Talent allocation in European football leagues: why competitive imbalance may be optimal?

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Abstract: Professional sports are part of the entertainment industry; as such, its business is developed based on the perceived interest in sporting events, which in turn depends on features like: the (i) degree of competitive balance that determines the uncertainty of the outcome; the (ii) concentration of gifted players in a team, whose interaction of talents on the field enhances the quality of the 'product joint' that is a sporting event; the (iii) joint aggregate quality of rival teams; the (iv) appeal of rivalries associated with fans' feelings of empathy and loyalty; etc. This paper focusses on the first three points by modelling the success of team-sport competitions as the result of the overall quality, which encompasses more than the mere sum of individual talents. Sport economists and practitioners generally acknowledge that competitive balance must be fostered to protect uncertainty about the outcome and thus achieve greater interest in sport competitions by fans and the media. In this paper, we argue that certain degree of imbalance in allocation of talent between teams may be preferable – rather than a perfect competitive balance – to broaden the interest of fans on the sport events and, thus, maximise economic outcomes. The paper also examines the discrepancies across the main European football leagues in this regard.

Keywords: sport leagues; professional football; competitive imbalance; optimal resources allocation; local and global superstars; winner-take-all

JEL Classification: J24; J33; J71

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1 Introduction

The business of professional sports is part of the entertainment industry. The degree of enjoyment and interest of sport entertainment consumers depends on several factors: the quality of contestants or competitor teams – which, in turn, depends on the presence of gifted players and appealing rivalries; the degree of competitive balance – which determines the uncertainty of outcome; the joint aggregate quality of rival teams; and other issues including empathy feelings and loyalty to the team.

This paper develops upon the hypothesis that, as far as fans' degree of interest is concerned, there are at least three key features that make sport competitions appealing: (i) the degree of competitive balance, which leads to uncertainty of outcome; (ii) talent concentration in certain some teams and leagues; and (iii) the total joint aggregate quality of competitors. There is a general consensus that competitive balance is desirable, as it increases the interest of fans (consumers of sports events) in sport competitions. The more even (uneven) talent distribution across teams, the greater uncertainty (certainty) about the outcome; and hence, the greater (smaller) interest of fans, which is the source of potential revenues.

In this paper, we argue that some degree of competitive imbalance may be actually better insofar as concentration of talent – in the same team or league – operates non-linear increases of outcomes in the sense of greater entertainment and economic achievements. This paper hypothesises that the overall entertainment outcome is more than the mere sum of individual talents. Accordingly, the concentration of talent is modelled such that it escalates, rather than simply aggregates, the degree of enjoyment, a fact that relates, among other factors, to the winner-take-all phenomenon. In this way, the concentration of gifted players in the same team is expected to increase more than proportionally the overall satisfaction of the fans that follow that particular team and league. As a matter of fact, having larger crowds that support a club or follow a league generates greater media visibility status and, ultimately, greater income to the team and league.

The paper is organised as follows. After the introduction, we review some related literature. Then, in Section 3, the baseline and extended models are developed, in which – for a given amount of talent in team-sport competitions – there is a trade-off between "competitive balance" and "talent concentration". Section 4 describes the data and empirical strategies to test the validity of the hypotheses; while Section 5 presents the results and discuss their implications. Finally, in Section 6, we summarise the main conclusions and suggest future research avenues.

2 Literature Review

Among the driving forces that make sport events attractive, the issue of "Competitive Balance" (CB) stands out. This topic – closely connected with "Uncertainty of Outcome" (UO) – has been a matter of interest from the beginnings of the sport economics discipline, as illustrated by the seminal early contributions from Rottenberg (1956) and Neale (1964). More recent studies address the relationship between CB and the UO hypothesis (Owen 2014). There is contrasting evidence of empirical studies on how CB influences the degree of attention afforded to sporting events.

Another area related to our topic concerns the quality of sporting events and how they could be measured. Of course, the quality of a sporting event will depend on the presence of talented individuals and iconic players. Prior studies have called attention on the role of superstar players (Gwartney 1975; Noll 1974; Rosen 1981). More recently, Dobson and Goddard (2001) report the presence of skewed earnings distributions that presumably derive from the scarce supply of inimitable skills of a short number of individuals. Closely linked to this idea is the "winner-take-all" phenomenon, extensively addressed by Frank and Cook (1995), who claim it affects an increasing number of labour markets. The most productive workers, located at the top end of the performance distribution, will concentrate the rewards and prizes, even if they are only marginally more productive than others. Among this type of labour markets, we find for instance the industry of arts, professional sports and pop culture.[1]

The role of media visibility in sports is another area of related literature. In particular, to measure the quality of football clubs, in the empirical section we initially follow the lines of previous research (Aguiar-Noury and Garcia-del Barrio 2022; Garcia-del Barrio 2018). Specifically, we use metrics based on the number of news articles reported by Google that refer to a particular player or team in a certain period. This method seems appropriate to accomplish the objectives of our study for various reasons. First, because it is able to jointly capture the players' sporting and personal skills, including their media appeal. Second, since the core business of professional football consists of delivering entertainment, an activity that is

1 These activities usually apply similar compensation schemes, where individuals at the top of the earnings distribution compete for few number of huge monetary prizes. Winner-take-all contests may involve wasteful activities and investments, as resources are employed in winning a contest rather than in seeking productivity gains. Precisely, the labour markets of professional sports are paradigmatic examples of the "winner-take-all" phenomenon, as previous papers documented (Garcia-del Barrio and Pujol 2007). Another distinctive feature that characterises sports markets is the peculiar interaction of cooperation and competition, which develops into a variant of the "arms race" phenomenon (Rosen and Sanderson 2001).

developed thanks to new communication technologies. Third, because this approach is immediately ready to deal with winner-take-all elements, as they also arise in the context of media exposure.

Concerning the objectives of football clubs, our paper considers the classic debate on whether clubs aim to maximise economic profitability or sporting achievements.[2] We actually consider two possible scenarios: either the clubs aim to maximise economic outcomes (annual revenues, in our case); or they prioritize the quality of their squad and the sport achievements, subject to a financial constraint.

At the same time, our approach recognises the prevalent role that must be given to the clubs' financial situation in the long-run. In fact, having a satisfactory economic situation makes it possible for clubs to achieve long lasting sporting achievements, which in turn reinforces financial stability, thereby ensuring sustainable success both on the field and in terms of economic profitability. Accordingly, in this paper we presume that football clubs tend to pursue expanding both the size of their business as well as their sporting success, while preserving a balanced financial situation. This is precisely the reason for selecting the two dependent variables – revenue and team quality – we use in the regression analyses of the empirical section.

3 Modelling the Economic Returns of Talent Allocation

This section describes a basic model to characterise the business of professional football by assuming that the long-run objective of sporting competition can be

2 Initially, economists assumed that clubs behave as profit maximisers (Rottenberg 1956; El-Hodiri and Quirk 1971; Noll 1974; Quirk and Fort 1997). Nonetheless, referring to European football, Sloane (1971) raised doubts about such an assumption, given the contrasting behaviour of North American franchise owners, who operate in closed leagues and tend to maximise profit, and the club managers of open European leagues, whose choices appear to be closer to utility maximization. Other papers have elaborated on the utility maximizing hypothesis (Quirk and El-Hodiri 1974), adopting a utility function that maximizes a weighted combination of profit and wins (Vrooman 1997; Dietl, Grossmann, and Lang 2011). Following Sloane (1971), Késenne (1996) and Késenne (2000) transformed utility maximization into win maximization, since they argue that in open leagues teams are compelled by the necessity to win for preventing relegation. Hence, European football clubs must be treated as win maximizers, subject to a profit break-even constraint, rather than as profit maximizers. Papers that support a similar position include Vrooman (2007); Garcia-del Barrio and Szymanski (2009); Peeters and Szymanski (2014). The literature also considered revenue maximization as an objective function of sports clubs, even if it seems restricted to not-for-profit leagues: the empirical evidence is confined to US collegiate sports (Fort 2018) or to amateur leagues in Europe. The literature on sports has also addressed the hypothesis of clubs or leagues that pursue multiple variables and objectives (Terrien and Andreff 2020; Garcia-del Barrio and Reade 2023).

reduced to generate entertainment and economic returns (sport success and revenue). Moreover, we postulate an approach where the optimal input management is a function depending on the share of talent that accumulates each pair of rival teams participating in a sporting competition.

Given the status of football as a source of entertainment, its capacity to generate revenue is initially defined to be the result of: (i) uncertainty of outcome, and (ii) the interest that rival teams generate among followers. The former factor depends on the competitive balance between rival clubs, whereas the latter is hypothesised to depend on the degree of talent concentrated on the stronger team of each pair of rivals. An extension of this model involves another crucial factor: (iii) the total combined quality of every pair of contestant teams of a competition. The two alternative *proxy* variables we use in the empirical section to capture the third factor may implicitly capture the fact that the capacity of clubs to generate income depends also on past sporting performance and historical achievements, features that build the brand status.[3] That said, the clubs in our modelling exercise are not identified, and as such our model allows for changing dynasties over time.

On one hand, we approximate the *joint aggregate quality* of each pair of rival teams by an index of media visibility, “MVI”, which captures the degree of interest in the club in the media. Specifically, we rely on the amount of news articles referring to players registered in each team roster, based on the figures reported by Google.com.[4] This variable seems to play a significant role as a driving factor of the clubs capacity to generate sporting and economic achievements. On the other

3 Our approach does address the dynamic interactions between wages and revenue. However, our theoretical framework implicitly recognises that the clubs that pay greater salaries tend to be the ones that accumulate more talent, which in turn leads to greater sport success and better economic perspectives in the future.

4 We follow the MERIT approach (*Methodology for the Evaluation and Rating of Intangible Talent*), which computes appraisals on the degree of visibility in the media by analysing the (relative) number of digital contents in Internet (news articles and web sites), while avoiding the spurious information that often circulates in social networks. This methodology counts the number of news articles and web pages contents, without examining the actual nature of them. Although the information that circulates in Internet represents only a fraction of all the information in the media, the outstanding development of new technologies suggests that this approach is accurate to obtain comparable measures of global attention. The media visibility appraisals are calculated by aggregation of the individual figures, expressed as the factor by which the number of news articles referred to a player multiplies those of the reference (average) player in a sample that comprises more than 5,000 players every year. More information on the MERIT methodology is available at the web site: www.meritsocialvalue.com.

hand, for the sake of robustness, we also use “Elo” ratings as an alternative approach to measure the *joint aggregate quality* of rival teams in the empirical models.[5]

3.1 Baseline and Extended Models

To address this issue, we adopt a Cobb-Douglas function that expresses the outcome (either teams quality or revenue generated from fans) as a function of talent allocation in each pair of rival teams. For the sake of simplicity, we initially consider two factors: (i) the *Competitive Balance* of each pair of rival teams, B, and (ii) the degree of *Talent Concentration*, C, in the strongest team. These two inputs are considered driven factors to generate returns in the form of entertainment and, ultimately, revenue:

$$y = A \cdot B^{\beta} \cdot C^{\gamma} \tag{1}$$

where parameter A translates input units into the scale in which the output is measured. The relative weight of B and C in determining the outcome y is determined by the magnitude of parameters β and γ. Taking logarithms of expression (1) yields:

$$\ln(y) = \ln(A) + \beta \ln(B) + \gamma \ln(C) \tag{2}$$

Before we carry out the empirical analysis, the theoretical framework is further developed by postulating simple procedures to measure, respectively, (i) the “Competitive Balance” of every pair of rival teams, and (ii) the degree of “Talent Concentration” they exhibit, which escalates exponentially along with the talent concentrated in the strongest team:

$$\diamond \text{ Competitive Balance: } B = 1 - (s - (1 - s))^2 \tag{3}$$

$$\diamond \text{ Talent Concentration: } C = s^{(1+\alpha)} \cdot (1 - s) \tag{4}$$

where “s” represents the share of talent of the stronger team, with values ranging between 0.5 and 1; while “$(1 - s)$” is the talent share of the weaker team, thus being positive but smaller than 0.5. In the second expression, parameter α is prescribed to be positive, implying that additional proportion of talent concentrated in the stronger team leads to expanding the outcome (entertainment/revenue) at an increasing pace.

5 Elo ratings are a rating system initially adopted in the context of chess (Elo and Sloan 1978), which has been adopted in other sporting disciplines, including football. The *Fédération Internationale de Football Association* (FIFA) introduced a new rating system based on this method in June 2018. Research in sports economics increasingly uses data on Elo ratings (Leitner, Zeileis, and Hornik 2010; Lasek et al. 2016; Cea et al. 2020; Reade and van Ours 2024).

This paper postulates that the two factors (i) and (ii) contribute to the fans enjoyment and, therefore, both are desirable features to generate entertainment and business, notwithstanding the fact that they are in a certain extent opposed to each other. According to the given definitions, so B as C depend on the share of talent allocated to each of the competitor teams. The value of the "Competitive Balance", B, grows bigger as the difference in talent share between the two rivals diminishes. On the contrary, the definition of the latter, C, is such that a greater share of talent concentrated in the strongest team (and, hence, less competitive balance) may be desirable for several reasons. First, given people's preferences concerning the competitive balance and the unequal satisfaction experienced when a weaker team beats a stronger team. Second, the imbalanced size of the crowds supporting the various clubs, which imply important differences in the intensity with which they may want for higher competitive balance and uncertainty of outcome.[6] Third, and more importantly, because the quality of a football team and its capacity to display spectacle is not the mere sum of individual talents, since there are 11 players interacting with the others in the pitch, which generates an escalating level of global spectacle. The α parameter is precisely introduced to account for all these features. Moreover, the fact that its value is not exogenously given means that the model may help us to refute or corroborate the relevant role of our "Talent Concentration" hypothesis. It is straightforward to see that, for α or γ equal to zero, C becomes ineffective and, hence, the hypothesis irrelevant.

Figure 1 illustrates, in a simplified way, the relationship of various arrangements of talent share – in percent – with "Competitive Balance", "Talent Concentration" and the combination of both elements.

We now develop the model and examine its implications both with and without assuming constant returns to scale, which is easily implemented by imposing $\beta + \delta = 1$.

A more comprehensive version of the model considers also the *joint aggregate quality* (overall aggregate talent), denoted as Q, of each pair of rival teams playing each other in a season. This feature is captured in the extended model with an additional "proxy" variable, whose inclusion into the model is straightforward.

$$y = A \cdot B^{\beta} \cdot C^{\gamma} \cdot Q^{\delta} \tag{5}$$

6 In the various empirical analyses, a couple of "proxy" variables are added to the models, which takes into account the market size of clubs. Besides, this issue relates to the importance of suspense and surprise, aspects that the literature claim as major factors driving the demand of entertainment in many industries (Ely, Frankel, and Kamenica 2015), a feature that applies also to audiences of sport events (Buraimo et al. 2020).

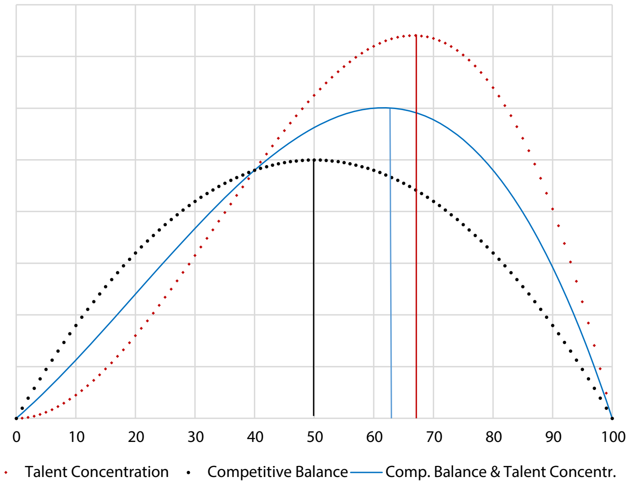

Figure 1: Talent share effect on competitive balance and talent concentration.

Again, the empirical section will address both the model without restrictions on the parameters, but also the case of constant returns to scale, in which we enforce the $\beta + \gamma = 1$ assumption.[7] The next sections develop and examine both the basic and expanded model of, respectively, expression (2) and expression (5).

3.2 Optimal Sharing of Talent in the Extended Model

In carrying out the topic under scrutiny, we consider – both at a theoretical and empirical level – a simple initial framework, labeled as "basic model", and also a more comprehensive framework, denoted as "extended model". The former model highlights the major role that talent shares allocated in rival teams may have, while the later one is the preferred model because it incorporates the third element and given it entails greater explanatory power.

Taking logarithms to expression (5) yields:

$$\ln(y) = \ln(A) + \beta \ln(B) + \gamma \ln(C) + \delta \ln(Q) \tag{6}$$

Given the specification of "B" and "C", expression (6) leads to the following objective function:

7 Alternatively, the assumption of constant returns to scale could have involved all three inputs, so that the constrained estimations of the extended model had imposed: $\beta + \gamma + \delta = 1$. Of course, this choice would have not affected the basic model in any case, since $\delta = 0$.

$\ln(y) = \ln(A) + \beta \ln\left(1 - (s - (1-s))^2\right) + \gamma \ln\left(s^{(1+\alpha)} \cdot (1-s)\right) + \delta \ln(Q)$; or, simplifying:

$\ln(y) = \ln(A) + \beta \ln(4s(1-s)) + (1+\alpha)\gamma \ln(s) + \gamma \ln(1-s) + \delta \ln(Q)$

Rearranging terms, the outcome is defined as a function of talent allocation (in each of the two rival teams) and of total combined quality. Notice that the variable *joint aggregate quality* is treated as exogenously given. The outcome is defined as a function of three elements: "s", "$(1-s)$", and "Q":

$$\ln(y) = \ln(4A) + (\beta + \gamma + \gamma\alpha)\ln(s) + (\beta + \gamma)\ln(1-s) + \delta \ln(Q) \qquad (7)$$

Expression (7) immediately conveys the risk of multicollinearity in the model, given the evident correlation between the two first regressors; a concern that was corroborated by the high values of the "vif" tests. However, multicollinearity does not frustrate the objectives of the current framework.[8] It is not a problem here, because our interest is not focussed on examining the value of each parameter separately, but to identify the optimal allocations of talent share in rival teams. Thus, in order to achieve our objective, there is no need to avoid even severe structural multicollinearity. To verify the validity of this theoretical statement, we empirically test it by confronting the results of two different procedures, finding identical values of s^* as in the model where we fully defined "C" and "B", thereby avoiding multicollinearity (This approach was performed by setting an specific value for α).

In the empirical analysis, two alternative dependent variables – team quality and revenue – are adopted, respectively, depending on whether the objective of clubs was to maximise sport achievements (subject to a financial constraint) or economic profitability. By renaming the parameters: $a = \ln(4A)$, $b = (\beta + \gamma + \gamma\alpha)$, $c = (\beta + \gamma)$, and $d = \delta$; expression (7) can be rewritten as: $\ln(y) = a + b\ln(s) + c\ln(1-s) + d\ln(Q)$.

Our model specification allows for any type of returns to scale to apply: increasing if $\beta + \gamma > 1$, constant for $\beta + \gamma = 1$, and decreasing if $\beta + \gamma < 1$. In the estimations we will also see what type of returns to scale is more likely to describe the situation in each of the three domestic leagues under scrutiny.

The main purpose of this paper is to calculate the optimal share of talent, in each league, that maximises the outcome, $\ln(y)$, in the form of sport or economic success, for a given amount of *joint aggregate quality*, "Q".

Accordingly, the first order condition for a maximum, with respect to s, requires that the first derivative must be zero:

8 Multicollinearity reduces the precision of the estimated coefficients, affecting their size and statistical significance, and also weakening the statistical power of the regression model. Furthermore, the estimated coefficients could change abruptly, since they are very sensitive to small changes. However, it does not harm the model's ability to deliver valid predictions.

$$\frac{\partial \ln(y)}{\partial s} = 0 + (\beta + \gamma + \gamma\alpha)\frac{1}{s} - (\beta + \gamma)\frac{1}{1-s} + 0 = 0 \tag{8}$$

The solution to the first order condition yields the following expression:

$$\left[s^* = \frac{(\beta + \gamma + \alpha\gamma)}{(\beta + \gamma + \alpha\gamma) + (\beta + \gamma)} = \frac{(\beta + \gamma) + \alpha\gamma}{2(\beta + \gamma) + \alpha\gamma} = \frac{b}{b + c}\right] \tag{9}$$

Observation of the result reported in expression (9) reveals, on one hand, that the product of parameters "$\alpha\gamma$" plays a crucial role in determining how relevant the "Talent Concentration" hypothesis is. On the other hand, it also makes clear that if this product were irrelevant to influence the outcome (a situation that will occur if $\alpha = 0$, or $\gamma = 0$, or both), the optimal allocation of talent will thus be precisely a *pure* competitive balance situation: $s^* = \frac{1}{2}$. In other words, expression (9) reveals that for $\alpha = 0$, meaning that there is no impact of talent concentration on outcome, the optimal talent share will be achieved where each rival team has 50 percent of the talent; and the same holds for $\gamma = 0$.

Figure 2 illustrates the idea that – according to our framework – the optimal distribution of talent, s^*, depends on "Competitive Balance", but also the intensity of "Talent Concentration", which in turn depends on the values of the parameters. The figure only represents the effect of the two parameters, α and β, even though the model actually has more dimensions (the value of parameter γ was taken as given, due to the limit of a three-dimension representation).

Then, the second order condition for a critical value, with respect to s, is given by:

$$\frac{\partial^2 \ln(y)}{\partial s^2} = \frac{(2\beta + \alpha\gamma + 2\gamma)^2\left((2\beta + 2\gamma + 2\alpha\gamma)s - (2\beta + 2\gamma + \alpha\gamma)s^2 - (\beta + \gamma + \alpha\gamma)\right)}{(\beta + \alpha\gamma + \gamma)^2(s-1)^2} < 0$$

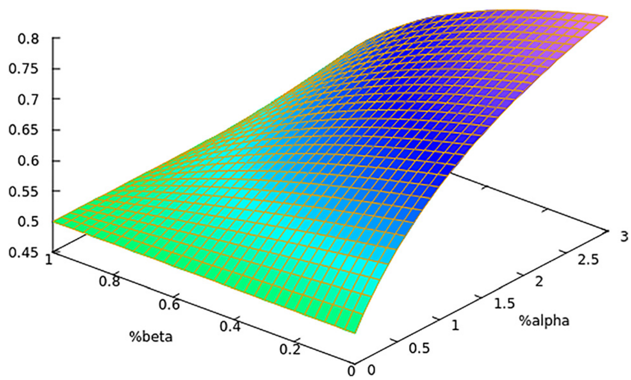

Figure 2: Optimal share of skills allocation depending on talent concentration weight and returns.

Or also:

$$\frac{\partial^2 \ln(y)}{\partial s^2} = -\frac{1}{s^2}(\beta + \gamma + \alpha\gamma) - \frac{1}{(1-s)^2}(\beta + \gamma) < 0 \tag{10}$$

The second-order condition reveals that the critical value of expression (9) defines a maximum, instead of a minimum. It is clear that the second derivative with respect to "s" is always negative (for positive values of the parameters), implying that the necessary condition for a maximum will be always fulfilled for whatever value defined by positive parameters. Substitution of the critical value s^*, defined in expression (9), into the second order condition, simplifies to:

$$\left.\frac{\partial^2 \ln(y)}{\partial s^2}\right|_{s^*} = -\frac{(2\beta + 2\gamma + \alpha\gamma)^3}{(\beta + \gamma + \alpha\gamma)(\beta + \gamma)} = -\frac{(b+c)^3}{bc} < 0 \tag{11}$$

Given the range of values of parameters α, β and γ, expression (11) is always negative, which implies that the necessary condition for a maximum is always satisfied. Once we know that the critical value reported in expression (9) is a maximum, we can delve into revealing implications of this result. The ratio that defines the optimal value of s^* is precisely defined by the relative weight that the estimated coefficient of the stronger team, represents as a faction of the sum of the two estimators associated to talent shares. In other words, the optimal allocation of talent must fulfill a certain specific proportion between the coefficients of the share of the stronger and weaker team (The empirical section describes the procedure to establish the relative status of teams' talent, which after exploring other alternatives, has been computed based on the number of points achieved at the end of the season).

In the empirical analysis, we will also consider the case of product functions with constant returns to scale, which is just a particular case where the change in the amount of inputs makes the output change by the same proportion. In our function, the constant returns to scale in such a way that they affect the two factors defined in terms of the share of talent allocation: "Competitive Balance" and "Talent Concentration", thereby imposing the constraint that $\beta + \gamma = c = 1$ (equivalent to $\gamma = 1 - \beta$). It implies that, when estimating the extended model, the third element – *joint aggregate quality* of a pair of teams – is not affected by the restriction of constant returns to scale. In the Cobb–Douglas function described in expression (5), which – after taking logarithms – is transformed into expression (6), the assumption of constant returns to scale leads to an optimal allocation of talent share given by:

$$\ln(y) = \ln(4A) + (1 + \gamma\alpha)\ln(s) + 1 \cdot \ln(1-s) + \delta \ln(Q) \tag{12}$$

Expression (12) is just a particular case of expression (9) for constant returns to scale, where – of course – the second orden condition for a maximum is always fulfilled.

4 Data Description and Empirical Strategy

Given the nature and characteristics of our data, we adopt an empirical strategy that consists in using combined (aggregate) figures of pairs of rival teams that play against each other in team-sports competitions. The fact that we treat some variables as *proxies* allow us to interpret, for instance, the combined revenues of each pair of teams competing into a league as an approximation of the economic returns their rivalry generates.

Specifically, we use a data set of 7,410 observations, which comprises teams from three main domestic European football competitions: the (English) Premier League, (Italian) Serie A, and (French) Ligue 1. In addition to conducting a pooled analysis for the whole sample including league dummies, we estimate also separately models for each domestic league (Appendix B displays some descriptive statistics of the main variables by league and seasons).

Figure 3 displays estimated Kernel probability density functions to illustrate the discrepancies among national leagues concerning the principal explanatory variables. Kernel density plots display smoother representations than relative frequencies of histograms. The figure on the left refers to the allocation of talent in the stronger teams, "*s*", expressed in percent. In searching for the *proxy* variable to approximate "talent shares", we also experimented with annual salaries. Nonetheless, since salaries are part of the objective function in one group of models, we discard this option. Besides, it is clear from our data that competitive balance is better captured through outputs (actual sport achievements), rather than through inputs. Hence, we decided to rely on the number of points accumulated by a team at the end of the season, relative to the sum of the combined points obtained by a pair of rival teams in that season.

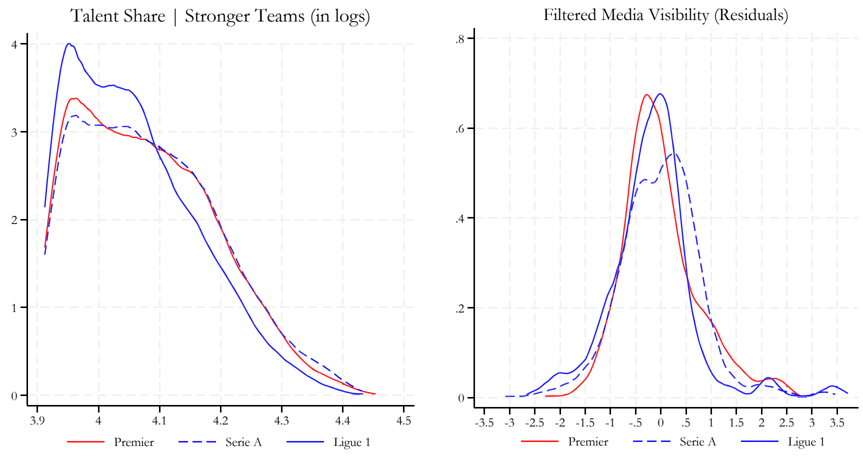

Figure 3: Kernel functions by domestic leagues: allocation of talent and media visibility.

Then, the figure on the right shows the discrepancies in media exposure observed between leagues. Using media visibility scores is a valuable contribution of our analysis, as European football generates revenue from a variety of sources, including television rights and commercial revenues, both dependent on media exposure and popularity.

Given that there are 19 rival teams competing the first division league (20 minus the own team), expression (13) defines the share of talent of each pair of rival teams:

$$s_i = \frac{p_i}{p_i + p_j}100, \text{ and } s_j = \frac{p_j}{p_i + p_j}100, \text{ for } i = 1 \ldots 20; j = 1 \ldots 19. \tag{13}$$

In carrying out the empirical analyses, we estimate regression models where the dependent variable is, respectively, either annual revenue, denoted by R; or annual wage, W; and where Q_ij accounts for the aggregate *joint aggregate quality* of every pair of rival teams:

$$\ln(R_i + R_j) = a + (\beta + \gamma + \gamma\alpha)\ln(s_i) + (\beta + \gamma)\ln(s_j) + \delta\ln(Q_ij)$$

$$\ln(W_i + W_j) = a + (\beta + \gamma + \gamma\alpha)\ln(s_i) + (\beta + \gamma)\ln(s_j) + \delta\ln(Q_ij) \tag{14}$$

Based on the estimations of the coefficients, we aspire to verify or refute several hypotheses. First, the role of the talent concentration hypothesis, which would be irrelevant if $\beta = 0$ or at least $\beta \simeq 0$; also the degree of returns to scale associated to talent concentration, whose weight can be assessed based on the size of the product $\alpha\gamma$; and also to examine how much the distribution of talent shares deviates from the optimum allocations, something that we evaluate based on deviations of optimal shares s^* from the actual s.

5 Discussion of the Results

Football clubs are organizations that operate in the entertainment sector. Our empirical analysis addresses the objectives of team-sport clubs, assuming that sport success and economic outcomes are their ultimate goals, notwithstanding our attempt of representing faithfully the behaviour of the actors involved in this business. Since the clubs aspire to enjoy continuity over time, they will prioritise financial stability and viability, even when they aim to maximise sporting achievements.

Over the years, economists (Alchian 1950) have argued that the organizations that aim to survive in the long run need to ensure a solid financial situation. This also applies to football clubs: if they want success in the long-run, they must try to expand their business size and economic outcomes. Accordingly, we initially examine the case of maximising an objective function defined by the joint annual revenue of every pair of rival teams. As a complementary approach, and given the evidence that European football clubs mostly aim – rather than to maximise profits – to maximise sporting success, subject to a financial sustainable constraint, we also consider another scenario, in which clubs try to maximise sporting achievements, while securing non-negative profits, at least in the long run.

This paper assumes that to achieve a sustainable sporting and financial success – at least in the long run – clubs must ensure sufficient economic returns. Thus, in the empirical section we follow two approaches, both consistent with this view: either the clubs aim to maximise their business and economic returns (that we approximate by annual revenue) or their sporting achievements, subject to a financial constraint (through annual wage bill). We consider that the use of annual wages as a *proxy* for sport outcomes is only meaningful when there is a financial constraint limiting the spending in hiring talent: the clubs try to maximise the quality of the squad with attractive remuneration, which cannot exceed the limit imposed by regulatory bodies. That is, according to our view, the scenario where European leagues operate, since the UEFA financial fair play regulations imply that the clubs' wage spending over a period must not reach more than about 75 % of annual revenues.[9]

The optimal allocation of talent share of the stronger team, out of two rival competitors, to maximise the outcome is reported in expression (9); its value can be rewritten as follows:

$$\left[s^* = \frac{(\beta + \gamma + \alpha\gamma)}{(\beta + \gamma) + (\beta + \gamma + \alpha\gamma)} = \frac{b}{b + c} = \frac{c + \alpha\gamma}{2c + \alpha\gamma} \right] \tag{15}$$

In this expression, the key role of the product $\alpha\gamma$ stands out, as it determines how relevant the "Talent Concentration", C, element is in the domestic leagues under scrutiny. Had C played no role, the main driver to determine the outcome would then be the "Competitive Balance", along with the *joint aggregate quality*. If this is the case, an allocation of talent of 50 % in each rival team will deliver the maximum outcome, thereby defining the optimal allocation of talent share. In this case, deviations of actual s with respect to such an hypothetical optimum $s^* = 1/2$ would indicate the existence of a "Talent Concentration" effect. Expression (16) defines the magnitude of the aforementioned deviations, where the crucial role of $\alpha\gamma$ is again clear:

9 A more sophisticated description of this approach can be developed defining the "Lagrangian" function to define an objective function that involves sport success, subject to a financial stability constraint. Yet, we considered it was unnecessary to develop the full description here, because the final result is basically similar to the model where annual wages are used as the dependent variable.

$$s^* - \frac{1}{2} = \frac{b}{b+c} - \frac{1}{2} = \frac{c+\alpha\gamma}{2c+\alpha\gamma} - \frac{1}{2} = \frac{\alpha\gamma}{4c+2\alpha\gamma} \quad (16)$$

In the following section, we estimate several regression models that result from considering the two aforementioned clubs' objectives along with different model specifications. Then, the main results are interpreted and discussed for the various frameworks (concerning returns to scale) and dependent variables (either revenue or sport success under a financial restriction).

5.1 Estimation Results for Models with and Without Constant Returns to Scale

This section offers several model estimations. On one hand, it reports the results of the "basic model" (Tables 1 and 4), where the regression analyses do not include the *joint aggregate quality* of pair of rival teams. Although these are not the preferred models (among other things given the test for omitted variables), we decided to report these results as well because they help make the point that our hypotheses about the role of B and C are significantly relevant on their own. Besides, different model estimations may be useful for the sake of robustness too (Detailed full estimation results of all the models are reported in Appendix A).

In any case, Tables 1–3 show the results of specification models that impose no restrictions on the returns to scale. The estimations suggest that the football industry exhibits a type of returns to scale that are largely decreasing, with the exception of the "Revenue" model in the case of the (French) Ligue 1, where the coefficients of the two parameters involved ($\beta + \gamma = c$) add up to more than 1. In all the other models, the product is smaller than 1, which means that increasing in certain proportion the amount of inputs will provoke an smaller increase in output.

In Tables 2 and 3, we estimate two approaches of the "extended model" by using alternative *proxy* variables. First, Table 2 incorporates "filtered MVI" to capture the aggregate *joint aggregate quality* of pairs of rival teams.[10] Second, Table 3 reports the results of a similar analysis when *joint aggregate quality* is approximated by "filtered Elo" variable. Remember that in both cases the variables have been

10 One way of capturing the combined quality of a pair of rival teams is through the ability they have to draw attention from the fans and the media. The approach of calculating media visibility scores adopted in previous studies, like (Garcia-del Barrio 2018), seems particularly appropriate insofar as the modern business of sport events generate revenues from sources such as television and media rights (Carmichael, Grix, and Marqués 2017), which are typically related to the popularity of teams among journalists, fans and the public (Aguiar-Noury and Garcia-del Barrio 2022).

Table 1: Estimations of the basic model – no restrictions on returns to scale.

	Parameters	Dep.Var.: Ln(Revenue)			
		Premier	Serie A	Ligue 1	POOLED
ln_talent1	$b = \beta + \gamma + \alpha\gamma$	0.9028	0.3154	1.3172	1.0710
ln_talent2	$c = \beta + \gamma$	0.3017	0.0641	0.2947	0.3546
Constant	a	6.5311	9.4509	3.9172	4.7504
	$\alpha\gamma = b - c$	0.6110	0.2513	1.0226	0.7164
Optimal s^*	$b/(b+c)$	0.7495	0.8311	0.8172	0.7513
	Parameters	**Dep.Var.: Ln(WageLimit)**			
		Premier	**Serie A**	**Ligue 1**	**POOLED**
ln_talent1	$b = \beta + \gamma + \alpha\gamma$	0.8453	0.5366	1.2236	0.8805
ln_talent2	$c = \beta + \gamma$	0.3183	0.1693	0.3253	0.2672
Constant	a	6.6171	7.8265	4.1465	5.8158
	$\alpha\gamma = b - c$	0.5270	0.3672	0.8983	0.6132
Optimal s^*	$b/(b+c)$	0.7264	0.7601	0.7900	0.7671

Table 2: Estimations of the extended model (with *Filtered MVI*) – no restrictions on returns to scale.

	Parameters	Dep.Var.: Ln(Revenue)			
		Premier	Serie A	Ligue 1	POOLED
ln_talent1	$b = \beta + \gamma + \alpha\gamma$	0.9410	0.4324	1.6371	1.0351
ln_talent2	$c = \beta + \gamma$	0.3289	0.0736	0.6004	0.3338
ln_quality(mvi)	$d = \delta$	0.2041	0.2828	0.3122	0.2632
Constant	a	6.3031	8.9220	1.5660	5.0286
	$\alpha\gamma = b - c$	0.6121	0.3587	1.0367	0.7013
Optimal s^*	$b/(b+c)$	0.7410	0.8545	0.7317	0.7562
	Parameters	**Dep.Var.: Ln(WageLimit)**			
		Premier	**Serie A**	**Ligue 1**	**POOLED**
ln_talent1	$b = \beta + \gamma + \alpha\gamma$	0.8831	0.6740	1.5630	0.8356
ln_talent2	$c = \beta + \gamma$	0.3452	0.1867	0.6497	0.2400
ln_quality(mvi)	$d = \delta$	0.2019	0.2966	0.3314	0.2621
Constant	a	6.3916	7.1846	1.6512	6.1539
	$\alpha\gamma = b - c$	0.5379	0.4873	0.9132	0.5956
Optimal s^*	$b/(b+c)$	0.7190	0.7831	0.7064	0.7769

Table 3: Estimations of the extended model (with *Filtered ELO*) – no restrictions on returns to scale.

	Parameters	Dep.Var.: Ln(Revenue)			
		Premier	Serie A	Ligue 1	POOLED
ln_talent1	$b = \beta + \gamma + \alpha\gamma$	0.8122	0.5895	0.9476	1.0348
ln_talent2	$c = \beta + \gamma$	0.2672	0.1820	0.0875	0.3345
ln_quality(elo)	$d = \delta$	0.0372	0.0841	0.0952	0.0698
Constant	a	7.0249	7.9488	6.1165	4.9672
	$\alpha\gamma = b - c$	0.5450	0.4075	0.8601	0.7004
Optimal s^*	$b/(b + c)$	0.7525	0.7641	0.9155	0.7557
	Parameters	**Dep.Var.: Ln(WageLimit)**			
		Premier	**Serie A**	**Ligue 1**	**POOLED**
ln_talent1	$b = \beta + \gamma + \alpha\gamma$	0.7639	0.8583	0.8266	0.8671
ln_talent2	$c = \beta + \gamma$	0.2873	0.3048	0.1027	0.2589
ln_quality(elo)	$d = \delta$	0.0334	0.0842	0.1022	0.0676
Constant	a	7.0614	6.0672	5.5085	5.8960
	$\alpha\gamma = b - c$	0.4766	0.5535	0.7239	0.6082
Optimal s^*	$b/(b + c)$	0.7267	0.7380	0.8895	0.7701

"filtered" by means of simple auxiliary regressions against all the other regressors of the respective considered model.

The analysis and discussion on the estimated optimal shares (s^*), and their deviations from actual talent allocations (s), is kept for another ulterior sub-section. Nevertheless, several implications are achieved from other elements and analyses.

On one hand, the estimated values of product $\alpha\gamma$ (capturing the extent to which more "Talent Concentration", C, translates into greater revenue or sport success) convey a very solid conclusion: C is found to be very significant in determining the outcome, a feature that applies to all the models. Moreover, the corresponding values of $\alpha\gamma$ are very large for the "basic model", but it is still far from zero in all the other models of Tables 2 and 3. It means that even when taking into account the market size and brand status of the clubs (models with "Elo ratings"), or when considering the clubs' media exposure and popularity (models with "MVI scores"), there is a substantial positive impact attached to the "Talent Concentration" hypothesis. This is because concentrating more talent in the strongest team does clearly pay off with greater sporting success and economic profitability.

Finally, there are also substantial discrepancies among domestic leagues in this regard: the preferred models (Tables 2 and 3, in which we control for the *joint* *aggregate quality* of rival teams) disclose that the (French) Ligue 1 stands out as the league where this feature seems more relevant, especially compared to the (Italian) Serie A.[11]

Then, Tables 4–6 collect similar analyses for models with constant returns to scale. In order to comply with the assumption of constant returns to scale, we carry out a constrained estimation by imposing $\beta + \gamma = 1$. Table 4 display the results of the "basic model", while Tables 5 and 6 collects those of the main results obtained for, respectively, models that use "MVI scores" and "Elo ratings" to capture the combined quality of pair of rival teams. The results are similar, in their essential elements, to the previous estimations (the ones in Tables 1–3), which suggests concluding that we obtained robust and consistent results.

Table 4: Estimations of basic model – constant returns to scale.

Constant returns	**Parameters**	**Dep.Var.: Ln(Revenue)**			
		Premier	**Serie A**	**Ligue 1**	**POOLED**
ln_talent1	$b = \beta + \gamma + \alpha\gamma$	2.0478	1.8706	2.4312	2.1229
ln_talent2	$c = \beta + \gamma = 1$	1	1	1	1
Constant	a	−0.7170	−0.3471	−3.2280	−1.9222
	$\alpha\gamma = b - c$	1.0478	0.8706	1.4312	1.1229
Optimal s^*	$b/(b + c)$	0.6719	0.6516	0.7086	0.6798
Constant returns	**Parameters**	**Dep.Var.: Ln(WageLimit)**			
		Premier	**Serie A**	**Ligue 1**	**POOLED**
ln_talent1	$b = \beta + \gamma + \alpha\gamma$	1.9632	1.9274	2.2893	2.0785
ln_talent2	$c = \beta + \gamma = 1$	1	1	1	1
Constant	a	−0.4588	−0.9124	−2.6890	−1.7752
	$\alpha\gamma = b - c$	0.9631	0.9274	1.2893	1.0785
Optimal s^*	$b/(b + c)$	0.6625	0.6584	0.6960	0.6752

11 Given the role of market size and the discrepancies across domestic leagues, we carry out separate estimations by leagues, or – in the pooled analysis – - we introduced dummy variables to control for this feature. Besides, our "filtered MVI" and "filtered Elo" variables may be also a way to capture market size. Moreover, since large part of clubs' revenues are obtained from sources other than gate revenues (or match of the day), and because attendances are limited – and hence distorted – by the stadium capacity, we preferred the two mentioned proxies, whose robust results support our choice. Alternative proxies like stadium capacity have the problem of remaining unchanged over the years.

Table 5: Estimations of extended model (with *Filtered MVI*) – constant returns to scale.

	Parameters	Dep.Var.: Ln(Revenue)			
		Premier	Serie A	Ligue 1	POOLED
ln_talent1	$b = \beta + \gamma + \alpha\gamma$	2.0415	1.9718	2.2679	2.1209
ln_talent2	$c = \beta + \gamma = 1$	1	1	1	1
ln_quality(mvi)	$d = \delta$	0.2044	0.2829	0.3128	0.2631
Constant	a	−0.6632	−0.7762	−2.4803	−1.8592
	$\alpha\gamma = b - c$	1.0415	0.9718	1.2679	1.1209
Optimal s^*	$b/(b+c)$	0.6712	0.6635	0.6940	0.6796
	Parameters	**Dep.Var.: Ln(WageLimit)**			
		Premier	**Serie A**	**Ligue 1**	**POOLED**
ln_talent1	$b = \beta + \gamma + \alpha\gamma$	1.9569	2.0358	2.1160	2.0781
ln_talent2	$c = \beta + \gamma = 1$	1	1	1	1
ln_quality(mvi)	$d = \delta$	0.2022	0.2967	0.3319	0.2620
Constant	a	−0.4056	−1.3717	−1.8959	−1.7192
	$\alpha\gamma = b - c$	0.9569	1.0358	1.1160	1.0781
Optimal s^*	$b/(b+c)$	0.6618	0.6706	0.6791	0.6751

Table 6: Estimations of extended model (with *Filtered ELO*) – constant returns to scale.

	Parameters	Dep.Var.: Ln(Revenue)			
		Premier	Serie A	Ligue 1	POOLED
ln_talent1	$b = \beta + \gamma + \alpha\gamma$	2.0140	1.9490	2.3890	2.1196
ln_talent2	$c = \beta + \gamma = 1$	1	1	1	1
ln_quality(elo)	$d = \delta$	0.0371	0.0844	0.0949	0.0698
Constant	a	−0.5819	−0.6156	−3.1283	−1.9135
	$\alpha\gamma = b - c$	1.0140	0.9490	1.3890	1.1196
Optimal s^*	$b/(b+c)$	0.6682	0.6609	0.7049	0.6794
	Parameters	**Dep.Var.: Ln(WageLimit)**			
		Premier	**Serie A**	**Ligue 1**	**POOLED**
ln_talent1	$b = \beta + \gamma + \alpha\gamma$	1.9327	2.0226	2.2439	2.0788
ln_talent2	$c = \beta + \gamma = 1$	1	1	1	1
ln_quality(elo)	$d = \delta$	0.0333	0.0844	0.1020	0.0676
Constant	a	−0.3372	−1.2477	−2.5820	−1.7815
	$\alpha\gamma = b - c$	0.9327	1.0226	1.2439	1.0788
Optimal s^*	$b/(b+c)$	0.6590	0.6692	0.6917	0.6752

Once the entire calculations, for each domestic league, are completed, the next step consists of comparing the optimal allocations of talent share (in every pairs of rival teams), with the actual shares observed in reality. This is precisely the task we try to perform in the following section.

5.2 Confronting Optimal and Current Allocations of Talent Shares

The most relevant results of the various analyses are summarized in Tables 7 and 8.

In the upper part of the tables, we firstly report the actual allocations of talent shares (of the strongest team) for each domestic league. Then, the table shows the theoretical optimal shares associated to the "basic model", as well as the two alternative optimal share estimated for the "extended model": regressions including "MVI scores" and models with "Elo ratings". Then, to facilitate the interpretation of our results, the lower lines of the tables shows deviations of theoretical shares from actual shares, computed for the different model specifications and leagues.

According to the results in Table 7, several conclusions emerge from both the pooled and the separate analyses by leagues. First, it seems clear that a certain degree of "competitive imbalance" (in allocating the talent share between rival teams) must

Table 7: Talent allocations – extended model without restrictions on returns to scale | Actual versus optimal talent shares (in %).

	Dep.Var.: Ln(Revenue)				**Dep.Var.: Ln(WageLimit)**			
	Premier	**Serie A**	**Ligue 1**	**POOLED**	**Premier**	**Serie A**	**Ligue 1**	**POOLED**
Actual share of talent, "*s*", by leagues	**59.6 %**	**59.8 %**	**58.2 %**	**59.2 %**	**59.6 %**	**59.8 %**	**58.2 %**	**59.2 %**
Optimal *s** basic model	74.9 %	83.1 %	81.7 %	75.1 %	72.6 %	76.0 %	79.0 %	76.7 %
Optimal *s** extended model with filtered MVI	75.2 %	76.4 %	91.6 %	76.6 %	72.7 %	73.8 %	88.9 %	77.0 %
Optimal *s** extended model with filtered Elo	74.1 %	85.4 %	73.2 %	75.6 %	71.9 %	78.3 %	70.6 %	77.7 %
Deviations of optimal *s** from actual "*s*":								
Basic model	15.38	23.27	23.52	15.92	13.08	16.17	20.80	17.51
Extended model with filtered MVI	15.68	16.57	33.35	16.37	13.11	13.96	30.75	17.80
Extended model with filtered Elo	14.54	25.61	14.96	16.41	12.33	18.47	12.43	18.48

The bold values indicate that they are the current or "Actual share of talent, "*s*", by leagues."

Table 8: Talent allocations – extended model with constant returns to scale ($\beta + \gamma = 1$) | Actual versus optimal talent shares (in %).

	Dep.Var.: Ln(Revenue)				Dep.Var.: Ln(WageLimit)			
	Premier	**Serie A**	**Ligue 1**	**POOLED**	**Premier**	**Serie A**	**Ligue 1**	**POOLED**
Actual share of talent, "*s*", by leagues	**59.6 %**	**59.8 %**	**58.2 %**	**59.2 %**	**59.6 %**	**59.8 %**	**58.2 %**	**59.2 %**
Optimal *s** basic model	67.2 %	65.2 %	70.9 %	68.0 %	66.3 %	65.8 %	69.6 %	67.5 %
Optimal *s** extended model with filtered MVI	66.8 %	66.1 %	70.5 %	67.9 %	65.9 %	66.9 %	69.2 %	67.5 %
Optimal *s** extended model with filtered Elo	67.1 %	66.4 %	69.4 %	68.0 %	66.2 %	67.1 %	67.9 %	67.5 %
Deviations of optimal *s** from actual "*s*":								
Basic model	7.62	5.32	12.65	8.78	6.69	6.00	11.39	8.31
Extended model with filtered MVI	7.26	6.25	12.29	8.74	6.34	7.08	10.97	8.32
Extended model with filtered Elo	7.56	6.51	11.20	8.76	6.62	7.22	9.70	8.31

The bold values indicate that they are the current or "Actual share of talent, "*s*", by leagues."

be preferred in order to maximise outcome in the football industry. This is a consistent result, irrespective of which of the two considered club objective prevails. Second, there exist large deviations of these optimal shares from the actual allocations of talent, which are particularly manifest for the case of Ligue 1 (and also perhaps, in the case of Serie A). Third, according to our results, the actual uneven distribution of talent shares (that concentrate around 58 or 59 % of talent in the strongest team) are below the optimum levels, which range between around 65 and 70 % in the models with constant returns to scale (Table 8) and even far beyond 70 % when no restrictions are imposed on the returns to scale (Table 7). These results suggest that the distribution of inputs (of talent) in the football industry may be more effectively arranged to maximise output and achieve the presumed objectives.

There are other conclusions that may be claimed based on the above results. Domestic football leagues in Europe seem to make decisions – as far as hiring and accumulation of talent is concerned – more closely to the win maximisation (similar to the "WageLimit" model), rather than to the profit maximisation behaviour (reflected in the "Revenue" model). This statement is clear given the smaller deviations of the former group compared to the latter group of models.

Another interesting feature is the fact that models with constant returns to scale deliver, in all cases, results associated with smaller deviations from actual talent shares. There may be however two opposing interpretations of this feature. On one hand, it might be that these model specifications (those collected in Table 7) work better to represent the facts of the football industry. But on the other hand, it might also be the case that the other group of models (the ones reported in Table 8) is actually more “realistic”, as they imposed no restrictions on the parameters. If this were the case, we should then conclude that there is still a much greater desirable imbalance between rival teams in order to achieve the goals of football clubs.

Finally, significant discrepancies are observed across domestic leagues. Perhaps the most consistent competition is the Premier League, which stands out as its optimal talent shares are closer to its actual shares than seems to occur in the other domestic leagues considered. Big disparities also emerge for models imposing no restrictions on returns to scale, as compared to the ones with constant returns. In the former case, the models disclose huge differences, especially concerning Ligue 1 and Serie A; whereas the results obtained for the latter group of models are much more similar among them. Hence, our preferred models are – in principle – those of Table 8.

6 Conclusions

In this paper, the business of professional football is characterised in a way that reduces the clubs’ objectives to the classical twofold alternatives: either the clubs aim to maximise sport success, subject to a financial constraint, or economic profitability (revenue). In our framework, the degree of fan enjoyment and, hence, the clubs’ ability to generate revenues are assumed to depend on the distribution of talent share between the two contestants of each pair of rival teams. Accordingly, we postulate a theoretical framework in which the optimal allocations of talent are developed. Then, the degree of interest of football – as an entertainment activity – is postulated to depend mainly on the following elements: (i) the uncertainty of outcome, which in turn depends on the competitive (im)balance between rival teams; (ii) the degree of entertainment delivered by an sport event, whose quality is modelled in such a way it escalates along with the talent share concentrated in the strongest rival team (producing more output than the sum of individual talents); and (iii) the *joint aggregate quality* of each pair of teams competing in an sport event.

In contrast with the notion that competitive balance must be encouraged to preserve outcome uncertainty, this paper has shown that certain (non-trivial) degree of imbalance in the allocation of talent – rather than a perfect competitive balance – seems to be preferable to stimulate the followers’ interest and expand media coverage, thus increasing the business size and revenue.

Different models and empirical analyses suggest the following conclusions. First, the fact that optimal talent shares are far from the *pure* competitive balance situations (50 % of the talent is allocated at each rival team); moreover, it appears to be the case that the optimal theoretical shares are even greater than the actual allocations of talent shares in all three domestic leagues examined. These results suggest that less rather than more competitive balance should be encouraged in the business of professional football to achieve the presumed objectives: sustained sport success in the long-run and economic profitability. The paper also discloses relevant discrepancies across European domestic football leagues, as far as the role of "Talent Concentration" (and the distribution of talent shares) is concerned. For instance, based on our parameter estimations, we find a consistent positive effect of the product $\alpha\gamma$, which captures the extent to which a greater "Talent Concentration" brings forth greater economic returns. Besides, the paper reveals the discrepancies that this feature shows in the different models and domestic leagues.

An important point to be raised from the analysis in this paper is that the identity of the teams that have the higher concentration of playing talent is not fixed. Because our theoretical model is static in nature, it cannot inform over this aspect. That is, whether a more Spanish-style situation where the teams with the highest concentration of talent have remained the same, or whether a more English variant is preferable, where the identity of the dominant team has changed with dynasties (Liverpool 1970s and 1980s, Manchester United 1990s and 2000s, Manchester City 2010s and 2020s).

A final conclusion that emerges from analysing the discrepancies between optimal and actual shares is that European football clubs distribute talent shares in a way that seems more consistent with win maximising ("WageLimit" models) than to the profit maximising hypothesis ("Revenue" models). We also consider valuable the robustness of our results, since the same essential results were derived from various model specifications, such as the one derived – for instance – from the two alternative *proxy* variables that we used to measure the joint quality of pairs of rival teams: models with "filtered Elo" and models with "filtered MVI". Despite this consistency of results, additional research is needed to corroborate the validity and scope of our findings.

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Appendix A: Full Estimations of Relevant Models – By Domestic Leagues

See Tables A.1.a–A.6.b.

Table A.1.a: Ln(Revenue).

	Premier (1.1)	**Serie A (1.2)**	**Ligue 1 (1.3)**	**Pooled (1.4)**
log t1	0.9028***	0.3154	1.3172***	1.0710***
	(0.183)	(0.301)	(0.434)	(0.200)
log t2	0.3017***	0.0641	0.2947	0.3546***
	(0.107)	(0.175)	(0.280)	(0.121)
y2011	0.0185	0.0726**	0.1264***	0.0504***
	(0.022)	(0.030)	(0.032)	(0.017)
y2012	0.1323***	0.1757***	0.1454***	0.1327***
	(0.025)	(0.033)	(0.036)	(0.019)
y2013	0.1598***	0.1841***	0.1755***	0.1577***
	(0.025)	(0.028)	(0.033)	(0.018)
y2014	0.4778***	0.1880***	0.2616***	0.2949***
	(0.023)	(0.033)	(0.037)	(0.019)
y2015	0.6350***	0.2018***	0.1764***	0.3282***
	(0.027)	(0.031)	(0.038)	(0.019)
y2016	0.6717***	0.3824***	0.2044***	0.4029***
	(0.021)	(0.033)	(0.037)	(0.019)
y2017	0.8014***	0.4700***	0.4237***	0.5486***
	(0.027)	(0.030)	(0.042)	(0.020)
y2018	0.7476***	0.4968***	0.3877***	0.5203***
	(0.021)	(0.034)	(0.038)	(0.020)
y2019	0.7580***	0.3498***	0.4543***	0.4968***
	(0.022)	(0.029)	(0.035)	(0.019)
y2020	0.7122***	−0.1347***	0.2651***	0.2781***
	(0.024)	(0.032)	(0.034)	(0.021)
y2021	0.7364***	0.4275***	0.3043***	0.4607***
	(0.022)	(0.030)	(0.033)	(0.018)
y2022	0.8974***	0.4202***	0.5471***	0.5944***
	(0.024)	(0.029)	(0.041)	(0.020)
Premier				1.0088***
				(0.010)
Serie A				0.4555***
				(0.011)
cl games	0.1252***	0.1593***	0.2426***	0.1639***
	(0.002)	(0.003)	(0.005)	(0.002)
eu games	0.0620***	0.0629***	0.1026***	0.0689***
	(0.002)	(0.003)	(0.005)	(0.002)
Constant	6.5311***	9.4509***	3.9172	4.7504***
	(1.136)	(1.864)	(2.794)	(1.254)
N.Obs.	2,451	2,432	2,451	7,340
R-squared	0.8450	0.6180	0.6846	0.7833
AIC	−646.40476	1,583.1312	2,057.3164	5,540.2289

*p<0.1; **p<0.05; ***p<0.01 (standard errors in brackets).

Table A.1.b: Ln(WageLimit).

	Premier (1.5)	**Serie A (1.6)**	**Ligue 1 (1.7)**	**Pooled (1.8)**
log t1	0.8453***	0.5366*	1.2236***	0.8805***
	(0.204)	(0.323)	(0.413)	(0.201)
log t2	0.3183***	0.1693	0.3253	0.2672**
	(0.120)	(0.186)	(0.264)	(0.121)
y2011	0.0344	0.0401	0.1202***	0.0466**
	(0.030)	(0.036)	(0.033)	(0.019)
y2012	0.1587***	0.0993**	0.1400***	0.1158***
	(0.028)	(0.040)	(0.033)	(0.020)
y2013	0.2076***	0.1360***	0.0827**	0.1275***
	(0.028)	(0.033)	(0.033)	(0.019)
y2014	0.3094***	0.1825***	0.1815***	0.2125***
	(0.027)	(0.040)	(0.036)	(0.020)
y2015	0.5154***	0.0871**	0.1303***	0.2391***
	(0.029)	(0.034)	(0.039)	(0.020)
y2016	0.6100***	−0.1263***	0.1960***	0.2083***
	(0.025)	(0.034)	(0.037)	(0.021)
y2017	0.5742***	0.5811***	0.3430***	0.4874***
	(0.031)	(0.032)	(0.040)	(0.020)
y2018	0.6313***	0.6363***	0.3808***	0.5295***
	(0.025)	(0.034)	(0.037)	(0.020)
y2019	0.6758***	0.4022***	0.4622***	0.4910***
	(0.028)	(0.030)	(0.035)	(0.019)
y2020	0.8056***	0.3342***	0.4803***	0.5278***
	(0.027)	(0.037)	(0.039)	(0.021)
y2021	0.7816***	0.6439***	0.6309***	0.6585***
	(0.026)	(0.031)	(0.037)	(0.019)
y2022	0.8751***	0.5831***	0.6377***	0.6744***
	(0.028)	(0.037)	(0.044)	(0.022)
Premier				0.8802***
				(0.010)
Serie A				0.2138***
				(0.012)
cl games	0.1001***	0.1574***	0.2152***	0.1457***
	(0.002)	(0.003)	(0.005)	(0.002)
eu games	0.0524***	0.0746***	0.0967***	0.0693***
	(0.002)	(0.003)	(0.004)	(0.002)
Constant	6.6171***	7.8265***	4.1465	5.8158***
	(1.266)	(1.995)	(2.650)	(1.261)
N.Obs.	2,451	2,470	2,451	7,378
R-squared	0.7810	0.6255	0.6509	0.7481
AIC	−328.5613	2,148.5592	2,099.0034	6,019.7112

**p*<0.1; ***p*<0.05; ****p*<0.01 (standard errors in brackets).

Table A.2.a: Ln(Revenue).

	Premier (2.1)	Serie A (2.2)	Ligue 1 (2.3)	Pooled (2.4)
log t1	0.9410***	0.4324*	1.6371***	1.0351***
	(0.151)	(0.231)	(0.341)	(0.162)
log t2	0.3289***	0.0736	0.6004***	0.3338***
	(0.090)	(0.135)	(0.218)	(0.098)
Filtered mvi	0.2041***	0.2828***	0.3122***	0.2632***
	(0.005)	(0.007)	(0.007)	(0.004)
y2011	0.0808***	0.0283	0.1014***	0.0610***
	(0.016)	(0.024)	(0.020)	(0.013)
y2012	0.2187***	0.1396***	0.1101***	0.1505***
	(0.018)	(0.024)	(0.025)	(0.014)
y2013	0.2124***	0.1834***	0.0792***	0.1551***
	(0.020)	(0.021)	(0.026)	(0.014)
y2014	0.4728***	0.1125***	0.3520***	0.2989***
	(0.017)	(0.026)	(0.026)	(0.015)
y2015	0.6181***	0.2633***	0.1061***	0.3205***
	(0.016)	(0.025)	(0.028)	(0.016)
y2016	0.6374***	0.4404***	0.1471***	0.3921***
	(0.015)	(0.024)	(0.027)	(0.016)
y2017	0.7290***	0.5966***	0.4088***	0.5523***
	(0.017)	(0.023)	(0.030)	(0.014)
y2018	0.7083***	0.5845***	0.2938***	0.5137***
	(0.013)	(0.024)	(0.025)	(0.015)
y2019	0.6771***	0.4124***	0.4258***	0.4791***
	(0.016)	(0.022)	(0.024)	(0.014)
y2020	0.5354***	−0.2293***	0.5644***	0.2595***
	(0.015)	(0.024)	(0.026)	(0.018)
y2021	0.6705***	0.4737***	0.2847***	0.4427***
	(0.016)	(0.022)	(0.023)	(0.014)
y2022	0.8350***	0.4540***	0.5081***	0.5753***
	(0.015)	(0.019)	(0.029)	(0.014)
Premier				0.9696***
				(0.008)
Serie A				0.4138***
				(0.009)
cl games	0.1277***	0.1590***	0.2115***	0.1588***
	(0.001)	(0.002)	(0.004)	(0.002)
eu games	0.0577***	0.0617***	0.1135***	0.0676***
	(0.001)	(0.002)	(0.004)	(0.002)
Constant	6.3031***	8.9220***	1.5660	5.0286***
	(0.943)	(1.433)	(2.191)	(1.015)
N.Obs.	2,451	2,432	2,451	7,340
R-squared	0.9128	0.7814	0.8205	0.8619
AIC	−2,055.2715	227.74973	677.86024	2,236.2685

**p*<0.1; ***p*<0.05; ****p*<0.01 (standard errors in brackets).

Table A.2.b: Ln(WageLimit).

	Premier (2.5)	**Serie A (2.6)**	**Ligue 1 (2.7)**	**Pooled (2.8)**
log t1	0.8831***	0.6740***	1.5630***	0.8356***
	(0.169)	(0.254)	(0.324)	(0.170)
log t2	0.3452***	0.1867	0.6497***	0.2400**
	(0.100)	(0.146)	(0.205)	(0.102)
Filtered mvi	0.2019***	0.2966***	0.3314***	0.2621***
	(0.005)	(0.009)	(0.008)	(0.005)
y2011	0.0960***	−0.0063	0.0937***	0.0572***
	(0.023)	(0.031)	(0.020)	(0.016)
y2012	0.2442***	0.0614**	0.1025***	0.1335***
	(0.020)	(0.031)	(0.022)	(0.015)
y2013	0.2597***	0.1351***	−0.0195	0.1248***
	(0.022)	(0.026)	(0.024)	(0.015)
y2014	0.3045***	0.1032***	0.2775***	0.2166***
	(0.020)	(0.029)	(0.025)	(0.016)
y2015	0.4987***	0.1508***	0.0557*	0.2331***
	(0.019)	(0.028)	(0.029)	(0.017)
y2016	0.5760***	−0.0657***	0.1352***	0.1975***
	(0.017)	(0.025)	(0.027)	(0.017)
y2017	0.5026***	0.7137***	0.3273***	0.4910***
	(0.020)	(0.024)	(0.027)	(0.016)
y2018	0.5924***	0.7282***	0.2810***	0.5228***
	(0.017)	(0.023)	(0.024)	(0.016)
y2019	0.5957***	0.4678***	0.4320***	0.4733***
	(0.020)	(0.027)	(0.022)	(0.015)
y2020	0.6307***	0.2439***	0.7979***	0.5091***
	(0.019)	(0.029)	(0.029)	(0.017)
y2021	0.7164***	0.6921***	0.6101***	0.6405***
	(0.020)	(0.020)	(0.024)	(0.015)
y2022	0.8134***	0.6185***	0.5963***	0.6553***
	(0.018)	(0.025)	(0.024)	(0.015)
Premier				0.8411***
				(0.008)
Serie A				0.1726***
				(0.009)
cl games	0.1026***	0.1570***	0.1823***	0.1406***
	(0.001)	(0.003)	(0.003)	(0.002)
eu games	0.0481***	0.0734***	0.1084***	0.0680***
	(0.001)	(0.002)	(0.003)	(0.002)
Constant	6.3916***	7.1846***	1.6512	6.1539***
	(1.054)	(1.568)	(2.072)	(1.065)
N.Obs.	2,451	2,470	2,451	7,378
R-squared	0.8634	0.7674	0.8175	0.8334
AIC	−1,483.1674	974.40593	511.89088	2,972.7482

**p*<0.1; ***p*<0.05; ****p*<0.01 (standard errors in brackets).

Table A.3.a: Ln(Revenue).

	Premier (3.1)	Serie A (3.2)	Ligue 1 (3.3)	Pooled (3.4)
log t1	0.8122***	0.5895***	0.9476***	1.0348***
	(0.160)	(0.222)	(0.325)	(0.172)
log t2	0.2672***	0.1820	0.0875	0.3345***
	(0.096)	(0.132)	(0.209)	(0.106)
Filtered elo	0.0372***	0.0841***	0.0952***	0.0698***
	(0.002)	(0.002)	(0.002)	(0.002)
y2011	0.0423**	0.0017	0.1590***	0.0552***
	(0.017)	(0.024)	(0.028)	(0.015)
y2012	0.1574***	0.0917***	0.1906***	0.1376***
	(0.020)	(0.024)	(0.034)	(0.017)
y2013	0.1779***	0.1165***	0.2195***	0.1626***
	(0.020)	(0.025)	(0.028)	(0.016)
y2014	0.4929***	0.1289***	0.3191***	0.2935***
	(0.019)	(0.023)	(0.030)	(0.016)
y2015	0.6446***	0.1105***	0.2810***	0.3325***
	(0.023)	(0.025)	(0.028)	(0.018)
y2016	0.6502***	0.2961***	0.3689***	0.4077***
	(0.018)	(0.023)	(0.029)	(0.016)
y2017	0.7977***	0.4364***	0.4830***	0.5531***
	(0.020)	(0.024)	(0.035)	(0.016)
y2018	0.7377***	0.4706***	0.4688***	0.5253***
	(0.017)	(0.024)	(0.030)	(0.016)
y2019	0.7449***	0.3165***	0.5499***	0.5016***
	(0.018)	(0.024)	(0.025)	(0.015)
y2020	0.6637***	−0.1110***	0.3474***	0.2733***
	(0.021)	(0.023)	(0.028)	(0.018)
y2021	0.7175***	0.4521***	0.3372***	0.4656***
	(0.017)	(0.022)	(0.027)	(0.015)
y2022	0.8496***	0.4601***	0.6465***	0.5994***
	(0.019)	(0.021)	(0.033)	(0.016)
Premier				1.0093***
				(0.009)
Serie A				0.4547***
				(0.009)
cl games	0.1265***	0.1554***	0.2461***	0.1637***
	(0.001)	(0.002)	(0.004)	(0.002)
eu games	0.0657***	0.0537***	0.1008***	0.0691***
	(0.002)	(0.002)	(0.003)	(0.002)
Constant	7.0249***	7.9488***	6.1165***	4.9672***
	(0.999)	(1.388)	(2.086)	(1.090)
N.Obs.	2,451	2,432	2,451	7,334
R-squared	0.8918	0.8025	0.8176	0.8532
AIC	−1,525.7107	−19.263395	717.09384	2,676.0352

**p*<0.1; ***p*<0.05; ****p*<0.01 (standard errors in brackets).

Table A.3.b: Ln(WageLimit).

	Premier (3.5)	**Serie A (3.6)**	**Ligue 1 (3.7)**	**Pooled (3.8)**
log t1	0.7639***	0.8583***	0.8266***	0.8671***
	(0.183)	(0.256)	(0.297)	(0.178)
log t2	0.2873***	0.3048**	0.1027	0.2589**
	(0.110)	(0.150)	(0.190)	(0.109)
Filtered elo	0.0334***	0.0842***	0.1022***	0.0676***
	(0.002)	(0.002)	(0.002)	(0.002)
y2011	0.0558**	−0.0312	0.1552***	0.0515***
	(0.025)	(0.032)	(0.028)	(0.017)
y2012	0.1814***	0.0150	0.1885***	0.1206***
	(0.024)	(0.030)	(0.030)	(0.017)
y2013	0.2239***	0.0672**	0.1300***	0.1323***
	(0.025)	(0.029)	(0.027)	(0.017)
y2014	0.3231***	0.1221***	0.2433***	0.2137***
	(0.022)	(0.028)	(0.027)	(0.016)
y2015	0.5241***	0.0015	0.2426***	0.2439***
	(0.026)	(0.027)	(0.028)	(0.018)
y2016	0.5906***	−0.2137***	0.3727***	0.2131***
	(0.022)	(0.025)	(0.027)	(0.019)
y2017	0.5709***	0.5463***	0.4067***	0.4918***
	(0.025)	(0.027)	(0.032)	(0.017)
y2018	0.6224***	0.6090***	0.4679***	0.5343***
	(0.022)	(0.027)	(0.026)	(0.017)
y2019	0.6640***	0.3680***	0.5649***	0.4958***
	(0.024)	(0.028)	(0.027)	(0.017)
y2020	0.7619***	0.3835***	0.5687***	0.5326***
	(0.023)	(0.028)	(0.030)	(0.017)
y2021	0.7646***	0.6673***	0.6662***	0.6633***
	(0.023)	(0.025)	(0.030)	(0.017)
y2022	0.8321***	0.6220***	0.7445***	0.6793***
	(0.024)	(0.030)	(0.036)	(0.019)
Premier				0.8800***
				(0.009)
Serie A				0.2147***
				(0.009)
cl games	0.1013***	0.1528***	0.2190***	0.1456***
	(0.001)	(0.003)	(0.004)	(0.002)
eu games	0.0557***	0.0655***	0.0949***	0.0694***
	(0.002)	(0.003)	(0.003)	(0.002)
Constant	7.0614***	6.0672***	6.5085***	5.8960***
	(1.146)	(1.591)	(1.905)	(1.125)
N.Obs.	2,451	2,470	2,451	7,372
R-squared	0.8280	0.7718	0.8178	0.8199
AIC	−919.16066	926.99935	506.91649	3,545.042

*p<0.1; **p<0.05; ***p<0.01 (standard errors in brackets).

Table A.4.a: Ln(Revenue).

	Premier (4.1)	**Serie A (4.2)**	**Ligue 1 (4.3)**	**Pooled (4.4)**
log t1	2.0478***	1.8706***	2.4312***	2.1229***
	(0.041)	(0.062)	(0.082)	(0.040)
log t2	1	1	1	1
	(0.000)	(0.000)	(0.000)	(0.000)
y2011	0.0207	0.0733**	0.1329***	0.0536***
	(0.022)	(0.030)	(0.031)	(0.017)
y2012	0.1338***	0.1794***	0.1440***	0.1338***
	(0.026)	(0.033)	(0.036)	(0.019)
y2013	0.1628***	0.1851***	0.1729***	0.1585***
	(0.025)	(0.028)	(0.033)	(0.018)
y2014	0.4791***	0.1901***	0.2631***	0.2965***
	(0.024)	(0.034)	(0.037)	(0.019)
y2015	0.6342***	0.2038***	0.1744***	0.3279***
	(0.027)	(0.031)	(0.038)	(0.019)
y2016	0.6793***	0.3825***	0.2118***	0.4077***
	(0.022)	(0.032)	(0.037)	(0.019)
y2017	0.8063***	0.4784***	0.4221***	0.5522***
	(0.028)	(0.030)	(0.042)	(0.020)
y2018	0.7496***	0.5030***	0.3875***	0.5226***
	(0.022)	(0.034)	(0.039)	(0.020)
y2019	0.7695***	0.3608***	0.4522***	0.5025***
	(0.022)	(0.030)	(0.035)	(0.019)
y2020	0.7162***	−0.1294***	0.2718***	0.2829***
	(0.025)	(0.032)	(0.034)	(0.021)
y2021	0.7414***	0.4365***	0.3063***	0.4653***
	(0.022)	(0.030)	(0.033)	(0.018)
y2022	0.9032***	0.4203***	0.5448***	0.5957***
	(0.024)	(0.029)	(0.042)	(0.020)
Premier				1.0090***
				(0.010)
Serie A				0.4560***
				(0.011)
cl games	0.1252***	0.1598***	0.2424***	0.1640***
	(0.002)	(0.003)	(0.005)	(0.002)
eu games	0.0616***	0.0627***	0.1020***	0.0687***
	(0.002)	(0.003)	(0.005)	(0.002)
Constant	−0.7170***	−0.3471	−3.2280***	−1.9222***
	(0.168)	(0.250)	(0.337)	(0.162)
N.Obs.	2,451	2,432	2,451	7,340
AIC	−615.05842	1,607.1156	2,063.0867	5,567.2921

*p<0.1; **p<0.05; ***p<0.01 (standard errors in brackets).

Table A.4.b: Ln(WageLimit).

	Premier (4.5)	**Serie A (4.6)**	**Ligue 1 (4.7)**	**Pooled (4.8)**
log t1	1.9632***	1.9274***	2.2893***	2.0785***
	(0.044)	(0.067)	(0.081)	(0.041)
log t2	1	1	1	1
	(0.000)	(0.000)	(0.000)	(0.000)
y2011	0.0366	0.0408	0.1264***	0.0504***
	(0.030)	(0.036)	(0.032)	(0.019)
y2012	0.1602***	0.1026**	0.1386***	0.1172***
	(0.028)	(0.040)	(0.033)	(0.020)
y2013	0.2106***	0.1366***	0.0802**	0.1283***
	(0.028)	(0.033)	(0.033)	(0.019)
y2014	0.3107***	0.1840***	0.1830***	0.2144***
	(0.027)	(0.040)	(0.036)	(0.020)
y2015	0.5147***	0.0934***	0.1284***	0.2403***
	(0.029)	(0.034)	(0.039)	(0.020)
y2016	0.6174***	−0.1264***	0.2031***	0.2138***
	(0.025)	(0.033)	(0.037)	(0.021)
y2017	0.5790***	0.5881***	0.3415***	0.4914***
	(0.031)	(0.032)	(0.040)	(0.020)
y2018	0.6332***	0.6413***	0.3806***	0.5320***
	(0.025)	(0.034)	(0.037)	(0.020)
y2019	0.6870***	0.4115***	0.4602***	0.4974***
	(0.028)	(0.030)	(0.036)	(0.019)
y2020	0.8095***	0.3392***	0.4867***	0.5334***
	(0.027)	(0.037)	(0.039)	(0.021)
y2021	0.7864***	0.6513***	0.6328***	0.6637***
	(0.027)	(0.031)	(0.037)	(0.019)
y2022	0.8807***	0.5829***	0.6355***	0.6759***
	(0.028)	(0.037)	(0.045)	(0.022)
Premier				0.8803***
				(0.010)
Serie A				0.2147***
				(0.012)
cl games	0.1001***	0.1579***	0.2151***	0.1458***
	(0.002)	(0.003)	(0.005)	(0.002)
eu games	0.0520***	0.0745***	0.0962***	0.0690***
	(0.002)	(0.003)	(0.004)	(0.002)
Constant	−0.4588**	−0.9124***	−2.6890***	−1.7752***
	(0.180)	(0.272)	(0.331)	(0.165)
N.Obs.	2,451	2,470	2,451	7,378
AIC	−302.61493	2,163.9907	2,103.996	6,053.8817

**p*<0.1; ***p*<0.05; ****p*<0.01 (standard errors in brackets).

Table A.5.a: Ln(Revenue).

	Premier (5.1)	**Serie A (5.2)**	**Ligue 1 (5.3)**	**Pooled (5.4)**
log t1	2.0415***	1.9718***	2.2679***	2.1209***
	(0.032)	(0.047)	(0.061)	(0.032)
log t2	1	1	1	1
	(0.000)	(0.000)	(0.000)	(0.000)
Filtered mvi	0.2044***	0.2829***	0.3128***	0.2631***
	(0.005)	(0.007)	(0.007)	(0.004)
y2011	0.0830***	0.0291	0.1051***	0.0643***
	(0.016)	(0.024)	(0.020)	(0.013)
y2012	0.2203***	0.1432***	0.1092***	0.1517***
	(0.018)	(0.024)	(0.025)	(0.014)
y2013	0.2154***	0.1844***	0.0776***	0.1559***
	(0.020)	(0.022)	(0.026)	(0.015)
y2014	0.4740***	0.1146***	0.3530***	0.3006***
	(0.017)	(0.026)	(0.026)	(0.015)
y2015	0.6173***	0.2652***	0.1048***	0.3202***
	(0.016)	(0.025)	(0.028)	(0.016)
y2016	0.6446***	0.4404***	0.1512***	0.3971***
	(0.015)	(0.024)	(0.028)	(0.016)
y2017	0.7336***	0.6049***	0.4079***	0.5560***
	(0.017)	(0.023)	(0.030)	(0.014)
y2018	0.7102***	0.5908***	0.2935***	0.5160***
	(0.014)	(0.024)	(0.025)	(0.015)
y2019	0.6881***	0.4233***	0.4246***	0.4850***
	(0.017)	(0.022)	(0.025)	(0.014)
y2020	0.5391***	−0.2241***	0.5687***	0.2644***
	(0.016)	(0.024)	(0.026)	(0.019)
y2021	0.6752***	0.4826***	0.2858***	0.4475***
	(0.016)	(0.022)	(0.023)	(0.014)
y2022	0.8405***	0.4541***	0.5067***	0.5767***
	(0.015)	(0.019)	(0.029)	(0.014)
Premier				0.9698***
				(0.008)
Serie A				0.4144***
				(0.009)
cl games	0.1277***	0.1595***	0.2114***	0.1589***
	(0.001)	(0.002)	(0.004)	(0.002)
eu games	0.0574***	0.0615***	0.1132***	0.0674***
	(0.001)	(0.002)	(0.004)	(0.002)
Constant	−0.6632***	−0.7762***	−2.4803***	−1.8592***
	(0.129)	(0.189)	(0.248)	(0.129)
N.Obs.	2,451	2,432	2,451	7,340
AIC	−2,002.7333	270.06607	680.23864	2,282.7908

*p<0.1; **p<0.05; ***p<0.01 (standard errors in brackets).

Table A.5.b: Ln(WageLimit).

	Premier (5.5)	**Serie A (5.6)**	**Ligue 1 (5.7)**	**Pooled (5.8)**
log t1	1.9569***	2.0358***	2.1160***	2.0781***
	(0.035)	(0.054)	(0.057)	(0.033)
log t2	1	1	1	1
	(0.000)	(0.000)	(0.000)	(0.000)
Filtered mvi	0.2022***	0.2967***	0.3319***	0.2620***
	(0.005)	(0.009)	(0.008)	(0.005)
y2011	0.0982***	−0.0057	0.0969***	0.0612***
	(0.023)	(0.031)	(0.020)	(0.016)
y2012	0.2458***	0.0646**	0.1017***	0.1350***
	(0.020)	(0.031)	(0.022)	(0.015)
y2013	0.2626***	0.1357***	−0.0209	0.1257***
	(0.022)	(0.026)	(0.024)	(0.015)
y2014	0.3057***	0.1047***	0.2784***	0.2185***
	(0.020)	(0.030)	(0.025)	(0.016)
y2015	0.4980***	0.1569***	0.0546*	0.2344***
	(0.019)	(0.028)	(0.029)	(0.017)
y2016	0.5831***	−0.0657***	0.1388***	0.2032***
	(0.017)	(0.024)	(0.028)	(0.017)
y2017	0.5071***	0.7206***	0.3264***	0.4952***
	(0.020)	(0.024)	(0.027)	(0.016)
y2018	0.5942***	0.7332***	0.2808***	0.5254***
	(0.017)	(0.023)	(0.024)	(0.016)
y2019	0.6065***	0.4769***	0.4309***	0.4799***
	(0.020)	(0.027)	(0.022)	(0.015)
y2020	0.6342***	0.2488***	0.8017***	0.5149***
	(0.019)	(0.029)	(0.029)	(0.017)
y2021	0.7210***	0.6994***	0.6111***	0.6459***
	(0.020)	(0.020)	(0.024)	(0.015)
y2022	0.8187***	0.6182***	0.5951***	0.6568***
	(0.018)	(0.025)	(0.024)	(0.015)
Premier				0.8412***
				(0.008)
Serie A				0.1736***
				(0.009)
cl games	0.1027***	0.1575***	0.1822***	0.1407***
	(0.001)	(0.003)	(0.003)	(0.002)
eu games	0.0478***	0.0733***	0.1081***	0.0678***
	(0.001)	(0.002)	(0.003)	(0.002)
Constant	−0.4056***	−1.3717***	−1.8959***	−1.7192***
	(0.144)	(0.217)	(0.233)	(0.136)
N.Obs.	2,451	2,470	2,451	7,378
AIC	−1,443.9423	999.25566	513.49173	3,029.4757

**p*<0.1; ***p*<0.05; ****p*<0.01 (standard errors in brackets).

Table A.6.a: Ln(Revenue).

	Premier (6.1)	**Serie A (6.2)**	**Ligue 1 (6.3)**	**Pooled (6.4)**
log t1	2.0140***	1.9490***	2.3890***	2.1196***
	(0.036)	(0.046)	(0.064)	(0.034)
log t2	1	1	1	1
	(0.000)	(0.000)	(0.000)	(0.000)
Filtered elo	0.0371***	0.0844***	0.0949***	0.0698***
	(0.002)	(0.002)	(0.002)	(0.002)
y2011	0.0446***	0.0022	0.1674***	0.0586***
	(0.017)	(0.024)	(0.028)	(0.015)
y2012	0.1590***	0.0947***	0.1886***	0.1388***
	(0.020)	(0.024)	(0.034)	(0.017)
y2013	0.1810***	0.1172***	0.2160***	0.1634***
	(0.021)	(0.025)	(0.028)	(0.016)
y2014	0.4943***	0.1306***	0.3208***	0.2952***
	(0.019)	(0.024)	(0.030)	(0.016)
y2015	0.6438***	0.1119***	0.2781***	0.3321***
	(0.023)	(0.026)	(0.028)	(0.018)
y2016	0.6581***	0.2959***	0.3780***	0.4126***
	(0.019)	(0.023)	(0.029)	(0.016)
y2017	0.8029***	0.4437***	0.4808***	0.5568***
	(0.021)	(0.025)	(0.035)	(0.016)
y2018	0.7398***	0.4760***	0.4683***	0.5276***
	(0.018)	(0.024)	(0.030)	(0.016)
y2019	0.7570***	0.3260***	0.5468***	0.5075***
	(0.018)	(0.024)	(0.026)	(0.015)
y2020	0.6679***	−0.1064***	0.3559***	0.2782***
	(0.021)	(0.023)	(0.028)	(0.018)
y2021	0.7228***	0.4600***	0.3397***	0.4703***
	(0.017)	(0.022)	(0.027)	(0.015)
y2022	0.8557***	0.4602***	0.6432***	0.6008***
	(0.019)	(0.021)	(0.033)	(0.016)
Premier				1.0095***
				(0.009)
Serie A				0.4553***
				(0.009)
cl games	0.1265***	0.1558***	0.2459***	0.1639***
	(0.001)	(0.002)	(0.004)	(0.002)
eu games	0.0653***	0.0535***	0.1001***	0.0688***
	(0.002)	(0.002)	(0.003)	(0.002)
Constant	−0.5819***	−0.6156***	−3.1283***	−1.9135***
	(0.147)	(0.187)	(0.263)	(0.138)
N.Obs.	2,451	2,432	2,451	7,334
AIC	−1,475.3047	17.020398	737.50364	2,719.6231

*p<0.1; **p<0.05; ***p<0.01 (standard errors in brackets).

Table A.6.b: Ln(WageLimit).

	Premier (6.5)	**Serie A (6.6)**	**Ligue 1 (6.7)**	**Pooled (6.8)**
log t1	1.9327***	2.0226***	2.2439***	2.0788***
	(0.041)	(0.053)	(0.060)	(0.036)
log t2	1	1	1	1
	(0.000)	(0.000)	(0.000)	(0.000)
Filtered elo	0.0333***	0.0844***	0.1020***	0.0676***
	(0.002)	(0.002)	(0.002)	(0.002)
y2011	0.0581**	−0.0308	0.1635***	0.0553***
	(0.025)	(0.032)	(0.028)	(0.017)
y2012	0.1829***	0.0175	0.1865***	0.1220***
	(0.024)	(0.030)	(0.030)	(0.017)
y2013	0.2270***	0.0676**	0.1265***	0.1332***
	(0.026)	(0.029)	(0.027)	(0.017)
y2014	0.3244***	0.1232***	0.2450***	0.2155***
	(0.023)	(0.028)	(0.028)	(0.017)
y2015	0.5233***	0.0065	0.2398***	0.2452***
	(0.026)	(0.027)	(0.028)	(0.018)
y2016	0.5984***	−0.2140***	0.3816***	0.2186***
	(0.023)	(0.025)	(0.027)	(0.019)
y2017	0.5759***	0.5520***	0.4045***	0.4958***
	(0.025)	(0.027)	(0.032)	(0.017)
y2018	0.6244***	0.6131***	0.4674***	0.5368***
	(0.022)	(0.027)	(0.027)	(0.017)
y2019	0.6758***	0.3757***	0.5619***	0.5022***
	(0.024)	(0.027)	(0.028)	(0.017)
y2020	0.7661***	0.3878***	0.5770***	0.5383***
	(0.023)	(0.028)	(0.031)	(0.017)
y2021	0.7697***	0.6736***	0.6687***	0.6685***
	(0.023)	(0.025)	(0.030)	(0.017)
y2022	0.8381***	0.6219***	0.7412***	0.6807***
	(0.024)	(0.030)	(0.036)	(0.019)
Premier				0.8802***
				(0.009)
Serie A				0.2157***
				(0.009)
cl games	0.1013***	0.1532***	0.2188***	0.1457***
	(0.001)	(0.003)	(0.004)	(0.002)
eu games	0.0553***	0.0654***	0.0941***	0.0691***
	(0.002)	(0.003)	(0.003)	(0.002)
Constant	−0.3372**	−1.2476***	−2.5820***	−1.7815***
	(0.166)	(0.216)	(0.247)	(0.145)
N.Obs.	2,451	2,470	2,451	7,372
AIC	−882.34394	945.01809	528.5183	3,594.7077

*p<0.1; **p<0.05; ***p<0.01 (standard errors in brackets).

Appendix B: Descriptive Statistics of the Main Variables (Pair of Teams) – By Season and League

	N.	Mean	Std. Dev.	Min.	Max.
Revenue (pair of teams)					
TOTAL	*7,334*	*278,269.8*	*217,595.7*	*34,313*	*1,416,145*
By season 2009-10	551	183,596.8	112,314.3	48,291	632,126
2010–11	570	182,135.2	106,422.2	44,875	619,597
2011–12	570	203,402.5	123,828.9	44,608	688,629
2012–13	570	210,216.6	134,843.5	41,446	740,876
2013–14	570	249,543.2	173,324.2	44,186	934,413
2014–15	551	270,838.2	195,925.4	51,258	982,535
2015–16	570	292,014.6	226,303.4	34,313	1,216,720
2016–17	551	337,588.0	237,233.1	57,563	1,230,031
2017–18	570	343,036.9	242,763.4	53,830	1,233,888
2018–19	570	356,919.2	274,100.6	64,695	1,322,006
2019–20	551	285,988.6	238,866.2	45,791	1,138,860
2020–21	570	337,384.0	248,417.2	51,900	1,237,336
2021–22	570	363,674.1	274,847.7	51,919	1,416,145
By league premier	2,451	445,156.7	237,819.5	110,665	1,416,145
Serie A	2,432	236,361.5	137,753.9	45,791	1,038,580
Ligue 1	2,451	152,966.2	144,964.1	34,313	967,701
Wages (pair of teams)					
TOTAL	*7,372*	*181,478.0*	*135,005.2*	*21,457*	*865,699.8*
By season 2009-10	551	122,110.0	75,116.8	33,076	420,254.0
2010–11	570	122,786.2	75,235.1	27,269	404,045.1
2011–12	570	133,173.4	80,980.9	27,804	450,819.4
2012–13	570	136,589.4	87,337.9	29,705	485,423.8
2013–14	570	147,846.0	93,754.7	32,306	507,876.8
2014–15	570	160,848.0	110,742.7	31,080	553,029.8
2015–16	570	163,302.3	131,133.2	21,457	633,820.0
2016–17	551	196,149.0	117,484.7	37,883	613,269.9
2017–18	570	217,960.3	135,631.6	30,899	632,184.0
2018–19	570	222,359.6	153,798.9	38,358	756,890.8
2019–20	570	224,200.7	156,736.3	37,936	771,780.0
2020–21	570	252,322.1	162,535.4	43,500	787,687.1
2021–22	570	258,077.4	192,677.0	44,986	865,699.8
By league premier	2,451	285,770.7	135,820.1	64,569	865,699.8
Serie A	2,470	145,556.9	92,594.6	25,900	584,500.0
Ligue 1	2,451	113,384.9	104,533.6	21,457	864,510.0

(continued)

	N.	Mean	Std. Dev.	Min.	Max.
Points (pair of teams)					
TOTAL	*7,410*	*103.3462*	*23.34547*	*36*	*195*
By season 2009-10	570	103.8667	21.94945	49	171
2010–11	570	102.6333	17.82035	55	158
2011–12	570	102.3333	20.72494	54	178
2012–13	570	103.2000	21.80434	52	167
2013–14	570	104.7667	24.69597	52	187
2014–15	570	103.7333	21.26382	43	166
2015–16	570	103.6667	21.44247	51	173
2016–17	570	105.4000	26.00077	44	182
2017–18	570	104.7333	25.71793	46	186
2018–19	570	104.2667	25.04918	42	195
2019–20	570	95.7000	25.66732	36	180
2020–21	570	104.8667	24.35105	43	170
2021–22	570	104.3333	24.10101	45	185
By league premier	2,470	104.6769	24.13940	42	195
Serie A	2,470	104.0769	24.09552	42	187
Ligue 1	2,470	101.2846	21.57805	36	182
MVI (pair of teams)					
TOTAL	*7,410*	*18.59960*	*25.63048*	*0.05335*	*254.2325*
By season 2009-10	570	25.00413	30.32533	1.18276	189.52740
2010–11	570	26.10789	19.85240	1.50824	102.67310
2011–12	570	20.37147	16.56626	1.61030	81.16901
2012–13	570	27.96933	21.37244	2.16883	132.10120
2013–14	570	18.90993	16.64244	0.73308	95.76019
2014–15	570	14.61568	16.98294	1.84314	109.63660
2015–16	570	14.41261	16.78527	0.86824	90.42859
2016–17	570	9.766674	13.23484	0.12606	76.22235
2017–18	570	15.64477	20.47514	0.53797	101.81950
2018–19	570	11.33878	20.14954	0.05334	103.67850
2019–20	570	24.34301	46.14447	0.05709	254.23250
2020–21	570	11.78650	18.41037	0.23670	97.09428
2021–22	570	21.52407	41.74971	0.26018	227.54180
By league premier	2,470	31.37368	31.29020	0.53572	254.2325
Serie A	2,470	16.80357	20.94619	0.05335	185.6197
Ligue 1	2,470	7.62156	16.32299	0.05709	152.3542

(continued)

	N.	Mean	Std. Dev.	Min.	Max.
Elo_100 (pair of teams)					
TOTAL	*7,410*	*160.678*	*11.84362*	*127.8331*	*199.8463*
By season 2009-10	570	161.0037	10.43301	137.8559	199.3445
2010–11	570	163.2929	9.97221	139.4597	199.5556
2011–12	570	160.4909	10.74856	135.0408	194.7609
2012–13	570	161.6413	10.49091	137.5030	198.0046
2013–14	570	160.7669	10.35398	141.6785	194.8350
2014–15	570	162.7072	11.91867	132.3371	196.6153
2015–16	570	163.3234	11.65670	136.3685	196.5564
2016–17	570	166.0837	10.97294	141.7450	194.1166
2017–18	570	161.9032	12.60419	132.2893	196.4033
2018–19	570	158.5925	12.63969	136.3207	199.5289
2019–20	570	153.3300	12.04174	127.8331	198.5147
2020–21	570	156.8914	12.07252	129.6178	199.8463
2021–22	570	158.7862	12.30641	132.1347	199.2710
By league premier	2,470	170.1295	10.36843	132.3371	199.8463
Serie A	2,470	158.0488	10.02774	127.8331	194.1166
Ligue 1	2,470	153.8555	8.367742	129.8963	188.7929
Talent share (leader team)					
TOTAL	*7,410*	*59.20282*	*6.745382*	*50*	*85.96491*
By season 2009-10	570	59.16957	6.498533	50	81.90476
2010–11	570	57.18266	5.800538	50	79.16666
2011–12	570	58.13036	5.962185	50	79.24529
2012–13	570	58.86122	6.207370	50	79.81651
2013–14	570	59.58814	6.692729	50	80.31496
2014–15	570	58.80893	6.245644	50	82.07547
2015–16	570	58.56787	6.832921	50	84.21053
2016–17	570	60.00935	7.127310	50	83.48624
2017–18	570	59.81505	6.846696	50	81.89655
2018–19	570	60.15495	7.422953	50	85.96491
2019–20	570	59.48550	7.204359	50	83.95061
2020–21	570	59.99375	7.307375	50	81.98198
2021–22	570	59.86928	6.692255	50	80.86957
By league premier	2,470	59.56560	6.872715	50	85.96491
Serie A	2,470	59.83958	6.993239	50	84.11215
Ligue 1	2,470	58.20328	6.233861	50	84.21053

Source: Number of points in domestic leagues were collected from: www.transfermarkt.de. Annual wages and revenues from: Deloitte ARFF (2005–2023), FML (2009–2022), clubs' accounts, and databases (Sabi and Amadeus). Media visibility index: Authors' own calculations based on MERIT methodology: www.meritsocialvalue.com.

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