An Application of Contest Success Functions for Draws on European Soccer

A contest success function (success function) maps the level of efforts into winning and losing probabilities in contest theory. We aim to assess the empirical performance of success functions for draws and analyse the differences between European soccer leagues in terms of home-bias, return on talent, and talent inequality. We use a dataset with 10569 matches acquired manually from *transfermarkt.co.uk* containing club based average market values of the line-up of teams for each match played through twelve seasons from seven major European soccer leagues. The results are obtained estimating the parameters of the success functions with a general maximum-likelihood method and the hypotheses suggested by success functions are controlled with a probit regression. Two of the success functions outperform one conclusively. The difference in the performance between these two groups results from the contrast in the main determinant of the success function in allocating the probability of a draw. The high performing success functions take difference in aggregate talent levels as the main determinant in drawing while the other takes the aggregate talent as the main determinant. The results also show that there are major differences across leagues in terms of return on talent, home-bias, and talent inequality despite the similarities in economic environment and the homogeneity in the rules of the game imposed across leagues. Our analysis sheds light on the contributions and implications of microeconomic theory to model sports and presents the differing characteristics of the European soccer leagues that impact match results significantly.

Keywords: Contest success function, draw, home-bias, European soccer leagues.

Subject classification codes: C51, D72, L83

Introduction

A Contest Success Function (success function for short, hereinafter) is a mathematical tool used in contest theory to determine the winning probabilities of each contender in a contest in terms of individual and aggregate effort/investment exerted. Its intuitive structure and convenient use has given rise to its use in various economic settings that possess an implicit or explicit contest structure. These applications include major fields in economics, business, and political science such as rent-seeking (Nitzan, 1991 and 1994), military conflicts (Garfinkel and Skaperdas, 2000; Corchón and Beviá, 2010), marketing (Schmalensee, 1976; Haan and Moraga-González, 2011), litigation (Robson and Skaperdas, 2008), and sports (Szymanski, 2003 and Szymanski and Kesenne, 2004).

Unlike all-pay auctions in which the highest investment/bid wins with certainty (see for example Baye, Kovenock, and de Vries (1996)), the contests mentioned above have an element of uncertainty. By capturing this uncertainty, success functions provide a theoretical tool to form expectations on the equilibrium outcome of and effort/investment in a contest.

Broadly speaking, success functions had been constructed and have been used to admit only two possible results for a contender, i.e. ‘win’ or ‘lose’. The most prominent of these are the ratio form of Tullock (1980) and the logit form of Hirshleifer (1989). The game theoretical expectations on aggregate efforts, outcomes, and rents dissipated when one studies success functions that only allow two possibilities are well studied and appreciated in the literature.[1] Recently, there has also been some effort to justify and compare success functions empirically; Hwang (2009) uses military data, Jia (2008) and Peeters (2010) use data from sports with this intention in mind. Experimental justification of the success functions also has

[1] A survey of the vast theoretical literature on contest theory may be found in Corchón (2007) and Konrad (2009).

been a matter of interest in the literature as exemplified by Millner and Pratt (1989), and Fonseca (2009).

Despite this widespread assumption and use, a third possible outcome exists in various contests: a draw. One can instantly enlist sports, military conflicts, rent-seeking, and promotional contests among those. In sports competitions such as soccer[2], which is also the main interest of this paper, chess, and cricket, a draw possibility is enforced by the design of the game. For military conflicts Garfinkel and Skaperdas (2007) and Blavatskyy (2010) argue that it is natural to anticipate contenders to end up in the same bargaining position they had before a military conflict. In rent-seeking, the lack of credibility of the authority gives rise to the possibility of a draw as studied by Kahana and Nitzan (1999). Finally, in promotional contests the recruiting body is entitled by law to deny the employment to all participants if it fails to encounter a fitting candidate.

Draws carry a particular importance in soccer. In a league championship fixture, a draw implies equal (one) point for both clubs and the point allocated in its occurrence makes it strictly better than losing the match which allocates zero points. Moreover, mostly because of the scoring system in and the nature of soccer, a draw is a highly probable outcome of a game; approximately 25%-30% of the matches played in professional soccer leagues end in a draw[3]. These properties of draws in soccer make them an important element to be reckoned with, and many coaches and managers contrive their field strategies accommodating or avoiding a draw depending on the strength of the contender.

There are currently three classes of success functions studied in contest theory that admit a possibility for a draw. The earliest one of those is by Blavatskyy (2010), who also

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[2] Soccer is used to signify the US equivalent of the word football (or association football) in Europe.

[3] See Table 1.

provides a microeconomic foundation for this success function[4]. This model implies that the probability of a draw gets infinitesimal as aggregate efforts/investments of the contestants grow. Blavatskyy (2010) argues that a draw should seldom be expected when both contenders exert high effort. However, there are contests for which this conjecture may not hold. Sports is an obvious contest environment where differences between teams is canonically thought to be more pertinent in draws. For instance, Peeters and Szymanski (2012) argue that Blavatskyy's success function may not be appropriate for sports. Especially for soccer, it is intuitive to expect two teams to draw with a relatively high probability when they have similar investment/talent[5] on the field, regardless of the magnitude of the aggregate level of investment/talent. The second class of success functions that admits a possibility of a draw is stochastically axiomatized by Jia (2012). According to this model, the probability of a draw is a function of the squared difference in efforts and depends on a 'coarseness-parameter' that serves as a threshold against which the difference is checked. The most recent axiomatization and analysis of a success function with draws is by Vesperoni and Yildizparlak (2016) in which the propensity of drawing in a contest is captured by a 'draw-inclination' parameter that determines the degree of the polynomial of effort difference. In this paper, the manner in which a draw is handled axiomatically and game theoretical expectations on aggregate effort and rent dissipation diverge profoundly from those in Blavatskyy (2010) and Jia (2012). Particularly for soccer, this model forecasts an adverse impact on investment/talent or aggregate squad effort for large draw points in games with heterogeneously resourceful teams. Moreover, it also implies that aggregate

[4] This form is stochastically axiomatized by Jia (2012).

[5] We use (aggregate) investment/talent/effort interchangeably throughout this paper. We discuss this choice of use later in the paper.

effort/investment is larger compared to the fixtures where draws are not possible, even when the draws are equivalent to losing in terms of prize/points. The former implication of Vesperoni and Yildizparlak (2016) may be a possible theoretical basis of the universal reduction in points allocated in case of a win from 2 points to 3 points, beginning in 1983 with the English *Premiere League*. In relative terms, this change reduces the points allocated for a draw.

There is a further issue for Blavatskyy's (2010) success function that may be relevant in empirical matters: this form is not homogenous of degree zero, i.e. the measurement of the efforts such as currency, energy, time etc. matter in determining the probability of an outcome. On the other hand, the success functions of Jia (2012), and Vesperoni and Yildizparlak (2016) are both homogenous of degree zero.

In this paper we first set out to assess the empirical performance of success functions for draws.[6] For this purpose we manually build a dataset from seven major European soccer leagues: English *Premier League*, Spanish *Primera División*, German *Bundesliga*, Italian *Serie A*, French *Ligue 1*, Turkish *Super Lig*, and Russian *Premier Liga*. The data contains the 'average market value'[7] of the line-up of each team, the result, and the home/away field team information for each match played for approximately twelve seasons. We acquired this data from *transfermarkt.co.uk* (*transfermarkt* for short, hereinafter) which keeps track of the market values of the individual professional soccer players throughout their career. By using

[6] For consistency we rule out other methods to capture draws used in empirical literature. For instance, the 'contest function' estimated by Peeters and Szymanski (2014) uses relative efforts (proxied by the wage bill paid by the club to the players) to determine the outcome of a match. However, this form does not constitute a success function in the theoretical sense as it does not define a probability function.

[7] The definition of the average market value is provided in the next section.

the average market value for each match as a proxy for aggregate club talent/investment, we compare the empirical performance of the three success functions aforementioned: the ones of Blavatskyy (2010), Jia (2012), and Vesperoni and Yildizparlak (2016). We also include a benchmark random choice model as a robustness check. We estimate the parameters of success functions, which imply a probability function each, by using a general maximum-likelihood procedure, and compare the goodness-of-fit of each success function with the test of Vuong (1989) for non-nested maximum-likelihood models.[8]

Our results favor the success functions of Jia (2012) and Vesperoni and Yildizparlak (2016), implying that the success functions that use relative differences in investment/talent as the major determinant for a draw (instead of aggregate investment/talent) are more relevant for soccer. Moreover, all the success functions used fare better than the benchmark model which suggests that the investments matter in the outcome. The results obtained from our maximum-likelihood procedure is also confirmed in the probit estimation for which we regroup the data into a binary variable of outcome as 'draw' and 'no-draw', and use aggregate talent and difference in talent per match as regressors.

Last, we compare some key features of the soccer matches that have major impact on results across European leagues: the return on talent, home-bias and talent inequality. The former two are designated and estimated by the maximum-likelihood procedure as parameters of success functions, and we build a conjecture on the latter from the data and summary statistics. Briefly, we find that European soccer leagues have widely different characteristics in return on talent and home-bias even though they operate on essentially

[8] To our knowledge, this method is first used by Peeters (2010) in order to compare the performance of Tullock's (1980) and Hirshleifer's (1989) success functions that allow only a single outcome for a match, i.e. some contestant wins with probability 1.

identical rules. These results were also established before by Pollard G. and Pollard R. (2005), and by Peeters and Szymanski (2014) more recently. The reasons for this effect are far from clear though; ranging from referee bias (Dohmen, 2008) to facility familiarity (Loughead et. al., 2003) and crowd size (Nevill et. al., 1996). Departing from the macro perspective taken in the majority of the research in home-bias[9], i.e. using points earned at home-field in excess of the points earned at away-fields, by using success functions, we take a match-based approach in which home-bias enters in the probability function as a multiplier of the average market value of a team. Thus, our method may crowd out some 'expected' home wins (e.g. matches played between two teams that immensely differ in aggregate talent, and the team with the larger talent holds the home-field advantage) and further refine home-bias estimations. We further find that there are major differences in terms of talent inequality between teams in different national leagues which may serve as a clue to explain the significantly different rates of draws among leagues.

Data

In order to compare the success functions for draws empirically we use data from the seven most valuable[10] European soccer leagues as measured by aggregate market value. This data is manually acquired from *transfermarkt* and contains observations for each league match played from season 2004-2005 to 2012-2013.[11] The championships included are

[9] An exception to this macro method is Peeters and Szymanski (2014) who use home-bias in determining thresholds for win, draw, and lose for each league based on individual fixtures.

[10] According to *transfermarkt*.

[11] Additional data is included for the league that is being considered at the time as the process is manual and every week a new set of matches are played. For instance, the Premier League data ranges to 2014-2015 first season.

English *Premier League*, Spanish *Primera División*, Italian *Serie A*, German *Bundesliga*, French *Ligue 1*, Turkish *Super Lig*, and Russian *Premier Liga*.

Each observation is comprised of the 'average market value' of the line-up of each team at the day of the match[12], the information identifying the team that plays in the home (away) field, and the result of the match designating the winning team or a draw. The market values found in *transfermarkt* are calculated for almost every professional soccer player individually starting from 2004. He (2013) reports that:

> [*transfermarkt*] records detailed information for major soccer players and evaluate their value based on data analysis, as well as opinions of experts. The values are not obtained by applying straightforward algorithms. Instead, factors from all aspects have to be taken into consideration to decide the digits of a market value.

We use the average market value of the line-up for each match as a proxy for the aggregate talent or efforts of the club. The implication contest theory has on sports is that the talent acquired by costly investment, which translates into winning probabilities for clubs, is one of the main determinants of an outcome of a match. *Transfermarkt* places a monetary value for a player's talent based on individual performance. Thus, in essence, it approximates aggregate talent a club possesses. Even though market values do not reflect a direct cost, they do represent the opportunity cost of a player to the club, i.e. if a player is over-paid (under-paid) relative to his performance, for his current club the player is a high-cost (low-cost) investment. Thus, by foregoing to sell a player, the clubs bear an opportunity cost of transfer payments. Therefore, our interpretation of the market values represents an indirect measure for club investment. On the other hand, as we do not test for Nash equilibrium predictions but

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[12] This is calculated by the *transfermarkt* and it is the average market value of the eleven players enlisted as playing on the day of the match.

the success functions themselves, the actual cost of a squad to the club does not affect our results.

Our choice for proxy may seem confusing firstly, because *transfermarkt* uses a combination of opinions and data analysis of performance of the individual players as He (2013) reports. Additionally, in similar empirical research on soccer, the major data source is the payroll (wage) data as in Szymanski and Smith (1997), Hall, Szymanski, and Zimbalist (2002), and Peeters and Szymanski (2012 and 2014). Unfortunately, the payroll data is unavailable for us.

Nevertheless, there are certain advantages we find by using average market values instead. Most importantly, our data offers richer dynamics because *transfermarkt* regularly (and occasionally irregularly if an important incident takes place in the career of the player) updates individual player market value based on player performance criteria. The market value of a player is also updated in the beginning of every season based on individual transfer market performance. Therefore, the time periods in which the market value of a player changes are more frequent than the one in the payroll data as the contract terms do not change frequently and are rather long. This feature enables us to observe a faster updating of the winning probabilities of the clubs whenever a squad member's market value changes within a season. The rapid updating is rather important as, generally, the young and talented players in the beginning of their career receive lower wages and while being watched closely and finally transferred by major clubs receive significant increases in their wages later in their career. Therefore, even if their individual input to overall talent of their previous clubs is large, the wage they receive when they are an early career player does not translate this into an augmentation in winning probabilities. The opposite case is even more obvious. If a player's performance decreases due to injury or other idiosyncratic reasons, the wage he receives stays the same until his contract ends or is terminated. Therefore, even if his wage would account for a large impact in the empirical expectation of his club's success, his real contribution would be much smaller or in some cases nil. We can provide recent examples of both cases. For the former, an example is Riyad Mahrez, who was awarded PFA Players' Player of the Year in the Premier League after a fruitful career in Leicester City (England). His market value has increased constantly from £1.06 million in January, 2014 to £25.50 million in August, 2016 in *transfermarkt*. He was transferred from AC Le Havre (France) in the beginning of the season 2014-2015 to Leicester City for a transfer fee of only £0.425 million while his transfer value is said to have risen to £30.1 million, which places him in the top 50 most valuable players in Europe (using "Leicester City", 2016, and "Leichester City winger", 2016). For the latter case a recent example is Robin van Persie, who was transferred from Manchester United (England) to Fenerbahce (Turkey) for a transfer fee of £4.6 million in the beginning of the season 2015-2016. After having a rather poor performance, often failing to make it to the line-up of the team due to injury or coach preference even though he is the highest paid member of the squad, his market value has declined from £12.75 million to £7.65 million in *transfermarket*. In both cases, if the wage the player earned in a season was used in the analysis, it would be highly likely to have estimated rather biased probabilities of winning, losing, and drawing for both Leicester City and Fenerbahce. This situation may be generalized to almost every professional player at some point in their career.

There are also some secondary advantages of using *transfermarkt* data. First, the average market values are reported based on the line-up squad of the team for each match. Thus, we are able to exclude the squad members who are not able to make an appearance due to injury and low performance. Moreover, as the market values are averaged within the line-up, we are able to remove some of the undesired bias related to a large inequality of talent within the squad. This is rather important in developing championships, such as the one in

Turkey, in which we can observe large disparities in pay within the team that results in a rather inflated aggregate talent level measured.

Obviously, there are also some disadvantages of using *transfermarkt* data. A major disadvantage may be its partial dependence on opinion, therefore fan bias. However, first, *transfermakt* does not evaluate each opinion equally (the members have trust scores based on the post-validity of their opinions in transfer seasons), and data analysis on player performance is a crucial part of market values reported. Moreover, Peeters (2016) finds that *transfermarkt* data is an unbiased estimator of international soccer matches and reports that there is no evidence of 'wishful thinking' from the crowd.

A concern about endogeneity may also be raised. Because, first, *transfermarkt* data allows for and updates the strategic measures taken by the manager or the coach for a particular match such as reserving important players, e.g. the ones played once championship is guaranteed before the league ends, the matches played against weaker teams, etc. However, these strategies are generally used by a coach when the championship is guaranteed or when it is obvious that the club would be demoted to a secondary league before the season ends. Thus, generally, the number of such fixtures are relatively few. Secondly, and more importantly, as the *transfermarkt* is responsive to in-field performance of individual players, the team probability of winning may be seen as affecting the market values of the players. However, first, as the individual player performance is the basis for evaluation it does not necessarily correlate with team performance. For instance, a large number of the players in Leicester City experienced a decrease in their market values even though the club performed spectacularly in 2015-2016 season and earned the championship for the first time in the *Premier League*. Secondly, the *transfermarkt* data is only updated twice a year ordinarily and once more in the end of the transfer-season. Thus, it only updates player data *more frequently* than the payroll data but not on a match basis. Last but not the least, as the team performance as a whole is also reflected in the ability of the clubs to be able to afford high talent, it may be argued that the same problem may also exist in the payroll data, which is used as the primary data source in the literature.

The last reason we think *transfermarkt* data is valid for its purpose here is, as we shall see later, that the estimates of essential parameters such as the one reflecting importance of investment/talent in high club performance (ROT)[13] in a certain league are in line with recent literature such as Peeters and Szymanski (2014). Thus, even though we are unable to test for correlation of our data with the payroll data, we believe it is appropriate to embark on our analysis using *transfermarkt* values. He (2013) may also be consulted to see an analysis of the validity of market values reported by *transfermarkt*.

Estimation Methodology

Now, we start explaining our method of estimation. We use three success functions that admit a possibility of a draw accompanied by a simpler random choice function that we call the naive model. Denoting the probability assigned by the success function f to the home team winning when it possesses the average market value x_{in} and the rival possesses the average market value x_{jn} on match n by $\pi_{iin}^{f}(\cdot)$, and the probability attached to the away team winning on the same match by $\pi_{jin}^{f}(\cdot)$, and the vector of average market values in match n by $x_n = (x_{in}, x_{jn})$, these three success functions and the naïve model are presented below.

$$\pi_{iin}^{B}(x_n) = \frac{\varphi x_{in}^{\alpha}}{b + \varphi x_{in}^{\alpha} + x_{jn}^{\alpha}}, \pi_{jin}^{B}(x_n) = \frac{x_{jn}^{\alpha}}{b + \varphi x_{in}^{\alpha} + x_{jn}^{\alpha}}, \quad (1)$$

[13] The name ‘decisiveness’ is coined for this parameter in contest theory as it reflects how *decisive* efforts are in the result of a contest, e.g. Hirshleifer (1991).

$$\pi_{din}^{B}(x_n) = \frac{b}{b + \varphi x_{in}^{\alpha} + x_{jn}^{\alpha}} \ ;$$

$$\begin{gathered}
\pi_{iin}^{J}(x_n) = \frac{\varphi x_{in}^{\alpha}}{\varphi x_{in}^{\alpha} + c x_{jn}^{\alpha}} \ , \ \ \pi_{jin}^{J}(x_n) = \frac{x_{jn}^{\alpha}}{\varphi c x_{in}^{\alpha} + x_{jn}^{\alpha}}, \\
\pi_{din}^{J}(x_n) = \frac{(c^2 - 1)\varphi x_{in}^{\alpha} x_{jn}^{\alpha}}{(\varphi c x_{in}^{\alpha} + x_{jn}^{\alpha})(\varphi x_{in}^{\alpha} + c x_{jn}^{\alpha})};
\end{gathered} \tag{2}$$

$$\begin{gathered}
\pi_{iin}^{VY}(x_n) = \left(\frac{\varphi x_{in}^{\alpha}}{\varphi x_{in}^{\alpha} + x_{jn}^{\alpha}}\right)^{k} \ , \ \ \pi_{jin}^{VY}(x_n) = \left(\frac{x_{jn}^{\alpha}}{\varphi x_{in}^{\alpha} + x_{jn}^{\alpha}}\right)^{k}, \\
\pi_{din}^{VY}(x_n) = \frac{\left(\varphi x_{in}^{\alpha} + x_{jn}^{\alpha}\right)^{k} - \varphi x_{in}^{\alpha k} - x_{jn}^{\alpha k}}{\left(\varphi x_{in}^{\alpha} + x_{jn}^{\alpha}\right)^{k}};
\end{gathered} \tag{3}$$

$$\pi_{iin}^{N}(x_n) = \frac{1+\varphi}{3} \ , \pi_{jin}^{N}(x_n) = \frac{1-\varphi}{3}, \pi_{din}^{N}(x_n) = \frac{1}{3}. \tag{4}$$

Expression (1) is the success function by Blavatskyy (2010), henceforth BSF, where $b > 0$. Expression (2) is by Jia (2012), henceforth JSF, where $c > 1$. And, Expression (3) is by Vesperoni and Yildizparlak (2016), henceforth VYSF, where $k > 1$. The last one is the naive model (NF). The common parameters in each success function are $\varphi > 0$, and $\alpha > 0$. The parameter φ denotes the home-bias, i.e. the (dis)advantage possessed in probability by playing in the home-field, in our paper. In estimations without home-bias, we impose $\varphi = 1$.[14] On the other hand, we call α the ROT (return on talent) parameter which determines the sensitivity of winning to the level of talent. The distinct parameters in each success function are b, c, and k, respectively for BSF, JSF, and VYSF. These are the draw parameters in each model as the exclusion of each of parameter from the original function boils down to the success function of Tullock (1980) with dual outcome set (win and lose). As might be

[14] $\varphi = 0$ for the Naive model. Note that the parameter φ in the Naive model is not equivalent to the same parameter in the other success functions. We prefer to abuse the notation slightly to avoid confusion in the presentation of the results.

discerned from the functional forms, in BSF, the probability of a draw is determined by and negatively correlated with the level of aggregate talent/investment. On the other hand, JSF and VYSF use difference in talent/investment levels for attaching the probability of a draw, though in different manners. The former uses a linear weighting of the squared differences while the latter uses a polynomial weighting in differences in investment. In both success functions the difference in talent/investment level is negatively correlated with the probability of a draw.

Denoting the vector of parameters for success function f by Φ_f $\left(\Phi_B = (\alpha, \varphi, b), \Phi_J = (\alpha, \varphi, c), \Phi_{VY} = (\alpha, \varphi, k)\right)$, the data for the average market values of the two teams as $X = (x_1, x_2)^N$, the data for home and away matches by $H = (h_1, h_2, .., h_n, .., h_N) \in \{1,2\}^N$, and the data for the result of each match by $Y = (y_1, y_2, .., y_n, .., y_N) \in \{0,1,2\}^N$, we define the log-likelihood function as:

$$\ell(Y|X, H, \Phi_f) = \sum_{n=1}^{N} \sum_{y\, \in\{0,1,2\}} \sum_{h\, \in\{1,2\}} \mathbb{I}\,(y = y_n)\, \mathbb{I}(h = h_n) \log\, \left(P(y|x_n, h, \Phi_f)\right). \tag{5}$$

In function (5), N is the number of observations (matches) for each league (all matches in data for the pooled estimations), $x_n = (x_{1n}, x_{2n})$ is the average market value of the line-up of the teams 1 and 2 for the match n in thousand pounds, $h_n \in \{1,2\}$ shows which team plays in the home field in match n, and $y_n = 1$ ($y_n = 2$) designates that team 1 (2) won match n, and $y_n = 0$ shows that the match ended in a draw, $\mathbb{I}(\cdot)$ is the indicator function that takes the value 0 or 1 depending on whether the values of y_n and h_n match the indexes $y \in \{0,1,2\}$ and $h \in \{1,2\}$. The identities of the clubs are irrelevant in the specifications of the success functions above. Thus, it is sufficient to designate which team played as the home (away) team and which team lost (won) the match. Denoting $i, j \in \{1,2\}$, $i \neq j$, as the team labels (i for the home and j for the away team), the pointwise likelihood function for match n is:

$$P(y|x_n, h, \Phi_\mathrm{f}) = \begin{cases} \pi_{iin}^{f} & \text{if } y = h = i, \\ \pi_{jin}^{f} & \text{if } y = j,\ h = i, \\ \pi_{din}^{f} = 1 - \pi_{iin}^{f} - \pi_{jin}^{f} & \text{if } y = 0,\ h = i. \end{cases} \tag{6}$$

In expression (6) π_{din}^{f} denotes the probability of a draw. The explicit form of the pointwise likelihood function above is given by the particular success function, f, used, i.e. by one of equations (1)-(4).

For the comparison within different specifications of a success function we use the likelihood ratio (LR) test. However, comparing results for different success functions requires a different test as each success function represents a non-nested model of each other, i.e. no success function we use can be obtained from any other by mathematical transformations. For this reason, we use Vuong's (1989) closeness test for non-nested models.

The log-likelihood values, estimations, standard errors and Vuong test results are calculated by a manually written code using MATLAB, which is available on demand.

For robustness check we also employ a probit estimation by regrouping the result of each match. This may sound confounding at first as; first, probit also uses a maximum likelihood technique; and second, the probit allows for a binary outcome set only. For the former, it may be discerned that the success functions define a special probability function whose parameters can only be estimated by defining a particular log-likelihood function for each success function used. This is the reason we were not able to use standard statistical package programs in the estimations of the success functions. However, each success function presents a certain hypothesis about the nature of draws: BSF's implicit hypothesis is that the likelihood of a draw increases as the aggregate talent on the field declines; on the other hand, JSF and VYSF suggest that the likelihood of a draw increases with the level of dissimilarity between two teams in talent on the field. These two hypotheses can be tested with a probit model which assumes a normally distributed binary outcome regressed over two measures that represent the hypotheses suggested by individual success functions and $N(0,1)$ distributed errors. For the latter, as the two hypotheses are mutually exclusive statements about the nature of a draw, we simply reconstruct the data by labelling each result as 'draw' and 'no draw', and estimate the regression coefficients (stated below in explicit form) using maximum-likelihood offered by standard statistical packages.

Using the probit model as explained above, we regress the result of a match n ('draw' or 'no draw') on the absolute difference in average market value (DMV_n), aggregate average market value (AMV_n)[15], and a dummy variable (MVA_n) that takes value 1 if the away team has a larger average market value than the home team, and 0 otherwise. The last variable is intended to crowd out the immense impact of the home-bias. Thus, the estimated pointwise likelihood function is:

$$\Pr\,(y_n = draw) = \xi(\beta_o + \beta_d DMV_n + \beta_a AMV_n + \beta_m MVA_n + \varepsilon_n), \qquad (7)$$

where $\xi(\cdot)$ is the cumulative distribution function of the standard normal distribution. This in turn refines the precision of our results by demonstrating whether aggregate talent or the difference in talent (or both) is (are) the main determinant in drawing.

The summary statistics presented below in Table 1 do not support a singular hypothesis in a conclusive manner. Indeed, the *MAMV* (Mean Aggregate Average Market Value) of the teams per match declines for all leagues except for France, which shows a small increase, in matches that ended in a draw. On the other hand, both *MDMV* (Mean Difference

[15] Even though the difference in average market value implies a relative difference in JSF and VYSF, we choose to use absolute difference in probit estimation as taking the relative difference renders the two hypotheses mutually non-exclusive (the absolute difference is scaled with the aggregate investment) and taking a simple derivative of the probability of drawing in JSF and VYSF shows that absolute difference produces a valid hypothesis about the nature of draws.

in Average Market Value) and *MRD* (Mean Relative Difference in Average Market Value) show a decline for the matches that end in a draw in all leagues. Therefore, for a clearer inference, we use the success functions in our empirical analysis as explained above.

Lastly, as we stated in the previous section, success functions equip us with an opportunity to estimate some parameters that influence the result of a soccer match profoundly. We call these parameters the ROT (Return on talent, α in equations (1)-(3)), and home-bias (φ in equations (1)-(4)). In contest theory, the former measures how sensitive the result is to effort level exerted by the contestants; in sports the equivalent interpretation is how aggregate talent is important in determining the result. Equivalent or identical parameters to ROT were formerly used by Szymanski (2003), Peeters (2010), Peeters and Szymanski (2012 and 2014) in sports economics. The latter is a general parameter in contest theory that measures any contestant-specific exogenous feature that increases or decreases the effort of a certain contestant in a multiplicative way. As the literature on soccer has concluded and our summary statistics in Table 2 point out, home-bias is a very influential parameter on the result of a match (see e.g. Clarke and Norman (1995), Carmichael and Thomas (2005), Koyama and Reade (2009)). Our statistics show that 46% of all the matches end up in home teams winning. For Italy and France, a draw is actually the second most likely outcome for a home team! Moreover, as we show later, our estimated parameters point out that moving from the away field to home field increases the probability of winning from at most 23% to 47% (Italy), to at least from 28% to 43% (Russia) in a match between two equal teams in average market value. Lastly, the measure MVA-HA% (Market Value Advantage versus Home Advantage) we include in Table 2 shows that the matches that end in a draw are more likely to be the ones where the home team does not hold the market value advantage. This is a clear indication that the home-bias enters in the probability of winning as a multiplier of the market values as success functions (1)-(3) imply. For these reasons, we choose this exogenous parameter to reflect the impact of playing in the home field.

Table 1. Summary statistics for key variables.[16]

League	England	Spain	Italy	Germany	France	Turkey	Russia	**Aggregate**
Teams	17	17	18	17	19	17	16	**121**
Gini	0.34	0.47	0.36	0.31	0.31	0.33	0.43	-
Observations	1604	1381	1754	1707	1622	1625	1295	**10987**
Draws	408 (25.5%)	314 (22.7%)	486 (27.7%)	446 (26.1%)	489 (30.1%)	418 (25.7%)	358 (27.6%)	2919 (26.6%)
Non-Draws	1196 (74.5%)	1067 (77.3%)	1268 (72.3%)	1261 (73.9%)	1133 (69.9%)	1207 (74.3%)	1197 (72.4%)	8068 (73.4%)
MAMV (Th. £)	16.99 (7.97)	12.96 (10.06)	11.46 (6.03)	9.20 (4.78)	7.28 (3.38)	3.72 (1.93)	5.07 (3.09)	**9.59 (7.28)**
Draws	16.15 (7.89)	11.46 (9.51)	11.02 (6.07)	8.66 (4.35)	7.30 (3.43)	3.55 (1.91)	5.00 (3.03)	8.99 (6.80)
Non-Draws	17.27 (7.98)	13.41 (10.18)	11.63 (6.00)	9.39 (4.90)	7.27 (3.36)	3.77 (1.93)	5.09 (3.11)	9.81 (7.44)
MDMV (Th. £)	6.48 (4.96)	7.02 (7.80)	4.81 (3.86)	3.30 (3.57)	2.44 (2.33)	1.48 (1.35)	2.29 (2.02)	**3.96 (4.59)**
Draws	5.58 (4.69)	5.54 (6.39)	4.42 (3.80)	2.87 (2.97)	2.35 (2.27)	1.33 (1.28)	2.09 (1.83)	3.39 (3.89)
Non-Draws	6.79 (5.01)	7.45 (8.12)	4.96 (3.88)	3.46 (3.75)	2.48 (2.35)	1.53 (1.37)	2.36 (2.08)	4.16 (4.80)
MRD	0.37 (0.22)	0.45 (0.26)	0.40 (0.24)	0.32 (0.21)	0.31 (0.20)	0.35 (0.23)	0.44 (0.23)	**0.37 (0.27)**
Draws	0.33 (0.22)	0.42 (6.39)	0.37 (0.23)	0.31 (0.20)	0.30 (0.21)	0.33 (0.22)	0.42 (0.25)	0.35 (0.23)
Non-Draws	0.38 (0.22)	0.46 (0.26)	0.40 (0.24)	0.33 (0.22)	0.31 (0.21)	0.36 (0.23)	0.45 (0.26)	0.38 (0.24)

[16] For every match sampled, MAMV (Mean Aggregate Average Market Value) is the average market value of two teams; MDMV (Mean Difference in Average Market Value), is the average market value difference between two teams; MRD (Mean Relative Difference), is the average market value difference between two teams divided by aggregate average market value of the two teams. Gini coefficient is calculated using the share of market values for each team.

Table 2. Summary statistics for home bias.[17]

League	England	Spain	Italy	Germany	France	Turkey	Russia	**Aggregate**
Home W %	46%	49%	47%	45%	46%	47%	43%	**46%**
Home L %	28%	28%	25%	28%	24%	27%	29%	**27%**
Home D %	25%	23%	28%	26%	30%	26%	28%	**27%**
MVA-HA %	49.8%	51.8%	49.9%	50.2%	51.8%	50.3%	48.9%	**50.4%**
Draws	46.1%	46.2%	45.1%	45.7%	49.7%	46.7%	43.9%	**46.3%**
Non-Draws	51.1%	53.6%	51.7%	51.8%	52.8%	51.5%	50.9%	**51.9%**

Results and Discussion

The estimation results presented in Tables (5-8) indicate that every parameter estimated for each success function are significant both with and without home-bias.[18] In Table 3 we present an example for the estimation output for pooled data with home-bias. [19]

[Table 3 here]

First of all, the likelihood ratio test indicates that the addition of the home-bias, which turns out to be an advantage as expected, significantly improves the fit.[20] More importantly, comparison using Vuong's closeness test in Table 4 shows that JSF and VYSF are almost equally appropriate for each league individually and also as a whole. In particular, the former

[17] MVA-HA% is the percentage of matches in which the home team also possesses the larger market value line-up. This measure is intended to address the multiplicative effect of the home-bias on individual club market values in success functions (1)-(3).

[18] Only the estimation results (with home-bias) for the *Premiere League* are presented in the appendix. The remaining results are omitted for brevity and are available on demand.

[19] Some data points were excluded in the pooled data due to time inconsistencies in the estimations.

[20] As this is evident from the differences in log-likelihood between specifications (see tables (5) - (19)), log-likelihood tests are not reported in text but provided on demand.

performs better for Spain, Germany, Turkey, and Russia while the latter performs better for England, Italy, and France and for the pooled data. However, these differences in performance are not significant as reported in Table 4.

We also see that JSF and VYSF generally fit data better than BSF. The significance is at the level 0.01 for the pooled data, 0.05 for England, Italy, France, Turkey, and Russia, and at 0.10 for Spain and Germany. This result is in accordance with the argument of Peeters and Szymanski (2012) who discuss the inadequacy of the BSF for sports. Therefore, we may safely conclude that a draw is more sensitive to the difference between the talent levels of the two competing teams rather than the aggregate talent level in a match.

[Table 4 here]

The results of the probit model estimated, which conforms to our judgement above, is reported in Table 5. As one may observe, the coefficient of the mean aggregate average market value ($MAMV$) is not significant. Moreover, it has conflicting signs across leagues whereas its theoretical expected sign is negative. On the other hand, the coefficient of the difference in average market value between teams ($MDMV$) is significant (except for Germany and France) and negative for every championship including the pooled data. Thus, we confirm our expectation that difference between market value decreases the probability of a draw in a given match. We also observe that, if the larger average market value team is playing away, it is generally more likely to observe a draw as the coefficient for MVA is significant (except for France) and positive for all championships and pooled data. This result shows the impact of the home bias partially offsetting the advantage of possessing a larger market value as implied by the success functions and our summary statistics in Table 2 indicate.

[Table 5 here]

Lastly, all success functions perform better than the NF. Even though the log-likelihood of the NF improves with the addition of the home-bias parameter, the improvement is surpassed by any of the success functions used. This shows the clear importance of average market values (or talent) in the performance of a soccer club.

Next we compare certain characteristics of the leagues with VYSF as it nominally outperforms the other two using pooled data. We further refine the results by using estimates with the home-bias parameter (φ) due to their conclusive superiority.

First of all, the estimated values for draw-inclination parameter, $\hat{k}$, are in conformity with the particular draw characteristic of the different leagues as we present in Table 6, i.e. the leagues with larger draw frequency attain larger values of k. It is worth noting that the estimated draw-inclination parameter is surprisingly very similar to the value where the efforts are theoretically maximized, i.e. $k \simeq 1.44$, in Vesperoni and Yildizparlak (2016). Even though this effort maximizing value is for the symmetric VYSF, estimated values without the home-bias also confirm this result. There is no clear explanation for this result; nevertheless, the theoretical conjecture is that in a completely fair league the draw-inclination parameter is such that the clubs would exert the largest possible investment.

[Table 6 here]

We also present the Gini coefficient[21] for each league in Table 6 to see if there is a relation with the frequency of draws and the inequality in mean market value, which is also illustrated in Figures (1)-(7) per league. Note that, as we confirmed that the probability of a draw is determined by and negatively correlated with the difference in average market value levels, a

[21] Here, the Gini coefficient designates the level of inequality in average market value across teams sampled in a league. A larger Gini coefficient points out a larger inequality in market values. The Gini coefficients reported are calculated manually, aggregating all seasons for each league.

league that hosts a large inequality would have a lower frequency of draws. Data shows that the lowest frequency of draws is in Spain (22%), which also has the largest Gini coefficient (0.47), i.e. the maximum talent inequality. However, Russia, for which the Gini coefficient is 0.43 presents the second largest draw frequency (28%). On the other end of the spectrum, the lowest Gini coefficient (0.31) coincides with the highest draw frequency (30%), which is for France. These results also are concordant with the maximum average market differences observed in overall fixtures, which is also reported in Table 6. However, generalizing a result from the Gini coefficient is impossible here as it requires data from many other soccer leagues. Thus, we leave this as future research.

Lastly, we discuss the estimated parameters that do not directly influence a draw, i.e. the ROT (α) and the home-bias (φ). Their estimated values are reported in Table 7. We also report the estimated elasticities (ϵ_h, ϵ_w) for each league of playing at home and away, respectively, in Table 7. Elasticity in our context is the percentage change in the probability of winning in response to a 1% change in investment of a team facing a rival that has the same level of investment. Formally, elasticity is calculated as $\epsilon = \frac{dp_i(x_i,x_j)}{dx_i}\frac{x_i}{p_i(x_i,x_j)}$, at $x_i = x_j$ which adds up to $\epsilon_h = \frac{\alpha k}{1+\varphi}$ and $\epsilon_w = \frac{\alpha k \varphi}{1+\varphi}$ for home and away field elasticities, respectively. The home and away field elasticities are different as VYSF changes between the two specifications in expression (3).

[Table 7 here]

Estimated values of the parameter ROT ($\hat{\alpha}$) point out that the aggregate talent/investment affect the outcome the most in the English *Premier League* and the least in the French *Ligue 1*. This result is concordant with the recent literature on soccer, e.g. Peeters and Szymanski (2014), especially for the *Premier League*. This difference makes a large impact on the elasticities; in the *Premier League* a 1% increase in average talent of a club increases the probability of winning for the home team by 0.43% (0.63% for an away team) against an identical opponent, while in the French *Ligue 1* it only makes a difference of 0.24% (0.64% for an away team). For away teams an increase in average market value is much more important as it is the only channel to overcome the home advantage of the rival.

On the other hand, we see that the home-bias is a very decisive element in the outcome of a match in general. The most dominant home-bias is estimated in the Italian *Serie A* which takes the probability of winning from 23% to 47% against an equal opponent if the team switches from away field to home field. Whereas, we observe that the least dominant home-bias is in the Russian *Premier Liga* which still takes the same probability of winning from 28% to 43%.

Last, we draw a general picture for the leagues in our data using our estimation results and summary statistics. The differences we observe seem to be a result of how ROT, home-bias, and inequality in average market values interact with each other for each league. In the *Premier League* (England) and *Bundesliga* (Germany) the home-bias and ROT seem to be similar. The former parameter being relatively low (the lowest second for the *Premier League* and the lowest third for *Bundesliga*) and the latter parameter high in comparison to other leagues (the highest and the second highest, respectively). Moreover, even though aggregate average market value is much larger in the *Premier League* the inequality in market values is relatively low. The result is the large response in probability of winning to an increase in aggregate talent (0.43% in the *Premier League* and 0.37% in *Bundesliga* for home teams). On the other hand, *Serie A* (Italy) seems to possess a very high home-bias belittling the importance of market values partially. *Ligue 1* (France) is indeed a curious case where the inequality among teams is the lowest, home-bias is moderate, and aggregate talent does not make an important difference (lowest in all leagues). This might be one of the reasons why we observe a large percentage of draws and often switching winners of the championship in France. In *Primera División* (Spain) what matters seem to be the inequality among teams; the Gini coefficient is the largest (0.47), and draws seem to be very low in occurrence (22%) even though talent and home field matters moderately. This might be explained by so few clubs - Real Madrid and Barcelona in particular (see Figure 2) – having an immense market value advantage compared to their contenders and sharing the championship almost exclusively. The developing leagues such as *Super Lig* (Turkey) and *Primer Liga* (Russia) also show quite different characteristics. In Turkey, the inequality is moderate, home-bias is relatively low, and market values highly matter. Whereas in Russia we observe a large Gini coefficient (0.43), but a rather low home-bias (lowest in all leagues) and ROT (second lowest in all leagues) which seem to be vaguely similar to Spain where inequalities seem to matter the most.

We have so far no evidence why these differences exist as these leagues are organised by similar market conditions and identical rules. This question remains as an issue of future research for the time being. Further, a dynamic use of the success functions in estimations may also demonstrate the long trends in these variables which has been the research issue in Pollard G. and Pollard R. (2005) for home-bias, even though the measure used in calculating the home-bias is rather different to ours in this paper.

Conclusions

Draws are one of the possible outcomes in various contests. In this paper, we have presented an empirical evaluation of the success functions that admit a possibility of a draw using data from the seven most valuable leagues in Europe. Moreover, we have analysed the difference between these major leagues in terms of some important characteristics such as investment inequality, home-bias and return on talent.

Our empirical evaluation has indicated that the two success functions, i.e. the ones by Jia (2012) and Vesperoni and Yildizparlak (2016), outperform the success function by

Blavatskyy (2010). The main reason for the difference in performance is the contrast between the two groups of functional forms in their allocation of draw probability: for the former group, Jia (2012) and Vesperoni and Yildizparlak (2016), the difference in effort is the main determinant in the probability of a draw, whereas Blavatskyy (2010), takes the aggregate effort for its main determinant in probability of a draw. We have also demonstrated the robustness of this result with a probit estimation in which we have found that the probability of a draw decreases significantly with the magnitude of the difference between the market values of the two teams. On the other hand, the aggregate market values do not seem to affect the probability of a draw significantly.

The estimated values obtained for the talent inequality, return on talent, and home-bias for each league have shown intriguing differences among individual leagues which may be connected to aggregate talent levels, inequality among teams, or the level of effectiveness in imposing the rules of the game. These results indicate that further research is necessary in this area to understand the reasons for the diverging characteristics of different leagues. Our method also has provided an opportunity to use micro (fixture-based) data in the estimation of home-bias, return on talent, and other important variables that may be of interest in the literature on soccer.

Obviously, our results only support the first two success functions exclusively for sports contests, particularly for soccer. In different contexts such as labour tournaments, rent-seeking contests, and military conflicts results might differ from the ones obtained here. Nevertheless, this paper has shown that the aforementioned classes of success functions are suitable for contest applications where the draw element is conspicuous and relevant.

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Tables

Table 3. Estimation results for four success functions with home-bias (Pooled Data) [22]

n = 10569	Pooled					
SF	$\hat{\varphi}$	$\hat{\alpha}$	$\hat{k}$	$\hat{c}$	$\hat{b}$	LL
VYSF	1.438 (0.016)	0.499 (0.016)	1.516 (0.010)	-	-	-10714
JSF	1.520 (0.044)	0.575 (0.044)	- -	1.895 (0.058)	-	-10715
BSF	1.688 (0.014)	0.498 (0.018)	- -	- -	1.777 (0.054)	-10886
Naive	0.247 (0.011)	- -	- -	- -	- -	-11375

Table 4. Vuong Test results including home-bias[23]

League	England	Spain	Italy	Germany	France	Turkey	Russia	**Aggregate**
VYSF vs JSF	0.797 (0.213)	-0.793 (0.787)	0.729 (0.233)	-0.879 (0.810)	1.243 (0.107)	-0.209 (0.835)	-0.145 (0.884)	0.417 (0.676)
VYSF vs. BSF	2.180** (0.015)	1.443* (0.075)	2.263** (0.012)	1.328* (0.092)	2.310** (0.011)	2.127** (0.033)	2.188** (0.029)	8.320*** (0.000)
JSF vs. BSF	2.020** (0.022)	1.531* (0.063)	2.118** (0.017)	1.416* (0.078)	2.118** (0.017)	2.141** (0.032)	2.074** (0.038)	8.088*** (0.000)

[22]This table reports the estimated values of the common parameters - home-bias (φ) and ROT (α), and the individual parameters, k, c, and b respectively for YSF, JSF, and BSF. Standard errors are shown in parenthesis.

[23]This table reports the Vuong's test results of the three success functions. The numbers are Z-values and the numbers in the parenthesis are the p-values. $(***)$, $(**)$, and $(*)$ shows the one-tailed test significance levels of 1%, 5%, and 10%, respectively.

Table 5. Probit Estimation

League	$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$
	$CONSTANT$	$MDMV$	$MAMV$	MVA
England	-0.517^{***} (0.087)	-0.029^{***} (0.008)	-0.001 (0.005)	0.114^{*} (0.001)
Spain	-0.710^{***} (0.071)	-0.022^{**} (0.009)	0.002 (0.006)	0.180^{**} (0.075)
Italy	-0.547^{***} (0.076)	-0.018^{*} (0.010)	0.003 (0.007)	0.157^{**} (0.064)
Germany	-0.573^{***} (0.084)	-0.024 (0.015)	-0.008 (0.011)	0.150^{**} (0.066)
France	-0.595^{***} (0.086)	-0.030 (0.020)	0.016 (0.013)	0.072 (0.065)
Turkey	-0.604^{***} (0.081)	-0.061^{*} (0.036)	-0.005 (0.025)	0.117^{*} (0.067)
Russia	-0.634^{***} (0.082)	-0.056^{**} (0.024)	0.016 (0.015)	0.162^{**} (0.075)
Aggregate	-1.121^{***} (0.038)	-0.043^{***} (0.008)	0.003 (0.004)	0.193^{***} (0.037)

Table 6. Draws and market value inequalities across leagues [24]

League	$\hat{k}$	Draw Frequency	Gini	Max-Diff	Max-MAMV
England	1.494	25%	0.34	22.46	46.72
Spain	1.426	22%	0.47	35.42	70.16
Italy	1.544	28%	0.36	17.25	32.92
Germany	1.482	26%	0.31	21.88	37.36
France	1.562	30%	0.31	16.68	22.88
Turkey	1.484	26%	0.33	6.29	18.06
Russia	1.516	28%	0.43	10.22	22.88

Table 7. ROT, home-bias, and elasticities across leagues[25]

League	$\hat{\alpha}$	$\hat{\varphi}$	$\hat{\epsilon}_h$	$\hat{\epsilon}_w$
England	0.708	1.468	0.43	0.63
Germany	0.611	1.425	0.37	0.61
Turkey	0.595	1.502	0.35	0.63
Italy	0.560	1.599	0.33	0.65
Spain	0.486	1.540	0.27	0.64
Russia	0.424	1.334	0.28	0.60
France	0.393	1.539	0.24	0.64

[24] This table reports the estimation results of VYSF including the summary statistics concerning draws and market values. Draw frequency is the percentage of draws in all the matches played. Gini coefficient is calculated using the share of market values for each team aggregated for all seasons, Max-Diff is the maximum difference in market values observed among all matches, and Max-MAMV is the maximum aggregate market values observed among all matches.

[25] This table reports the estimation results of VYSF for the ROT ($\hat{\alpha}$), and home-bias ($\hat{\varphi}$) parameters and elasticities for home and away fields ($\hat{\epsilon}_h$, $\hat{\epsilon}_w$), respectively. Standard errors may be found in Tables (6)-(22).

Table 8. Estimation results for three success functions with home-bias (1)

n = 1604	England					
SF	$\hat{\varphi}$	$\hat{\alpha}$	$\hat{k}$	$\hat{c}$	$\hat{b}$	LL
VYSF	1.468 (0.047)	0.708 (0.050)	1.494 (0.026)	-	-	-1567.7
JSF	1.540 (0.056)	0.809 (0.056)	- -	1.860 (0.053)	-	-1568.6
BSF	1.723 (0.007)	0.846 (0.027)	- -	- -	4.831 (0.61)	-1585.3
Naive	0.242 (0.028)	- -	- -	- -	- -	-1726.7

Figures

Figure 1: Mean Market Value Distribution.