ARE FORMER PROFESSIONAL ATHLETES AND NATIVE BETTER COACHES? EVIDENCE FROM SPANISH BASKETBALL

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Abstract: This paper analyzes the efficiency of coaches in the Top Spanish Basketball League and what determines this efficiency. To accomplish this, a stochastic production function is estimated. Among others, the inefficiency determinants considered are whether the coach is an ex-professional player and whether he is from Spain. The results demonstrate that foreign coaches are more efficient. To build upon these results, a new approach to estimate the efficiency of coaches, in which efficiency is obtained by comparing their performance with expectations attained from betting odds, is proposed. The results were principally reinforced.

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Introduction

Running a sports club involves making many decisions. One of the most important decisions is choosing the manager (head coach) of the team. Kahn (1993) found that in Major League Baseball, the more experienced managers with better past winning records raised teams' performances. Other studies have focused on the role of being an ex-professional player (Bridgewater, Kahn, & Goodall, 2011; Dawson & Dobson, 2002; Goodall, Kahn, & Oswald, 2011; Kelly, 2008). Goodall et al. (2011) documented a correlation between brilliance as a player and winning percentage, after controlling for the team's quality using the team's salary payroll in the NBA. Bridgewater et al. (2011) similarly used data from British football and found that managers who had themselves played at a higher level raised the productivity of less skilled teams more so than highly skilled teams. These results are reinforced by Dawson & Dobson (2002), who found that achieving international recognition as a player is especially important for managers' efficiency.

This paper attempts to shed some light on the latter discussion by calculating coaches' efficiency and its determinants in the Spanish basketball league, in which the top league is run by the Basketball Club Association (ACB). This league is known worldwide as ACB. To achieve our goal, three alternative production functions were estimated using a stochastic frontier model that allows for the incorporation of variables that affect inefficiency. According to Lee (2006) and Lee & Berri (2008), to obtain accurate efficiencies of the managers in a production function, *ex ante* quality measure of the roster should be used. Data from the SuperManager[1], which is the official fantasy league of the ACB, was used to measure the players' quality. Similar to González-Gómez, Picazo-Tadeo & García-Rubio (2011), we used the budget of each team. The principal results show that Spanish coaches have a statistically significantly lower performance than foreign coaches, and former professional basketball players perform better, although this is only significant in one out of the three models.

Betting odds have already been used for economic purposes in addition to in the betting market itself. For instance, Soebbing & Humphreys (2013) used data from betting markets to confirm the existence of tanking in the National Basketball Association (NBA). Bowman, Ashman & Lambrinos (2013), Bowman, Lambrinos & Ashman (2013) and Paul et al. (2009) used betting odds to analyze the competitive balance. In this paper, their use is proposed to estimate the efficiency of coaches, where efficiency is obtained by comparing coaches' performance with the expectations from betting odds. Particularly, the efficiency is calculated as the inverse of the probability from betting odds of getting more victories than the actual ones. It is important to note that Humpreys, Paul & Weinbach (2011), Silver (2014) and van Ours & van Tujil (2014) have already used a similar approach, but they calculated the difference between actual wins and expected wins from betting odds as a coach performance indicator. The results from this new method reinforce those obtained from the production function approach regarding the origin of the coach, but no statistical relationship has been found between efficiency and whether the coach was a professional player.

[1] SuperManager establishes the value for each player using the expected performance of each player based on player past performance by a group of experts.

The remainder of this article is organized as follows. First, we briefly review some relevant literature. The methodology is then outlined, and a description of the data and the empirical model is provided, followed by a presentation of the results. The article concludes with a summary of the main findings.

Literature review

Several papers have analyzed the efficiency of sports managers or coaches within a league. Berri et al. (2009) analyzed how managers in the NBA affect the performance of individual players. However, the most prominent approach is that of estimating a production function by using either a stochastic frontier model (Dawson, Dobson & Gerrard, 2000a; Fort, Lee & Berri, 2008) or Data Envelopment Analysis (Fizel & D'Itri, 1997; González-Gómez et al., 2011). When doing so, it is first necessary to select the output and inputs. With regard to the output, the general consensus is that the number of points or matches won at the end of the season should be used. On the other hand, there are two alternative approaches with which to measure inputs. The first uses *ex post* measures of player qualities. The paper by Porter & Scully (1982) was the first to use this methodology. In particular, these authors estimated the managerial efficiency in the MLB by using the team slugging average (total bases divided by times at bat) and team pitching by the team strike-out to walk ratio as inputs. Hadley et al. (2000) and Hofler & Payne (1997) subsequently used this approach in American football and basketball, respectively. However, Lee & Berri (2008) and Dawson et al. (2000a) argued that to calculate the managers' efficiency accurately, it is necessary to use *ex ante* measures of player quality.

Several papers have used different *ex ante* measures of player quality. The players' wage bills is the most frequently used (de Dios Tena & Forrest, 2007; Frick & Simmons, 2008; Kern & Süssmuth, 2005; Volz, 2009). Given that the percentage of player salaries that are over the total budget is rather high, González-Gómez et al. (2011) used the budget as a measure of the quality of the roster. Gerrard & Dobson (1999) used the hedonic price method to calculate a hypothetical transfer price of the players, and Dawson et al. (2000a) and Dawson et al. (2000b) subsequently used these prices to analyze the efficiency of the managers from the English Premier League. Related to this idea, Bell, Brooks & Markham (2013) used the transfer price provided by www.transfermarkt.com to analyze the efficiency of English managers. Other papers have used statistics from previous seasons to obtain a measure of the players (Fort et al., 2008; Lee & Berri, 2008). An alternative means to obtain a measure for the players' quality is to use the players' value in fantasy leagues at the beginning of the season (del Corral, 2012). Fantasy leagues are simulation games regarding team management in which virtual players choose a roster with a budget constraint.

Methodology

Stochastic production function

A production function can be defined as the maximum output attainable given a set of inputs (Greene, 2008). Measurement of (in)efficiency is the empirical estimation of the extent to which observed agents (fail to) achieve the theoretical ideal. Thus, an index of efficiency would be the ratio of actual output and potential output. This index is usually used as a performance indicator to construct a performance ranking of the Decision Making Units (Greene, 2004; Kirjavainen, 2012; Breu & Raab, 1994).[2]

In this paper, three alternative production functions are estimated using a stochastic frontier

[2] It is important to note that the interpretation of this index as a performance indicator should be carried out cautiously. For instance, if the production process is represented from heteroscedastic data to use the efficiency index in order to provide a performance ranking, the results could be misleading. There is a graph in the appendix that helps to understand this issue using actual data from ACB (2006-2014).

model[3]. Stochastic frontier models for cross-section data were proposed by Aigner, Lovell & Schmidt (1977) and can be written as:

$$ln\, y_i = f(x_i) + \mathcal{E}_i; \qquad \mathcal{E}_i = v_i - u_i \tag{1}$$

where y is the output, $f(x)$ is the representation of the technology, x is a vector of inputs, and $\mathcal{E}$ is a random error term composed of two terms. Component v captures statistical noise and other stochastic shocks that enter the definition of the frontier items, such as refereeing, injuries, etc., and it is assumed to follow a normal distribution centered at zero. On the other hand, u is a non-negative term that reflects coaches' technical inefficiency, which is assumed to follow a semi-normal distribution. Furthermore, it is necessary to assume that u and v are i.i.d. By using these assumptions, it is possible to estimate such a model using maximum likelihood techniques. The stochastic frontier model depicted in equation [1] allows measurement of an index for TE, which is defined as the ratio of the observed output (y) and maximum feasible output (y^*):

$$TE_i = \frac{y_i}{y_i^*} = \frac{f(x_i;\beta)\cdot exp(v_i - u_i)}{f(x_i;\beta)\cdot exp(v_i)} = exp\,(-u_i) \tag{2}$$

Unfortunately, u is not observable, and therefore it is not possible to calculate the TE directly from the estimates, but $\mathcal{E}$ is observable. Jondrow et al. (1982) demonstrated that coach-level TE can be calculated from the error term ε_i by calculating the expected value of $-u_i$ conditional on ε_i, which is given by:

$$TE_i = exp(E(-u_i)|\varepsilon_i) = exp\left(-\frac{\sigma_u\cdot\sigma_u}{\sigma}\cdot\left[\frac{f((\varepsilon_i)\cdot\lambda/\sigma)}{1-F((\varepsilon_i)\cdot\lambda/\sigma)} - \frac{(\varepsilon_i)\cdot\lambda}{\sigma}\right]\right) \tag{3}$$

Several papers have extended this framework (Battese & Coelli, 1995; Caudill, Ford & Gropper, 1995; Kumbhakar, Ghosh & McGuckin, 1991) to analyze the extent to which

[3] A very good overview of stochastic frontier model applied to Sport Economics is Lee (2014).

certain variables influence the inefficiency term u_i. Specifically, Caudill et al. (1995) developed a model in which the determinants of inefficiency are evaluated using a multiplicative heteroscedasticity framework and assuming that u follows a half-normal distribution. That is,

$$\sigma_{u_i} = exp\left(\delta_0 + \sum_m \delta_m \, . \, z_{im}\right) \qquad (4)$$

where z_{im} is a vector of variables that explains the inefficiency of coaches, and δ are unknown parameters. Given that inefficiency is assumed to follow a half-normal distribution, a decrease in the variance will lead to increments in the efficiency level. In this approach, the parameters for the production frontier and the inefficiency model are estimated jointly using the maximum likelihood technique (Caudill et al., 1995).

Efficiency from betting odds

Odds for basketball matches offered in the betting market can be reconverted into probabilities for each possible result (*i.e.*, home win and away win). If the betting market were efficient, then these probabilities would reflect the true probabilities of each event. Although there is no consensus in the literature (Forrest & Simmons, 2008; Kain & Logan, 2014; Levitt, 2004; Sauer, 1998) as to whether betting odds are efficient, in the sense that the expected rate of return to bettors has an upper bound of zero (Sauer, 1998), Forrest & Simmons (2008) stated that at least weak efficiency appears to characterize this market. The probabilities embedded in betting odds could therefore be used as prior probabilities, or at minimum, as a fair approximation.

To ameliorate some of the possible biases of the odds, it might be useful to use the average odds from various bookmakers rather than using one particular bookmaker. The betting odds from www.oddsportal.com, which are the average odds from different bookmakers, have been used. It is important to note that odds were not available at www.oddsportal.com for 16 matches in the 2008-2009 season. The odds for these matches were established by a professional bookmaker from CODERE APUESTAS.

Basic probability theory tells us that the joint probability of two independent events (e.g., a victory by the same team in two different basketball matches) equals the product of their probabilities. This simple formula for all the possible combinations of match results of each team can be used to compute the probability of each team within a league obtaining a certain amount of victories, i.e., the density function of victories at the end of the season. The following figure shows as an example the density function of victories for Regal F.C. Barcelona in the 2009-2010 season and for Valladolid in the 2011-2012 season. The vertical lines indicate the actual number of victories in that season.

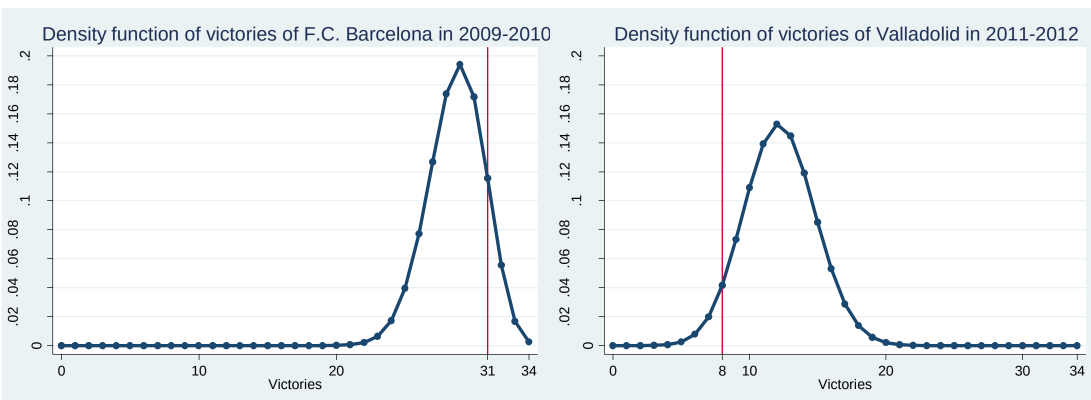

Figure 1. Two examples of efficiency from betting odds

From these density functions, it is possible to calculate the probability of obtaining more victories than the actual result. In the above figure, in the case of F.C. Barcelona, it will be the probability of obtaining 32 victories, 0.055, plus the probability of obtaining 33 victories, 0.02, plus the probability of obtaining 34 victories, virtually zero, which equals 0.075. The inverse of that probability can be viewed as an efficiency index for managers in the sense that a value that is closer to one will reflect a better performance, while a value that is closer to zero will reflect a worse performance, *i.e.*, 0.925 in the example. It is true that to be fully efficient, F.C. Barcelona would have had to have won all matches, but this is an extreme case for a really good team. In the above figure, the example for Valladolid in the 2011-2012 season, when it was a low expectation team, is also shown. As can be observed, this team only would have had to win 21 out of 34 matches to be fully efficient.[4]

Managers with higher efficiencies would be those that have performed better than the expected results from the odds. This better performance could be due to luck or to fortunate referees' decisions, but the most plausible reason is good coaching, in the same way that the underperformance of teams managed by a particular coach could be due to injuries or bad luck, but the most plausible reason would be bad coaching. The efficiency index can thus be understood as a measure of the managers' performances.

It has been seen that a potential drawback of the stochastic frontier methodology is that it can provide misleading performance rankings from the technical efficiency indices. However, one of the advantages of betting odds methodology is that it allows the best teams' performance to be measured with greater accuracy than when using the stochastic frontier methodology. Let us assume that Regal F.C. Barcelona won 20 matches in the 2009-2010 season. By using the stochastic frontier and assuming that the frontier was winning all of the matches, the efficiency index would be 0.57 (i.e., 20/34). As seen below, many coaches obtained efficiencies that were lower than this value using the stochastic frontier

[4] One of the referees noted a possible problem of endogeneity in the sense that inefficient coaches will have lower expectations and will appear more efficient with this approach. We tested this hypothesis using a natural experiment, the midseason replacement of head coaches on Spanish soccer teams (there are too few data from Spanish basketball teams). The results show that there is no endogeneity problem. These results are available upon request. Thus, even though it could be one of the shortcomings of this methodology, it does not seem to be a serious one.

methodology. However, as can be observed in the density function, obtaining 20 victories would have been an extremely bad season that corresponds to an efficiency index of zero.

It is important to note that this problem is not only concerned with sports efficiency but also with other sectors such as education (e.g., school ranking measurement). This is an area that merits further research to develop models that are able to handle this problem without using betting odds.

Data and empirical model

The ACB is composed of 18 teams (although there were only 17 teams in the 2008-2009 season) that compete in a regular season/play-off season scheme. The regular season is played in a double round robin system, and the best 8 teams participate in a final knock-out play-off. The play-off knock-out rounds are played to the best of either 3 or 5 matches in which the best team to have classified in the regular season has home advantage (i.e., playing one more game at home). Obtaining a better classification during the regular season is therefore very important. To ease the empirical analysis, we consider only the data from the regular seasons.[5] The data are specifically taken from the 2008-2009, 2009-2010, 2010-2011 and 2011-2012 seasons.

The data from the SuperManager contain the value of each player at the beginning of each season, such as the player position (i.e., guard, forward, center), and the teams' budgets. The results of the matches were obtained from the ACB website. Moreover, given that one of the objectives of the paper is to analyze the determinants of the technical efficiency of the coaches, some of the variables related with the coaches were obtained from the ACB website

[5] A similar approach is used in the NBA, as the NBA Coach of the Year Award is conceded based only on the results in the Regular Season.

at www.acb.com/enciclopedia.php.

Lee (2006) argued that to avoid endogeneity problems, the estimation of coaches' production functions should use *ex ante* measures of the quality of the roster. In this paper, the values provided by the SuperManager are used. Lee & Berri (2008) and Fort, Lee & Berri (2008) estimated the production functions of basketball of teams using three inputs: guards, forwards and centers quality. Similarly, our production function includes those three inputs. The maximum number of players hired by a team is 15. However, their importance for the team is very different, although most coaches usually use 2 guards, 4 forwards and 4 centers in each game. We decided to obtain the quality of each position by using the average of the value of the 2 most valuable guards, the 4 most valuable forwards and the 4 most valuable centers at the beginning of the season, as using the other players could lead to misleading values of the quality.[6] Therefore, a unique production frontier was estimated by transforming all of the seasons' values from the SuperManager to obtain the same mean for each position in all seasons. This approach allowed us to avoid the mislabeling of some coaches as inefficient.

Given that we are interested in the coaches' efficiency, the unit of observation is the coach in each season, which leads to 83 observations. The output is the ratio between victories and matches in the regular season. Three alternative input specifications are considered. In the first, the team's budget is considered as input. In the second, the mean values of guards, forwards and centers from SuperManager are used as separate inputs, and

[6] It is important to note that those players account for close to 90% of the minutes of play (own calculations based on ACB stats).

in the last, the aforementioned means are aggregated into a unique value for each team. The functional form used is the Cobb-Douglas.

Dawson & Dobson (2002) included three types of variables to explain managerial efficiency in English football. They included variables related to the managers' career as a player, managerial experience to date and other general variables, such as a dummy variable for Scottish managers, given the popular perception that Scottish nationals are "better" managers than others. We used a similar specification. More specifically, four variables related to the coaches were included as inefficiency determinants. The first is a dummy variable that is given the value of one if the coach was a professional basketball player. Dawson & Dobson (2002) argued that managers who played at the highest level should have a greater appreciation of the game and should find it easier to inspire and motivate players. Basketball seems to be no different from football in this respect, and a negative coefficient is therefore expected (a rise in efficiency). We also test whether Spanish coaches are more efficient than foreign ones by incorporating a dummy variable that is given the value of one if the coach was born in Spain. The coach's efficiency may be dependent on whether he has had a prior affiliation with the current club, so we incorporate a dummy variable (team experience) that is given the value of one if the coach has had a prior affiliation with the current club as a player, assistant coach or coach. We expect a negative sign for this coefficient. Lastly, we include the age of the coach to proxy experience. The model to estimate is:

$$\begin{gathered} lny_i = \beta_0 + \sum_k \beta_j \cdot lnx_{ik} + v_i - u_i \\ \sigma_{u_i} = exp\left(\delta_0 + \sum_m \delta_m \cdot z_{im}\right) \end{gathered} \qquad (5)$$

where *i* indicates coach at a given season, and the subscript *k* is used for inputs. It is assumed that v follows a normal distribution, while u follows a half-normal distribution. Table 1 shows the descriptive statistics. As will be noted, the proportion of Spanish coaches in comparison to non–Spanish coaches is high (0.79), but the ratio of ex-professional players is rather low (0.22).

Table 1. Descriptive statistics

Variables	Mean	SD	Min	Max
Victories/matches	0.48	0.20	0.11	0.91
Budget (€)	8,980,328	7,694,871	1,956,518	31,500,000
Guards (€)	568,753	146,058	220,952	836,957
Forwards (€)	597,931	139,047	335,898	958,247
Centers (€)	668,970	125,432	365,930	1,053,135
Guards+Forwards+Centers (€)	1,835,655	309,280	1,289,681	2,582,310
Ex pro player (dummy)	0.22	0.41	0.00	1.00
Spanish (dummy)	0.82	0.39	0.00	1.00
Team experience (dummy)	0.63	0.49	0.00	1.00
Age (years)	45.12	6.72	31.00	64.00
Number of observations		83		

Results

Table 2 reports the estimation results of equation (5).

Table 2. Stochastic frontier Cobb-Douglas production function estimates

	Model 1	Model 2	Model 3
	Coefficient	Coefficient	Coefficient
Frontier			
Constant	-3.976***	-0.436***	-11.537***
Budget (€)	0.227***		
Guards (€)		0.407***	
Forwards (€)		0.199***	
Centers (€)		0.483**	
Guards (€)·Guards (€)		0.152	
Forwards (€)·Forwards (€)		1.694	
Centers (€)·Centers (€)		0.046	
Guards (€)·Forwards (€)		0.399	
Guards (€)·Centers (€)		-0.588***	
Forwards (€)·Centers (€)		-0.235	

Guards+Forwards+Centers (€)			0.781***
Inefficiency model			
Constant	-3.883***	-2.783**	-2.482**
Ex pro player (dummy)	-0.759*	-0.660	-0.540
Spanish (dummy)	2.407***	1.678***	1.779***
Team experience (dummy)	-0.171	-0.206	-0.195
Age (years)	0.016	0.011	0.007
σ_u	0.334	0.437	0.537
σ_v	0.114	0.000	0.000
Log-Likelihood	-18.326	-10.737	-20.879
Number of observations	83	83	83

*$P < 0.10$; **$P < 0.05$; ***$P < 0.01$.

Output elasticities are positive and significant in all models. Moreover, in the three models, as expected, the relation between the output and inputs is concave. The coefficient of correlation of the TE among the models is Model 1-Model 2: 0.92; Model 1-Model 3: 0.95; Model 2-Model 3: 0.96. We also considered other specifications, such as estimating the models without technical inefficiency determinants or without the mean transformation, and the coefficient of correlation was always above 0.91. Hence, we prefer to show only the efficiencies from the preferred model, i.e., Model 2. The following table shows the coaches' efficiency in all of the seasons studied (derived from Model 2) and those derived from the betting odds.

Table 3. Coaches' TE in the seasons studied from model 2 and betting odds

Coach	2008-09		2009-10		2010-11		2011-12	
	SF	Odds	SF	Odds	SF	Odds	SF	Odds
José Luis Abós					0.73 (12)	0.87 (5)	0.69 (12)	0.84 (3)
Sito Alonso	0.83 (7)	0.95 (2)	0.51 (15)	0.29 (16)			0.96 (2)	0.95 (1)
Alberto Ángulo	0.38 (20)	0.18 (19)						
Ricard Casas	0.40 (19)	0.10 (20)						
Luis Casimiro	0.58 (14)	0.20 (18)	0.92 (5)	0.92 (5)	0.83 (8)	0.62 (10)	0.69 (10)	0.25 (15)
Manel Comas	0.18 (21)	0.10 (21)						
Moncho Fernández			0.27 (21)	0.15 (20)			0.61 (14)	0.69 (7)
Porfirio Fisac			0.57 (14)	0.59 (11)	0.97 (4)	0.87 (4)	0.51 (17)	0.32 (14)
Aíto García Reneses	0.84 (6)	0.88 (4)	0.75 (10)	0.28 (17)	0.55 (17)	0.18 (18)		
Roberto González							0.38 (18)	0.14 (16)
Luis Guil	1.00 (1)	0.76 (6)	0.58 (13)	0.32 (15)				
Pepu Hernández			0.43 (18)	0.25 (18)	0.81 (9)	0.28 (17)		
Manuel Hussein	0.43 (18)	0.35 (15)			0.20 (22)	0.14 (19)		
Javier Imbroda	0.46 (16)	0.44 (14)						
Duško Ivanović	0.94 (5)	0.99 (1)	0.88 (8)	0.96 (1)	0.69 (13)	0.43 (13)	0.80 (5)	0.58 (9)
Fotis Katsikaris	0.60 (11)	0.45 (12)	0.94 (4)	0.95 (2)	0.97 (5)	0.83 (6)	0.74 (7)	0.45 (12)
Pablo Laso	0.60 (12)	0.46 (11)	0.72 (12)	0.53 (13)	0.65 (14)	0.33 (15)	0.73 (8)	0.57 (10)
Salvador Maldonado	1.00 (1)	0.93 (3)	0.50 (16)	0.33 (14)	1.00 (1)	0.98 (2)	0.66 (13)	0.75 (5)
Pedro Martínez	0.68 (8)	0.62 (9)	1.00 (1)	0.56 (12)	1.00 (1)		0.69 (11)	
Chus Mateo					0.75 (10)	0.76 (8)		
Ettore Messina			0.86 (9)	0.67 (9)	0.94 (6)	0.76 (7)		
Emanuele Molin					0.91 (7)	0.72 (9)		
Paco Olmos					0.37 (19)	0.06 (21)		
Xavi Pascual	1.00 (1)	0.88 (5)	1.00 (1)	0.93 (4)	0.73 (11)	0.42 (14)	1.00 (1)	0.71 (6)
Velimir Perasović							0.70 (9)	
Svetislav Pešić					1.00 (1)	1.00 (1)		

Joan Plaza	0.97 (4)	0.65 (8)	0.94 (3)	0.83 (6)	0.65 (15)	0.5 (12)	0.75 (6)	0.56 (11)
Trifón Poch	0.59 (13)	0.44 (13)	0.74 (11)	0.71 (8)	0.36 (20)	0.06 (22)	0.57 (16)	0.08 (17)
Jaume Ponsarnau	0.60 (10)	0.69 (7)	0.88 (7)	0.63 (10)	0.51 (18)	0.31 (16)	0.87 (3)	0.76 (4)
Oscar Quintana			0.49 (17)	0.71 (7)	0.21 (21)	0.10 (20)	0.60 (15)	0.62 (8)
Curro Segura	0.44 (17)	0.20 (17)	0.37 (19)	0.20 (19)				
Neven Spahija	0.57 (15)	0.30 (16)	0.92 (6)	0.94 (3)				
Edu Torres			0.20 (22)	0.05 (21)				
Txus Vidorreta	0.64 (9)	0.53 (10)	0.32 (20)	0.05 (22)	0.59 (16)	0.52 (11)	0.81 (4)	0.94 (2)

Notes: the ranking of the coach in that season is shown in parenthesis.
The appendix contains a table showing which team was coached by each coach in each season.
The Spearman rank correlation between efficiency from odds and stochastic frontier are 0.91 in the season 2008-2009, 0.79 in the season 2009-2010, 0.89 in the season 2010-2011 and 0.57 in the season 2011-2012.

During the 2008-2009 season, it is worth noting the difference in Joan Plaza's (Real Madrid) rank utilizing both approaches. In the production frontier, he attained an efficiency of 0.97, which was fourth in the rank, but in the betting odds approach, his efficiency is 0.65, which was eighth in the rank. On the other hand, Sito Alonso (Joventut) was the seventh rank by the stochastic frontier analysis and the second rank using the betting odds methodology. Other noteworthy differences during the 2009-2010 season were obtained by Aito García Reneses (Unicaja) and Oscar Quintana (Alicante), who was seventeenth in the stochastic frontier and seventh in the betting odds. A large difference in the ranking of the two coaches, Duško Ivanović (Baskonia) and Pedro Martínez (Gran Canaria), emerges from the difference in the valuation of the players by the SuperManager and the betting odds. Duško Ivanović was ranked number eight in the stochastic frontier model, but he was the most efficient in the betting odds. Analyzing the data further, it can be seen that the value of the players in the SuperManager displayed a large overvaluation compared with the team budget. Thus, Duško Ivanović was also the most efficient coach in Model 1 of the stochastic frontier models. The opposite case is seen for Pedro Martínez, in which the value of the players in the SuperManager are really undervalued according to the team budget. Hence, the coach's rank in Model 1 is nine, which is in accord with the results from the betting odds. José Luis Abós' (Zaragoza) rank positions were much better utilizing the betting odds methodology (i.e., 5th in the 2010-2011 season and 3rd in the 2011-2012 season) than in the stochastic frontier methodology (i.e., 12th in both seasons). Furthermore, in the last season analyzed, Salvador Maldonado (Joventut), Oscar Quintana (Murcia) and Moncho Fernández (Obradoiro) clearly improve their ranking when the betting odds approach, rather than the production function approach, is used. However, Duško Ivanović (Baskonia), Pablo Laso (Real Madrid) and Xavi Pascual (F.C. Barcelona) are examples of the opposite case. Especially telling is the case of Xavi Pascual, who was classified as first rank in the stochastic frontier, but sixth in the betting odds methodology. It would thus appear that with the production function approach, the correlation between the coach's efficiency and the team's budget is high, whereas the betting odds approach provides efficiency indices that are less sensitive to the budget than is desirable. The following table shows the coefficient of correlation between the efficiencies from both methodologies and the budget of the teams coached by each coach for each season. It is clear that the efficiencies from the betting odds are less sensitive to the team budget than the efficiency from the production function.

Table 4. Coefficient of correlation between efficiencies and budget

2008-2009		2009-2010		2010-2011		2011-2012		All	
SF	Odds	SF	Odds	SF	Odds	SF	Odds	SF	Odds
0.52	0.42	0.44	0.36	0.24	0.13	0.47	0.04	0.38	0.24

When discussing English football, Kuper & Szymanski (2009; p. 111) stated that "only a few managers, such as Brian Clough or Bill Shankly, consistently perform better with their teams than the players' wage bill suggests that they should". Berri et al. (2009) similarly suggest that, according to their evidence, mangers in the NBA are the "principal clerks" in the Adam Smith sense, given that most coaches do not statistically impact player performance. We have studied this idea to analyze whether the ranks of the efficiencies from the different seasons appear to be similar. If the ranks were similar across seasons, there would be consistently good coaches and bad coaches. If not, there would be good seasons and bad seasons for the coaches. To test this hypothesis, we implemented the Friedman ANOVA test in which the null hypothesis is that the ranks from different distributions are statistically the same. The different distributions are the efficiencies in each season. The test has been carried out for both approaches (*i.e.*, production function and betting odds), and the results indicate that the null hypothesis of the same rankings can be rejected. We have thus obtained favorable results for the hypothesis that coaches are not as important as presumed in the long run.

With regard to the determinants of inefficiency, we found that the coefficient of the ex-professional players was significant and negative in one of the models, and negative but do not significant in the other two models, suggesting a positive relationship between efficiency and being a former professional basketball player. Figure 2 shows the box plot of the efficiency scores according to the ex-professional player dummy variable when using both methodologies to obtain the efficiencies. In the stochastic frontier methodology, as indicated by the estimated coefficient, the distribution of the efficiencies for ex-professional players is above the efficiency distribution for non ex-professional players. However, in the betting odds methodology, this difference seems to disappear, suggesting that the evidence that ex-professional players are more efficient is not conclusive.

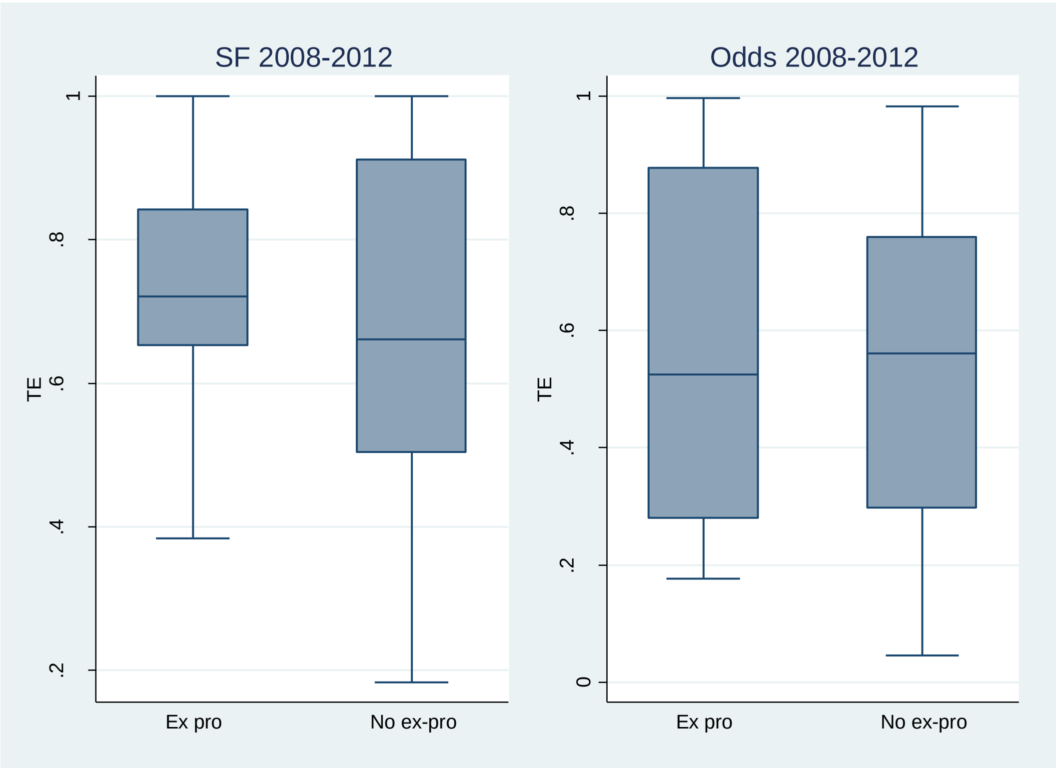

Figure 2. Box Plots of TE Using the Ex-Professional Player Dummy

The estimated coefficient for Spanish coaches was positive and significant, suggesting that foreign coaches are more efficient. These results can be viewed in the box plots, but on this occasion, the box plot from the betting odds methodology reinforces the results obtained from the stochastic frontier. In fact, the 75th percentile for the Spanish coaches is close to the median for the non-Spanish coaches, and it is even lower in the stochastic frontier methodology.

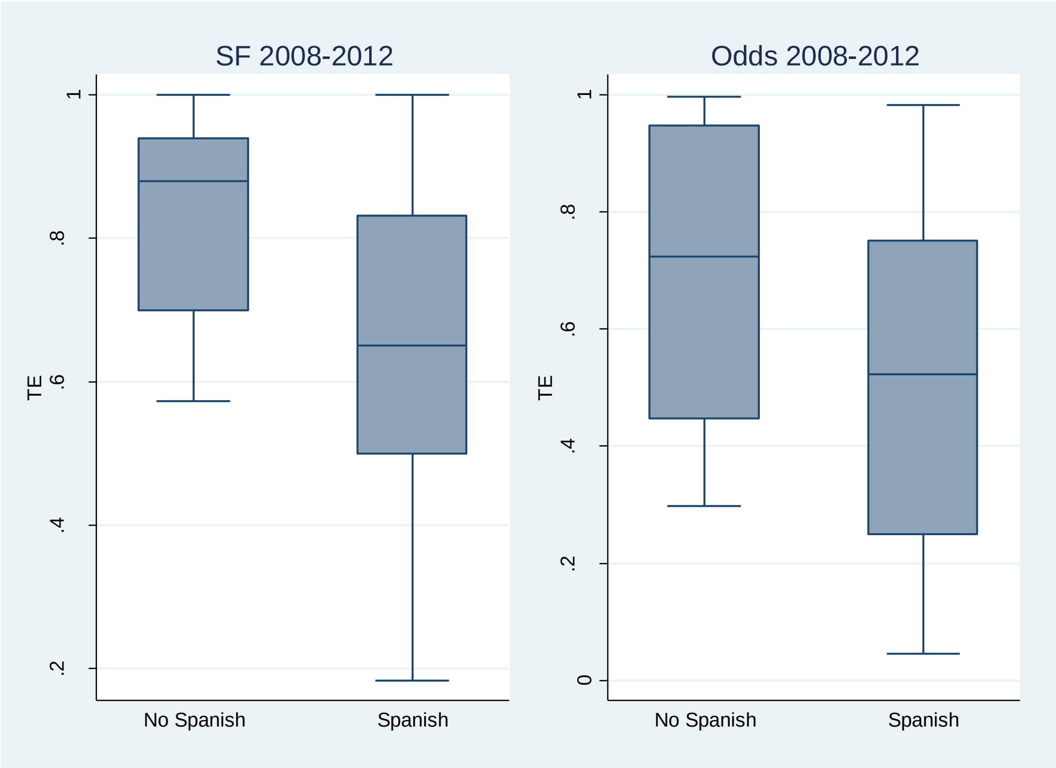

Figure 3. Box plots of TE using the Spanish dummy

Moreover, the coefficient of the variable related to experience on the team was negative in the three models, but there was no significance in any model. Lastly, the age of the coach was not found to be significant in any of the models.

The following table shows the linear regression of the efficiencies from the betting odds with the same variables used as inefficiency determinants in the stochastic frontier model. It can be observed that the only significant variable is the Spanish dummy with a negative coefficient, reflecting that Spanish coaches have been less efficient than foreign coaches.

Table 5. OLS estimation of betting odds efficiency determinants

	Coefficient	SE
Constant	0.704***	(0.254)
Ex pro player (dummy)	-0.031	(0.081)
Spanish (dummy)	-0.220**	(0.086)

Team expierence (dummy)	0.059	(0.066)
Age (years)	-0.000	(0.005)
R^2	0.08	
Number of observations	83	

*P< 0.10; **P< 0.05; ***P< 0.01.[7]

Concluding remarks

This paper has analyzed the coaches' efficiency and its determinants from the Spanish Top League of Basketball between 2008 and 2012. Two alternative approaches have been used: estimating stochastic production function and a new approach in which efficiency is obtained by comparing the teams' performances with the expectations from betting odds. The results indicate that the coaches' efficiency rankings were different from season to season, indicating that in general, there are not better coaches or bad coaches, but rather there are seasons with good coaching and seasons with bad coaching. Foreign coaches were found to be statistically more efficient than Spanish coaches in both approaches. Ex-professional players were found to be statistically more efficient in the stochastic frontier approach, but this result was not reinforced by the betting odds efficiencies.

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[7] It was tested for heteroscedasticity, and the results showed that the null of constant variance was not rejected.

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Appendix

In the following graph, the dots represent some actual number of victories of five types of teams (i.e., very low budget, low budget, medium budget, high budget, very high budget). It is important to note that the minimum and maximum are true values between the 2006-2007 and 2013-2014 seasons.

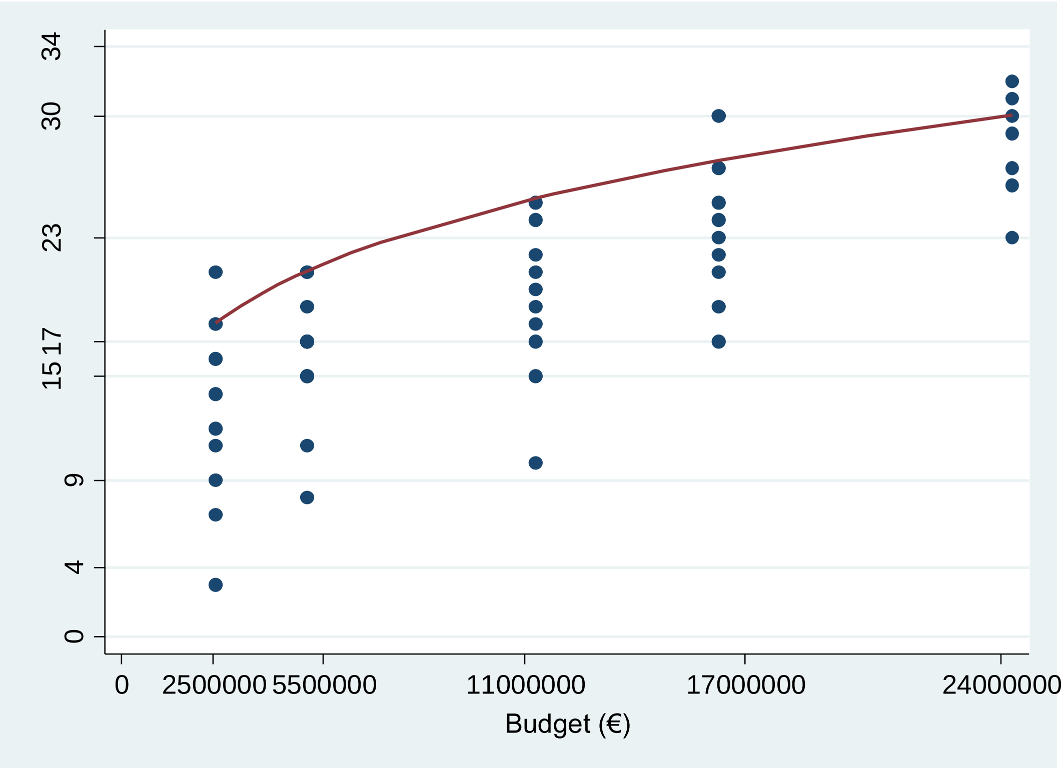

Figure A1: Predicted production function and some real data

Note: The dots are from teams as follows: very low budget teams: CB Valladolid (2013-2014), Gran Canaria (2006-2007); low budget teams: Bruesa Guipozcoa (2006-2007), Gran Canaria 2014 (2010-2011); medium budget teams: Cajasol Sevilla (2008-2009), Joventut (2007-2008); high budget teams: Unicaja Málaga (2011-2012), Valencia Basket (2013-2014); very high budget teams: FC Barcelona (2012-2013), Real Madrid (2011-2012), FC Barcelona (2013-2014), FC Barcelona (2011-2012), Real Madrid (2012-2013), FC Barcelona (2009-2010), Real Madrid (2013-2014).

The ratio between the worst performance for each group of teams and the predicted number of victories are: 0.16 (very low budget teams), 0.38 (low budget teams), 0.40 (medium budget teams), 0.62 (high budget teams), and 0.76 (very high budget teams). Thus, the minimum efficiency for each group of teams is really different. However, it make sense that the worse possible performance for each group of teams should lead to a similar performance ranking, and as it can be seen, this is not true. Therefore, using the stochastic frontier production approach to construct a performance ranking through the inefficiencies could lead to some bias, given that the efficiency index provides an indicator between the distance of actual output and predicted output, but (though related) not the performance.

Table A1. Coaches and teams 2008-2012

Coach	2008-2009	2009-2010	2010-2011	2011-2012
José Luis Abós			Zaragoza	Zaragoza
Sito Alonso	Joventut	Joventut		S. Sebastián
Alberto Ángulo	Zaragoza			
Ricard Casas	Menorca			
Luis Casimiro	Estudiantes	Estudiantes	Estudiantes	Unicaja
Manel Comas	Sevilla			
Moncho Fernández		Murcia		Obradoiro
Porfirio Fisac		Valladolid	Valladolid	Fuenlabrada
Aíto García Reneses	Unicaja	Unicaja	Unicaja	
Roberto González				Valladolid
Luis Guil	Fuenlabrada	Fuenlabrada		
Pepu Hernández		Joventut	Joventut	
Manuel Hussein	Murcia		Valencia	
Javier Imbroda	Menorca			
Duško Ivanović	Baskonia	Baskonia	Baskonia	Baskonia
Fotis Katsikaris	Valencia	Bilbao	Bilbao	Bilbao
Pablo Laso	S. Sebastián	S. Sebastián	S. Sebastián	R. Madrid
Salvador Maldonado	G. Canaria	Fuenlabrada	Fuenlabrada	Joventut
Pedro Martínez	Sevilla	G. Canaria	G. Canaria	G. Canaria
Chus Mateo		Fuenlabrada	Unicaja	
Ettore Messina		R. Madrid	R. Madrid	
Emanuele Molin			R. Madrid	
Paco Olmos			Menorca	
Xavi Pascual	Barcelona	Barcelona	Barcelona	Barcelona
Velimir Perasović				Valencia
Svetislav Pešić			Valencia	
Joan Plaza	R. Madrid	Sevilla	Sevilla	Sevilla
Trifón Poch	Granada	Granada	Granada	Estudiantes
Jaume Ponsarnau	Manresa	Manresa	Manresa	Manresa
Oscar Quintana		Alicante	Alicante	Murcia
Curro Segura	Zaragoza	Obradoiro		
Neven Spahija	Valencia	Valencia		
Edu Torres		Murcia		
Txus Vidorreta	Bilbao	Bilbao	Alicante	Alicante