40% of the sample. However, the importance of efficiency is obvious when we look at the correlation for the clubs that reach the semifinal stage. The correlation between efficiency and the sports results in this phase is 72%. By observing these results, we can conclude that for all kinds of club, whether large or small, efficiency is significant, positive and highly correlated with reaching the final phases of the UCL.

Table 2.3. Correlation between efficiency and sports results

		Entire sample		Semifinalists	
		EffScore	SR	EffScore	SR
EffScore	Pearson correlation	1	.393**	1	.722**
	Sig. (2-tailed)		.000		.000
	N	768	768	96	96
SR	Pearson correlation	.393**	1	.722**	1
	Sig. (2-tailed)	.000		.000	
	N	768	768	96	96

Note: EffScore = efficiency score; SR = sports results

** Correlation is significant at the 0.01 (2-tailed).

Individually, one of the most highlighted performances when observing both efficiency and sports results was Internazionale in the 2009/10 season (calculated in windows 4, 5 and 6); a team characterized by Jose Mourinho's stamp, playing mostly in counter attack, using one of the simplest and most known tactics in football, the numerical superiority of players. In a decade characterized by an ornate play style of the victorious Barcelona and Spanish selection, the ball possession style was considered one of the main outcomes of football. However, it is important to note that ball possession is not an important outcome. At the end of the match, it does not matter if a team has had a high percentage of ball possession if the team loses the match. Although fans would undoubtedly prefer to see their team controlling ball possession, they would obviously rather win the match. Internazionale and its coach proved that "alternative" tactics could and must be employed (including for major clubs) to surprise and win competitions. Based on the results calculated and obtained by means of DEA, Internazionale won the

competition that season without wasting its resources. Looking for other performance indicators (not included in our model) of this team in 2009/10, we could confirm a different style of play: only 45% of ball possession; the team that committed the most fouls and received the most yellow cards in the season; and also the one with more offsides. All these characteristics are the opposite of the norm in recent years. Most teams have tried to imitate Barcelona, and it is undeniable that they had a beautiful style of play. Fans have enjoyed watching Barcelona, especially as the team was winning. This seemed the perfect tactic, but it is not available to everyone. José Mourinho has noted this and made an intelligent and efficient use of this information and its resources.

Figure 2.3.A. Relationship of efficiency evolution and sports results evolution during window 1 (seasons 2004/05-2006/07, n=15)

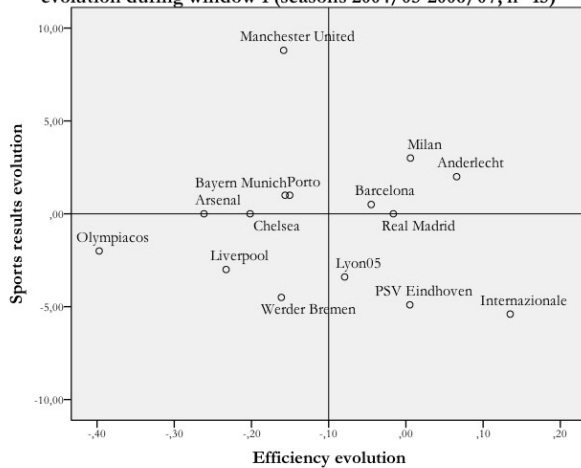


Figure 2.3.B. Relationship of efficiency evolution and sports results evolution during window 2 (seasons 2005/06-2007/08, n=14)

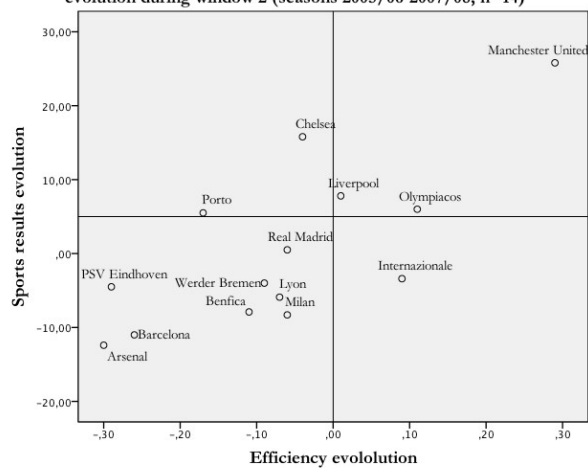


Figure 2.3.C. Relationship of efficiency evolution and sports results evolution during window 3 (seasons 2006/07-2008/09, n=17)

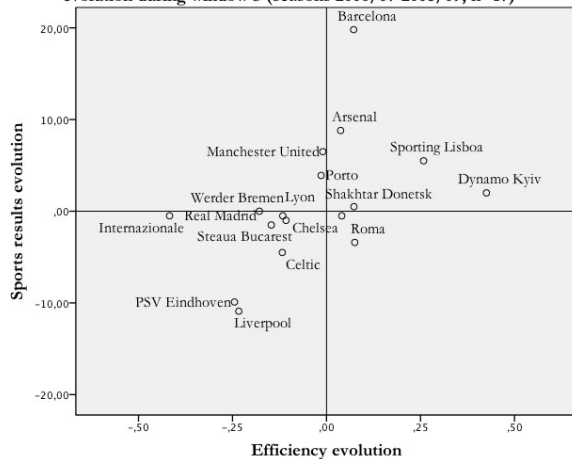


Figure 2.3.D. Relationship of efficiency evolution and sports results evolution during window 4 (seasons 2007/08-2009/10, n=11)

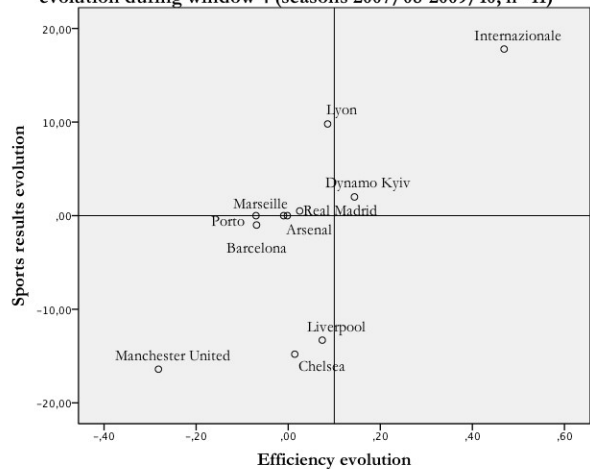


Figure 2.3.E. Relationship of efficiency evolution and sports results evolution during window 5 (seasons 2008/09-2010/11, n= 9)

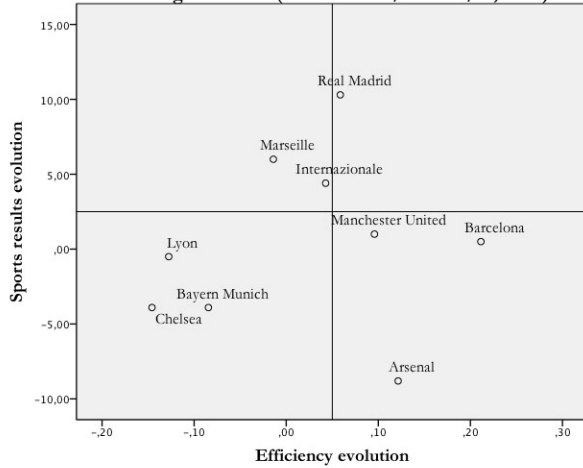


Figure 2.3.F. Relationship of efficiency evolution and sports results evolution during window 6 (seasons 2009/10-2011/12, n=10)

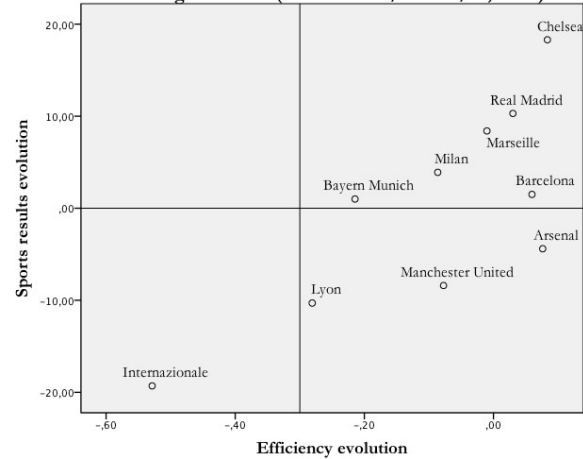
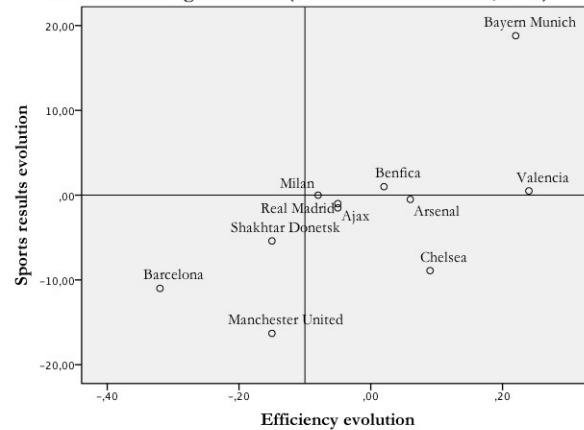


Figure 2.3.G. Relationship of efficiency evolution and sports results evolution during window 7 (seasons 2010/11-2012/13, n=11)



Figures (2.3.A–2.3.G) show results from the relation between the evolution of efficiency scores and the evolution of sports results. The evolution is calculated on the basis of the difference between the last and the first season of each analyzed window. Regular windows in this paper are composed of three seasons, so they contain 96 efficiency ratios. As we mentioned above, several clubs could not participate in the UCL on an ongoing basis. Therefore, we merely analyzed the evolution of those clubs that played in all three years in each window. From an overall view of all seven analyzed windows, we can see a clearly positive trend, except for windows 1 and 5. This trend means that clubs that improve their efficiency enhance their sports results and vice versa.

2.6. Discussion of results and conclusions

The aim of this paper is to analyze efficiency and its evolution in teams that played in the UEFA Champions League taking advantage of the panel data we have for nine sport seasons. This paper contributes to sports efficiency literature by presenting a research procedure to identify the most accurate methodology to be applied to panel data. First, we analyzed the existence of a temporal trend using the S statistic proposed by Brockett and Kemperman (1980). We have calculated the Kruskal-Wallis statistic to verify if there is stability in relative ranks. The results of the aforementioned tests have indicated that window analysis is an accurate methodology to apply to the UCL sample. This methodology enables us to assess the robustness of efficiency ratios to detect the best benchmark clubs. Windows analysis also allows for more reliable conclusions on the evolution of efficiency. Our efficiency ratios have been calculated using super-efficiency (Andersen & Petersen, 1993), which enables us to discriminate efficient units among them.

To the best of our knowledge, this paper is the first empirical study on international football competitions applying WDEA to incomplete panel data. Until now, studies such as Sala-Garrido et al. (2009) have analyzed those clubs that participated in the competition during all the seasons in the analyzed time horizon. Sala-Garrido et al. (2009) analyzed eight seasons of the Spanish league, from 2000/01 to 2007/08. Their panel data was complete, but from a sporting point of view, biased towards teams with a good performance.

Our general results show a low efficiency level in the analyzed sample. These results agree with previous findings by Zambom-Ferraresi et al. (2017) and with Espitia-Escuer and García-Cebrián (2010) when they analyzed its sample in an intertemporal approach. We have used WDEA to calculate efficiency as it allows us to evaluate robustness in results. In the present

paper, teams with an efficiency ratio above one can be qualified as efficient with a high level of assurance and they can be proposed as benchmarks for inefficient clubs. We have also found robust efficient teams in all stages in the championship, which opens the possibility of evaluating teams not exclusively from a sport success standpoint, but taking a combination of resources and sport results into account.

We have verified the existence of a temporal trend in efficiency and stability in efficiency rankings. We can then extract more in-depth characteristics about the championship than in previous papers studying efficiency in the UEFA Champions League. The existence of a temporal trend during the analyzed time horizon means that technical changes occurred between the 2004/05 and 2012/13 seasons that led to changes in the efficiency frontier. The best example was Internazionale's sports performance and efficiency in 2009/10. Additionally, in our study, teams did not maintain their relative efficiency. This means that, over time, efficient units have changed. This is corroborated by the analysis of efficiency evolution in a window and efficiency in the first period of the window. We have identified that it is hard for clubs to maintain their efficiency during their time in the UCL environment. In fact, we have not found any club capable of maintaining its efficiency.

In all the stages in the competition we have found a positive and significant correlation between sports results and efficiency. However, the most remarkable, significant, positive and strong correlation between estimated efficiency scores and sports results was found in those teams that reached the semifinals of the UCL. This is an important finding for the top best teams in Europe: some simple changes in technology may represent an improvement in efficiency. This finding may assume greater significance if we consider other important findings, namely that an improvement in efficiency could also be an improvement in sports

results. Even better is that this improvement could happen without the need for more inputs, which are very scarce nowadays in a football scope.

Although the correlation between efficiency and sport results is weak in teams playing in only the first stages of the championship, the observation between the evolution of efficiency and the evolution of sports results in the majority of the windows indicates that if teams improve their efficiency, they could enhance their sports results. Consequently, even though pursuing efficiency is essential for all kinds of clubs, it seems crucial for small and medium clubs competing in the field with the largest clubs in Europe. The most remarkable benchmarking observation in this regard was attained by Apoel 2011/12.

Finally, if efficiency is positively correlated with sport results, teams could successfully change their style of play without using more resources. And the lack of continuity in efficient teams adds emotion to the championship.

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3. And if the ball does not cross the line? A comprehensive analysis of football clubs' performance

Abstract

The football club market is changing fast in the social media era. In this global market, clubs must maintain or improve fans' attendance at the stadium; simultaneously, they need, more than ever, to take care of social media. The aim of this paper is to test and discuss a comprehensive approach to analysing the performance of football clubs regarding their multiplicity of objectives. We analyse the efficiency of English Premier League (EPL) clubs during three seasons (2012/13–2014/15). The methodologies employed are data envelopment analysis (DEA) and a bootstrapped DEA model. The input is the market value of the squad, and the outputs are sports results, total revenue, the ratio of stadium utilization during the season, and an index of social media impact. The results are robust to alternative estimation methods and indicate that EPL clubs still have a margin for improving their overall efficiency, mainly the medium clubs. The analysis of football clubs' performance with the proposed comprehensive approach provides a useful tool to help managers with evaluation and feedback considering the actual context of the market. The approach brings closer the opportunity to design appropriate strategies to improve clubs' efficiency as well competition policies.

Keywords: Football; efficiency; performance; Premier League; social media; DEA

3.1. Introduction

The dichotomy of football clubs' objectives has been discussed in depth in the sports economics literature (Sloane, 1971; Szymanski & Smith, 1997; Garcia-del-Barrio & Szymanski, 2009). According to the existent theory, sports results are the undeniable output of football clubs. Together with sports results, the total revenue (TR) is a representative outcome. The TR measures the capability of a club to generate income, independently of the objectives of its shareholders, who could be win or profit maximizers. During the last fifteen years, the literature has focused on these two main aspects, the sportive and the financial aims.

Nevertheless, the football club market is changing fairly and fast – from a local market (most fans attending the stadium) to a global market (with TV, media, and social networks) – which is having an important effect on clubs' performance overall. From the constant increase in live premium sports content, an open question emerges: how will clubs manage the unstoppable growth of global platforms and social media and at the same time not lose the attendance of fans at the stadium (Deloitte, 2016)?

This paper aims to propose a comprehensive approach to analysing the performance of football clubs considering the dimension of social media impacts, which as far as we know are not included in other models.

3.2. Literature review

Holistic analyses have previously been proposed to analyse the performance of football clubs. The approach developed by Haas (2003) should be highlighted, which included the number of spectators to explain performance in the Major Soccer League in the US by applying the DEA, but the effects of social media were not considered. Recently, Plumley et al. (2014) developed an

empirical model based on a multidimensional approach, but it was limited to the usual financial and sporting indicators weighted using subjective criteria.

Nevertheless, as argued previously, the effects of social media on the management of sport clubs in the context of a global market seem to be essential and critical (Deloitte, 2016). Recently, different authors (McCarthy et al., 2014; Dima, 2015) have introduced the analysis of social media marketing tools and considered how clubs manage their brand presence through social media in the sports industry. The main findings have indicated that the development of social media strategies has the potential to deliver interaction and engagement, community growth and belonging, and commercial gains. Dima (2015) also found a positive but moderate correlation between social media impacts and sports results. However, none of these studies has considered the impact of social media as part of the overall outcome of football clubs.

3.3. Methodology, variables, and data

Considering the recent questions raised in the literature, we propose a more comprehensive approach to analysing the most important outputs that clubs have to pursue nowadays. We estimate efficiency using the DEA and bootstrapped DEA methodologies. The efficiency scores of firms are measured by their distance from an estimated production frontier. DEA provides a single measure of technical efficiency in the case of multiple inputs and outputs; it is a valuable methodology when the correct weighting of inputs and outputs is unknown or cannot be derived. Bootstrapped DEA allows the correction of the bias of efficiency estimators and the estimation of confidence intervals for the efficiency measures, which enable statistical inference (Cooper et al., 2007; Simar & Wilson, 2000). Variable returns to scale (VRS) are assumed, and both estimations are oriented towards output maximization.

The sample is composed of all the 20 clubs that played in the English Premier League (EPL) during three seasons, from 2012/13 to 2014/15. Considering the clubs that were relegated and promoted, our sample contains 25 different clubs. The input of our model is the squad market value (SMV), and the outputs are the sports results, total revenue, stadium capacity utilization (SCU), and social media impact.

The SMV was recommended by Dawson et al. (2000) as an *ex ante* input measure based on start-of-the-season player characteristics. Our data on market value are compiled by an online community ([Transfermarkt](#)) at the start of each season. Frick and Prockl (2016) documented the quality of this data source.

To measure the outcome, sports results (SRs) are the undeniable output of football clubs. One of the most-used measures in the literature is the total points at the final of the league in each season. These data are taken from the official site of the EPL (www.premierleague.com). The total revenue (TR) is the most representative financial indicator of a club's output. This measure represents all the main incomes that a club could generate. The sources of the TR are [Delloite](#), [Companies House](#), [Fame](#), and [The Guardian](#). Both measures (SR and TR) are largely used in applied research regarding football clubs' performance.

To analyse the influence of fans' impact, we consider two variables. First, we incorporate the percentage of utilization of clubs' stadiums (SCU). However, with the growth of social media and online platforms, fans' attendance is not limited to the stadium. For this reason, we include the Sport Social Media Index (SSMI). This index is an annual league table of all 148 British professional football, rugby, and cricket teams, ranked according to the best use of social media by their official club channels, including Twitter, Facebook, Pinterest, Instagram, Vine, Google+, and LinkedIn (SSMI, 2016).

The inclusion of SCU and the SSMI in our approach will enable us to analyse the football clubs' performance in a more integral way. table 3.1 provides the summary statistics and a short description of the variables.

Table 3.1. Summary statistics

Variable	Description	Mean	SD
SMV (I)	Ex ante measure of all squad market value	199.82	148.60
SR (O)	Points achieved in the current season	52.35	17.56
TR (O)	Total revenue at the end of the season	187.73	126.54
Stadium utilization (O)	Percentage stadium capacity utilization during the entire season	95.42	5.97
SSMI (O)	Index of social media impact of British clubs	58.37	5.68

Note: (I) = input; (O) = output.

3.4. Results

The results⁷ are robust to both estimation methods (VRS and VRS bootstrapped), presenting a correlation of 0.982, which is significant at the 0.01 level (2-tailed). The results indicate that EPL clubs have good efficiency levels considering the inputs employed, as can be observed in table 3.2, although, in general terms, EPL clubs still have a margin for improvement.

We divided the clubs into three different groups considering their SMV. We found a group of small clubs (with an SMV up to 100 million), a group of medium clubs (SMV between 100 and 200 million), and a group of large clubs (SMV over 200 million). The results of a one-way ANOVA indicate that there are significant differences among the groups, the most efficient clubs being the large clubs and the least efficient being the medium clubs (F3.998, p<0.05).

The big clubs, like Arsenal, Chelsea, Liverpool, and Manchester United, are efficient (under the VRS assumption) in all the seasons observed. Considering the high market value of the large

⁷ All obtained using the FEAR software library provided by Wilson (2008).

clubs and the fact that this is the only input measure of our approach, this result highlights how well these large clubs are managed. This should be emphasized particularly in the case of the EPL, a highly competitive league that demands excellent management of the available resources.

Table 3.2. Results of efficiency estimations (VRS)

Club	2014/15	2013/14	2012/13
Arsenal	1	1	1
Chelsea	1	1	1
Liverpool	1	1	1
Manchester United	1	1	1
Manchester City	1	1	0.981
Tottenham Hotspur	0.998	0.994	1
Everton	0.996	1	1
Newcastle United	0.986	0.966	0.966
Sunderland	0.847	0.89	0.926
West Ham United	1	1	0.996
Aston Villa	0.928	0.882	0.964
Queens Park Rangers	0.983		0.984
Fulham		0.975	0.997
Swansea City	1	1	0.996
Southampton	1	1	1
Stoke City	0.985	0.977	0.989
West Bromwich Albion	0.977	0.988	1
Hull City	0.938	1	
Crystal Palace	0.986	1	
Leicester City	1		
Burnley	1		
Cardiff City		0.992	
Norwich City		1	1
Reading			1
Wigan Athletic			0.813
Mean	0.981	0.983	0.981
Standard deviation	0.038	0.035	0.044

Note: VRS = variable return to scale; light grey = more than 200 million of SMV (squad market value), dark grey = less than 100 million of SMV.

Nevertheless, some clubs still have a margin for improvement. In particular, some medium clubs, such as Sunderland and Aston Villa, have the lowest scores of the sample, even when compared with relegated teams, which are the smaller ones in the sample. Another interesting result concerning the relegated teams is that these clubs perform very well considering the

resources employed. This result means that these clubs, by increasing the inputs and maintaining the good management, have possibilities to increase their outputs. Wigan Athletic is an exception; it has outstanding inefficiency among the nine clubs relegated during the three seasons analysed.

3.5. Conclusions

We propose a comprehensive approach to measuring the overall football club performance in the English Premier League. Following the literature, we employ an *ex ante* input measure and some of the main outcomes that a club must pursue nowadays. The results are robust to alternative estimation methods and indicate that EPL clubs in general terms have good efficiency levels; nevertheless, there is still a margin for improvement, mainly among the medium clubs. The relegated clubs mostly present high efficiency levels. In this sense, the recommendation for these clubs to improve their results is to increase the quality of the squad. To achieve this without increasing the clubs' costs, some potential alternatives could be to invest in training young players and develop more advanced systems to sign undervalued players. The performance of Leicester in 2015/16 is a good example of this strategy.

Our conclusions emphasize the relevance of considering simultaneously sports results, incomes and costs, the fan base, and the social media impact. Furthermore, this approach provides managers with a useful tool to help with evaluation and feedback regarding the club's management. Finally, the high efficiency values of English clubs obtained in our study might be closely associated with the consideration of the EPL as one of the most important and attractive national football competitions in the world.

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4. Are football managers as efficient as coaches?

Performance analysis with *ex-ante* and *ex-post* inputs in the Premier league

Abstract

There is a controversy on sport performance literature about what type of inputs might explain more deeply the performance of sports clubs (inputs specification controversy). By one side, several papers have analysed sports teams' performance using the match-related statistics or wages as inputs, well-known as *ex-post* inputs. By other side, some authors have criticized the use of these *ex-post* inputs, and recommend the use of *ex-ante* inputs, as the market value of the players. To put some light on this open discussion we have analysed the performance of football teams estimating technical efficiency with three different inputs specification. The methodologies employed were data envelopment analysis (DEA) and a bootstrapped DEA. Our sample is composed by English Premier League football clubs, during three seasons (2012/13 - 2014/15). The DEA results indicate that the correlation between the three models is positive and significant. The DEA bootstrapped results help to restate the robustness of the estimations and endorsed the inputs choices. The correlations of the estimations with market value and match-related statistics are the most striking (90 and 94%, DEA and bootstrapped DEA), which indicate that the existent discussion related to the use of match-related statistics as input is unjustified, because it does not affect significantly the efficiency' estimations. Some caution is

recommended when using wages as input. In most cases, if the measure faithfully represents the players' skills and abilities will lead to similar results.

Keywords: Sports economics; controversy; input specification; DEA; English football

4.1 Introduction

Once upon a time, a modest team from a relatively small city returned, after a decade away, to the top level of football league competition in his country. After struggling to keep the category, unexpectedly, the next season won the competition with a lot of efforts and a little of fortune. This history might be described as a fairy tale to tell children loving football. However, this is not a story, it is a true history that happened in England with the Leicester City. From a scientific perspective, if we consider the squad' market value at the start of the season 2015/16, they should never have won. Leicester ranked nineteen, with a global market value equivalent to one-sixth of Chelsea's market value, for example. On the three previous seasons, the correlation among the market value and the sports performance of the teams was between 80 and 88% and in 2015/16 decreased to only 42%. By not considering the performance on-field of the teams this season, we would be making an important mistake.

In sports economics literature, is widely accepted that the on-field success is directly related to players' skills and abilities (i.e., Szymanski & Kuypers, 1999 and Carmichael et al., 2011). Considering this strong relationship, in open sports system like the European football, with less regulations related with salary caps than the North American sport system, the competition could be focus on getting money to hire the best players and wait to win the championship. Assuredly we should analyse the management of football clubs, but we must not forget what this sport is all about; basically, eleven against eleven kicking the ball. Consequently, to analyse the

performance of football clubs by ignoring what players do on-field or consider it inappropriate, is minimally meaningless.

In professional sports team the output is conventionally measured in terms of team success, represented by winning performance. The players' talent is the input of this peculiar production process. This representation was defined more than four decades ago in Scully' (1974) seminal work. Subsequently different approaches were developed, varying the methodology employed, the units under analysis or the inputs specification. Currently is fairly accepted that the production function in football like in other activities have two or more stages. In a first stage, the players with his abilities and skills will produce some plays during the match. In the second stage, these plays will produce an output, which could be to win, to tie, or to lose (in the case of a single match). Regarding these stages, there is a controversy in the literature about the inputs specifications. In other words, what kind of inputs might explain and predict the best teams' performance. On the one hand, several works use *ex-post* input measures (e.g. game-related statistics) to analyse the performance in sports (Carmichael et al., 2000; Espitia-Escuer & García-Cebrián, 2006; Guzmán & Morrow, 2007; Zambom-Ferraresi et al., 2017). On the other hand, some authors assert (Lee, 2006; and Lee & Berri, 2008) that the only way to analyse the performance of football clubs must be done through *ex-ante* inputs that measured the players' skills and abilities before the start of the season; such as players' market value (Dawson et al., 2000; Lee & Berri, 2008; del Corral et al., 2015). Moreno and Lozano (2014) have analysed both stages and have found that there is a significant difference between what we expect of the players considering its skills and what players really do.

Motivated by this literature controversy, this paper attempts to fulfil this gap with empirical analysis, by utilizing a data set that contains information that allows analyse football clubs' performance following the two strands of research. We will estimate the efficiency in the English

Premier league (EPL) by using three different models. The three models have the same output, but different inputs specifications. The input employed in the first model is the squad' market value (input ex-ante). This input, used to be the best accepted in literature, but as in the case of Leicester City, is not accurate in all the cases. In the second model, we used match statistics of the plays performed by clubs (input ex-post); and in the third one we used the squad' wages (input ex-post). This input is the most criticized on literature. That way, the main objective of this paper is to offer empirical results to contribute to this open discussion about sports team' performance analysis.

Currently, the EPL has the highest revenues, wages and profitability. From to 2016 to 2019 the EPL clubs will to share £8.3 billion TV windfall (Rumsby, 2016). The EPL is also the world's highest earning sports league from media rights in non-domestic markets (Deloitte, 2016). These circumstances, jointly with seriousness that the EPL is managed since long time ago, make it one of the most important national football leagues in the world. So, to carry out our objective, the efficiency of EPL clubs will be estimated with DEA methodology. We have 60 observations and 25 different clubs, from 2012/13 to 2014/15 season. To verify the robustness of the estimations, we will also estimate a Bootstrapped DEA.

The reminder of this paper is structured as follows. First, the peculiarities of the football clubs' production function, the existent theory and the main empirical findings are exposed in the next section. On the methodology and data section we explain how the study was carried out. The main results were exposed on fourth section and finally, some conclusion thoughts were discussed.

4.2. Framework and background

4.2.1. Production function of sports teams

The transformation of inputs into outputs is called production process, which is described by a production function (PF). Scully (1974) was the first one to adapt this approach to measure performance of sport teams. He assumed that teams are engaged in the production of a constant number of games with a certain level of quality. This quality would be team success during a season (measured by per cent wins), which is related to two general categories of inputs: a vector of specific playing skills, and a vector of non-player inputs such as managers, coaches, capital, team spirit, etc. Summarizing, Cadenas et al. (2010) presents the production function of football clubs modelled as following:

$$Y_i = Y_i(X_i), i = 1, 2, \dots, n, \quad (4.1)$$

where Y_i is the football output measured for team i (usually the percentage of points or victories obtained) and X_i is a vector of inputs. Usually, the inputs in the sport production function are variables that measure the technical abilities of the players.

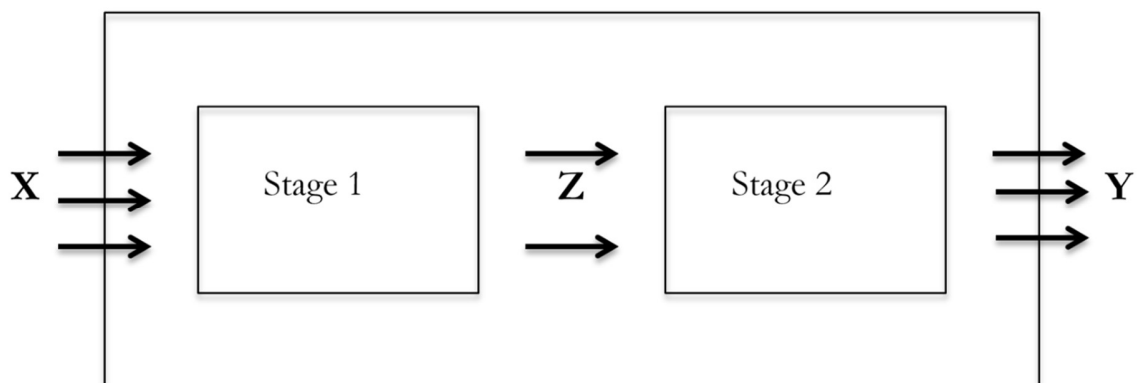


Figure 4.1. The two-stage production process in football (Adapted from Desposits & Koronakos, 2014).

Observing in more detail, this PF can be divided in two stages as is shown in Figure 4.1. The team produces in two stages, with output from the first stage becoming input to the second stage. In a first stage, a squad and coaching staff with their given skills (X) will train through their pre-match work (technical, tactical, and physical workouts) to produce attack and defense plays (Z). In the second stage, during the match, the combination of these plays will generate an outcome, the sports result (Y).

All these processes are related and also feedback. Studies such as Szymanski and Kuypers (1999) and Carmichael et al. (2011) indicate that on-field success can be directly related to players' skills and abilities, and that revenue is positively related to on-field success. Wage expenditure is also shown to systematically reflect player skills and performances (Frick, 2011).

4.2.2. Empirical evidence

We have considered two stages in the PF of sport football clubs. Different studies have followed this approach to analyse the performance in sports leagues. For example Yang et al. (2014) evaluates the efficiency of National Basketball Association (NBA) teams during six seasons. Kern et al. (2012) analysed off-field and on-field efficiency of the EPL while Sexton and Lewis (2004) estimated the efficiency of Major Baseball League considering intermediate products.

On the other hand, several papers have only considered a stage, analysing the relationship between the inputs (X) and the final output (Y) (e.g., Lee & Berri, 2008; del Corral, 2012; del Corral, 2015; Zambom-Ferraresi et al., 2016). Finally, other stream has analysed the second stage of the production process with inputs (Z), i.e. the play performed during the game, as resources to produce the output (Y) (Espitia-Escuer & García-Cebrián, 2006; Bosca et al., 2009; Zambom-Ferraresi et al., 2017, etc.).

Independently of the stages of the PF and which are the possibilities of input measures, there is a consensus in this point; the inputs in sports teams' performance analysis must represent the quality of the workforce, i.e. the players' skills and abilities. The ex-post inputs in sports economics literature used to be: sports statistics, e.g., shots, in soccer; rebounds, in basketball; batting, in baseball (Carmichael et al., 2000; Sexton & Lewis, 2003; Espitia-Escuer & García-Cebrián, 2006; Bosca et al., 2009; Tiedemann et al., 2011; Moreno & Lozano, 2012; and Zambom-Ferraresi et al., 2017); or wages/salaries (Haas, 2003; Frick & Simmons, 2008; Ribeiro & Lima, 2012). These ex-post inputs are employed to analyse the second stage of PF where intermediate inputs (Z) produced output (Y).

However, Dawson et al. (2000), Lee (2006), Lee and Berri (2008), del Corral (2012), and del Corral et al. (2015) criticised the use of ex-post inputs. Lee and Berri (2008) and Dawson et al., (2000) argued that to calculate the efficiency accurately, it is necessary to use ex-ante measures of players' quality. Also, Lee (2006) argued that the ex-ante inputs should be used to avoid endogeneity problems. In addition, some authors disparaged the use of ex-post financial expenditure (wages and salaries) as input measure. In particular, Dawson et al. (2000) have found that performance estimations are highly sensitive to the use of this kind of ex-post input. They recommended *ex-ante* input measures based on start-of-season players' characteristics or predicted transfer values as more appropriate on theoretical and empirical grounds.

Usually, the ex-ante inputs employed are: the market value (Bell et al., 2013; and Zambom-Ferraresi et al. 2016); statistics from previous seasons (Lee & Berri, 2008); the valuation in fantastic leagues and virtual games (del Corral, 2012; and del Corral et al., 2015); and team budget (Moreno & Lozano, 2012). This input specification could be found when the analysis is focused on the overall production process, where a team or a manager employed inputs (X) to produce outputs (Y).

Considering that the two-stages of the production process is widely accepted in sports economics literature, this paper focus on the discussion about inputs specifications. In other words, we would like to offer empirical evidence about if the inputs choice affects the efficiency estimations of football teams.

4.3. Methodology and Data

4.3.1. Methodology

The methods to estimate efficiency used to be classified as parametric and nonparametric. To estimate the sports teams' efficiency, among the parametric methodology, stochastic frontier is the most employed (e.g.: Frick & Simmons, 2008; Lee & Berri, 2008; and del Corral, 2012) and the non-parametric methodology most used is data envelopment analysis (DEA) (e.g.: Espitia-Escuer & García-Cebrián, 2006; Guzmán & Morrow, 2007; and Tiedemann et al., 2011).

In this study, we have employed a DEA to estimate the technical efficiency (TE) of football teams because it provides a single measure in the case of multiple inputs and outputs and it is suitable when the correct weighting of inputs and outputs is unknown or cannot be derived (Cooper et al., 2011). The variable return to scale (VRS) model proposed by Banker et al. (1984) was employed because the EPL clubs have different sizes. Moreover, the models were oriented to output maximization (Espitia-Escuer & García-Cebrián, 2006; Zambom-Ferraresi et al., 2016). The formal expression of the model is:

$$\begin{aligned}
 & \max_{\phi, \lambda} \phi, \\
 & \text{st} \quad -\phi q_i + Q\lambda \geq 0, \\
 & \quad \quad x_i - X\lambda \geq 0, \\
 & \quad \quad I1'\lambda = 1 \\
 & \quad \quad \lambda \geq 0,
 \end{aligned} \tag{4.2}$$

where $1 \geq \phi$, and $\phi - 1$ is the proportional increase in outputs that could be achieved by the i -th club, with input quantities held constant. Note that $1/\phi$ defines a technical efficiency score that varies between zero and one.

In order to test the robustness of our estimations we also employed a bootstrapped DEA methodology (Simar & Wilson, 1998; 2000; 2013). This methodology enables to estimate bias-corrected DEA scores and obtain confidence intervals. The bootstrapped DEA estimates the efficiency through DEA with a pseudo data set, resampling the original DEA scores, and repeating the estimations many times.

4.3.2. Data

The EPL forms the upper level of England's professional football structure. It was established in 1992 to replace the First Division of the then four division English football leagues. It is regulated by the Football Association and run separately from the remaining three divisions comprising the football league. The EPL and the top division of the football league are linked by the system of promotion and relegation in the end of the season, whereby the bottom three EPL clubs are relegated and replaced by three football league clubs. The final ranking is determined by accumulated match points over regular season (3 for a win, 1 for a draw, and 0 for a loss). The tradition of the EPL combined with the actual quality of their stars, make it one of the most important national football leagues in the world and consequently one most watched and followed. Due the relegation and promotion system of the EPL, our sample is composed by 60 observations, 25 different clubs, for the seasons 2012/13, 2013/14 and 2014/15.

We estimate three different models to calculate efficiency of EPL teams. In all models, we consider the same output (Y). The difference between them is the alternative inputs choice. The

inputs specifications also appoint the model, so the models are: ex-ante (X), ex-post (Z) and ex-postW (Z). Table 4.1 summarized the three models.

Table 4.1. Models

Model	Inputs	Production process
Ex-ante	Market value	$X \Rightarrow Y$
Ex-post	Plays performed	$Z \Rightarrow Y$
Ex-post (f)	Wages	$Z \Rightarrow Y$

Note: (f)= financial expenditure

The outputs were defined attempting to achieve more comprehensive analysis of football clubs' outcome (Andrikopoulos & Kaimenakis, 2009; Plumley et al., 2014; and Zambom-Ferraresi et al., 2016). On the one hand, the sports results and the total revenue are the most common measures of football clubs output (García-del-Barrio & Szymanski, 2009). In our case, the sports results are measured as the total points achieved in league. On the other hand, it is a fact that football clubs exist and survive thanks to the fans. They have impact on revenue, on the show, and also help to improve the teams' sports performance being a strong support for the team. To reflect the fan's impact, we incorporate two different variables. The first one is the stadium capacity utilization that measures the direct support of fans and it is an important situational variable (Haas, 2003; Mackenzie & Cushion, 2013). The second one is the fans impact on the social media, with growing importance in the context of a global market (McCarthy et al., 2014; Dima, 2015; and Deloitte, 2016). To measure it we used the Sport Social Media Index (SSMI, 2016), an index that ranked the clubs according how clubs manage its social media, from its official channels (e.g. Twitter, Facebook, Pintrest, Instagram, Vine, Google+ and LinkedIn).

In the ex-ante model, the input used was the squad market value. The community's market-value estimations are excellent predictors of actual transfer fees (Herm et al., 2014). This input

measure is based on start of the season player characteristics (Dawson et al., 2000; del Corral, 2012). Following Zambom-Ferraresi et al. (2016), the market value was compiled from an online community (Transfermarkt) at the start of each season. In the ex-post model, the inputs are three match-related statistics well known in available literature of performance analysis. These inputs represent the main three groups of performance indicators of football: (i) variables related to scoring (shots on target); (ii) variables related to attacking and passing (passes); and (3) variables related to defending (ball recoveries) (Liu et al., 2015). In the ex-postW model the input is the wages of the squad (Dawson et al., 2000; Haas, 2003; Ribeiro & Lima, 2012). Table 4.2 show the sources and a summary of descriptive statistics.

Table 4.2. Descriptive statistics

Variable		Source	Mean	SD	
Inputs	Ex-ante	Squad market value	Transfermarkt	199.82	148.60
	Ex-post	Shots on target	Opta Sports	168.43	37.05
		Passes	Opta Sports	17,731.28	2,967.65
		Ball recoveries	Opta Sports	2,172.65	191.01
	ExpostW	Wages	The Guardian	95.07	55.60
Outputs		Points	EPL oficial website	52.35	17.56
		Total revenue	Deloitte, Companies House, Fame and The Guardian	187.73	126.54
		Stadium utilization	Deloitte	95.42	5.97
		Social media impact	Sport Social Media Index	58.37	5.68

Note: SD=standard deviation; W= wages.

We have a panel data of three seasons, and estimate the efficiency of all period as a whole. The clubs and leagues' contracts with sponsors and televisions change from periods of more than one year, and we cannot control this kind of changes, but we have normalized all monetary values to control the inflation. In the same way, in football leagues in one season the winner could achieved 60 points and in the follow season 90, we have employed the same normalization process with the points. We apply a max-min normalization to our raw data, scaling the total

points between 0 and 1. This solution maintains the rankings and the variability of the data allowing to homogenize the monetary values and the points and allow to run an intertemporal analysis. The normalized indicator of e_i for variable E in the i^{th} row is calculated as:

$$\text{Normalized } (e_i) = (E_i - E_{\min}) / (E_{\max} - E_{\min}) \quad (4.3)$$

where E_{\min} denotes the minimum value for variable E , and E_{\max} is the maximum value for variable E .

4.4. Results

Firstly, we will analyse the performance of the EPL clubs. The main results indicate that they have high efficiency level. The VRS estimations of the three models present very high efficiency scores and small standard deviations. To easily interpret the results, when a club cannot improve its outputs without employ more inputs, this club have an efficiency score of 1 and is consider efficient; any other result is considered inefficiency. The VRS bootstrapped estimations also present high efficiency scores and small standard deviations for the three models. The results of VRS and VRS bootstrapped for each one of the three models have a minimum correlation of 98% among them. These results indicated the robustness of the both methodologies' estimations.

Table 4.3 shows the main results of performance (VRS) for all the clubs of the sample. In this analysis, the only club that has been efficient in the three seasons analysed was Manchester United. This results means that for the inputs employed, in the three differ rent models, Manchester United achieved the most efficient level of outputs combination of all possible performances analysed. Namely, independent of the inputs considered (the market value, the plays developed on-field, or the squad' wages) Manchester United was efficient.

In terms of efficiency, Chelsea, Arsenal, and Liverpool were the follow better overall performances. Swansea City, Tottenham Hotspur, and West Ham United also have performed of an efficient (or close) way during the period analysed. Sunderland and Aston Villa present lower results than the rest of the sample. Wigan Athletic highlighted among the clubs that underperformed, but at same time, when the efficiency was estimate with the wages as input surprisingly Wigan Athletic was efficient. From the clubs that didn't play the competition in all observed seasons, Burley and Leicester City were efficient in the seasons that they participated.

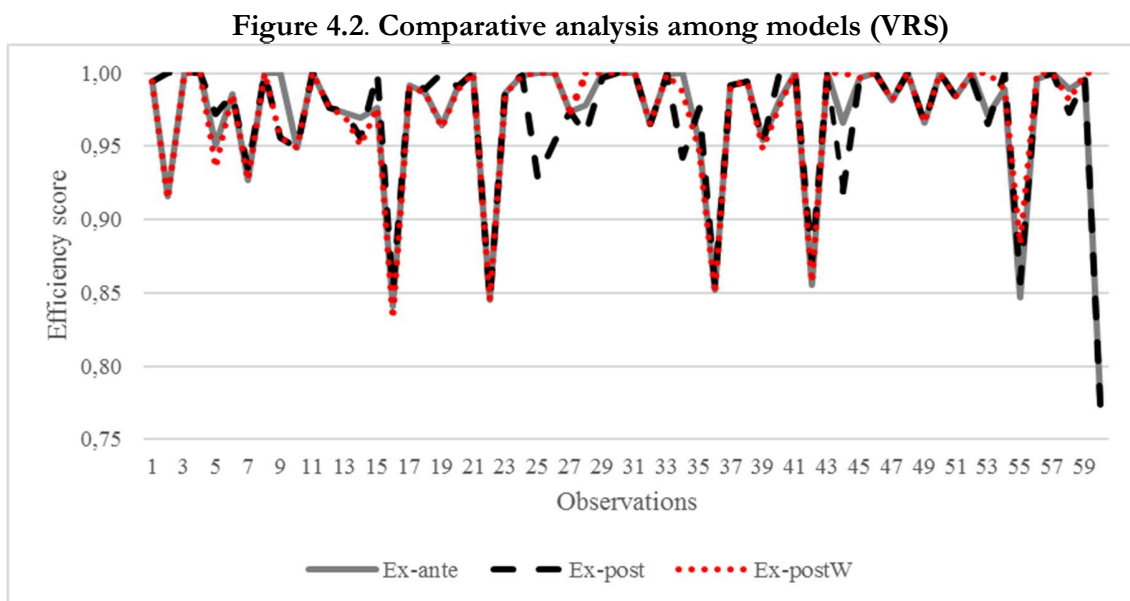
Table 4.3. Efficiency scores (VRS)

	2012/13			2013/14			2014/15		
	Ex-ante	Ex-post	Ex-pW	Ex-ante	Ex-post	Ex-pW	Ex-ante	Ex-post	Ex-pW
Arsenal	1	1	1	1	1	1	0.994	0.994	0.994
Aston Villa	0.8550	0.8704	0.8574	0.8450	0.8456	0.845	0.9156	1	0.914
Burnley							1	1	1
Cardiff City				0.9864	0.9915	0.986			
Chelsea	1	1	1	0.9980	0.998	0.998	1	1	1
Crystal Palace				1	0.9285	1	0.9511	0.9720	0.9353
Everton	0.9663	0.919	1	1	0.9533	1	0.9860	0.986	0.986
Fulham	0.997	0.997	0.997	0.974	0.974	0.974			
Hull City				0.9780	0.9583	1	0.92711	0.93412	0.9271
Leicester City							1	1	1
Liverpool	1	1	1	1	0.997	1	1	0.956	0.956
Manchester City	0.9810	0.981	0.981	1	1	1	0.949	0.949	0.949
Manchester United	1	1	1	1	1	1	1	1	1
Newcastle United	0.966	0.966	0.966	0.965	0.965	0.965	0.976	0.9760	0.976
Norwich City	1	1	1	0.999	0.999	0.999			
Queens Park Rangers	0.9840	0.984	0.984				0.9726	0.974	0.9702
Reading	1	0.9953	1						
Southampton	0.9711	0.9651	1	1	0.9419	0.9874	0.9693	0.9555	0.9504
Stoke City	0.989	1	0.989	0.952	0.976	0.946	0.976	1	0.976
Sunderland	0.846	0.857	0.883	0.852	0.856	0.850	0.841	0.851	0.833
Swansea City	0.9960	0.996	1	0.992	0.992	0.992	0.9917	0.9944	0.991
Tottenham Hotspur	1	1	1	0.994	0.994	0.9945	0.9861	0.989	0.9862
West Bromwich Albion	0.9890	0.973	0.9817	0.9542	0.9521	0.9479	0.9647	1	0.9622
West Ham United	0.9960	0.996	1	0.9813	1	0.9783	0.9903	0.9908	0.9881
Wigan Athletic	0.7762	0.7718	1						
Mean	0.966	0.964	0.982	0.974	0.966	0.973	0.969	0.976	0.965
SD	0.063	0.062	0.040	0.045	0.045	0.046	0.039	0.036	0.040

Note: VRS=variable return to scale; SD=standard deviation; Ex-pW= Ex-post Wage.

Observing the relation of efficiency with the sports results, all the league' champions (Manchester United in 2012/13, Manchester City in 2013/14, and Chelsea in 2014/15) was efficient in the respective season. Regarding the teams with the worst sports results, Burley (2014/15), Norwich City (2013/14) and Reading (2012/13) employed its scarce resources in efficient or really close way, in spite of they were relegated.

Secondly, we are going to analyse the three models comparatively. The efficiency scores of the three models could be observed graphically in figures 4.2 and 4.3. The 60 observations of the sample are represented in numerical order on the x axis of the graphs, and its efficiency changes among the models can be easily observed.

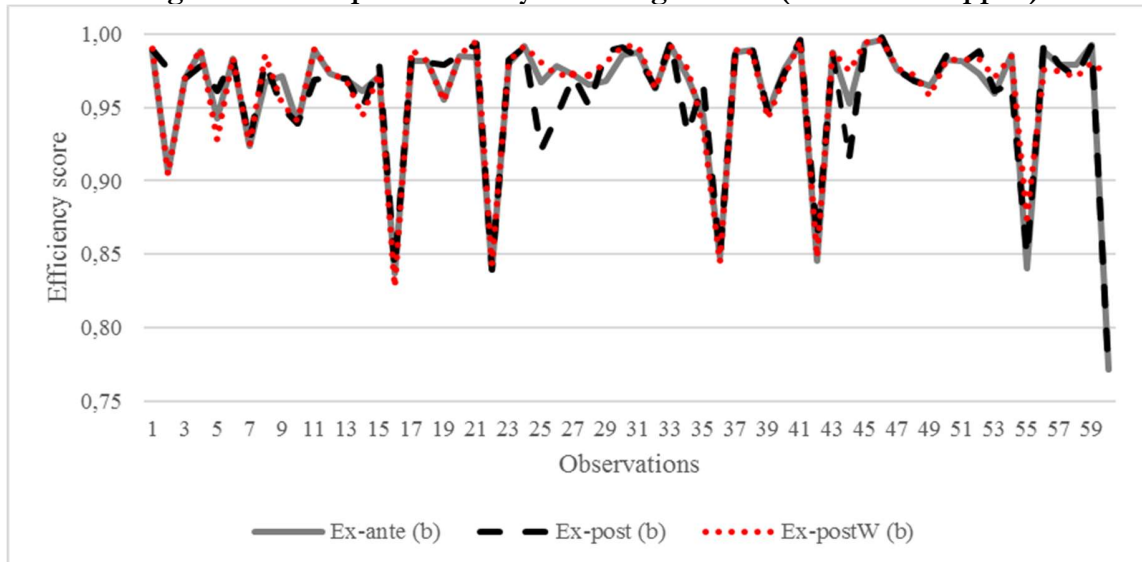


Note: VRS=variable return to scale.

In Figure 4.2, it is shown that the efficiency scores are very similar independently of the kind of inputs applied. Only in the case of ex-postW model, the efficiency is slightly higher than the other two models, although there is no regular behaviour pattern. Analysing the observations, there are teams that obtain better results with the ex-ante inputs, others with the

ex-post and ex-postW, while 25 observations do not change. In the case of the bootstrap method (Figure 4.3), the results are also very similar among the three models.

Figure 4.3. Comparative analysis among models (VRS bootstrapped)



Note: VRS=variable return to scale, (b)=bootstrapped.

At a glance, the efficiency scores obtained by VRS and VRS bootstrapped in figures 4.2 and 4.3 are very similar. In order to confirm this similarity, table 4.4 shows the correlations between the three models and both methodologies. The most striking result indicate that there is a 90% positive and significant correlation ($p < 0.00$) between the models that estimates the efficiency of the EPL clubs using the players' market value (ex-ante) and the model that uses sports performance indicators (ex-post) as input. The correlation of the bootstrapped model was even higher, reaching a 91% of positive and significant correlation ($p < 0.00$). The correlation between the ex-ante and ex-postW financial expenditure models, attaining a 78 and 82% with the VRS and VRS bootstrapped, respectively. Finally, the correlations between the ex-post model (plays performed as input) and the ex-postW of financial expenditure model (wages as input) are of 66

and 74% for VRS and VRS bootstrapped, respectively. These are also significant moderate/high correlation values, but are not so high as the ex-ante and ex-post correlation.

Table 4.4. Correlation matrix (models and methodologies)

		Ex-ante	Ex-ante (b)	Ex-post	Ex-post (b)	Ex-postW	Ex-postW (b)
Ex-ante	PC	1	.984**	.905**	.913**	.784**	.816**
	Sig. (2-tailed)		.000	.000	.000	.000	.000
	N	60	60	60	60	60	60
Ex-ante (b)	PC	.984**	1	.921**	.940**	.767**	.821**
	Sig. (2-tailed)	.000		.000	.000	.000	.000
	N	60	60	60	60	60	60
Ex-post	PC	.905**	.921**	1	.985**	.662**	.717**
	Sig. (2-tailed)	.000	.000		.000	.000	.000
	N	60	60	60	60	60	60
Ex-post (b)	PC	.913**	.940**	.985**	1	.674**	.738**
	Sig. (2-tailed)	.000	.000	.000		.000	.000
	N	60	60	60	60	60	60
Ex-postW	PC	.784**	.767**	.662**	.674**	1	.979**
	Sig. (2-tailed)	.000	.000	.000	.000		.000
	N	60	60	60	60	60	60
Ex-postW(b)	PC	.816**	.821**	.717**	.738**	.979**	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	
	N	60	60	60	60	60	60

Note: (b)= bootstrapped; W= wage; PC= Pearson Correlation;
 **. Correlation is significant at the 0.01 level (2-tailed).

4.5. Discussion and conclusions

We have analysed the performance of EPL clubs during three seasons, from 2012/13 to 2014/15, with three different models. The three models have the same outputs (points, revenues, attendance, and fans impact on social media) and three different inputs are: the market value (ex-ante); the plays performed during the match (ex-post); and the wages (ex-postW). To test the robustness of the efficiency estimations, we have applied two methodologies: DEA and DEA bootstrapped. All the estimations were highly correlated, positive and significant, except the correlation of the both ex-post models, which is moderate/high.

Considering the sample analysed, our results indicate that the controversy about the inputs specifications is unfounded, mainly in the case of the criticism with match-related statistics; suggesting that the inputs choice to represent players' skills is irrelevant. Knowing the productive process that is being analysed, the input selection will lead to similar results because they are measuring the same, the players' skills and abilities. In other words, to explain performance of football teams, we could use ex-ante inputs and match-related statistics. However, this does not mean that it could be not advisable the choice of the input which represent the best the unit and the stage of the PF under analysis.

In the case of inputs choice our results corroborate the empirical evidenced developed by Dawson et al. (2000). On the one hand, when comparing the ex-ante and ex-post inputs models, we could consider that both types of inputs are interchangeably because both represent faithfully the players' skills, not affecting significantly the efficiency' estimations. On the other hand, when using the ex-post financial expenditure (wages) our results have showed not so highly sensitive than Dawson et al. (2000), but it also should be taken with caution.

To explain our results, we have analysed the relation between the players' skills and abilities and the measures used to represent it. As we highlighted before, all the production process of professional football clubs is related and feedback. Clubs with better players will archive better sports results that will report higher revenues, which in turn will enable to pay high wages and to hire better players, and so on (Szymanski & Kuypers, 1999; Carmichael et al., 2011).

The relation between market value, transfer fees and wages with sports results and revenue is fairly discussed in sports economics literature. By one side, the bargain' power in different stages of contracts, the players' high or under valuation (Weimar & Wicker, 2014), and the media impact of some players (Franck & Nüesch, 2012) are the aspects that muddier this relationship.

By other side, we must consider that the management of the clubs is becoming more professional. Also, the football players' performance is being analysed so seriously as in other sports like basketball and baseball for example. Then, the players' market value, the performance on-field and the wages are becoming more similar. For example, Frick (2011) has found that more than 60% of the observable variance in players' salaries is related with their skills and abilities, and performance on-field. To test this argument, we have calculated the correlations between the three different inputs considering two different outputs, points and revenues. Table 4.5 in the Appendix shows these correlations. As we can observe in this table, the correlation between market value and wages is pretty high (95%, $p < 0.000$), and also the correlation between wages and revenue (95%, $p < 0.000$). The market value and the wages are also high correlated with the points (84%, $p < 0.000$ and 81%, $p < 0.000$) respectively, values only surpassed by the correlation of shots on target and the points (88%, $p < 0.000$).

One important question to consider is the fact that we analysed the efficiency of the whole team, and the inputs are the sum of individual players' values, nor of the entire team. Ribeiro and Lima (2012) have found that a wider wage distribution within each team is associated with better performance. Their findings agree with the tournament theory, where the size of the difference in pay rank increases as contestants approach the top. Szymanski and Wilkinson (2016) also have found that most expensive players tend to have the largest impact on the game whereas the least expensive players have little impact; which reinforces the relationship between the different input measures. In this regard, coaches have many possible combinations of its players (inputs). Teams with different players could vary technically, tactically, physically, and psychologically. Squads could have twenty-five players in EPL, eleven players compose the first team and other five players will be on the bench, available to the coach that could substitute none or three players' maximum during the match. So, the relation between the different efficiency estimations

and the teams' performance could be explained by the overall composition of teams. As it is commonly said, a team is more than the simple sum of 11 players.

Our results have some practical implications for the strategic decisions in football clubs. Recalling our title' question; are manager as efficient as coaches? We cannot answer this question, but our efficiency analysis of both units (managers and coaches), through the employ of different inputs; indicate that in the case of EPL clubs (from 2012/13 to 2014/15) his performances are strongly correlated. Probably because one's work directly impacts the work of the other, and vice versa. Traditionally, these two different agents are being considered as essential to an efficient management of the clubs. In some clubs, the manager takes the most important decisions about what football player should be hired and about the levels of wages, playing the coach a minor role in the decision-making. However, in other clubs, the coach assumes the responsibility for the team success. In these situations, his ability to manage the squad and the selection of the tactics required in each match are fundamental to get success. According to our results, this distinction lacks interest. So important and necessary is to hire the right players as the different tactics combinations on the field. Then, manager and coach should interact in the same direction to get the club success. For example, the coaches might be the best advisors to the manager for creating a promising roaster for the future, based on the limitations suffered by the team in the present. Also, a wide and adequate wage distribution made by the manager might be a helpful tool for the coach in order to introduce extra motivation and incentives among the squad in order to obtain a better performance. Managers and coaches may work together to activate the most productive inputs combinations (first and bench teams) in order to get an efficient team.

The main limitation of this study is related to the sample analysed, that lead us to suggest extend the sample in future research to generalize ours results. Also, although the relation

between market value and salaries with the performance on-field was deeply analysed on sports economics literature, the analysis of the relationship between individual and the team performance is an interesting issue for further research and could help clubs' managers and coaches at time to hire players and compose powerful squads.

Appendix

Table 4.5. Correlations between measures

		Market value	Shots on target	Passes	Ball recovery	Wages	Points	Revenue
Market value	PC	1	,769**	,701**	,270*	,950**	,836**	,946**
	Sig. (2-tailed)		,000	,000	,037	,000	,000	,000
	N	60	60	60	60	60	60	60
Shots on target	PC	,769**	1	,773**	,294*	,721**	,878**	,741**
	Sig. (2-tailed)	,000		,000	,023	,000	,000	,000
	N	60	60	60	60	60	60	60
Passes	PC	,701**	,773**	1	,383**	,701**	,756**	,715**
	Sig. (2-tailed)	,000	,000		,003	,000	,000	,000
	N	60	60	60	60	60	60	60
Ball recovery	PC	,270*	,294*	,383**	1	,365**	,303*	,321*
	Sig. (2-tailed)	,037	,023	,003		,004	,019	,012
	N	60	60	60	60	60	60	60
Wages	PC	,950**	,721**	,701**	,365**	1	,808**	,959**
	Sig. (2-tailed)	,000	,000	,000	,004		,000	,000
	N	60	60	60	60	60	60	60
Points	PC	,836**	,878**	,756**	,303*	,808**	1	,823**
	Sig. (2-tailed)	,000	,000	,000	,019	,000		,000
	N	60	60	60	60	60	60	60
Revenue	PC	,946**	,741**	,715**	,321*	,959**	,823**	1
	Sig. (2-tailed)	,000	,000	,000	,012	,000	,000	
	N	60	60	60	60	60	60	60

Note: PC= Pearson Correlation; **. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

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5. Determinants of Sport Performance in European Football: What Can We Learn from the Data?

Abstract

The performance analysis (PA) of football has inherent problems given it is a multifaced and complex phenomenon. This study analyses the importance of a large number of possible determinants of sport performance in the “Big Five” European football leagues during the period 2012/13–2014/15. To this end, Bayesian model averaging techniques and relative importance metrics are employed. The results obtained point to the existence of a set of robust determinants in sport performance. This set of drivers would consist of (i) the assists, (ii) the shots conceded, (iii) the saves made by the goalkeeper, (iv) the number of precise passes with respect to the total number of passes, and (v) the shots on target. The study also finds strong support for the idea that offensive actions are more relevant than defensive ones. The main implications of the findings could help football clubs on issues related to technical and tactical improvements, as well for the management section. Moreover, for further PA research, the study highlights performance indicators that have usually been ignored by previous analyses but that its estimations suggest are likely to be a key part of sport success in football.

Keywords: performance analysis; Big Five; league; success; Bayesian model averaging; relative importance analysis

5.1. Introduction

The growing availability of football performance indicators (PIs) has considerably increased scientific production in the field of sport science in recent years. The literature on performance analysis (PA) has focused on the performance of the players (Tiedmann et al., 2011) or the team as a whole (Carmichael et al., 2000; Oberstone, 2009), establishing associations between PIs (Nevill et al., 2002), combining them (Oberstone, 2009), observing independent samples (Bradley et al., 2013; Lago-Ballesteros & Lago-Peñas, 2011), or relating samples (Delgado-Bordonau et al., 2013).

The basic competition structures to carry out research in the context of football are (i) round-robin (i.e., the case of regular leagues) and (ii) knockout tournaments, which characterise the vast majority of cups. Moreover, there are tournaments with a mixed structure, usually with a single or double round-robin and a knockout phase. The PA literature has focused on regular leagues such as the English *Premier* league (Carmichael et al., 2000; Collet, 2013; Oberstone, 2009; Vecer, 2013), the Spanish *Liga* (Boscá et al., 2009; Collet, 2013; Lago-Ballesteros & Lago-Peñas, 2010; Lago-Peñas and Lago-Ballesteros, 2011; Lago-Peñas et al., 2010; Villa & Lozano, 2016), the Italian *Serie A* (Boscá et al., 2009; Collet, 2013), the French *Ligue One* (Collet, 2013), the German *Bundesliga* (Collet, 2013; Tiedemann et al., 2011), and knockout competitions such as the UEFA Champions League (Collet, 2013; Lago-Peñas et al., 2010), the UEFA Europe League (Collet, 2013), and the FIFA World Cup (Barreira et al., 2014; Castellano et al., 2012; Delgado-Bordonau et al., 2013; Hughes & Franck, 2005; Moura et al., 2013).

However, in the case of football, previous sport performance (SP) research has not identified a clear set of indicators determining the main actions that distinguish winners from losers. In this regard, the main criticisms of previous analyses on the determinants of SP,

highlighted by Mackenzie and Cushion (2013), Carling et al. (2014), and Sarmiento et al. (2014), are mainly methodological and refer to (i) the sample size, (ii) the set of variables considered and their definition, and (iii) the statistical methods employed to perform inference. Additionally, this strand of research usually fails to derive implications useful for practitioners.

The main samples, methodologies, and PIs employed by other studies related to our focus can be observed in table 5.1. A common drawback in many of these PA studies is the reduced sample size. A small sample size entails problems of generalisation and implies a low number of degrees of freedom, which could negatively affect the quality of statistical estimates. Examples of studies suffering from this problem included in Table 5.1 are those of Barreira et al. (2014), Boscá et al. (2009), Castellano et al. (2012), Delgado-Bordonau et al. (2013), Hughes and Franck (2005), and Moura et al. (2013), in which the coverage of games is limited.

Second, SP literature focusing on football has employed limited sets of variables, which is likely to create artificially narrow confidence intervals ignoring the uncertainty surrounding the true model or data generating process (DGP). Moreover, the omission of relevant explanatory variables that could affect SP patterns is of major importance from an econometric perspective, given that estimates may be inefficient and/or biased. The consequences of biased and/or inefficient estimators include results with restricted reliability. This problem appears in a number of studies, such as those of Collet (2013) and Vecer (2013), in which the lack of controls is likely to create biased estimates.

Table 5.1. Literature review

Study	Sample (N); period (T)	Methodology	Explanatory variables	Dependent variable
Barreira <i>et al.</i> , (2014)	N= 4 semi-finalists (24 matches) FIFA World Cup; T= 1 cup (2010)	ANOVA (one and two way); Multinomial and binary logistic regression analysis	BR patterns: direct (by interception, by tackle, by intervention of GK) and indirect (start of offensive phase, by opponent violation of the game' laws, by corner kick, by goal kick, by dropped ball, by throw-in); and zone of the pitch (1-12)	BR with efficacy (play finished with a shot); BR with no efficacy (loss BP without finished the play)
Boscá <i>et al.</i> , (2009)	N= Italian and Spanish leagues; T= 3 seasons (2000/01-2002/03)	DEA	Offensive: goals scored, shots on goal, attacking plays, centre plays, possession; Defensive: goals conceded, shots at goal, attacks in area, centre in area, BP	Goals scored (attack output), goals conceded (defense output)
Carmichael <i>et al.</i> , (2000)	N= Premier league (380 matches); T= 1 season (1997/98)	Regression analysis with and without fixed effects	Difference in: shots on target and off, blocked shots, shots hitting woodwork, % of all successful passes, % of passes in scoring zone, tackles made, clearances, blocks and interceptions, dribbles/runs with possession retained and lost, controlled in first touch, free kicks away from fouls, hand ball, and off-side, YC, RC, % of successful GK distributions, ball caught by GK, ball dropped by GK, cumulative team goal dif. before a game; playing home (dummy)	Difference of goals (scored - conceded)
Castellano <i>et al.</i> , (2012)	N= FIFA World Cup; T= 3 cups (2002, 2006, 2010)	Discriminant analysis, ANOVA, and multivariate analysis	Attacking play: goals scored, total shots, shots on target, shots off target, BP, number of off-sides committed, fouls received and corners; and defence play: total shots received, shots on target received, shots off target received, off-sides received, fouls committed, corners against, YC and RC	Winning, drawing and losing teams

Table 5.1. (Continued)

Study	Sample (N) and period (T)	Methodology	Explanatory variables	Dependent variable
Collet (2013)	N= Big Five (5478 matches); N= UEFA Champion League (395 matches) N= 3 seasons (2007/08-2009/10); N= UEFA Europe League (205 matches), N= 1 season (2009/10)	2 stages - proportional odds models (the 1st assessed the bivariate relationship between BP and aggregated team success, and 2nd individual match level)	Possession time and passing	1st: (i) points won per match played; (ii) goals scored per match played; (iii) shots taken per match played (4) FIFA points (for national teams); 2nd: home loss (-1), draw (0), win (1)
Delgado-Bordonau <i>et al.</i> , (2013)	N= FIFA world Cup (54 matches); T= 1 cup (2010)	Student's independent t-test	Offensive and defensive PI (attempts for and against): total shots, shots on goal, shots off goal, % of shots on goal from total shots, % of shots off goal from total shots, offensive and defensive effectiveness 1 (goals/total shots), and offensive and defensive effectiveness 2 (goals/shots on goal)	Reach semi-finals (successful and unsuccessful teams)
Hughes & Franck (2005)	N= FIFA World Cup (52 and 64 matches), T= 2 cups (1990 - 1994)	Ratios (the data were normalized by dividing the number of goals scored in each team possession by the frequency of that sequence length.	Passing sequences and possession length	Successful and unsuccessful teams (shots; shots/goal; projected goals)
Lago-Peñas <i>et al.</i> , (2010)	N= La Liga (380 matches); T= 1 season (2008/09)	Univariate (t-test) and multivariate (discriminant) analysis	Total shots, shots on goal, shot effectiveness, assists, crosses, offsides committed and received, corners, BP, crosses against, fouls committed and received, corners against, YC, RC, and venue	Winning, drawing and losing teams
Lago-Peñas <i>et al.</i> , (2011)	N= UCL (288 matches of group stage); T= 3 seasons (2007/08- 2009/10)	One way ANOVA and discriminant analysis	Total shots, shots on goal, effectiveness, passes, successful passes, crosses, offsides committed and received, corners, BP, crosses against, fouls committed and received, corners against, YC, RC, venue, and quality of opposition.	Winning, drawing and losing teams

Lago-Ballesteros & Lago-Peñas (2010)	N= La Liga (380 matches); T= 1 season (2008/09)	One way ANOVA	Goal scored (goals for, goals against, total shots, shots on goal, shooting accuracy, shots for a goal) offense (assists, crosses, offsides, committed, fouls received, corners, BP) defense (crosses against, offsides received, fouls committed, corners against, YC, RC)	3 groups: top 4, middle 12 clubs and bottom 4
Lago-Peñas & Lago-Ballesteros (2011)	N= La Liga (380 games); T= 1 season (2008/09)	Univariate (t-test and Mann-Whitney U) and multivariate (discriminant analysis)	Independent: Game location (home or away) and team quality (effects on performance profiles). Game-related statistics: goals scored, total shots, shots on goal, attacking moves, box moves, crosses, offsides committed, losses of possession, fouls received, assists, passes made, successful passes made, dribbles, successful dribbles, ball possession, gains of possession, fouls committed, YC, RC, clearances	4 groups (1-5, 6-10, 11-15, and 16-20 of final ranking)
Moura <i>et al.</i> , (2013)	N= FIFA World Cup (Group stage); T= 1 cup (2006)	Principal component and cluster analysis	Shots, shots on goal, goal performed, fouls committed, fouls suffered, corner kicks, free kicks to goal, offside, own goals, YC, second YC, RC, BP (time and %)	Winning, drawing and losing teams
Oberstone (2009)	N= Premier league; T= 1 season (2007/08)	Multiple regression (robust, statistically significant, six independent variable model); ANOVA (one-way)	Defending (blocks, clearances and interceptions, tackles, goals conceded, av. goals conceded per game, %tackles won); crossing (%crosses completed, total crosses); passing (total passes, short passes, % short passes completed, % long passes completed, long passes, shot passes/long passes, % pass completion); discipline (fouls committed, YC, RC); goal attempts (goals, av. goals per game, shots (excluding blocked), % goals scored outside box, % goals to shots, % goals scored inside box, % shots on target)	Final league standings (multiple regression), 3 groups: top 4, middle 12 clubs and bottom 4
Villa & Lozano (2016)	N= La Liga; T= 1 season (2013/14)	Network DEA	Home and away teams: BP, shots, corners penalties, saves, turnover, steals and team value	Goals
Vecer (2013)	Premier league (1780 games); T= (2008-2013)	Regression analysis	Home team, points for and against, good and bad open play corners	Goals

Note: GK= goalkeeper; BR= ball recovery; BP= ball possession; YC= yellow card; RC= red card; **Source:** Own elaboration.

Third, although the univariate tests and the ANOVA analyses in Lago-Balesteros and Lago-Peñas (2010), Lago-Peñas et al. (2010), and Lago-Peñas and Lago-Ballesteros (2011) provide insights on the characteristics of different types of teams, they do not help to explain to what extent a variable is responsible for sport success in football. Similarly, the conventional regression analyses employed by Carmichael et al. (2000) and Vecer (2013), whenever regressors are correlated among themselves, as is likely to be the case, will fail to obtain precise estimates of importance. This is because in the case of correlated determinants, there is no obvious way to analyse how the fitted variability of the model can be decomposed across regressors (Groemping, 2007).

This paper aims to solve the aforementioned methodological limitations in SP studies by analysing the relative importance of PIs in the final sports result through (i) the consideration of a greater set of determinants, (ii) a greater sample of observations, and (iii) the use of an innovative modelling methodology. The paper makes several novel contributions to the literature. First, we analyse SP employing a set of 24 possible explanatory variables, which contrasts with the limited set of controls employed in the literature. Moreover, instead of restricting our study to a single regression model estimation, we perform inference based on a Bayesian model averaging (BMA) econometric analysis. In particular, we use the Monte Carlo Markov Chain Model Composition (MC^3) methodology for linear regression models developed by Madigan et al. (1995). This analysis aims to compute the posterior inclusion probability (PIP) for the different variables in order to generate a probabilistic ranking of relevance for the various SP determinants. The key feature of this econometric procedure is that it eliminates the need to consider all possible models by constructing a sampler that explores relevant parts of the large model space. Hence, contrary to previous studies on SP in which inference is based on single econometric model analysis, the BMA approach has the

advantage of minimising the likelihood of producing (i) biased estimates and (ii) artificially low confidence intervals (Moral-Benito, 2015).

Secondly, the sample used in this study includes a greater number of observations (i.e., teams) than most previous studies, which helps to obtain representative results of modern high-competition football⁸. Therefore, to generalise our results to competitions with a high competitive level, we analyse the major national leagues of European football, the so-called “Big Five” — the English *Premier League*, the German *Bundesliga*, the Spanish *Liga*, *Serie A* Italian *Calcio*, and the French *Ligue 1* — during the period from 2012/13 to 2014/15. Notice that this implies our sample data cover 5,532 games.

Third, we complement the BMA analysis with a relative importance analysis. Assigning shares of relative importance to each or to a set of regressors is one of the key goals of researchers in applied studies and in sciences that work with observational data. Advances in computational capabilities have led to increased applications of computer-intensive methods like averaging over orderings that enable a reasonable decomposition of the model variance. Thus, in a second phase, relative importance metrics allowing for all possible causal patterns among the regressors are computed (Groemping, 2007). These metrics perform an R^2 decomposition enabling more detailed analysis of the relative contribution of each variable to SP differentials than previous decompositions.

After this introduction, Section 5.2 briefly presents the data used to analyse SP in the major European football leagues. Section 5.3 explains the modelling methodology. Section 5.4

⁸ The only exception is Collet (2013), who employed a data set covering 5,478 regular national league games, 395 UEFA Champions League games, and 205 Europe League games. However, an important drawback of this study is that to explain PIs such as the points, the goals, etc., only two regressors are employed (possession time and passing).

discusses the main empirical findings of the paper, and Section 5.5 offers the main conclusions from this work.

5.2. Data

Our sample of data is composed of three seasons ranging from 20012/13 to 2014/15 of the “Big Five”, which implies a data coverage of 5,532 games in total. The data source is the OPTAPro, whose reliability has been previously tested by Liu et al. (2013). To analyse SP, we take as our outcome variable the number of points of each of the teams in each league and season. However, there are two potential problematic issues that may arise when comparing SP across teams and leagues. The first is that different leagues have different numbers of teams, which implies the scores of leagues with more teams/games are likely to be higher than in the case of leagues with fewer teams. This is the case of the Bundesliga with 18 participants per season, while the other four leagues have 20 clubs playing the competition by season. To solve this problem, we apply a max–min normalisation to our raw data by scaling the total points between 0 and 1. This normalisation maintains the final ranking and the variability of the data, allowing us to homogenise the points of the different leagues and allowing us to perform comparisons across leagues. In particular, the normalised indicator of SP for each team i at period t , $I_{i,t}$, is calculated as:

$$I_{it} = \frac{e_{it}^l - e_{min,t}^l}{e_{max,t}^l - e_{min,t}^l} \quad (5.1)$$

where $e_{min,t}^l$ denotes the minimum score in points in league l during the season t , $e_{max,t}^l$ stands for the maximum score of any team in league l during season t , and e_{it}^l is the score of team i in league l during season t . A second concern carefully analysed by Lago-Peñas and Lago-Ballesteros (2011) is the potential effect of situational variables such as the venue (i.e., to play at home or away) and the power of the opposite team. However, given that in our context we analysed double robin-round tournaments, the advantages and disadvantages are mitigated since all the teams play against each other twice, once at home and the other away, which is not the case in knockout competitions.

Table 5.2 shows the descriptive statistics and operational definitions of all variables employed in the analysis. In addition, in Table 2 we include a column in which we provide information on the expected effect based on a review of the literature.

Table 5.2. Definitions and Descriptive Statistics of the Explanatory Variables

Variable	Definition	Mean	STD	Expected Effect
Outcome Variable				
Sport Performance	Normalised total points archived by clubs at the end of a season	0.4	0.269	
A. Attack plays				
Total Shots Attempted	Shot: An attempt to score a goal, made with any part of the body, either on or off target. The outcomes of a shot could be: goal, shot on target, shot off target, blocked shot, post	367.80	60.83	+
Shots on Target	Total shots on target	164.76	36.42	+
Total Passes, Crosses, and Corners	(excl. Pass: An intentionally played ball from one player to another)	15902.81	2739.50	+
Passing Accuracy (excl. Crosses and Corners)	Successful passes/total passes	0.78	0.05	+
Assists	The final pass or cross leading to the recipient of the ball scoring a goal	34.13	12.66	+
Crosses Attempted	Any ball played into the opposition team's area from a wide position	603.79	131.86	+
Corners Taken Short Corners	(incl. A corner kick is a method of restarting play. It is awarded to the attacking team when the ball leaves the field of play crossing the goal line)	192.19	32.62	+
Dribbles and Runs Attempted	An attempt by a player to beat an opponent in possession of the ball. A successful dribble: the player beats the defender; unsuccessful: the dribbler is tackled	746.89	161.07	+
Dribble and Run Success Rate	Effective dribbles and runs with respect to the total number attempted	0.45	0.07	+
Long Pass Final Third	A pass over 32 metres on the final third of the field (attack of the reference team)	931.76	156.55	+
Through Ball	A pass playing a player through on goal, which could lead to a goal scoring opportunity. The pass needs to split the last line of defence and plays the teammate through on goal.	27.60	18.70	+
Offsides	Being caught in an offside position resulting in a free kick to the opposing team	88.71	19.14	?

Table 5.2. (Continued)

Variable	Definition	Mean	STD	Expected Effect
B. Defence plays				
Total Shots Conceded	Total shots attempted for the opposite team	164.76	29.78	-
Tackles Attempted	The act of gaining possession from an opposition player when he is in possession of the ball	754.60	79.47	-
Tackled Possession Retained (%)	A tackle won when a player makes a tackle and possession is retained by his team	0.23	0.03	+
Recoveries	The event given at the start of a team's recovery of possession from open play. The defending team must have full control of the ball and must start a new passage of play.	2071.00	297.60	+
Recoveries in Opp Half	A recovery on the opposite team's field (attack of reference team)	400.63	93.26	+
Clearances, Blocks, and Interceptions	Attempts to get the ball out of the danger zone when there is pressure. A defensive block, blocking a shot going on target. An interception is given when a player intercepts a pass with some movement	1750.02	246.97	?
Total Fouls Conceded	Any infringement that is penalised as foul play by a referee	517.86	73.38	-
Fouls Conceded in Danger Area	Infringement that is penalised as foul play by a referee in the lower 1/3	106.59	18.87	-
Yellow Cards	Indicates that a player has been officially cautioned/penalised due to infringement. A player receiving two yellow cards in a match is sent off.	75.59	20.28	-
Red Cards	A red card is shown by a referee to signify that a player has been sent off.	4.46	2.66	-
Saves Made	The goalkeeper prevents the ball from entering the goal with any part of his body.	112.22	20.79	+
Catches	The goalkeeper catching a cross or a ball played into the area when there is pressure from the rival	52.11	17.18	+

Notes: Own elaboration; Sources: Liu et al. (2013) and OPTA (2012)

5.3. Empirical Methodology

To analyse the determinants of SP, we begin by considering a *linear regression model* given by Equation 2:

$$y = \alpha \mathbf{1}_{nt} + X\beta + \varepsilon \quad (5.2)$$

where y denotes a $NT \times 1$ dimensional vector consisting of observations for the normalised SP index for each team $i = 1, \dots, N$ and period $t = 1, \dots, T$, X is an $NT \times K$ matrix of exogenous aggregate covariates with associated response parameters β contained in a $K \times 1$ vector. α reflects the constant term, and $\mathbf{1}_{nt}$ is an $NT \times 1$ vector of ones. Finally, $\varepsilon = (\varepsilon_1, \dots, \varepsilon_N)'$ is a vector of i.i.d disturbances whose elements have zero mean and finite variance σ^2 .

5.3.1. Bayesian Model Averaging

A large literature on BMA in regression models already exists (for detailed reviews on the literature, see Fragoso & Louzada-Neto, 2015; Hoeting et al., 1999; Moral-Benito, 2015). To get an intuition behind the BMA approach, notice that for any set of possible explanatory variables of size K , the total number of possible models is 2^K and $K \in [0, 2^K]$. This implies there are 2^K sub-structures of the model in Equation 2 given by subsets of coefficients $\delta^k = (\alpha, \beta^k)$ and combinations of regressors X_k . Hence, there are many different candidate models for estimating the effect of X_j on y with $j \in K$. In this circumstance, one can either i) select a single model base and make inference using that selected model, ignoring the uncertainty surrounding the model selection process, or ii) estimate all candidate models and

then compute a weighted average of all the estimates for the coefficient of X_j . In the second context, the researcher considers not only the uncertainty associated to the parameter estimate conditional on a given model, but also the uncertainty of the parameter estimate across different models. In particular, BMA inference on the parameters $\eta = (\delta, \sigma)$ is based on probabilistic weighted averages of parameter estimates of individual models:

$$p(\eta | y, X) = \sum_{k=1}^{2K} p(\eta_k | M_k, y, X) p(M_k | y, X) \quad (5.3)$$

The weights and the posterior model probabilities (PMPs) are given by:

$$p(M_k | y, X) = \frac{p(y, X | M_k) p(M_k)}{\sum_{k=1}^{2K} p(y, X | M_k) p(M_k)} \quad (5.4)$$

Model weights can be obtained using the marginal likelihood of each individual model after eliciting a prior over the model space. The marginal likelihood of model M_k is given by⁹:

$$p(y, X | M_k) = \int_0^\infty \int_{-\infty}^\infty p(y, X | \delta, \sigma, M_k) d\delta d\sigma \quad (5.5)$$

⁹ In particular, we employ a normal-gamma conjugate prior for $\delta = [\alpha, \beta]$ and σ :

$$\begin{aligned} p(\delta) &: N(c, \Sigma) \\ p\left(\frac{1}{\sigma^2}\right) &: \Gamma(d, v) \end{aligned}$$

However, $p(\delta_k)$ is adjusted following the convention in BMA analysis by means of the g-prior hyper-parameter, which takes the value of $g_k = 1/\max\{n, K^2\}$ such that:

$$p(\delta_k | \sigma^2) = N\left[0, \sigma^2 (g_k X_k' X_k)^{-1}\right]$$

The employment of the g-prior scales in the variance of the coefficients in δ_k reflects the strength of the prior. Lastly, we employ a binomial prior on the model space $p(M_k) = \phi^k (1-\phi)^{K-k}$, where each covariate k is included in the model with a probability of success ϕ . We set $\phi = 1/2$, which assigns equal probability $p(M_k) = 2^{-K}$ to all models under consideration.

Inference on parameters of the model relies on the computation of the posterior mean (PM) and the posterior standard deviation (PSD).

$$E(\eta | y, X) = \sum_{k=1}^{2K} E(\eta_k | M_k, y, X) p(M_k | y, X) \quad (5.6)$$

$$PSD = \sqrt{Var(\eta | y, X)} \quad (5.7)$$

where the $Var(\eta | y, X)$ is given by:

$$Var(\eta | y, X) = \sum_{k=1}^{2K} Var(\eta_k | M_k, y, X) p(M_k | y, X) + \sum_{k=1}^{2K} (E(\eta_k | M_k, y, X) - E(\eta | y, X))^2 p(M_k | y, X) \quad (5.8)$$

where the first term reflects the variability of estimates across different regression models, and the second term captures the weighted variance across different models. Additionally, it is possible to compute the conditional posterior positivity of a parameter h as:

$$p(\eta_h \geq 0 | y, X) = \sum_{k=1}^{2K} p(\eta_{k,h} | M_k, y, X) p(M_k | y, X) \quad (5.9)$$

where values of conditional positivity close to 1 indicate that the parameter is positive in the vast majority of considered models. Conversely, values near 0 indicate a predominantly negative sign. Finally, with the aim of generating a probabilistic ranking of relevance for the various SP determinants, we compute the PIPs for a variable h as the sum of the PMPs including the variable h :

$$PIP = p(\eta_h \neq 0 | y, X) = \sum_{k=1}^{2K} p(\eta_k | M_k, y, X) p(M_k | \eta_h \neq 0, y, X) \quad (5.10)$$

In the BMA analysis, rather than estimating the 2^K possible models, we will work with a relevant sub-sample of the model space drawn by means of the MC^3 algorithm developed by Madigan and York (1995). The algorithm to sample models relies on the following acceptance rule to explore the model space:

$$P = \min \left[1, \frac{p(M' | y)}{p(M | y)} \right] \quad (5.11)$$

where $p(M | y)$ denotes the probability of model M (i.e., the current model) and $p(M' | y)$ denotes the probability of an alternative model M' . Thus, if $p(M' | y) > p(M | y)$, the sampler will move to model M' . The vector of log-marginal values for the current model M and the proposed alternative models M' are scaled and integrated to produce Equation X.

5.3.2. Relative Importance Metrics

In order to complement the BMA analysis, we explore the relative importance of the various factors that could affect SP. To that end, we study the relative contribution of the various factors with the LMG method (Groemping, 2007; Lindeman et al., 1980), the Genizi, and the CAR scores (Genizi, 1993; Zuber & Strimmer, 2010, 2011). The decomposition procedures used in each of these metrics are detailed below.

Let the variance of the dependent variable Y be given by σ_y^2 , the variance of the set of regressors contained in X be denoted by Σ , and the covariance of Y and the covariates by Σ_{yX} . Let P denote the correlations among regressors and P_{yX} marginal correlations between regressors and Y , such that:

$$\Sigma = V^{\frac{1}{2}} P V^{\frac{1}{2}} \quad (5.12)$$

and

$$\Sigma_{yX} = V^{\frac{1}{2}} P_{yX} V^{\frac{1}{2}} \quad (5.13)$$

where $V = \text{diag}(\text{Var}(X_1), \dots, \text{Var}(X_p))$. Defining the correlation between the model estimates and Y as $\Omega = \text{corr}(Y, \hat{Y})$, then the squared multiple correlation coefficient is expressed as:

$$R^2 = \Omega^2 = P_{yX} P^{-1} P_{Xy} \quad (5.14)$$

Then, the unexplained variance can be written as $\sigma_y^2(1-\Omega)$ and the explained variance of a model with X_k regressors with indices in the set S as $\text{evar}_S = [\sigma_y^2 \Omega]_{X_k, k \in S}$. Finally, the sequential added explained variance when adding the regressors with indices in M to a model that already contains the regressors with indices in S as $\text{svar} = [\sigma_y^2 \Omega]_{M \cup S} - [\sigma_y^2 \Omega]_S$. This implies that the true coefficient of determination is given by:

$$R^2 = \Omega^2 = \frac{\text{evar}(S)}{\sigma_y^2} \quad (5.15)$$

With these definitions in hand for any model with P regressors, the r-squared can be expressed as:

$$R^2 = \Omega^2 = \sum_{k=1}^p \phi^m X(k) \quad (5.16)$$

where m denotes the decomposition method. The LMG method assigns to each regressor X_k the following share:

$$\phi^{LMG} X(k) = \frac{1}{p} \sum_{i=0}^{p-1} \left(\sum_{S \subseteq k+1, \dots, p, n(S)=i} \frac{svar(\{k\} | S)}{\binom{p-k}{i}} \right) \quad (5.17)$$

where $svar$ denotes the sequentially added explained variance as defined above. Thus, the share ϕ_k assigned to regressor k is the average over model sizes i of average improvements in explained variance when adding regressor k to a model of size i that did not contain k . Hence, the LMG metric performs a R^2 decomposition by averaging marginal contributions of independent variables over all orderings of variables and using sequential sums of squares from the linear model, the size of which depends on the order of the regressors in each particular model. Finally, to check the robustness of our results, we also compute two alternative metrics of relative importance: (i) the Genizi (1993) and the (ii) CAR scores. The weights associated to the Genizi (1993) and CAR measures are given by:

$$\phi^{GEN} Z(k) = \sum_{p=1}^p \left[\left(P^{\frac{1}{2}} \right)_{kp} \left(P^{\frac{-1}{2}} P_{xy} \right)_p \right]^2 \quad (5.18)$$

and

$$\phi^{CAR} Z(k) = \omega_k^2 \quad (5.19)$$

with $\omega = P^{\frac{-1}{2}} P_{xy}$.

5.4. Results

5.4.1. Main Results

Table 5.3 reports the results obtained when implementing the MC^3 algorithm for the 5,000 top models out of the 8,149 generated by the sampler, where the number of draws to carry out the sampling exercise on the model space was 100,000. The concentration of the posterior density in this context was high, given that the top 1% of models concentrate 52.41% of the mass, whereas the top 5% concentrate 75.55%. We scale the PIPs of the different variables to classify evidence of robustness of inequality regressors into three categories so that regressors with $PIP \in [0-20\%]$ are considered as weak determinants, with $PIP \in [20-80\%]$ of medium importance, and with $PIP \in [80-100\%]$ as very important.

Column 1 show the PIPs, while Columns 2 to 5 show the mean and the standard deviation of the posterior parameters' distributions, along with the lower and upper bounds, conditional on the variable being included in the model¹⁰. To complement these statistics, Column 6 reports the fraction of models where the t-stat of the corresponding variables is higher than 1.96 (which implies statistical significance at the 5% level), while Column 7 presents the results of the posterior sign certainty, which measures the posterior probability of a positive coefficient expected value, conditional on inclusion.

¹⁰ The key difference with respect to unconditional posterior estimates of Equations 6 and 7 is that conditional posterior estimates for a particular variable are obtained as the weighted average over the models in which the variable is included. On the contrary, the unconditional posterior estimate is the averaged coefficient over all models, including those in which the variable does not appear, hence having a zero coefficient. Thus, the unconditional PM can be computed by multiplying the conditional mean in Column 3 times the PIP in Column 1.

Table 5.3. Main Results: Model Averaged Estimates

Variable	PIP	Lower 5%	Cond Post. Mean	Cond Post. Std	Upper 95%	T-Stat > 1.96	Sign Pos.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Assists	0.999	0.00868	0.00992	0.00110	0.01098	1.00	1.00
Shots Conceded	0.999	-0.01012	-0.00959	0.00065	-0.00921	1.00	0.00
Saves Made	0.999	0.00820	0.00882	0.00086	0.00945	1.00	1.00
Passing Accuracy	0.998	0.70022	0.90790	0.22871	1.22442	1.00	1.00
Clearances, blocks and interceptions	0.581	0.00005	0.00008	0.00003	0.00010	0.93	1.00
Shots on Target	0.229	0.00056	0.00076	0.00031	0.00117	0.40	1.00
Total Fouls Conceded	0.210	0.00006	0.00017	0.00009	0.00033	0.34	1.00
Recoveries in Opp. Half	0.183	-0.00030	-0.00016	0.00008	-0.00005	0.46	0.00
Recoveries	0.171	0.00002	0.00006	0.00003	0.00011	0.67	1.00
Crosses Attempted	0.154	0.00007	0.00011	0.00004	0.00017	0.63	1.00
Total Passes	0.110	-0.00001	0.00000	0.00000	0.00001	0.25	0.19
Total Shots Attempted	0.103	-0.00005	0.00024	0.00009	0.00053	0.17	0.91
Fouls Conceded (danger area)	0.100	-0.00156	-0.00088	0.00036	-0.00034	0.52	0.00
Tackles Attempted	0.087	-0.00023	-0.00016	0.00005	-0.00008	0.44	0.00
Red Cards	0.056	0.00144	0.00282	0.00082	0.00425	0.03	1.00
Dribble Run Success Rate	0.042	-0.08440	0.02976	0.02350	0.15284	0.01	0.64
Dribbles and Runs Attempted	0.042	-0.00006	-0.00002	0.00001	0.00001	0.00	0.12
Yellow Cards	0.040	-0.00012	0.00018	0.00008	0.00050	0.00	0.85
Through Ball	0.038	-0.00027	0.00014	0.00010	0.00062	0.01	0.69
Corners Taken	0.038	-0.00051	-0.00010	0.00006	0.00017	0.01	0.34
Catches	0.033	-0.00017	0.00004	0.00007	0.00028	0.00	0.56
Long Pass Final Third	0.033	-0.00011	-0.00001	0.00001	0.00005	0.16	0.63
Tackled Poss. Retained%	0.032	-0.00422	0.11059	0.04030	0.24587	0.00	0.94
Offsides	0.031	-0.00023	-0.00008	0.00006	0.00007	0.00	0.21

Notes: The dependent variable in all regressions is the normalized indicator of sport performance based on the points obtained during the season. All the results reported here correspond to the estimation of the top 5,000 models from the 16.77 million possible regressions including any combination of the 24 regressors. Prior mean model size is 12. Variables are ranked by Column (1), the posterior inclusion probability. Columns (2) to (5) reflect the lower 5% bound, the posterior mean, standard deviations and upper 95% bound for the linear marginal effect of the variable conditional on inclusion in the model, respectively. Column (6) is the fraction of regressions in which the coefficient has a classical t-test greater than 1.96, with all regressions having equal sampling probability. The last column denotes the sign certainty probability, a measure of our posterior confidence in the sign of the coefficient.

As observed in Column 1, there is a set of top variables that appears with high frequency in the group of very important determinants. The assists, the shots conceded, the saves made by the goalkeeper, and the passing accuracy appear to be the most relevant determinants and in all cases display PIPs of 99.9%. In the range of medium importance, we find the number of clearances blocks and interceptions (58.1%), the shots on target (22.9%), and the total number

of fouls conceded (21%). On the other hand, the group of weak SP determinants with PIPs below 20% is conformed by a myriad of factors. Therefore, for the remainder of the paper, we will discuss only the results for the regressors with a PIP above 20%.

Column 6 shows that for the group of very important determinants, the variables appear to be significant at the 5% level in all of the regression models. On the other hand, the statistical significance of the regressors included in the group of medium relevance oscillates between 93% of the regression models in the case of the clearances, blocks, and interceptions and 34% of the models in the case of the fouls conceded. As shown in Column 7, the effects of the determinants of higher and medium levels of importance are robust across regression models and display the same sign of the PM in all cases. Among the top determinants of SP, only the number of shots conceded displays a negative effect, while the determinants that have a positive effect on SP are (i) the assists; (ii) the saves made; (iii) the passing accuracy; (iv) the number of blocks, clearances, and interceptions; (v) the shots on target; and (vi) the total fouls conceded.

One of the advantages of including regressors that capture both the efficiency in a type of behaviour or style of play (i.e., passing accuracy) and the intensity of this (i.e., total passes) is that by analysing the values of the PIPs we can see whether it is the brute force or the accuracy that matters. For the most remarkable determinants, the PIs related to efficiency/accuracy take a higher probability of inclusion than their absolute counterparts. In the context of passes, we find that passing accuracy (100%) displays a higher PIP than the total number of passes (11%). Similarly, regarding shots, we find that shots on target (23%) appear to be more relevant than the total number of shots attempted (10%). These results indicate that among the determinants with high PIP the accuracy/efficiency ratios are more important than the total actions performed.

Table 5.4 reports the results of the analysis of relative importance. For a proper interpretation of the R^2 decomposition performed, recall that in the context of a linear regression model the R^2 informs on the model's explained variability across observations. Thus, decompositions on the relative importance of a factor X^k tell us the percentage of explained disparities in SP across the observations by k . In the present context, the $R^2 = 0.88$, while the unexplained variability is $\sigma_y^2(1-\Omega) = 0.12$, which implies our decomposition explains most of the differences in SP across teams and seasons. Given that results produced by them were similar, we will discuss just the average share reported in the last column of Table 5.1.

The first salient feature of the relative importance decomposition is that the variability in SP that can be attributed to attack actions is 62.6%, while the sum of defence variables accounts for 37.6% of the differences in SP, which suggests that attack actions are more relevant than defence ones. Among the set of attack factors, we find the most relevant factors are, in decreasing order, the assists (17.88%), the shots on target (9.79%), the passing accuracy (7.86%), the total passes (7.08%), and the total shots attempted (6.02%). However, the most relevant factor is a defensive one: the shots conceded. This factor explains by itself 21.5% of the SP of a football team. In a lower level of explanatory power of the SP, we find the saves made (5.8%) and the fouls conceded (3.3%). Notice that these results imply that relative importance metrics produce a similar group of factors to that suggested by the BMA analysis. The most remarkable differences can be seen in the fact that relative importance analysis attributes a relatively high share to the total passes and to the total shots and a relatively low importance to the total fouls conceded when compared to the BMA. Taken together, the two methodologies point to the existence of a set of key variables, such as (i) the number shots

conceded, (ii) the assists, (iii) the passing accuracy, (iv) the saves made, and (v) the shots on target.

Table 5.4. Relative Importance Decomposition: Main Results

Variable	LMG Metric	CAR Scores	Genizi Decomposition	Average Importance
A. Attack	0.626	0.626	0.618	0.624
Total Shots Attempted	0.070	0.048	0.068	0.062
Shots on Target	0.103	0.101	0.090	0.098
Total Passes	0.079	0.061	0.073	0.071
Passing Accuracy	0.079	0.084	0.074	0.079
Assists	0.161	0.226	0.150	0.179
Crosses Attempted	0.005	0.004	0.007	0.005
Corners Taken	0.038	0.022	0.038	0.033
Dribbles and Runs Attempted	0.010	0.005	0.013	0.009
Dribble and Run Success Rate	0.006	0.005	0.009	0.007
Long Pass Final Third	0.014	0.011	0.021	0.015
Through Ball	0.049	0.047	0.058	0.051
Offsides	0.013	0.012	0.018	0.014
B. Defense	0.374	0.374	0.382	0.376
Shots Conceded	0.182	0.294	0.168	0.215
Tackles Attempted	0.003	0.002	0.005	0.003
Tackled and Possession Retained %	0.004	0.001	0.005	0.003
Recoveries	0.012	0.016	0.016	0.015
Recoveries in Opp. Half	0.016	0.003	0.015	0.011
Clearances, blocks and intercept.	0.017	0.010	0.022	0.017
Total Fouls Conceded	0.011	0.001	0.010	0.007
Fouls Conceded in the Danger Area (inc pens)	0.030	0.032	0.037	0.033
Yellow Cards	0.006	0.003	0.007	0.005
Red Cards	0.005	0.004	0.007	0.005
Saves Made	0.084	0.006	0.085	0.058
Catches	0.003	0.001	0.004	0.003

Notes: The dependent variable in all regressions is the normalized indicator of sport performance I obtained during the season. The decomposition applies to a model with $R^2 = 0.88$ while the unexplained variance $\sigma_y^2(1 - \Omega) = 0.12$

These results support previous analyses in the literature and provide new insights on the relevance of some regressors. Our findings regarding the positive and relevant effect of assists in the performance is in line with previous discriminant analyses performed by Lago-Ballesteros and Lago-Peñas (2010) and Lago-Peñas et al. (2010). Second, the relevance of the passing accuracy indicator supports Carmichael et al. (2000) and Oberstone (2009). Regarding defensive actions, two PIs appear to be key determinants in our empirical analysis: the shots

conceded and the saves made. As far as we know, no papers analysing a set of determinants of SP have included the saves made in their modelling. This result ultimately implies that future research should take this factor into account. On the other hand, the negative effect related to the shots conceded tends to corroborate the findings of Castellano et al. (2012). Furthermore, the results stemming from the group of medium importance such as the clearances, blocks and interceptions, shots on target, and total fouls conceded are in agreement with the previous literature. The clearances, blocks, and interceptions are positively related to success, as suggested by Carmichael et al. (2000). Similarly, the shots on target also appear to be a relevant determinant independently of the methodology employed (Carmichael et al., 2000; Castellano et al., 2012; Delgado-Bordonau et al., 2013; Lago-Ballesteros & Lago-Peñas, 2010; Lago-Peñas et al., 2010, 2011; Moura, 2013). Additionally, we find that the results obtained here regarding the relevance and the effect of fouls committed are similar to those of Oberstone (2009). Finally, the negative estimated effect of recovery in the opposite half and the positive effect of all ball recoveries corroborate the results of Barreira et al. (2012), who found recovering directly the ball possession in mid-defensive central zones increases attacking efficacy.

However, some of the findings in our analysis are in contrast to those previously found in literature. This is the case in the set of regressors displaying relatively low PIPs. For instance, the indicator measuring the crosses attempts displays a PIP of 15% and has a positive effect on teams success, which is in contrast to the results of Vercer (2013), in which the net effect of crossing is negative for most teams. However, this difference could be explained by the fact that the analysis of Vercer only focuses on Premier League games. In the same vein, the low relevance of total shots and total passes that we observe is at odds with the findings of Oberstone (2009), whereas the results regarding the tackle attempts, offsides, and yellow and red cards differ from those of Carmichael et al. (2000).

5.4.2. Robustness Checks

The analysis carried out so far suggests the existence of a group of robust determinants of SP in the European football league. In the remainder of this section, the robustness of previous findings is investigated.

As a first robustness test, we examine to what extent the results may be sensitive to the choice of the measure used to quantify the SP in the sample teams. To that end, we test an alternative measure of SP based on a transformation of the final position in the league such that:

$$SP_{it} = \ln\left(\frac{X+1-C_{it}}{C_{it}}\right) \quad (5.20)$$

where X is the number of teams in the league, and C_{it} denotes the classification of the team i in the league t .

Table 5.5 summarises the results of the BMA when using the alternative SP metric. As is observed, (i) the number of shots conceded, (ii) the assists, (iii) the passing accuracy, (iv) the saves made, and (v) the shots on target also appear to be among the top determinants of SP.

An additional issue is to examine to what extent previous findings are contingent on the specific football league. To that end, we perform the BMA analysis and the relative importance decomposition for each individual league for the period 2012/13–2014/15. Tables 6 and 7 summarise the PIPs by factor and the average share of the R^2 attributed to each factor across metrics, respectively.

Table 5.5. Dependent Variable Robustness Check (I): BMA Ranking in League

Variable	PIP	Lower 5% Cond Post.	Cond Post.	Upper 95%	T-Stat	Sign	
	(1)	(2)	Mean (3)	Std (4)	(5)	>1.96 (6)	Pos. (7)
Shots Conceded	1.000	-0.02929	-0.02660	0.00322	-0.02524	1.00	0.00
Saves Made	1.000	0.02436	0.02602	0.00416	0.02855	1.00	1.00
Assists	0.991	0.01535	0.01912	0.00393	0.02218	1.00	1.00
Catches	0.334	0.00268	0.00333	0.00163	0.00384	0.60	1.00
Clearances, blocks and intercept.	0.120	0.00011	0.00020	0.00008	0.00026	0.06	1.00
Recoveries	0.109	0.00008	0.00015	0.00006	0.00024	0.04	1.00
Corners Taken	0.109	0.00050	0.00148	0.00057	0.00377	0.12	1.00
Long Pass Final Third	0.087	-0.00047	-0.00033	0.00010	-0.00025	0.07	0.00
Red Cards	0.086	0.01380	0.01746	0.00603	0.02032	0.01	1.00
Dribble and Run Success Rate	0.069	-0.77155	-0.56249	0.19162	-0.31309	0.01	0.00
Passing Accuracy	0.066	0.48877	1.24473	0.35903	3.18904	0.11	0.99
Shots on Target	0.060	0.00050	0.00381	0.00083	0.00665	0.45	0.97
Total Shots Attempted	0.052	0.00065	0.00159	0.00033	0.00328	0.27	1.00
Crosses Attempted	0.052	-0.00006	0.00010	0.00006	0.00023	0.00	0.86
Offsides	0.050	-0.00150	-0.00098	0.00041	-0.00054	0.00	0.00
Recoveries in Opp. Half	0.039	-0.00058	-0.00013	0.00009	0.00009	0.00	0.22
Yellow Cards	0.039	-0.00014	0.00071	0.00035	0.00134	0.00	0.92
Through Ball	0.039	-0.00190	-0.00066	0.00041	0.00034	0.00	0.13
Fouls Conceded (danger area)	0.036	-0.00007	0.00096	0.00041	0.00186	0.00	0.94
Total Passes	0.036	-0.00004	0.00000	0.00000	0.00003	0.08	0.44
Tackled Possession Retained (%)	0.035	-0.35535	0.04169	0.18434	0.41473	0.00	0.57
Total Fouls Conceded	0.035	0.00008	0.00033	0.00010	0.00051	0.00	0.97
Tackles Attempted	0.035	-0.00013	0.00005	0.00007	0.00021	0.00	0.69
Dribbles and Runs Attempted	0.035	0.00006	0.00014	0.00004	0.00023	0.01	1.00

Notes: The sport performance dependent variable is the transformed of the ranking in the league such that $y_i = \log(X+1-C_i)/C_i$ where X is the number of teams in the league and C denotes their classification. The results reported here correspond to the estimation of the top 5.000 models from the 16.77 million possible regressions including any combination of the 24 regressors. Prior mean model size is 12. Variables are ranked by Column (1), the posterior inclusion probability. Columns (2) to (5) reflect the lower 5% bound, the posterior mean, standard deviations and upper 95% bound for the linear marginal effect of the variable conditional on inclusion in the model, respectively. Column (6) is the fraction of regressions in which the coefficient has a classical t-test greater than 1.96, with all regressions having equal sampling probability. The last column denotes the sign certainty probability, a measure of our posterior confidence in the sign of the coefficient.

Table 5.6. Robustness Check (II): Posterior Inclusion Probabilities by League

Variable	<i>Big Five</i>	<i>Premier</i>	<i>La Liga</i>	<i>Serie A</i>	<i>Bundesliga</i>	<i>Ligue 1</i>
Total Shots Attempted	0.103	0.3744	0.0460	0.0960	0.1260	0.0465
Shots on Target	0.229	0.9903	0.0437	0.1073	0.0880	0.0336
Total Passes	0.110	0.0362	0.1418	0.0385	0.0521	0.0370
Passing Accuracy	0.998	0.0364	0.0569	0.0513	0.0530	0.0624
Assists	1.000	0.9986	1.0000	1.0000	0.9997	1.0000
Crosses Attempted	0.154	0.0423	0.1463	0.0418	0.0342	0.0426
Corners Taken	0.038	0.2561	0.0392	0.0347	0.1361	0.0344
Dribbles and Runs Attempted	0.042	0.0534	0.0489	0.0570	0.0380	0.1069
Dribble and Run Success Rate	0.042	0.0353	0.2908	0.0567	0.0962	0.0813
Long Pass Final Third	0.033	0.0426	0.0453	0.0740	0.0564	0.0476
Through Ball	0.038	0.1115	0.0401	0.6101	0.0329	0.0400
Offsides	0.031	0.0469	0.0327	0.2361	0.0328	0.0387
Shots Conceded	1.000	1.0000	1.0000	1.0000	1.0000	1.0000
Tackles Attempted	0.087	0.0341	0.0483	0.3646	0.0380	0.0563
Tackled and Possession Retained %	0.032	0.0437	0.0323	0.0499	0.0342	0.0320
Recoveries	0.171	0.1979	0.1404	0.2573	0.0340	0.0453
Recoveries in Opp. Half	0.183	0.0779	0.6225	0.0674	0.0346	0.0386
Clearances, block and intercept.	0.581	0.0369	0.9315	0.1989	0.2826	0.0396
Total Fouls Conceded	0.210	0.0475	0.6616	0.0478	0.0559	0.0445
Fouls Conceded (Danger Area)	0.100	0.0341	0.1334	0.0521	0.0354	0.5401
Yellow Cards	0.040	0.0345	0.0647	0.0279	0.0435	0.1119
Red Cards	0.056	0.0982	0.2114	0.1459	0.0742	0.2487
Saves Made	1.000	1.0000	0.9953	0.9991	0.9998	1.0000
Catches	0.033	0.0453	0.0550	0.0378	0.0782	0.0346

Notes: The dependent variable in all regressions is the normalized indicator of sport performance based on the points obtained during the season. All the results reported here correspond to the estimation of the top 5,000 models.

As observed in Table 5.6, the PIPs by factor in the different European football leagues are very similar, which implies the top determinants we identified before by means of the BMA analysis are robust across leagues. The assists, the number of shots conceded, and the saves made have a PIP of 100% in all leagues. However, the passing accuracy does not display a high PIP value for each of the individual leagues. While the PIPs in the Bundesliga (Germany) closely follow the overall aggregate European PIP values, there are some interesting differences in the actions related to success across the other leagues, which ultimately imply that the strategies for success and playing styles are different across countries. In the Premier League (England), the shots on target and the total shots attempted appear in the top

positions. In La Liga (Spain), we find that the group of factors of major importance also consists of the number of clearances, the blocks and interceptions, the recoveries in the opponent half, and the total fouls conceded. In the Calcio (Italy), the number of through balls and tackles attempted display high values, and in the Ligue 1 (France) the fouls conceded in the danger area are likely to be relevant.

Table 5.7. Robustness Check (III): Relative Importance Decomposition by League

Variable	<i>Big Five</i>	<i>Premier</i>	<i>La Liga</i>	<i>Serie A</i>	<i>Bundesliga</i>	<i>Ligue 1</i>
A. Attack						
Total Shots Attempted	0.062	0.078	0.066	0.066	0.066	0.057
Shots on Target	0.098	0.156	0.085	0.085	0.092	0.067
Total Passes	0.071	0.064	0.058	0.058	0.099	0.076
Passing Accuracy	0.079	0.067	0.068	0.068	0.083	0.105
Assists	0.179	0.193	0.202	0.202	0.158	0.131
Crosses Attempted	0.005	0.002	0.004	0.004	0.004	0.012
Corners Taken	0.033	0.052	0.032	0.032	0.032	0.023
Dribbles and Runs Attempted	0.009	0.030	0.015	0.015	0.011	0.013
Dribble and Run Success Rate	0.007	0.005	0.010	0.010	0.013	0.005
Long Pass Final Third	0.015	0.031	0.005	0.005	0.005	0.025
Through Ball	0.051	0.040	0.055	0.055	0.052	0.047
Offsides	0.014	0.003	0.054	0.054	0.006	0.013
B. Defense						
Shots Conceded	0.215	0.135	0.148	0.148	0.157	0.189
Tackles Attempted	0.003	0.008	0.011	0.011	0.024	0.004
Tackled Possession Retained %	0.003	0.005	0.007	0.007	0.003	0.008
Recoveries	0.015	0.008	0.022	0.022	0.006	0.012
Recoveries in Opp. Half	0.011	0.027	0.020	0.020	0.008	0.012
Clearances, Blocks and Intercept	0.017	0.020	0.013	0.013	0.016	0.022
Total Fouls Conceded	0.007	0.007	0.016	0.016	0.022	0.009
Fouls Conceded (Danger Area)	0.033	0.023	0.028	0.028	0.041	0.104
Yellow Cards	0.005	0.002	0.027	0.027	0.036	0.003
Red Cards	0.005	0.003	0.006	0.006	0.016	0.003
Saves Made	0.058	0.040	0.046	0.046	0.024	0.049
Catches	0.003	0.005	0.004	0.004	0.024	0.009

Notes: The dependent variable in all regressions is the normalized indicator of sport performance based on the points obtained during the season. The decomposition applies to a model with $R^2 = 0.88$ while the unexplained variability is $\sigma_v^2(1-\Omega) = 0.12$.

5.5. Conclusions

This study analyses the relative importance of a large number of possible determinants of football performance during the period 2012/13–2014/15 for the most important European leagues. The key contributions are methodological, given that we consider the effect of a great number of determinants employing two innovative methodologies in this context: the BMA technique and the relative importance metrics. These methods enable us to compute the PIPs for the different indicators to generate a probabilistic ranking of relevance for the various SP determinants and decompose the R^2 of the model. Our results reveal a set of robust determinants of SP in football. These PIs consist of (i) the assists, (ii) the shots conceded, (iii) the saves made by the goalkeeper, (iv) the passing accuracy, and (v) the ratio of goals and total shots.

Moreover, we find strong support for the idea that offensive actions are more relevant than defensive ones. In particular, from the relative importance analysis, we find that attack plays had an average importance of 62%, whereas the defensive variables explained 38% of the variability in SP. Importantly, the shares of importance are highly concentrated in few indicators. Out of the 62% of the importance related to attack tactics, the indicators related to scoring (total shots, shots on target, and assists) accounted for more than a half part (33%). In a similar vein, out of the 38% of variability explained, 21% are related to scoring (shots conceded).

There are three main implications of our findings. The first is related to the tactics (for the coaches) and techniques (for the players). We observed that assists and through balls are much more important than dribbles, runs, and crosses. Hence, improving the technical and tactical execution in these plays is essential. However, we also observed that accuracy is more

important than the amount of executions. This point is related to the first, because we cannot forget that diversifying the game is fundamental to avoid predictability.

The second main implication is related to the clubs management section. When hiring players, managers should consider signing players with skills and abilities associated with those determinants that have an impact on the team success (always weighting the possible combinations of players that the team already has and/or lacks). For example, considering the importance of the shots conceded and the saves made, if a team already has a relatively high value of shots conceded, a good strategy could be to increase the quality of the goalkeeper.

As observed in this study, SP in football analysis has inherent problems given that it is a multifaceted and complex phenomenon. One of the main implications of our findings for future research in this field is the need for controlling for the assists and the saves made by the goalkeeper. These variables have usually been ignored by previous analyses, but our estimations suggest they are likely to be a key part of sport success in football. This, on the one hand, leads us to emphasise the importance of the goalkeeper, while, on the other hand, it suggests the need to include additional variables related to his particular function in the analysis. In the same vein, the development of new PIs is crucial to increase the explanatory power of the results. This could be achieved by increasing the number of situational variables, such as match status and the pitch zones where the actions take place. We believe this could be an important point to further extend our knowledge on the determinants of sport success. The employment of aggregate variables that do not inform on the situational context in which the specific action takes place may hide relevant information.

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Conclusions

This thesis is an experimental exploration of my interest in assessing the bases of performance of European football teams. For a sports lover, to know the entrails of the business that football has become is hard. Throughout this thesis' development, periods of falling out of love alternated with those when a small team wins the big one or simply playing a friendly match. Each chapter has self-contained conclusions, discussed therein. Here, the main overall conclusions and the conclusions that have emerged throughout the process from one chapter to another will be commented.

In **chapter 1** the performance of UCL clubs was analysed. The main objective was to determine technical efficiency through the analysis of a wide time horizon and trying to provide useful information on the sources of the clubs' inefficiency. To this end, a well-known data envelopment analysis (DEA) approach and a bootstrapped DEA model were employed. A data sample extending over ten seasons was used (from 2004/05 to 2013/14) and the new output measure using the coefficients applied by the UEFA from UCL revenue distribution proposed seems to be suitable to reliably represent the sports results achieved by clubs in this qualifying competition type.

The results are robust when applying alternative estimation methods and show, first, that there is a high level of inefficiency in UCL over the period studied: Only 10% of the teams seem to be efficient. Over the course of the large number of seasons analysed, no club managed to maintain an efficient score, highlighting the hard level of this competition. Furthermore, it is important to note that clubs and resources employed change from one season to another, as do opponents; thus, an efficient club that employed the same resources might not be efficient in another season. Thus, teams have many problems in

maintaining their efficiency from season to season. Second, the champion is always efficient. Third, from the analysis of inefficient clubs, the main sources of inefficiency are player technique and the tactics employed. In this case, the responsibility for both falls mainly on the coach. To solve this problem clubs are encouraged to look carefully at their reference unit, to learn how efficient clubs develop their tactics and employ their resources. In terms of sport management, benchmarking is an essential tool for sports and economic survival of football clubs. Otherwise, if the efficient medium and small clubs want to improve their sports result, they should increase the amount of inputs employed.

In **chapter 2**, our main concern is about the evolution of the sports efficiency of football clubs playing in the UCL in the 2004/05-2012/13 period. As the sample is panel data, we propose a research procedure to find the most accurate methodology to analyse efficiency. Analysing constant return to scale (CRS) and super-efficiency DEA models, we estimated efficiency. The S statistic was employed to check for temporal trends and the Kruskal-Wallis statistic was run to analyse stability in relative ranks. We detected a temporal trend; teams do not maintain their relative rankings over time. According to these results, Window Data Envelopment Analysis (WDEA) emerges as the most appropriate method to estimate the efficiency of UCL teams. WDEA estimated efficiency scores can be used to evaluate teams' robustness and analyse the evolution of their efficiency more rigorously.

The WDEA results in this paper indicate that there is a low efficiency level (6%) in the nine seasons observed. This result corroborates our findings in the first chapter. There is a strong correlation (72%) between sports results and the efficiency of semi-finalists. From the analysis, we conclude that improvement in a club's efficiency could enhance its sports results. Finally, as for practical implications, we highlight benchmark teams and alternative sports tactics to help clubs become more efficient and achieve better sports results in the context of the UCL. In this sense, the main recommendations of the efficiency analyses of the first block are related to the need for technological (tactical) changes in the production of football clubs; to make it possible, further research might help to point alternative solutions.

The football club market is changing fast in the social media era. In this global market, clubs must maintain or improve fans' attendance at the stadium; simultaneously, they need, more than ever, to take care of social media. Attempting to respond rapidly to the changes in football clubs' production process, **chapter 3** proposed an approximation to the reality, where only one club can be the champion, but other clubs are performing well and earning more money than the champion. Regarding that, we have tested and discussed a comprehensive approach to analysing the multiplicity of objectives of football clubs. The efficiency of English Premier League (EPL) clubs during three seasons (2012/13–2014/15) was estimated through DEA and a bootstrapped DEA model. The input is the market value of the squad, and the outputs are sports results, total revenue, the ratio of stadium utilization during the season and an index of social media impact. The results are robust to alternative estimation methods and indicate that EPL clubs, especially the medium-sized clubs, still have a margin for improving their overall efficiency. The analysis provides a useful tool to help managers with evaluation and feedback considering the actual context of the market. The approach brings the opportunity to design appropriate strategies to improve clubs' efficiency as well as competition policies closer. Some potential alternatives could be to invest in training young players and develop more advanced system to sign undervalued players.

Chapter 4 is an extension of the analysis of chapter 3 and arises from discussions in several workshops and conferences where previous chapters were exposed. This discussion is a controversy that also has been manifested in the literature, and is about what type of inputs might explain more deeply the performance of sports clubs (inputs specification controversy). On one hand, several papers have analysed sports teams' performance using match-related statistics or wages as inputs (so-called ex-post inputs). On the other hand, some authors have criticized the use of these ex-post inputs, and recommend the use of ex-ante inputs, such as the market value of the players. To shed some light on this open discussion we have analysed the performance of football teams, estimating technical efficiency with three different input specifications. The outputs are: sports results, total revenue, the ratio of stadium utilization during the season and an index of social media impact. The three inputs specified are: the squads' market value (ex-

ante), the match-related statistics (ex-post) and the wages of the players (ex-post financial expenditure input). As in chapter 3, the methodologies employed are DEA and a bootstrapped DEA and the sample is composed of EPL football clubs, whose performance over the course of three seasons (2012/13-2014/15) was examined. However, this time, to take advantage of panel data, the efficiency was estimated for the period as a whole in an intertemporal approach. To do it a max-min normalization of raw data was implemented.

The DEA results indicate that the correlation between the three models is positive and significant. The DEA bootstrapped results help to restate the robustness of the estimations and reaffirm the input choices. The correlations of the estimations with market value and match-related statistics are the most striking (90 and 94%, DEA and bootstrapped DEA respectively), which indicate that the existing discussion related to the use of match-related statistics as input is unjustified, because it does not significantly affect the efficiency estimations. Some caution is recommended when using wages as input. In most cases, if the measure faithfully represents the players' skills and abilities it will lead to similar results. These results have some practical implications for strategic decisions in football clubs. The recommendation is that managers and coaches should interact to enable the club to achieve success. Both agents are important and necessary at the time to hire the right players and to find the best tactical combinations on the field.

From the main results of the first and the second block of the thesis, the differences between the competitions analysed highlighted very different efficiency levels. Although the analyses were different, employing different inputs and outputs and sometimes also a different stage of the production process, the efficiency of the clubs playing in the UCL is low and the efficiency of the EPL clubs is high. Besides the clear differences between the competition structures, the differences among the clubs are huge. On one side, the Premier League has one of the fairest television revenue sharing arrangements, one of the reasons that the squad with the highest market value has six times the value of the team with the lowest. On the other hand, in the UCL context, clubs of small leagues play with the worlds' big clubs, i.e. some big clubs have a squad with a market value more than 20 times the smallest. This consideration is important when

medium and small clubs are pursuing promotion to a top league or qualification for international competitions. Clearly, when there is a sportive possibility to opt for promotion, club managers normally do not think about other possibility and invest all their resources on doing it. The short-term economic rewards for this kind of clubs are dizzying. However, the expenditures, and mainly those related to the players (transfer fees, salaries and wages), are established over the medium and long term; when normally these clubs no longer participate in top competitions and do not have the same incomes.

In closing the efficiency analysis block, some concluding thoughts are necessary. Several works analyse the relation between efficiency and sports results, even some of this thesis. Our findings (chapter 2) indicated moderate/high correlation between efficiency and sports results. In this regard, our main concern is that much of this work used it to point out the robustness of the results. The first problem is that in most cases, the sports result is the only measure used as output, which leads to an endogeneity problem when analysing the correlation of the sports result and the efficiency scores estimated with itself. The second concern is also serious, because when analysing sports result we are approaching the effectiveness that is related with success in achieve the objectives, independently of the resources employed. However, the concept of efficiency is related to the best possible use of available resources, without waste. Thus, the two approaches are not measuring the same thing. Therefore, surely efficiency could be analysed and compared with the sports results, which is the most outstanding output in sport; but they never will indicate if the efficiency scores are accurate or not.

In order to close this experiential thesis, the last chapter also attempts to answer doubts that were emerging throughout the process. In **chapter 5** we ask what we can learn from the data, which are the determinants that best explain sports performance of European football clubs. This study analyses the importance of a large number of possible determinants of sport performance in the “Big Five” European football leagues during the period 2012/13–2014/15. To this end, innovative techniques in this field are employed; they are Bayesian model averaging and relative importance metrics.

The results obtained point to the existence of a set of robust determinants of sport performance. This set of drivers would consist of (i) assists, (ii) shots conceded, (iii) saves made by the goalkeeper, (iv) the number of precise passes with respect to the total number of passes, and (v) shots on target. The study also finds strong support for the idea that offensive actions are more relevant than defensive ones. Related to inclusion of regressors that capture both the efficiency in a type of behaviour or style of play (i.e., passing accuracy) and the intensity of this (i.e., total passes), among the most remarkable determinants, the performance indicators related to efficiency/accuracy have a higher probability of inclusion than their absolute counterparts. These results indicate that the accuracy/efficiency ratios are more important than the total actions performed. The main implications of the findings could help football clubs on issues related to technical and tactical improvements, as well for management section. Moreover, for further performance analysis research, the study highlights performance indicators that have usually been ignored by previous analyses but that its estimations suggest are likely to be a key part of sport success in football.

From the relation between the three blocks of this thesis we can conclude that, like other organizations, football clubs must pursue efficiency. In this regard, the main findings of this thesis also could be useful for the big clubs, but the main concerns are related to medium and small clubs, which do not have enough resources to hire star players and need to improve their performance with alternative solutions. The main internal solutions without any doubt starts with the managers, who must understand deeply both the business and the game, and pass fundamentally by the coach, who should know the best inputs combination, and how to manage so peculiar kinds of inputs. Another solution is related to chapter 5's findings, and depending on the clubs' structure could be internal or external. Without considerably increasing the inputs employed, clubs should develop more advanced systems to sign undervalued players ("Moneyball" approach) and maximize their own players' potential.

Beyond our results, in a globalized economy, the big real winners (global plutocrats) have found a way to distract the world's masses from reality (and add more to their gargantuan wealth). In this regard, considering that professional football is an industry with an enormous capacity to generate income, our

main concern is that governments should not invest a penny in this activity, and increasingly restrict and regulate the extent to which clubs receive the same treatment as regular companies. The social responsibility of professional football clubs should go further, investing in programs of grassroots sport, women's sport, and helping to promote long-term programs of physical activity and exercise to the population in general.