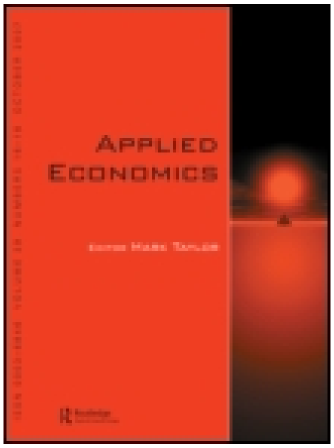

Applied Economics
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/raec20

Cost efficiency of French soccer league teams

Carlos Pestana Barros[ab], Nicolas Peypoch[c] & Scott Tainsky[d]

[a] Instituto Superior de Economia e Gestão, Technical University of Lisbon, 1249-078 Lisbon, Portugal

[b] UECE (Research Unit on Complexity and Economics), Lisbon, Portugal

[c] University of Perpignan Via Domitia, F-66860 Perpignan Cedex, France

[d] University of Illinois, Champaign, 61820 IL, USA

Published online: 21 Jan 2014.

To cite this article: Carlos Pestana Barros, Nicolas Peypoch & Scott Tainsky (2014) Cost efficiency of French soccer league teams, Applied Economics, 46:8, 781-789, DOI: 10.1080/00036846.2013.854304

To link to this article: http://dx.doi.org/10.1080/00036846.2013.854304

Applied Economics, 2014
Vol. 46, No. 8, 781–789, http://dx.doi.org/10.1080/00036846.2013.854304

Routledge
Taylor & Francis Group

Cost efficiency of French soccer league teams

Carlos Pestana Barros[a,b,*], Nicolas Peypoch[c] and Scott Tainsky[d]

[a]*Instituto Superior de Economia e Gestão, Technical University of Lisbon, 1249–078 Lisbon, Portugal*
[b]*UECE (Research Unit on Complexity and Economics), Lisbon, Portugal*
[c]*University of Perpignan Via Domitia, F-66860 Perpignan Cedex, France*
[d]*University of Illinois, Champaign, 61820 IL, USA*

This article evaluates the operational activities of French soccer clubs from 2003 to 2011 by using a finite mixture model that allows controlling for unobserved heterogeneity. In doing so, a stochastic frontier latent class model, which allows the existence of different technologies, is adopted to estimate cost frontiers. This procedure not only enables us to identify different groups of French soccer clubs but also permits to analyse their cost efficiency. The main result is that there are two groups among the French soccer clubs, both following completely different 'technologies' to obtain league points, suggesting that business strategies need to be adapted to the characteristics of the clubs. Some managerial implications are developed.

Keywords: cost efficiency; latent class model; soccer clubs

JEL Classification: L83; C23

I. Introduction

Efficiency is a vital managerial consideration across industries and indeed sport is no exception. Despite the historical leniency regarding spending regulation within European football (soccer), the relative performance of different franchises may yet be related to the efficient use of resources (Coates and Humphreys, 2011). Indeed, as the European football governing body Union of European Football Associations (UEFA) slowly institutes spending regulation, efficiency of spending will become increasingly more important in determining organizational success. Much of this spending reform is being championed by UEFA President and former French football star Michel Platini. The framework for 'Financial Fair Play' (FFP) regulation was agreed upon in 2009 and applied beginning with the 2011–2012 football season. In brief, FFP requires clubs to balance football expenditures over multi-year periods with stiff penalties for clubs failing to cover spending with football-related revenues – an increasingly troublesome consideration with the proliferation of wealthy benefactors regarding footballing as a leisure activity rather than business investment. Thus it is easily argued that with FFP comes a growing emphasis on efficiency. The economics literature proposes the estimation of technological frontiers (i.e., production, cost function or revenue functions), and the comparison between such frontiers and firm performance yields efficiency scores.

Within sports, the subject of efficiency has attracted considerable attention in the realm of team sports such as American football (i.e. Hofler and Payne, 1996; Hadley *et al.*, 2000; Einolf, 2004), baseball (i.e. Porter and Scully, 1982; Koop, 2002; Smart *et al.*, 2008), basketball (i.e., Zak *et al.*, 1979; Hofler and Payne, 1997) and hockey (Kahane, 2005). The efficiency of soccer clubs or soccer managers likewise have been analysed in many European

*Corresponding author. E-mail: cbarros@iseg.utl.pt

leading soccer leagues. For example, the efficiency of English football has been analysed by Dawson *et al.* (2000a), Carmichael *et al.* (2001), Barros and Leach (2006a, b) and Haas (2003a). The Spanish soccer league was analysed by Espitia-Escuer and García-Cebrian (2004) and the German league by Kern and Süssmuth (2005). With a French former soccer player legend, Platini, presently heading UEFA, this article focuses on French first football league efficiency, expanding on previous research in this field. Beyond this, the French league provides a nice example of many teams operating under typical business constraints, while others such as Paris Saint-Germain FC and AS Monaco represent the aforementioned franchises functioning without such limitations.

The present article aims to fill a part of this gap of the literature by analysing the efficiency of the French soccer league, Ligue 1. Specifically, panel data is used to analyse the cost efficiency of Ligue 1 teams over the period 2002/2003 to 2010/2011. In doing so, this sets a benchmark by which future research can compare results to the time prior to the introduction of FFP.

Two alternative frameworks are commonly used in efficiency analysis. First is the nonparametric technique, specifically Data Envelopment Analysis (DEA). This approach was followed, for instance, by Porter and Scully (1982), Fizel and D'Itri (1996, 1997), Haas (2003a, b), Espitia-Escuer and García-Cebrian (2004), Barros and Leach (2006b) and Gutierrez and Lozano (2012, forthcoming). Second are parametric techniques in which a functional form has to be assumed. In the context of sports, these techniques have been applied by Scully (1994), Hofler and Payne (1997), Dawson *et al.* (2000a), Carmichael *et al.* (2001), Kahane (2005) and Barros and Leach (2006a). Other methods adopted include logistic regression (Kokolakakis *et al.*, 2012).

We prefer to use stochastic frontier analysis rather than DEA for several reasons. DEA is more sensitive to outliers than stochastic frontier and all variation between production units is interpreted as inefficiency in DEA, while stochastic frontiers allow for the existence of random terms – these features could be relevant to our analysis since stochasticity is a fundamental component of sports results. On the other hand, DEA does not require distributional assumption about efficiency, while stochastic frontier models need to assume some functional form and to make some distributional assumption about the inefficiency component.

The precise method, notwithstanding an important feature in the sport literature on efficiency, is based on the assumption that all teams use the same technology.[1] If this assumption is wrong, then this could lead to overestimating the inefficiency scores of some teams as technology differences could be interpreted as inefficiency (Orea and Kumbhakar, 2004). Hence, we advocate using a stochastic frontier latent class model[2] to control for unobserved heterogeneity (Orea and Kumbhakar, 2004; Greene, 2005). These models assume that there are a finite number of classes that use different technologies among them, and each unit can be assigned to a particular group using the estimated probabilities of class membership. Moreover, the number of different groups is tested by the estimations. Each class is interpreted as a cluster in a sample, signifying heterogeneity in the sample analysed. Clubs aggregated to each cluster share common characteristics among the cluster group, distinct from the other cluster. As all sample football clubs are characterized by the same variables, this distinction is necessarily attributed to the level of the variables used.

The rest of the article is organized as follows. In Section II, the contextual setting is presented; in Section III, a literature survey is presented; in Section IV, the methodology is presented. Section V contains data and empirical specification. Results are presented in Section VI. Finally some conclusions are drawn in Section VII.

II. Contextual Setting

French League-1 Soccer has become one of the most important soccer leagues and such French football demand has been analysed by Falter and Perignon (2010) from 1997 to 1999. Despite its importance, no published paper has analysed the efficiency of French soccer teams. Table 1 shows financial and sport data of clubs from the French first division for the period 2010 to 2011 season. One anecdotal characteristic of the French League-1 Soccer League is that in recent years Olympique Lyonnais (Lyon) has owned many of the top players in the league and, consequently, achieved the highest position in the league. Competition for Lyon has come from Paris Saint Germain and Olympique de Marseille. Lastly, since the early 1990s, most of the French clubs have assumed corporate status. Hence it is enforced that financial accounts are published regularly.

It can be observed that there is a high degree of heterogeneity among teams in terms of attendance, stadium capacity, wages and game results, measured as the position attained in the league. Stadiums are usually owned by the club with exceptions such as Toulouse and Nice that play in municipal stadiums. Additionally, the Rennes stadium has been owned by the French luxury mogul Francois Pinault's family since 1998 and Paris Saint Germain's has been

[1] To the best of our knowledge, Barros *et al.* (2008) is the only exception.
[2] Latent class models are also called finite mixture models in the literature.

Table 1. Teams averages (2010–2011 season)

Teams	Stadium name	Stadium capacity	Attendance (persons)	Wages (thousand €)	Position
A.C. Ajaccio	Stade Francois Coty	8219	3414	7209	18
A.J. Auxerre	Stade Abbé Deschamps	21 379	10 668	16 220	6
F.C. Girondins de Bordeaux	Stade Chaban Delmas	34 327	24 247	20 204	2
Le Mans Union Club 72	Stade Léon-Bollée	17 801	11 437	12 433	9
Racing club de Lens	Stade Félix Bollaert.	41 229	34 445	18 746	4
LOSC Lille	Stade Lille-Metropole	18 185	13 198	14 757	3
Olympique Lyonnais	Stade Gerland	42 000	34 465	51 131	1
Olympique de Marseille	Stade Vélodrome	60 000	49 200	35 873	5
F.C. de Metz	Saint-Symphorien	10 000	16 039	9277	19
A.S. Monaco F.C.	Stade Louis II	36 371	11 182	38 864	10
A.S. Nancy Lorraine	Stade Marcel Picot	20 085	17 163	10 346	12
F.C. Nantes Atlantic	Olympique de Colombes	45 000	29 449	24 496	14
O.G.C. Nice	Stade du Ray	17 400	10 903	9806	8
Paris Saint Germain	Parc des Princes	46 480	40 486	31 634	11
Stade Rennais F.C.	de la Route de Lorient	31 127	25 000	16 493	7
A.S. Saint-Etienne	Geoffroy Guichard	36 600	29 111	11 472	13
F.C. Sochaux Montbeliard	Auguste Bonal	20 025	14 257	14 240	15
Toulouse F.C.	Stadium Municipal	37 000	18 875	9609	16
E.S. Troyes Aube Champagne	Stade de l'Aube	20 400	13 795	9638	17

owned by Qatar investments since 2006. French football clubs quoted in the stock exchange include Olympique Lyonnais, Aglietta *et al.* (2010). Further details about French Football League can be found in Andreff (2007) and Gouguet and Primault (2006).

III. Literature Survey

As mentioned above, there are two main approaches to measure efficiency – first, the econometric or parametric approach and, second, the nonparametric approach. With regard to the first, several papers have used the econometric approach to efficiency analysis in soccer. For instance, Dawson *et al.* (2000a) analysed the managerial efficiency of English soccer, estimating several production frontiers. They used winning percentage as the output and several measures of player quality as inputs. Using a similar approach, Dawson *et al.* (2000b) provided wide-ranging empirical evidence on the robustness of estimates of coaching efficiency in English soccer. Although they used a variety of methods and input–output specifications, they did not use a latent class model. Carmichael *et al.* (2001) analysed the efficiency of the English Football Association Premiership clubs, using the number of points attained during the season as output. Barros and Leach (2006b, 2007) estimated cost stochastic frontiers for the English Premiership, using both team points and spectator attendance as outputs. Ascari and Gagnepain (2007) estimated average wage equations in Spanish soccer, using a stochastic frontier model, to empirically evaluate the consequences of the rent-seeking behaviours on team costs. Finally, Barros *et al.* (2008) identified three segments in the Spanish Soccer League using a latent class model in a cost frontier framework, and Barros *et al.* (2008) analysed the cost efficiency of Spanish soccer teams using a random parameter model.

Looking beyond soccer, several papers have used the econometric approach to efficiency analysis in sports economics. For example, Zak *et al.* (1979) explored production efficiency in the National Basketball Association (NBA) using a deterministic frontier. Porter and Scully (1982) studied the managerial efficiency of baseball managers using a similar deterministic approach and stochastic frontier model. Scully (1994) showed that coaching tenure was related to managerial efficiency in basketball, baseball and soccer using survival analysis. Hofler and Payne (1997) applied a stochastic frontier model to the NBA, using the number of wins as output. Kahane (2005) investigated the relationship between inefficiency and discriminatory hiring practices in the National Hockey League (NHL) using a stochastic frontier model and the proportion of potential points gained in the regular season as output.

Among the papers adopting a nonparametric approach, Espitia-Escuer and García-Cebrian (2004) examined the efficiency of Spanish First Division soccer, where clubs are decomposed into technical efficiency and scale efficiency using DEA. They too used the number of points achieved in the league season as the output measure. Haas (2003b) examined the efficiency of the US Major Soccer League with DEA. Other papers not on soccer include Fizel and D'Itri (1997), who applied the DEA technique to measure the managerial efficiency in college basketball. They used simple winning percentage as output and *ex-*

ante measures of player quality as inputs. This article analyses the French football league with the Orea and Kumbhakar's (2004) latent stochastic frontier model. A recent paper on Stochastic Frontier model presented for Stata software (Belotti *et al.*, 2013, forthcoming) omits the presentation of this model, demonstrating its relatively low popularity when compared to the stochastic frontier model. Still its distinctiveness for cluster identification makes it useful generally and particularly in this context.

IV. Methodology

The dual approach (i.e. cost functions or profit functions) is preferable to the primal approach (i.e. production function) in characterizing the production process. A cost frontier represents the minimum expenditure required to produce any output given input prices (Kumbhakar and Lovell, 2000, p. 33). Therefore, a cost frontier envelops the data in such a way that all teams must lie on the frontier or above it. Thus, a cost frontier is specified as follows:

$$C = C^*(w, y, T) \tag{1}$$

where C is cost, w is input prices, y is output and T represents the state of the technology. Based on the cost frontier definition, the stochastic frontier analysis (Aigner *et al.*, 1977; Meeusen and van den Broeck, 1977) offers an analytical framework for estimation. Using this approach a stochastic cost frontier is specified as follows:

$$C = C^*(w, y, t) \cdot \exp(\varepsilon); \;\; \varepsilon = v + u; \quad u \geq 0; \tag{2}$$

where ε is the two-component error term. The symmetric component, v, captures statistical noise and is assumed to follow a distribution centred at zero, while u is a nonnegative term that reflects inefficiency and is assumed to follow a one-sided distribution (i.e. truncated normal, half-normal and exponential). When $u = 0$, the team is producing on the cost frontier (i.e. at minimum cost), whereas a positive u indicates that the soccer club cost is above the minimum cost. A cost efficiency index can be defined as the ratio of the minimum feasible cost (C*) and observed cost (C):

$$CE = \frac{C^*}{C} = \frac{C(y, w, t) \cdot \exp(v)}{C(y, w, t) \cdot \exp(u + v)} = \exp(-u) \tag{3}$$

Since C* must be always lower than or equal to C, the cost efficiency index is bounded between 0 and 1 and achieves its upper bound when a club is producing its output level at minimum cost (i.e. $C = C$*) given input prices and available technology. Furthermore, given that the estimation procedure contained in Equation 2 yields merely the residual ε, rather than the inefficiency term u, the latter must be calculated indirectly using the Jondrow *et al.* (1982) formula as the conditional expectation of u_{it}, conditioned on the realized value of ε_{it}.

We can write Equation 2 as a latent class model as follows:

$$\ln C_{it} = C^*(w, y, t)\big|_j + v_{it}\big|_j + u_{it}\big|_j \tag{4}$$

where subscript i denotes club, t indicates time and j represents group or class to which the club belongs. The vertical bar signifies that there is a different model for each class j. Moreover, it is assumed that each club belongs to the same group in all periods.[3] This assumption can be considered restrictive, but is needed for identification purposes and only implies that managerial behaviour for each club is related throughout the period.

An important issue in these models is how to determine the number of classes. The usual procedure is to estimate several models with different numbers of groups and then use a statistical test in order to choose the preferred model. Hence, information criteria such as the Akaike Information Criterion (AIC) or the Schwarz Bayesian Information Criterion (SBIC) are appropriate for this purpose. These statistics are calculated using the following expressions as follows:

$$SBIC = -2 \cdot \log LF(J) + \log(n) \cdot m \tag{5}$$

$$AIC = -2 \cdot \log LF(J) + 2 \cdot m \tag{6}$$

where *LF(J)* is the value that the likelihood function takes for J groups, m is the number of parameters used in the model and n is the number of observations. The favoured model will be that for which the value of the statistic is lowest.

V. Data and Empirical Specification

To estimate the cost frontier, we used an unbalanced panel data on French first soccer league over nine seasons from 2002 to 2011 available on Ligue 1 site (www.lfp.fr/actualiteLFP/dncg.asp). It is important to note that we gathered the data of all teams that participated in Ligue 1 (i.e. 20 teams each season) in the years analysed; but due

[3] Further technical details on the estimation procedure are provided in the Appendix.

to the promotion and relegation system,[4] it yielded an unbalanced panel data set.

In order to estimate a cost frontier, we include one output and two input prices. Among the possibilities for outcome price selected, we have chosen the number of points achieved in a season, following the practice of many previous studies (e.g. Carmichael *et al.*, 2001; Haas, 2003a; Espitia-Escuer and García-Cebrián, 2004; Barros and Leach, 2007). Furthermore, we include two input prices. A proxy for PL (price of labour), measured as total wages paid by the club to players divided by the number of players, a proxy for PK1 (price of capital premises), measured by dividing amortization and reconstruction expenditure by net assets and liabilities and PK2 (price of capital funding), measured by the dividing debts by the total assets. PK2 is used to normalize the endogenous variable and the price of inputs. A number of distributional models are usually adopted in stochastic frontier models – the half-normal specification, the truncated normal specification, the exponential specification and the gamma. The option for any specification is based on simulation of different models and choosing the specification that better fits the data. In the present research, the half-normal specification was chosen.

Table 2 shows the descriptive statistics of the variables used in the empirical analysis.

The empirical specification of the average cost frontier is the Translog specification. We also include time dummies for each season in order to account for temporal changes. Thus, the equation to estimate is as follows:

$$\begin{aligned}\ln\left(\frac{\mathrm{cost}_{it}}{\mathrm{PK2}_{it}}\right) &= \beta_0 + \beta_1 Trend + \beta_2 \cdot Point\,s_{it}\\ &+ \beta_3 \cdot \left(\frac{PL_{it}}{PK2_{it}}\right) + \beta_4 \cdot \left(\frac{PK1_{it}}{PK2_{it}}\right) + \beta_5 1/2 (point\,s_{it})^2\\ &+ \beta_6 1/2 (\frac{PL_{it}}{PK2_{it}}) + \beta_7 1/2 \left(\frac{PK1_{it}}{PK2_{it}}\right) + \beta_8 (point\,s_{it})\\ &\ln\left(\frac{PL_{it}}{PK2_{it}}\right) + \beta_9 \ln(point\,s_{it}) \ln\left(\frac{PK1_{it}}{PK2_{it}}\right)\\ &+ \beta_{10} \ln\left(\frac{PL_{it}}{PK2_{it}}\right) \ln\left(\frac{PK1_{it}}{PK2_{it}}\right)\\ &+ \sum_{t=2010}^{2003} \lambda_t \cdot D_t + (v_{it} - u_{it})\end{aligned} \tag{7}$$

where league points at the end of the season is the output, *PL* denotes the price of labour, *PK* is the price of capital, *v* is a random error which reflects the statistical noise and is assumed to follow a normal distribution centred at zero, and *u* reflects inefficiency and is assumed to follow a half-normal distribution.

Table 2. Descriptive statistics of the data (2003–2011)

Variable	Mean	SD	Minimum	Maximum
Cost	41 287	26 156	10 682	98 945
Trend	5	6.36	2002 = 1	2011 = 10
Points	51	12	29	84
PL – labour price	655	468	121	1869
PK1 – Capital price1	0.05	0.08	0.00	0.43
PK2 – Capital price2	0.21	0.14	0.05	0.82

Note: The monetary variables are expressed in constant euros.

VI. Results

The latent class model in Equation 7 was estimated by maximum likelihood using Limdep 9.0 (Greene, 2007). The model with two groups was the preferred one according to SBIC and AIC criteria. Table 3 displays the estimations of the two class models and the standard stochastic cost frontier, which assumes that only one cost frontier represents all data in the sample. As expected, total variance is smaller when there two different groups are allowed. In fact, latent class models classified observations by reducing within group variance in order to maximize the value of the total likelihood function (LF). On the other hand, the high λ value in the latent class model estimations tells us that randomness is less important than inefficiency in explaining the distance to the frontier. Hence, when teams with the same technology are compared, either good or bad fortune tends to disappear throughout the league. From that we can infer that managerial decisions are more important than sheer luck for the soccer clubs in our sample.

The estimated coefficients have the expected signs, as price elasticities are positive except for the price of capital for Group 2. Therefore, the higher the labour and capital prices, the higher the cost needed to obtain points. At the same time, the coefficients of points are negative, reflecting that the average costs are decreasing. Likewise, the coefficient on points for Group 1, which consists mainly of high-budget teams, is lower in absolute terms than thta for Group 2.

An important result that supports the latent class model estimation is that the differences of the input price coefficients among groups are statistically significant, suggesting two different technologies used in obtaining points by

[4] In contrast to US professional sport leagues that use a closed structure, most European leagues are organized in such a way that at the end of each season some teams are transferred between divisions. The best-ranked teams in each division at the end of the season are promoted to the division above and, at the same time, the worst-ranked teams are relegated to the lower division. See Noll (2003) for a study which analyses the differences between these two systems.

Table 3. Estimation results

	Standard SF.	Latent class model	
		Group 1	Group 2
Constant	3.192***	4.170***	1.154***
	(0.47)	(0.03)	(0.45)
Trend	0.217***	0.315***	0.421***
	(0.00)	(0.01)	(0.00)
Points	−0.510***	−0.449***	−0.773***
	(0.17)	(0.01)	(0.09)
PL	0.812***	0.658***	1.234***
	(0.06)	(0.00)	(0.10)
PK1	0.031	0.037***	−0.095***
	(0.03)	(0.00)	(0.01)
½(Points)^2	0.21	0.32	0.22
	(0.00)*	(0.01)*	(0.02)*
½(PL)^2	0.15	0.27	0.31
	(0.02)*	(0.12)	(0.14)
½(PK1)^2	0.57	0.38	0.54
	(1.28)	(1.04)	(1.32)
Points × PL	0.743***	0.581***	0.629***
	(0.00)	(0.02)	(0.01)
Points × PL	0.167***	0.175***	0.124***
	(0.00)	(0.01)	(0.02)
PL × PK	0.345***	0.518*	0.189*
	(0.03)	(0.01)	(0.03)
Season 2003–2004	−0.005	−0.070***	0.098***
	(0.08)	(0.01)	(0.02)
Season 2004–2005	−0.106	−0.021***	−0.094***
	(0.08)	(0.01)	(0.03)
Season 2005–2006	0.190**	0.102***	0.113***
	(0.08)	(0.01)	(0.02)
Season 2006–2007	0.175**	0.032***	0.051***
	(0.07)	(0.03)	(0.01)
Season 2007–2008	0.181**	0.191***	0.276***
	(0.01)	(0.02)	(0.00)
Season 2008–2009	0.053**	0.084***	0.016***
	(0.00)	(0.03)	(0.00)
Season 2009–2010	0.132**	0.264***	0.125***
	(0.01)	(0.02)	(0.00)
$\sigma = \left(\sigma_v^2 + \sigma_u^2\right)^{1/2}$	2.250***	0.285***	0.189***
	(0.65)	(0.03)	(0.03)
$\lambda = \sigma_u/\sigma_v$	0.380***	13 595	13 664
	(0.00)	(9013)	(11 307)
Estimated probabilities for class membership		0.574	0.426
Log-likelihood function	10.911	37.711	
Observations	160	160	

Notes: *, ** and *** indicate significance at the 1%, 5% and 10% levels, respectively. SEs are shown in parenthesis.

Table 4. Characteristics of the estimated groups

	Group 1	Group 2
Cost	48 718	29 540
	(25 574)	(22 853)
Points	52	48
	(13)	(9)
Wages	21 030	12 902
	(13 529)	(7804)
Labour price	773	468
	(541)	(225)
Capital price	0.07	0.03
	(0.10)	(0.04)
Average cost	909	584
	(362)	(372)
Marginal cost	500	132
	(200)	(84)
Pooled efficiency	0.64	0.81
	(0.09)	(0.15)
Latent class model efficiency	0.82	0.88
	(0.14)	(0.10)
Number of observations	49	31

Note: SDs are shown in parentheses.

Table 5. Group composition

Group 1	Group 2
Paris Saint-Germain	F.C. Nantes Atlantic
Olympique Lyonnais	S.M. Caen
A.S. Monaco F.C.	A.J. Auxerre
Olympique de Marseille	S.C. Bastia
A.S. Saint-Etienne	E.A. de Guingamp
L.O.S.C. Lille Metropole	Le Mans Union Club 72
F.C. Girondins de Bordeaux	Racing Club de Lens
O.G.C. Nice	F.C. Sochaux Montbeliard
Stade Rennais F.C. A.S.	F.C. de Metz
Toulouse F.C.	C.S. Sedan Ardennes
	C.S. Sedan Ardennes
	E.S. Troyes Aube Champagne
	F.C. Istres
	Le Havre A.C.
	A.C. Ajaccio

Ligue 1 teams. Likewise, it can be observed that the group with the highest labour elasticity is Group 2.

Teams were assigned groups using the posterior probability of class membership. In Table 4, we show the means of some representative variables for the groups obtained in the latent class model, while Table 5 shows the composition of the groups. Group 1 is the cluster of top French football teams. These would be known by fans from other nations as some of the teams have competed and had success in European cups and include the teams that have been suggested as operating out of the bounds of FFP in recent years. Group 2 is the cluster of smaller regional France clubs. These clusters are defined statistically by the model and since it is based on the variables used, it represents distinct values for the variables. Additional features of the two clusters are presented in the following.

Group 1 features clubs from France's largest cities and across the country. Furthermore, the teams in Group 1 reside in the epicentre of economic activity within each one's respective region. The cities are also where the top French universities are located. According to recent governmental reforms (PRES, Grand Emprunt), these will be the 'regional' universities in France – a kind of consortium of universities in each major French region. As to the teams themselves, the clubs in Group 1 (e.g. Marsailles, Lyon, PSG, Bordeaux and Saint-Etienne) are known for their past footballing success, both in the national league and European competition. Of late, European qualification and success has become a benchmark for these teams as well as a means to acquire future resources to achieve sustained on-the-field success via the increasingly costly international player transfer market (e.g. AS Monaco, a small club relative to most of Group 1, completed a £51m transfer of Radamel Falcao during the 2013 transfer season). The clubs are also known for their large private sponsorship deals, new and renovated stadia (e.g. Lille, Rennes) and relative continuity of leadership by some of the most recognizable and respected figures in French football.

Group 2 clubs have realized some measures of competitive success, but are mostly known as developmental for the larger clubs. Nantes and Auxerre, for example, have been highly successful in the French youth competitions. Top-level clubs' success is the exception rather than the rule for Group 2 teams, in large part due to the top players moving onto Group 1 teams or internationally. Moreover, many of the top French players have risen through the youth training centres at Group 2 clubs. In the case of Auxerre, the very revenues earned via the transfer market were in turn invested back into the development of the training centre. Hence, Group 2 clubs may in aggregate earn almost as many points as those from Group 1, but have not regularly reached the top of the league.

It can be seen that labour price and average cost are clearly higher in Group 1 than in Group 2. However, the number of points and position are roughly similar between groups. Moreover, in both groups, the efficiency estimates from the latent class model are higher than the pooled model. This result suggests that relative to the latent model the standard stochastic frontier, which imposes only one technology, overestimates the inefficiency. Finally, the marginal cost is higher in Group 1 than in Group 2. This result makes sense since it is more difficult to increase the number of points for an already high-budget team than for a low-budget team.

The results of this research illustrate several important points related to team management. Relative to the top European soccer leagues such as in England, Spain, Germany and Italy, the big French clubs are relatively few in European competition, and often unable to advance far in the top European tournament. For the betterment of the entire league, it could be suggested that policy to increase top-level competitiveness should be focused on improving those in the Group 1 cluster. The present revitalization of Germany football clubs can serve as a model for the French football clubs to succeed in European competition. Revenue sharing agreements where the rich teams of Cluster 1 receive funds equal to the lower teams in the league in spite of the clear differences in team popularity may be serving to reduce top clubs' success in European club competition. This is evidenced by the high costs borne by that cluster of teams without similar high yields in league points. If top clubs' success in Europe serves to increase the popularity of the entire league, in addition to the successful clubs themselves, then policies aimed at increasing the quality of the lower-level teams may actually serve to hamper that very outcome.

VII. Conclusions

This article has proposed a simple framework for the comparative evaluation of the French soccer clubs and the rationalization of their operational activities. The analysis was conducted by means of the implementation of a stochastic frontier latent class model that allows the incorporation of a broad variety of inputs and outputs while permitting researchers to account for segments in the sample and the existence of heterogeneity in the data. The main result is that there are two groups among the French soccer clubs, both following completely different 'technologies' to obtain league points. This result is important since it may explain the changes observed in Ligue 1 where teams have not reached the pinnacle in European competition since 2000. Policies focused on Cluster 1 are needed for French football clubs to improve the performance efficiency of French clubs on the international stage, as these are clubs that have been the ones capable of winning Ligue 1 to advance to the Champions Cup. This study has identified the distinct segments among French soccer clubs, suggesting that business strategies need to be adapted to the characteristics of the clubs. That is, if a particular team follows a successful business strategy employed by a team from the other group, it will incur in a great deal of inefficiency. Thus as long as there are strong incentives for clubs to reach the European competition, clubs will emulate those who have been successful in doing so. However, it would be inefficient for those coming from Cluster 2 to imitate those in Cluster 1 based on their levels of resources. While strategies to become the exceptional franchise from Cluster 2 that reaches and performs well in European competition, this is not likely to resemble the means utilized by the top teams in Cluster 1.

In order to offer more conclusive policy prescriptions, a larger data set would be required. Indeed, the limitations of the present article suggest directions for new research. The main limitation of this article stems from the data set, since the available data span is relatively short. Thus, additional research is needed to confirm the results of this article, as well as to clarify some of the issues identified here. Moreover, how group assignments form in the presence of new regulations is a particularly relevant consideration. Indeed, will FFP ultimately result in new strategy formation and the homogenization of efficient strategies? This is a question of primary importance to contemporary managers. Lastly, from a scholarly perspective, we suggest that future research on sport leagues in other countries take into account the presence of heterogeneity.

References

Aglietta, M., Andreff, W. and Drut, B. (2010) Floating European football clubs in the stock market. Working Paper 24, Economix.u. Paris 19. France.

Aigner, D. J., Lovell, C. A. K. and Schmidt, P. (1977) Formulation and estimation of stochastic frontier production function models, *Journal of Econometrics*, **6**, 21–37.

Andreff, W. (2007) French Football: a financial crisis rooted in weak governance, *Journal of Sports Economics*, **8**, 652–61.

Ascari, G. and Gagnepain, P. (2007) Evaluating rent dissipation in the Spanish football industry, *Journal of Sports Economics*, **8**, 468–90.

Barros, C. P., del Corral, J. and Garcia-del-Barrio, P. (2008) Identification of segments of soccer clubs in the Spanish League First Division with a latent class model, *Journal of Sports Economics*, **9**, 451–69.

Barros, C. P. and Garcia-del-Barrio, P. (2008) Efficiency measurement of the English Football Premier League with a random frontier model, *Economic Modelling*, **25**, 994–1002.

Barros, C. P., Garcia-del-Barrio, P. and Leach, S. (2009). Analysing the technical efficiency of the Spanish Football League first division with a random frontier model, *Applied Economics*, **41,** 3239–47.

Barros, C. P. and Leach, S. (2006a) Analyzing the performance of the English F.A. Premier League with an econometric frontier model, *Journal of Sports Economics*, **7**, 391–407.

Barros, C. P. and Leach, S. (2006b) Performance evaluation of the English Premier League with data envelopment analysis, *Applied Economics*, **38**, 1449–58.

Barros, C. P. and Leach, S. (2007) Technical efficiency in the English Football Association Premier League with a stochastic cost frontier, *Applied Economics Letters*, **14**, 731–41.

Belotti, D., Ilardi, G. and Atella, V. (2013, forthcoming) Stochastic frontier analysis using Stata. *Stata Journal*.

Carmichael, F., Thomas, D. and Ward, R. (2001) Production and efficiency in Association Football, *Journal of Sports Economics*, **2**, 228–43.

Coates, D. and Humphreys, B. R. (2011) The effect of professional sports on the earnings of individuals: evidence from microeconomic data, *Applied Economics*, **43**, 4449–59.

Dawson, P., Dobson, S. and Gerrard, B. (2000a) Stochastic frontier and the temporal structure of managerial efficiency in English Soccer, *Journal of Sports Economics*, **1**, 341–62.

Dawson, P., Dobson, S. and Gerrard, B. (2000b) Estimating coaching efficiency in professional team sports: evidence from English Association Football, *Scottish Journal of Political Economy*, **47**, 399–421.

Einolf, K. (2004) Is winning everything? A data envelopment analysis of major League Baseball and National Football League, *Journal of Sports Economics*, **5**, 127–51.

Espitia-Escuer, M. and García-Cebrian, L. I. (2004) Measuring the efficiency of Spanish First-Division Soccer Teams, *Journal of Sports Economics*, **5**, 329–46.

Falter, J. M. and Perignon, C. (2010) Demand for football and intramatch winning probability: an essay on glorious uncertainty of sports, *Applied Economics*, **32**, 1757–65.

Fizel, J. L. and D'Itri, M. P. (1996) Estimating managerial efficiency: the case of college basketball coaches, *Journal of Sport Management*, **10**, 435–45.

Fizel, J. L. and D'Itri, M. P. (1997) Managerial efficiency, managerial succession and organizational performance, *Managerial and Decision Economics*, **18**, 295–308.

Gouguet, J. and Primault, D. (2006) The French exception, *Journal of Sports Economics*, **7**, 47–59.

Greene, W. (2005) Reconsidering heterogeneity in panel data estimators of the stochastic frontier models, *Journal of Econometrics*, **126**, 269–303.

Greene, W. (2007) *Limdep Version 9.0*, *Econometric Software*, Plainview, New York, NY.

Gutierrez, E. and Lozano, S. (2012, forthcoming) A DEA approach to performance-based budgeting of formula one constructors. *Journal of Sport Economics*.

Haas, D. J. (2003a) Productive efficiency of English Football teams – a data envelopment approach, *Managerial and Decision Economics*, **24**, 403–10.

Haas, D. J. (2003b) Technical efficiency in the Major League Soccer, *Journal of Sports Economics*, **4**, 203–15.

Hadley, L., Poitras, M., Ruggiero, J. *et al.* (2000) Performance evaluation of National Football League teams, *Managerial and Decision Economics*, **21**, 63–70.

Hall, S., Szymanski, S. and Zimbalist, A. (2002) Testing Causality between Team Performance and Payroll: the cases of major Baseball League and English Soccer, *Journal of Sports Economics*, **3**, 149–68.

Hofler, R. A. and Payne, J. E. (1996) How close to their offensive potential do national football club teams play, *Applied Economics Letters*, **3**, 743–7.

Hofler, R. A. and Payne, J. E. (1997) Measuring efficiency in the National Basketball Association, *Economics Letters*, **55**, 293–9.

Jondrow, J., Lovell, C. A. K., Materov, I. *et al.* (1982) On the estimation of technical inefficiency in the stochastic frontier production function model, *Journal of Econometrics*, **19**, 233–8.

Kahane, L. H. (2005) Production efficiency and discriminatory hiring practices in the National Hockey League: a stochastic frontier approach, *Review of Industrial Organisation*, **27**, 47–71.

Kern, M. and Süssmuth, B. (2005) Managerial efficiency in German Top League Soccer: an econometric analysis of club performances on and off pitch, *German Economic Review*, **6**, 485–506.

Kokolakakis, T., Lera-López, F. and Panagouleas, T. (2012) Analysis of the determinants of sports participation in Spain and England, *Applied Economics*, **44**, 2785–98.

Koop, G. (2002) Comparing the performance of baseball players: a multiple output approach, *Journal of the American Statistical Association*, **97**, 710–20.

Kumbhakar, S. and Lovell, K. (2000) *Stochastic Frontier Analysis*, Cambridge University Press, Cambridge.

Meeusen, W. and van den Broeck, J. (1977) Efficiency estimation from a translog production function with composed error, *International Economic Review*, **18**, 435–44.

Noll, R. (2003) The organization of sports leagues, *Oxford Review of Economic Policy*, **19**, 530–51.

Orea, L. and Kumbhakar, S. (2004) Efficiency measurement using a latent class stochastic frontier model, *Empirical Economics*, **29**, 169–83.

Porter, P. and Scully, G. W. (1982) Measuring managerial efficiency: the case of baseball, *Southern Economic Journal*, **48**, 642–50.

Scully, G. W. (1994) Managerial efficiency and survivability in professional team sports, *Managerial and Decision Economics*, **15**, 403–11.

Smart, D., Winfree, J. and Wolfe, R. (2008) Major League Baseball Managers: do they matter?, *Journal of Sport Management*, **22**, 303–21.

Zak, T. A., Huang, C. J. and Siegfried, J. J. (1979) Production efficiency: the case of professional basketball, *Journal of Business*, **52**, 379–92.

Appendix

Assuming that v is normally distributed and u follows a half-normal distribution, the LF for each team i at time t for group j is (Greene, 2005) as follows:

$$LF_{ijt} = f\left(C_{it}|x_{it,}\beta_j,\sigma_j,\lambda_j\right) = \frac{\Phi\left(\lambda_j\cdot\varepsilon_{it|j}/\sigma_j\right)}{\Phi(0)}\cdot\frac{1}{\sigma_j}\cdot\phi\left(\frac{\varepsilon_{it|j}}{\sigma_j}\right) \tag{A1}$$

where $\varepsilon_{it|j} = lnC_{it|j} - \beta_j' x_{it}$, $\sigma_j = \left[\sigma_{uj}^2 + \sigma_{vj}^2\right]^{1/2}$, $\lambda_j = \sigma_{uj}/\sigma_{vj}$, and ϕ and Φ denote the standard normal density and cumulative distribution function, respectively.

The LF for team i in group j is obtained as the product of the LFs in each period:

$$LF_{ij} = \prod_{t=1}^{T} LF_{ijt} \tag{A2}$$

The LF for each team is obtained as a weighted average of its LF for each group j, using as weights the prior probabilities of class j membership.

$$LF_i = \sum_{j=1}^{J} P_{ij} LF_{ij} \tag{A3}$$

The prior probabilities must be in the unit interval $0 \le P_{ij} \le 1$. Furthermore, the sum of these probabilities for each individual must be one: $\sum_j P_{ij} = 1$. In order to satisfy these two conditions, we parameterized these probabilities as a multinomial logit. That is:

$$P_{ij} = \frac{\exp(\delta_j q_i)}{\sum_{j=1}^{J}\exp(\delta_j q_i)} \tag{A4}$$

where q_i is a vector of variables which are used to split the sample, and δ_j is the vector of parameters to be estimated. One group is chosen as the reference in the multinomial logit. The overall log-LF is obtained as the sum of the individual log-LFs:

$$\log LF = \sum_{i=1}^{N} \log LF_i = \sum_{i=1}^{N} \log \sum_{j=1}^{J} P_{ij} \prod_{t=1}^{T} LF_{ijt} \tag{A5}$$

The log-LF can be maximized with respect to the parameter set $\theta_j = \left(\beta_j,\sigma_j,\lambda_j,\delta_j\right)$, using conventional methods (Greene, 2005). Furthermore, the estimated parameters can be used to estimate the posterior probabilities of class membership, using Bayes Theorem:

$$P(j/i) = \frac{P_{ij}LF_{ij}}{\sum_{j=1}^{J} P_{ij}LF_{ij}} \tag{A6}$$

Moreover, the latent class model classifies the sample into several groups even when sample-separating information is not available. In this case, the latent class structure uses the goodness of fit of each estimated frontier as additional information to identify groups of units (Orea and Kumbhakar, 2004).