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Competitive Balance Analysis in European Football: addition of in-game data

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Abstract

Research concerning Competitve Balance (CB) in football has produced mixed results. Literature suggests this is due to inappropriateness of measuring techniques and data. This paper discusses whether using in-game data can provide added value in conducting CB analysis. It describes conventional analytical methods and provides an investigation of top football leagues employing in-game data. Findings include that, while actual scores are more imbalanced than performances suggest, some teams consistently manage to overachieve relative to performance. The significance of results emphasizes the value from in-game data. The paper concludes by eliciting two areas for regulation, redistribution of money and talent.

Key words: Competitive Balance, European Football, Sports Economics, Data, Comparative Study

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1. Introduction

European Football has witnessed many controversies over recent years. Whether there have been attempts of a party of "elite" clubs trying to establish a new pan-European "Super League", the introduction of the Video Assistant Referee or an increasingly tight match calendar caused by regulatory reforms. The resulting criticism from supporters and traditionalists has circled the argument of football becoming too commercialized, claiming that the authorities and club owners would "abuse" the sport solely for revenue maximization (Brannagan et al. 2021). This criticism results from the concern of leagues becoming further imbalanced in terms of competitiveness, as it is mainly those "elite" clubs which drive profit and, therefore, benefit substantially when the competitions they play in generate more revenue (Brannagan et al. 2021).

Evidence, however, remains largely inconclusive. Within European professional football, literature is painting an unclear picture. Some studies detected no changes across European leagues, including German, French and Spanish first divisions (Goossens 2006), and English first division (Szymanski 2001). Others report a decline in competitive balance in some leagues, , English, German, Italian and Dutch first divisions (Groot 2008) and Spanish first division (Montes et al. 2014).

The contrast in these studies also reflects broader issues concerning competitive balance research. As Pawlowski (2013) states, it may be that the empirical evidence is "wrong" because the proxies used to measure competitive balance are inadequate. Dobson & Goddard (2011) have found that the issues concerning competitive balance research have gained much attention in the field recently. Research exhibits numerous measures of concentration of inequality that were applied, some of which originate from industrial economics. Many indices are proposed and used for competitive balance, some of which can be found in Groot's (2008) and Mitchie & Oughton's (2004) texts.

The most fundamental issue in sports economics is the "uncertainty of outcome" hypothesis. According to this hypothesis, the greater the uncertainty of the outcome of a sporting event, the greater the demand. Sports leagues have consistently justified competitive restraints because they permit resource distribution, which promotes outcome uncertainty and benefits the consumer by providing a more attractive league product. In any other context, agreements among the clubs to restrain economic competition, such as salary caps, roster limits, draft rules, transfer fee systems, or agreements to share income from ticket sales, broadcasting, or merchandising, would be prohibited. Yet the courts have accepted such agreements and even encouraged by the legislature, primarily based on the uncertainty of outcome hypothesis.

Outcome uncertainty is a concept requiring careful definition. Knowles et al. (1992) stated that the UOH is "predicated on the assumption that fans receive more utility from observing contests with an unpredictable outcome and posits that the more evenly playing abilities are matched, the less certain the game's outcome and the greater the game's attendance will be". Similarly, Forrest & Simmons (2002) defined uncertainty of outcome as "a situation where a given contest within a league structure has a degree of unpredictability about the result".

The research on competitive balance is vast, yet it exhibits inconclusive evidence resulting from difficulties concerning the measuring techniques or, even more fundamentally, in the conceptual definitions to be analyzed.

2. Research Question

Literature and theory suggest a more even league would excite fans, generating more revenue. However, research has in part shown that CB has declined in the top 5 leagues of Europe. Other academic sources imply that it has not. A problem often associated with this inconclusiveness is that of the measuring techniques and data (end-of-game data) employed. The question that naturally follows:

"Can the additional use of in-game data from football matches add value to analyzing competitive balance? Do conclusions change?"

In attempting to answer this question, this paper shall capitalize on the work of other authors to develop sensible methods of analysis. Further, the study shall be based on in-game data: *xG (expected goals) and xPts (expected points).* In the context of this paper, the notion of in-game data, compared particularly to end-of-game data, refers to data that reflects an aspect of the game more adequately than the final scoresheet. The final score might be subject to many random factors, while xG and xPts indicate teams' performances. According to the author's research, xG and xPts have not yet been employed in competitive balance analysis, presenting a new avenue for research and practices.

In particular, the paper will structurally follow the outline below: first, it will familiarize the reader with conventional CB analytical tools. Second, the alternative data, xG and xPts, will be scrutinized, and the application of the data within the analytical approach explained. Third, the analysis, designed in a gradual, complementing fashion, will be provided. Finally, the conclusion shall point to further research and potential policy implications.

3. Methodology

a. Concentration vs. Dominance

This section is dedicated to familiarizing the reader with conventional methods of measuring competitive balance. In sports economics, Ramchandani et al. (2018) distinguish two aspects of competitive balance – the level of concentration and the level of dominance. These measures are used to assess the degree of competitiveness within a league. The first relates to the closeness between teams in a league within a season. In contrast, the latter considers the extent to which the same teams consistently achieve milestones, such as winning the league across several seasons. The essential difference between these two concepts is that the team's identity

does not matter for measures of concentration but for measures of dominance. Simply put, a league with fewer different title winners over a long time suggests that that league displays higher dominance.

Concentration measures evaluate the spread of success or resources (like talent or wins) among teams within a league.

1. Concentration Ratios (CR):. CR calculates the proportion of league points won by the top teams (e.g., the top 3 or 4 teams).

2. Herfindahl-Hirschman Index of Competitive Balance (HICB): Originally used to measure market concentration, HHI sums the squares of the market shares (in this case, the share of league points or wins) of all the teams in a league. It measures how concentrated the league is in terms of team success. An HHI close to 0 indicates deficient concentration (high competitive balance), while an HHI close to 1 (or 10,000 if using percentage market shares) indicates high concentration (low competitive balance).

3. Title & Survival Gaps: The title gap describes the difference between the points per game scored by the first-placed team and the average points scored by other likely title contenders. To examine the competition for survival, the average points per game of the teams in the last three places are compared with the corresponding number of teams placed immediately ahead of them.

Dominance measures look at the persistence of success among a small number of teams over time.

1. Variation in Championship Wins: This measure looks at the number of teams winning the league championship over a set period. A greater number of different winners indicates a higher level of competitive balance.

2. Time-Series Models: These models can evaluate the persistence of team rankings over time.

If the same teams are consistently at the top (or bottom), it implies dominance (or lack of competitiveness).

b. Own approach & Data

Considering the depicted peculiarities and difficulties in measuring competitive balance, this piece aims to conduct a novel approach. The journalistic and practising football world has recently started using new types of statistics to discuss the course of events and the outcome of football matches. The so-called "expected goals" (or xG) metric has started to become widely accepted across media and fans (Whitmore 2023). Data providers compute xG in real-time (provisional values subject to correction), analyzing situations during a game based on algorithms which refer to a vast amount of data (ca. 10.000 games).

Regarding analysis and interpretation, xG and xPts provide added value as they reflect teams' performances during the game, ultimately allowing for inferences about the "ability" of teams. Hence, a more sophisticated view of the spread of ability and competitive balance can be taken by approximating the ability within a league and between teams. As xPts is, generally, already higher for the top teams, it can be viewed as a measure of (im)balance by itself. By analyzing the differences between expected and actual points, research might uncover why specific teams persistently score results (even) better than their performances indicate. Such knowledge could eventually aid in developing new regulations or new practices for coaches, scouts and club executives (e.g., emphasising specific abilities that could make more persistent "overperformance" more likely).

According to Schwerdtfeger (2021), expected goals (xG) are a statistical measure used in football analytics to evaluate the quality of scoring opportunities and predict future performance. xG assigns a value to a shot attempt based on the likelihood that the shot will result in a goal. This value represents the probability of a particular shot being scored, considering various factors. The probability is calculated using historical data from similar shot

situations. Large datasets are analyzed to determine how often a shot from any given position is scored, generating an xG value typically between 0 (no chance of scoring) and 1 (certain goal). The exact probabilities derived can differ across data providers.

xG is used to assess teams and players by comparing the number of goals they scored against the number of goals an average player would be expected to score from the same position. It can indicate whether a team or player is „overperforming“ or „underperforming“ based on the quality of chances created or conceded compared to the scoresheet or points achieved. It provides a more nuanced picture of a match beyond the final score, showing how many goals a team should have scored given their chances. This can be used to evaluate the effectiveness of both attacking play and defensive setup and generally indicates overall performance during matches. The data needed for determining an xG value includes the following:

1. **Shot Location:** Where on the pitch the shot was taken.
2. **Shot Type:** The play leading up to the shot, such as open play, set-piece, penalty, or header.
3. **Player Positioning:** The location of players, particularly defenders and the goalkeeper, affects the likelihood of the shot being successful.
4. **Additional Factors:** Other aspects like whether the shot was taken with the foot or head, the part of the goal aimed at, and the phase of play.

The xG values from all shots of each team are summed to obtain the value for the whole game. From “full game” xG, expected points (xPts) can be determine. Hence, expected points extend the concept of expected goals by estimating how many points a team will earn from a match. This estimate considers the likelihood of a team winning and the probability of drawing or losing based on the quality and quantity of shots taken (xG) by both

teams. There are generally two approaches to calculating expected points from expected goals (Thustrup 2024):

1. **Simple Method (Win/Draw/Lose):** This method compares xG for each team, and points are allocated based on which team has a higher xG:

   If Team A's xG > Team B's xG, team A gets 3 points.

   If Team A's xG = Team B's xG, both teams get 1 point.

   If Team A's xG < Team B's xG, Team B gets 3 points.

2. **Probabilistic Method (Decimal xPts):** This method calculates the probability of each possible match outcome based on the xG figures and then uses these probabilities to estimate an expected points value.

   Formula: $xPts = P(Win) \times 3 + P(Draw) \times 1 + P(Lose) \times 0$

To calculate these probabilities, a model is used that compares the xG values for both teams and incorporates historical data about how often a team with xG value X beats a team with xG value Y. This model could be a logistic regression, a Poisson distribution, or another statistical model suitable for predicting outcomes based on scoring rates.

Suppose in a match between Team A and Team B:

- Team A has an xG of 1.2.
- Team B has an xG of 0.8.

A Poisson model might estimate:

- $P(Win) = 0.60 P(Win) = 0.60$
- $P(Draw) = 0.25 P(Draw) = 0.25$
- $P(Lose) = 0.15 P(Lose) = 0.15$

Using the formula for xPts:

- xPts for Team A=0.60×3+0.25×1+0.15×0=2.05xPts for Team A=0.60×3+0.25×1+0.15×0=2.05

Based on the expected goals, Team A is expected to earn approximately 2.05 points from this match. Expected points calculated using the probabilistic method provide a more nuanced view of a team's performance potential than the simple method (Thustrup 2024). It considers the likeliness of winning and the dynamics of the match (in terms of potential draws and narrow wins or losses) and their effect on the overall points outcome. This can allow for insights throughout several games (or an even more extended time frame), indicating whether a team has managed to over- or underperform its expected collection of points based on the quality of scoring opportunities it has generated.

The analysis was conducted based on data from "Understat", a provider of xG and xPts data covering all top 5 European leagues :

1. Bundesliga (Germany)
2. Premier League (England)
3. LaLiga (Spain)
4. Serie A (Italy)
5. Ligue 1 (France)

The data result from a trained neural network prediction algorithm with a large dataset (>100,000 shots, over ten parameters for each) (Understat 2014). To ensure comparability, the same source was used for each league. Ligue 1 was excluded from the analysis, as the 19/20 season was declared over in April due to governmental restrictions, making it unpractical to consider results from Ligue 1 under the same conditions as the other leagues.

The time frame of seven seasons was chosen based on Ramchandani et al. (2018), who used six seasons, deeming it long enough for analytical purposes. Even though the data is founded on xG, the analysis focuses on xPts. For all seven seasons and across all four leagues, the final

ranking, points and xPts were retrieved. From that, expected rankings and relative & absolute differences between actual points and xPts were determined. Furthermore, league ranks were divided into groups: upper, middle, and lower, allowing for a more granular analysis of CB. For each season, the average of the absolute differences for the whole league and each group was calculated and standard deviations for the absolute differences (Figure 1). Ultimately, an average of those indicators was determined across all seasons (Figure 2).

Teams/Season	2016/17							
	Points	xPts	Diff	abs. Diff	Rank	xRank	Share of points	share of xPts
Bayern Munich	82	73,76	-8,24	8,24	1	1	9,72%	8,72%
RB Leipzig	67	59,54	-7,46	7,46	2	3	7,94%	7,04%
Borussia Dortmund	64	68,06	4,06	4,06	3	2	7,58%	8,04%
Hoffenheim	62	55,44	-6,56	6,56	4	4	7,35%	6,55%
Cologne	49	48,75	-0,25	0,25	5	7	5,81%	5,76%
Hertha Berlin	49	40,4	-8,6	8,6	5	13	5,81%	4,77%
Freiburg	48	39,14	-8,86	8,86	7	14	5,69%	4,63%
Werder Bremen	45	38,82	-6,18	6,18	8	15	5,33%	4,59%
Mgladbach	45	47,31	2,31	2,31	8	8	5,33%	5,59%
Schalke	43	46,37	3,37	3,37	10	11	5,09%	5,48%
Frankfurt	42	50,68	8,68	8,68	11	5	4,98%	5,99%
Leverkusen	41	49,63	8,63	8,63	12	6	4,86%	5,87%
Augsburg	38	34,81	-3,19	3,19	13	16	4,50%	4,11%
Hamburg	38	31,51	-6,49	6,49	13	17	4,50%	3,72%
Mainz	37	46,47	9,47	9,47	15	9	4,38%	5,49%
Wolfsburg	37	46,38	9,38	9,38	15	10	4,38%	5,48%
Ingolstadt	32	42,54	10,54	10,54	17	12	3,79%	5,03%
Darmstadt	25	26,47	1,47	1,47	18	18	2,96%	3,13%

		SDs	HICB	xHICB
Average Diff. Points vs. xPts	6,32	3,11	108,35	106,07

Groups	Avg. Diff	SDs
Upper	5,86	1,88
Middle	6,34	2,04
Lower	7,72	2,48

Figure 1. *Exemplary table retrieved and determined from xG data, containing actual points, xPts, differences, absolute differences, ranks and xranks, and average differences between points & xPts (and standard deviations) for the whole league and across tiers.*

Based on the actual and expected rankings, the number of teams that ended up in either the upper, middle, or lower tier was counted such that a percentage could be calculated showing how many of the teams that have participated in the competition during the past seven seasons obtained in a rank in the three tiers (Figures 8-11). Finally, to understand trends of under- or overperformance, based on the cumulated average ranks over the past seven seasons, a table was created showing which teams regularly obtained more points than expected (Figures 12-15).

5. Analysis

The analysis of the four respective leagues was conducted based on the data described above. The structure started from a more general viewpoint on concentration, working gradually to a more sophisticated, in-depth picture. For this work, it was decided to add the notion of "degree of unpredictability", describing the nature of xG and xPts, which are designed to reflect a team's performance, which is assumed to approximate expectations formed by the viewers. This demonstrates the analysis' interpretation of the uncertainty of outcome hypothesis (UOH), which is interpreted to relating the unpredictability of results on the course of the game and the teams' respective performances (Buraimo & Simmons, 2008). As Szymanski et al. (2010) have pointed out, an essential factor that makes football matches "worth talking about" is to which degree the final scoresheet adequately reflects (or does not) the course of the game. Transferring that conclusion to this work, xG and, consequently, xPts throughout a season are indicative of what could have been expected based on the course of the game(s) in terms of the final score. Hence, the difference between the final score and the expectations built from observing the game is assumed to be sparking viewer interest. Consequently, the initial assumption underlying the analysis is that a larger difference between actual and expected points implies more unpredictability. In this context, it serves as an additional measure of CB alongside concentration and dominance. In the analysis, the concept of unpredictability will be dissected and analyzed in terms of team quality (tiers), dominance and performance ability, and the direction of performance deviations.

a. Concentration & Unpredictability

This section first establishes the idea of unpredictability by analyzing concentration measures. Then, based on time and team ranking, the source of unpredictability is examined.

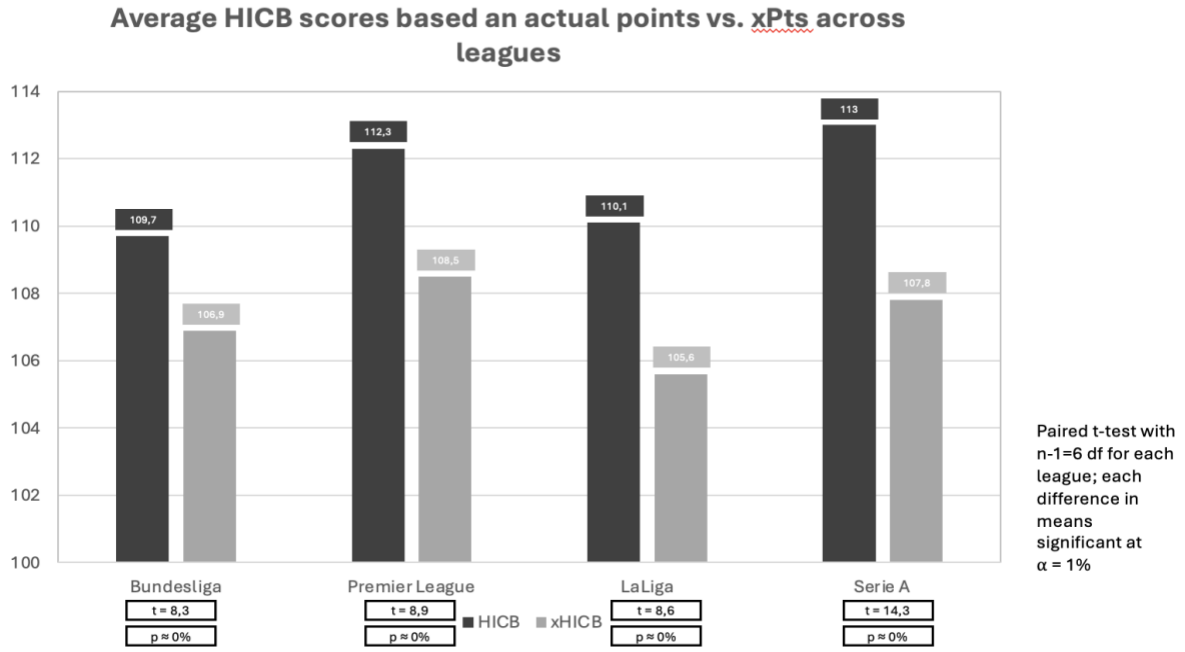

Figure 2. Average HICB scores actual points vs. xPts over the last seven seasons & t-stat + p-value for two-sided paired t-test of equality

Figure 2 shows the mean HICB scores for each league under consideration using actual and expected points. For all leagues, the score is lower using xPts. Further, using a paired t-test on the mean differences between the two data sets, these divergences were shown to be significant ($p < 0.01$). That implies that when comparing the points obtained from actual scores to expected points, there is more imbalance than expected. Notably, this result shows that actual scorelines are significantly more in favour of top teams than performances would predict.

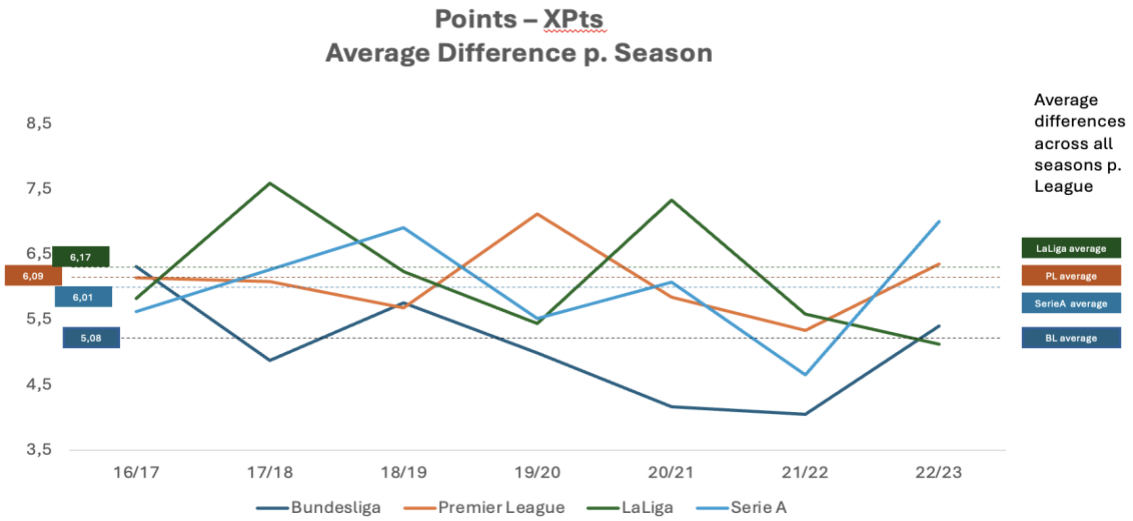

Figure 3. Graph comparing the development of the average differences between points and pets over the last seven seasons between Bundesliga, Premier League, LaLiga, and Serie A.

Figure 3 compares, over time, the average differences between actual points and xPts between the top 4 leagues. These differences can be negative or positive. For this depiction, absolute differences were used, as the direction of deviation is not yet considered (implying that the average difference need not be zero).

The graphs only exhibit little disparities between the competitions. Generally, if a graph does not follow a clear trend, that implies no significant changes in the degree of unpredictability within leagues during the considered time frame. Notably, the German Bundesliga exhibits a somewhat lower average score (5.08) compared to the other leagues. The league also appears to show a particular trend in the development of the average difference, hinting towards a lowering degree of unpredictability during the considered time frame. This might translate to Bayern Munich's increasing dominance during the last decade. The spikes that can be observed for LaLiga (green) and the Premier League (orange) might be indicative of seasons that saw one or a small set of teams excessively deviating from their expected performance (e.g. Liverpool 19/20, obtaining 99 points) without necessarily implying a trend. Overall, the lower the differences depicted in the graphs, the lower the deviation between performance and actual

scores across leagues. To further scrutinize the nature of the differences observed, the analysis turns to a more granular approach, subdividing rankings into three tiers.

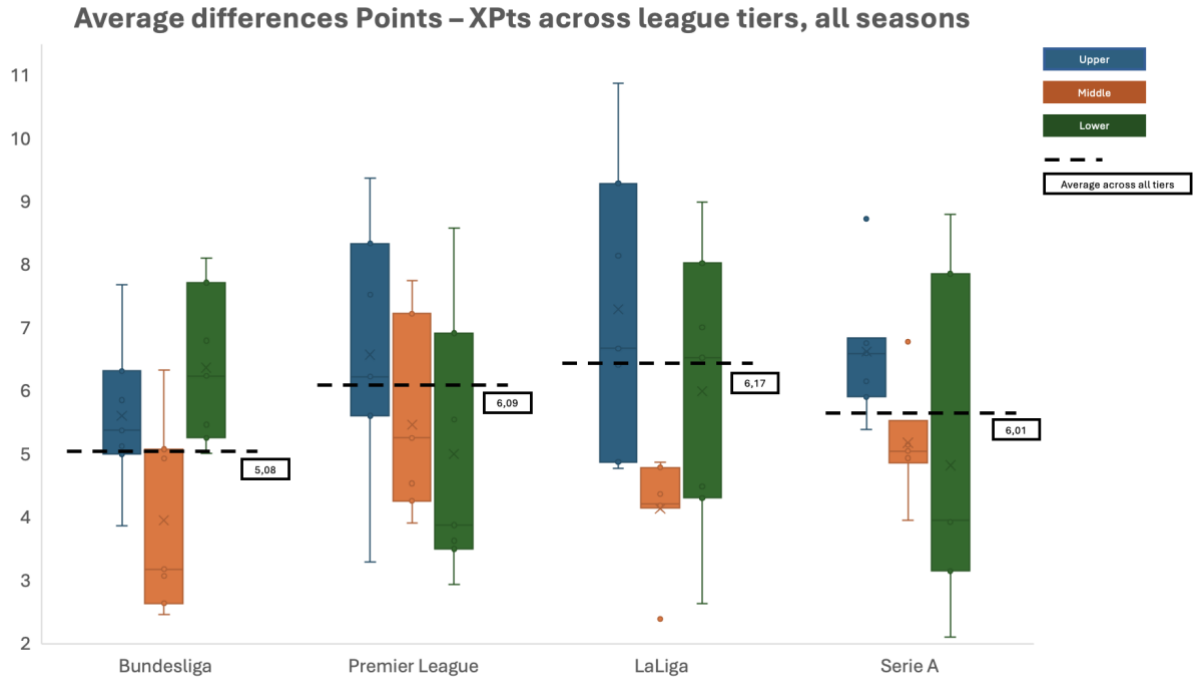

Figure 4. Boxplots comparing the average differences between points and xPts within tiers over the last seven seasons between Bundesliga, Premier League, LaLiga, Serie A.

The boxplots, 3 per league, represent the tiers into which the leagues were divided (upper, middle, lower). Blue boxes represent the upper tier in each league, and orange and green represent the middle and lower tiers, respectively. The dotted line represents the average across all tiers (hence, the league average). The further the boxplots are above the average, the stronger they imply a relatively high degree of unpredictability from within that tier. Conversely, the further a boxplot is found below the league average, the stronger the implication for a low degree of unpredictability. The length of a box shows the level of volatility in differences within that tier across the last seven seasons. Figure 4 shows similarities across all leagues under consideration. The upper tier boxes are at least partly above the respective league averages. In comparison, Serie A and Bundesliga have relatively short upper-tier boxes, indicating low volatility in the deviations of relatively strong teams. In the middle tier, Bundesliga, LaLiga

and Serie A boxes are entirely below the dotted line. Disparities exist about the location of the boxplots representing the lower tiers and the middle-tier box from the Premier League. While the Bundesliga's lower tier is above the league average, hinting towards performance-to-result deviation from relatively weaker teams, the other leagues' lower tiers are only partly below their respective average. For Italy, the lower tier is by far the most volatile, possibly implying a certain degree of dominance in the league. Notably, the Premier League is the only competition for which the middle tier is not the group with the lowest sitting boxplot.

These observations enable an understanding of which kind of teams are mainly responsible for a league's degree of unpredictability. Across all four leagues, the upper tier seems a driving force. The length of the upper tier boxes for LaLiga and Premier League show a higher volatility for top teams in these leagues, possibly a sign of more unpredictability (emphasized by the general notion that e.g. the Premier League is more exciting than the Bundesliga). Excluding the Premier League, middle tier teams obtain more predictable results based on their performances, decreasing the competition's unpredictability. While insights on the structure and emergence of unpredictability were collected, the nature of unpredictability is still unclear.

b. Dominance/nature of Unpredictability

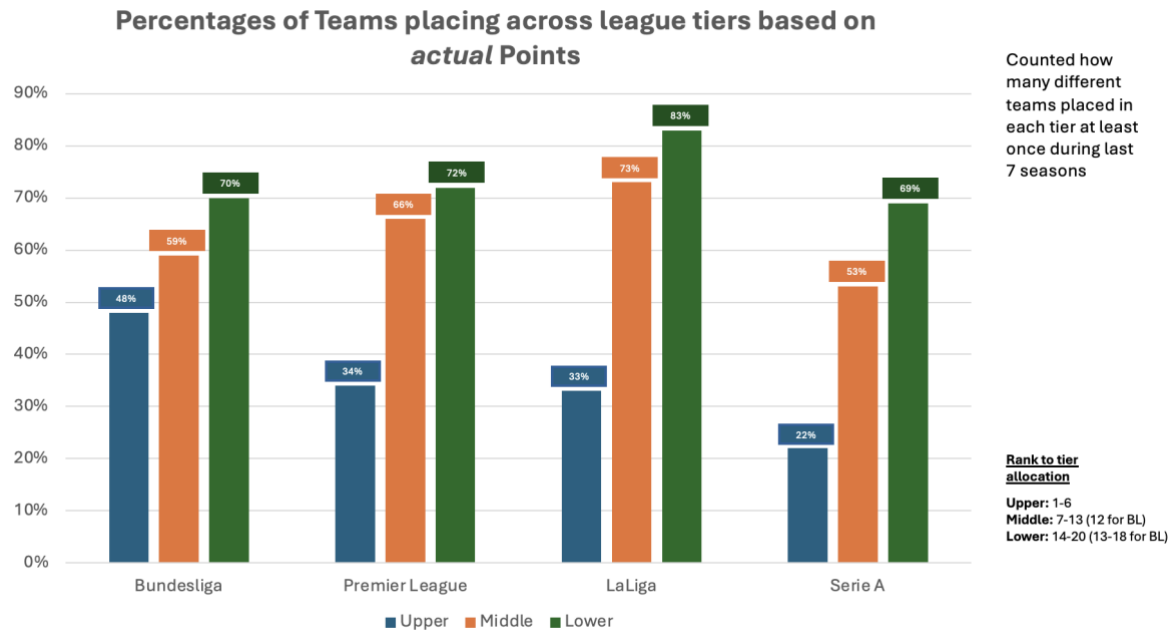

Figure 5. Bar chart comparing the percentage of teams that have participated in the Bundesliga/Premier League/LaLiga/Serie A which have ended in the different tiers based on actual points.

Extending the discussion from pure degree of unpredictability to dominance allows to gather insights on the nature of unpredictability. This might help to understand whether under- or overperformance can be linked to the strength of a team (which tier is allocated to) or if such deviations are evenly distributed across a league. The notion of under- or overperformance refers again to the difference between actual points and xPts. If a team has obtained more points than its xPts predicts, it is said to have overperformed. This section is, therefore, dedicated to understanding the nature of unpredictability (negative or positive) within the tiers.

Figure 5 shows the percentages of teams participating in the respective competition and were placed at least once in one of the respective tiers. A high fraction implies that many teams could obtain the necessary results to end up in a ranking belonging to that tier. E.g., a low percentage in the upper tier means that, over the last seven seasons, only a few teams could obtain high rankings (e.g., to qualify for Europe and be better rewarded through domestic leagues).

All four leagues exhibit the same stairway pattern, showing that the nr. of teams increases, the lower the tier becomes. Interestingly, the Bundesliga has the highest fraction of teams that could enter the upper tier at least once (48%), whereas in Serie A, only 22% of competing teams could do so. Generally, Serie A has the lowest fractions in all tiers compared to the other three leagues, implying relatively less "travel" between tiers in Italy. In the Premier League and LaLiga, many teamshave entered either the middle or lower tier, while the upper tier in both leagues seems more challenging to reach.

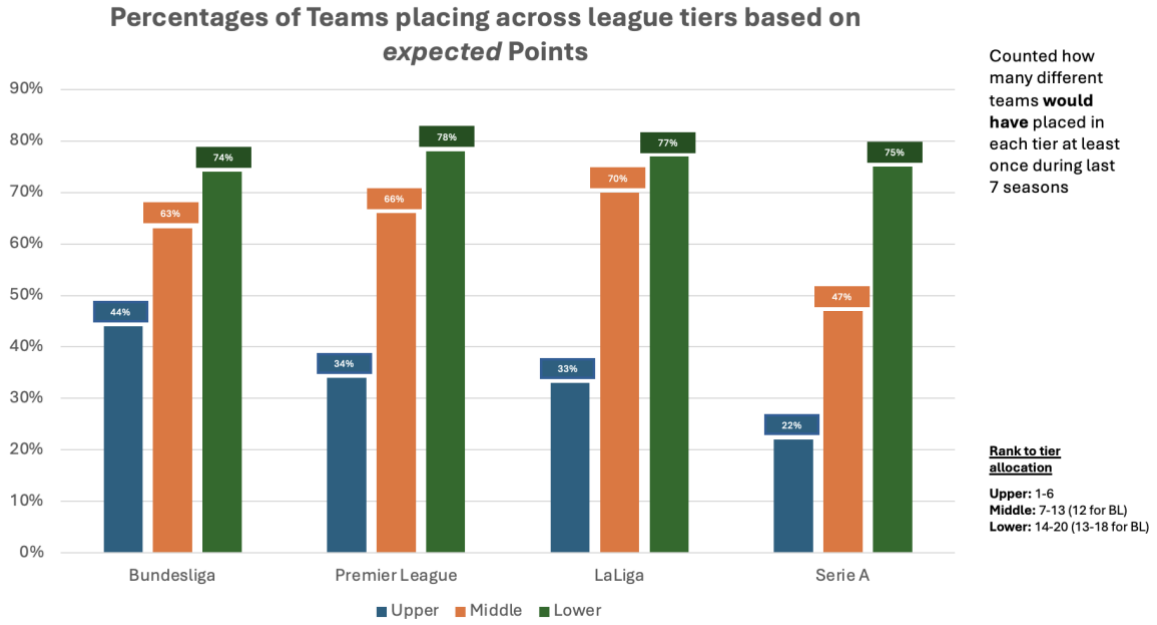

Figure 6. Bar chart comparing the percentage of teams that have participated in the Bundesliga/Premier League/LaLiga/Serie A which have ended in the different tiers based on xPts.

Figure 6 shows the percentages of teams participating in the respective competition and would have been placed at least once in one of the respective tiers. A high percentage implies that many teams could perform at a level that would result in a ranking belonging to that tier. For example, a low percentage in the upper tier implies that only a few teams could perform sufficiently to reach a high ranking. Possible differences in the numbers depicted in Figure 5 might mean that performances were not entirely reflective of results, indicating a higher degree

of unpredictability. Moreover, a low percentage, e.g. in the upper tier, could hint towards a persisting gap in performance abilities between tiers.

As before, all four leagues exhibit a stairway pattern. While some percentages have marginally changed, the overall impression persists, even after moving from actual points to expected points. Most notably, only the Bundesliga shows a slight difference in the upper tier fraction (48% actual, 44% xPts), implying that more teams could enter the upper tier than performance relative to the other teams would have indicated. Compared, the upper tier fraction has not changed for the other leagues. On the other side, the middle and lower tier percentages have changed across the board. Hence, the relative performance abilities seem to be much more concentrated within those tiers, whereas the upper tier teams might enjoy some persisting gap in ability.

	actual			expected		
	upper	*middle*	*lower*	*upper*	*middle*	*lower*
Bayern Munich	7	0	0	7	0	0
RB Leipzig	7	0	0	6	1	0
Borussia Dortmund	7	0	0	7	0	0
Hoffenheim	3	4	0	3	3	1
Cologne	1	2	3	1	3	2
Hertha Berlin	1	3	3	0	4	3
Freiburg	2	3	2	1	1	5
Werder Bremen	0	4	2	0	2	4
Mgladbach	2	5	0	3	4	0
Schalke	1	2	3	1	2	3
Frankfurt	2	5	0	4	2	1
Leverkusen	6	1	0	6	1	0
Augsburg	0	1	6	0	2	5
Hamburg	0	0	2	0	0	2
Mainz	0	4	3	0	5	2
Wolfsburg	2	3	2	2	4	1
Ingolstadt	0	0	1	0	1	0
Darmstadt	0	0	1	0	0	1
Hannover	0	0	2	0	0	2
Stuttgart	0	2	3	0	3	2
Dusseldorf	0	1	1	0	0	2
Nuremberg	0	0	1	0	0	1
Paderbon	0	0	1	0	0	1
Union Berlin	2	2	0	1	3	0
Bielefeld	0	0	2	0	0	2
Bochum	0	1	1	0	1	1
Furth	0	0	1	0	0	1
	13	**16**	**19**	**12**	**17**	**20**
	48%	**59%**	**70%**	**44%**	**63%**	**74%**

Figure 7. Table of counts, showing how often each team ended in each tier & counting how many different teams ended in each tier, Bundesliga.

	actual			expected		
	upper	*middle*	*lower*	*upper*	*middle*	*lower*
Juventus	7	0	0	7	0	0
Roma	5	2	0	7	0	0
Napoli	6	1	0	7	0	0
Atalanta	5	2	0	7	0	0
Lazio	6	1	0	3	4	0
AC Milan	7	0	0	4	3	0
Inter	6	1	0	7	0	0
Fiorentina	0	6	1	0	6	1
Torino	0	5	2	0	6	1
Sassuolo	0	7	0	0	6	1
Sampdoria	0	4	3	0	5	2
Cagliari	0	2	4	0	0	6
Udinese	0	7	0	0	6	1
Chievo	0	1	2	0	1	2
Bologna	0	5	2	0	4	3
Genoa	0	2	4	0	2	4
Crotone	0	0	3	0	0	3
Empoli	0	0	4	0	1	3
Palermo	0	0	1	0	0	1
Pescara	0	0	1	0	0	1
SPAL	0	0	3	0	1	2
Verona	0	3	2	0	3	2
Benevento	0	0	2	0	0	2
Parma Calcio	0	1	2	0	0	3
Frosinone	0	0	1	0	0	1
Brescia	0	0	1	0	0	1
Lecce	0	0	2	0	1	1
Spezia	0	0	3	0	0	3
Salernitana	0	0	2	0	0	2
Venezia	0	0	1	0	0	1
Monza	0	1	0	0	1	0
Cremonese	0	0	1	0	0	1
	7	**17**	**22**	**7**	**15**	**24**
	22%	**53%**	**69%**	**22%**	**47%**	**75%**

Figure 8. Table of counts, showing how often each team ended in each tier & counting how many different teams ended in each tier, Serie A.

Illustrating and complementing the discussion on a possible performance/ability gap are Figures 7 and 8, contrasting the two cases of Bundesliga and Serie A. These figures showcase the teams' identities that obtained rankings in the different tiers. The same seven teams in Serie A could secure upper tier spots regarding actual and expected points. Accordingly, in the Bundesliga, only Hertha Berlin obtained an upper tier ranking once without showing a matching performance in expected points. A similar picture emerges in Figures 14 & 15 in the appendix (Premier League & LaLiga). Besides a few exceptions (West Ham, Crystal Palace, Athletic Club), the teams that obtain upper tier rankings also performed in accordance, relative to the other teams in the league.

Yet it remains unclear whether deviations between actual and expected points follow a pattern, i.e., whether some teams tend to overperform and some tend to underperform, or whether those deviations (and therefore, the unpredictability) are random.

Teams	Sum of Differences	cumulated ranks	nr. of seasons	avg. Rank
Bayern Munich	-27,53	7	7	1,00
Borussia Dortmund	-23,27	16	7	2,29
RB Leipzig	-1,7	23	7	3,29
Leverkusen	2,02	39	7	5,57
Union Berlin	-18,37	26	4	6,50
Hoffenheim	-6,02	53	7	7,57
Mgladbach	7,46	54	7	7,71
Frankfurt	10,38	57	7	8,14
Freiburg	-30,78	62	7	8,86
Wolfsburg	4,69	66	7	9,43
Mainz	19,02	82	7	11,71
Cologne	27,24	71	6	11,83
Hertha Berlin	6,28	83	7	11,86
Werder Bremen	-2,77	72	6	12,00
Schalke	12,29	73	6	12,17
Bochum	-1,97	25	2	12,50
Stuttgart	23,6	63	5	12,60
Dusseldorf	-1,92	27	2	13,50
Augsburg	0,94	96	7	13,71
Hamburg	1,1	30	2	15,00
Hannover	4,79	30	2	15,00
Bielefeld	-10,9	31	2	15,50
Ingolstadt	10,54	17	1	17,00
Darmstadt	1,47	18	1	18,00
Nuremberg	16,12	18	1	18,00
Paderbon	8,67	18	1	18,00
Furth	8,48	18	1	18,00

Figure 9. table based on average ranks Bundesliga, showing summed differences between points and xPts.

Figures 9-12 show tables for each league based on the average rankings of all the clubs competing during the last seven seasons. Those tables indicate the sum of differences each club accumulated throughout the seasons they played. The difference in each season is calculated by subtracting actual points from xPts. A negative difference (e.g. 73xPts – 90 points) would indicate an overperformance, meaning the team obtained better results than expected. The sum of differences underlines whether a team has persistently under-, overperformed, or matched its results to its performances (when close to 0). Figures 9-12 highlight negative sums in green and positive sums in red.

Across all four leagues, there is a clear tendency for higher-ranking teams to have obtained positive sums. In Serie A, the difference between green and red "blocks" is particularly striking, further underlining Italy's possibly concentrated, "reserved" upper tier. The Bundesliga stands out as even the top teams have not accumulated differences of < -30, compared to the other three leagues, where at least three teams have far exceeded that benchmark.

However, although the gap might vary in size, all leagues display strong evidence of a performance gap between the top teams, which regularly take the top spots, and the middle and lower-tier teams, which barely ever make it into the upper rankings.

c. Potential policy implications

The analysis established the existence of consistent "overperformance" of top teams across all 4 European top leagues, underscored by the HICB measures, showing that actual scores are more imbalanced than expected scores generated from data. Considering dominance measures, a persistent gap in ability between top teams compared to middle and lower tier teams could be observed. This gap is not reflected in the performance captured by xG and xPts. This condition should be a source of concern for continental and domestic league authorities (UEFA for Europe, DFL in Germany, FA in England, RFEF in Spain, FIGC in Italy), as it ultimately undermines the competitive balance of the leagues under consideration. This section shall discuss possible policy implications in response to these findings.

Even though it is subject to further research, intuition suggests that the gap in ability might result from superior playing talent. "To score from nothing" or "To avoid an almost certain goal" are much-used sentences in football describing the ability of individual players to create or hinder goals against the odds of the situation they are facing. Such players can be assumed to be scarce. However, due to a widening gap in financial potency, certain clubs can accumulate

such players at bearable financial risks (Chelsea, Manchester City, Real Madrid). Hence, the current circumstances can be broken down as follows:

1. More potent clubs have better players, allowing them to achieve better results and enjoy higher rewards.
2. More potent clubs enjoy higher rewards, allowing them to accumulate better players and reinforce their financial superiority.

Hence, domestic and continental football associations (the aforementioned governing bodies) might target the financial superiority of top teams or their accumulation of top players. Redistribution of money might be an avenue to take for regulators. An equality-oriented pay-out policy might help stop the financial gap from widening. More liberally, an anti-progressive pay-out might even help to effectively reduce that gap. However, such policies might negatively impact incentives for teams that neither compete for the top spots for European competition, which offer additional financial rewards, nor relegation, resulting in heavy monetary losses. Hence, teams that can anticipate achieving a middle tier ranking might cease to compete at maximum effort, eventually decreasing value for viewers. This disincentive, theoretically, can be alleviated if players could easily switch to better teams. This can be observed in US sports, where the draft system creates a flow of transfers.

Deliberate redistribution of talent might be another option. A notable measure to redistribute playing talent is the aforementioned “draft system”, designed to allow last season’s worst team to draw the top pick, usually the most promising young player. Due to the relegation system and the duration some players take to develop an impactful ability in football, replicating this system is not sensible. However, a possible idea could be collectively subsidising the transfer fees through a league fund. This subsidy would need to be bound to specific criteria and limited in number to ensure fairness in market conduct. A possible design might be that a club that

wants to bid for a particular player needs to have placed at least six ranks below the club of the player it is bidding for (effectively excluding the top-ranking teams from using the subsidy). A subsidy would only cover up to 25% of the agreed transfer fee, freeing up capital for other purposes such as salary. A club can only apply for subsidy after the transfer is agreed upon and can only subsidize one transfer per season. However, this approach's feasibility strongly depends on players willing to transfer to a lower-ranked club. In practice, this can happen with players from top teams that have fallen out of favour due to injury or other circumstances. However, even with a 25% subsidy, there is room for doubt that many clubs can convince players to "downgrade" when they have achieved a certain level and status in their careers. A relevant downside of strengthening competitive balance within leagues is that if other leagues do not do so, one might suffer a decrease in the relative quality of top teams. This can be considered detrimental as the top teams represent their domestic league in international competition. International performances will likely suffer if that domestic league improves CB from its own resources. As prestige from and performance in such competitions (e.g. UEFA Champions League) can be factors in revenue generation for leagues and the clubs competing internationally, incentives might be ambiguous (leagues) or low (clubs) to engage in redistributing policies (Storm & Solberg, 2018). Conclusively, rules would have to be applied at the UEFA level to ensure cohesion between leagues and to counter the incentives from international competition on national football associations.

6. Limitations

The findings from the above analysis are, however, subject to limitations. This section is dedicated to naming and explaining those, putting the conclusions drawn into perspective. While the analysis treated xG and xPts as reflective of "performance", it must be stated that many other factors contribute to the performance that is not considered in the data, which mainly resembles the ability to create and hinder goalscoring opportunities. The tiers used in

the analysis were chosen to divide the competitions into equal parts. However, in the case of the Bundesliga or LaLiga, there is a persistent gap within the upper tier (Bayern Munich in Germany, Barcelona and Real Madrid in Spain). This is not reflected in the approach to analyzing the upper tier.

Further, the data itself is generated and provided by different providers and, therefore, might differ depending on the source. If results using data from other sources vary significantly, it would decrease the meaningfulness of this paper's analysis. Also, the data is only available for relatively recent seasons and top leagues, making it more challenging to conduct longitudinal studies to report on the long-term development of the competitive balance of broader scope (i.e. considering more minor leagues). Finally, similar metrics might not exist in all team sports (Baseball) or might not be as meaningful, limiting the possibility of using this approach outside of football.

7. Conclusion

The analysis has shown that conventional methods, such as concentration measures, can be successfully adapted and utilized when using xG and xPts. The additional value in using expected data lies in the power of comparison. As discussed during the analysis, if there is a significant gap between expected data and actual results, it indicates other factors that must explain this divergence.

Also, the work in this paper unveiled that even by employing in-game data, a mere analysis of concentration/unpredictability without consideration for the identity of teams (analysis of dominance) is not meaningful. This is in accordance with conventional analysis. Initially, the measures of concentration and unpredictability indicated that the top leagues in Europe are more imbalanced than performances based on xPts would suggest. After scrutinizing dominance measures and considering the identity of teams, this impression was amplified (with the Bundesliga being somewhat of an exception).

Concerning conclusions, the analysis has shown that deviations between actual scores and expected points exist, implying some unpredictability. Within the considered time frame, these differences were consistent. Further, the deviations appear more significant in the upper and lower tiers of the leagues under consideration (excluding the Premier League). However, it became evident that while many teams have obtained rankings in the lower and middle tiers, the upper tier seems to be reserved for only a small fraction of teams (excluding the Bundesliga). Generally, the teams that manage to achieve upper tier rankings also seem to consistently overperform relative to their expected goals and points and other teams. This was found across all four leagues during the considered time frame. Hence, there is evidence for some degree of a performance/ability gap (dominance from ability, which is not reflected in xPts) between top teams and middle and lower-ranking ones that might limit the seemingly existing degree of unpredictability. In summary, the analysis using in-game data did provide additional insights into the factors that restrict competitive balance. However, due to the recency of the data's emergence, it fails to provide meaningful insights concerning the development of competitive balance.

However, the aforementioned ability gap could concern football associations such as UEFA. While teams show a relatively even spread in their performances across the four leagues, top teams must possess certain qualities which others cannot compensate for by performance captured by xG. Intuitively, the individual quality of players, e.g. "to score from nothing" or "to avoid an almost certain goal", might hold some explanatory power in this context. More substantial redistribution of money (or even redistribution of talent), as practised in US sports, could be an avenue to avoid the accumulation of superior playing talent. More creative solutions, such as a subsidy system (outside the upper ranks), might enable consistent middle or lower tier teams to slowly close the gap to the top teams. However, incentives for league associations, with regard to the international performance of its clubs, might be at least

ambiguous. This could be circumvented if regulations were established on the continental, that is, UEFA, level.

Ultimately, the future of European football will strongly depend on whether governing bodies will be able and willing to foster more even competition through stricter or more innovative regulation. With a new Champions League format coming up and the rise of the European Super League continuing, the domination from top teams will most likely not end.

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Appendix

List of Figures

EXEMPLARY

GERMANY SEASON 16/17

Teams/Season	2016/17							
	Points	xPts	Diff	abs. Diff	Rank	xRank	Share of points	share of xPts
Bayern Munich	82	73,76	-8,24	8,24	1	1	9,72%	8,72%
RB Leipzig	67	59,54	-7,46	7,46	2	3	7,94%	7,04%
Borussia Dortmund	64	68,06	4,06	4,06	3	2	7,58%	8,04%
Hoffenheim	62	55,44	-6,56	6,56	4	4	7,35%	6,55%
Cologne	49	48,75	-0,25	0,25	5	7	5,81%	5,76%
Hertha Berlin	49	40,4	-8,6	8,6	5	13	5,81%	4,77%
Freiburg	48	39,14	-8,86	8,86	7	14	5,69%	4,63%
Werder Bremen	45	38,82	-6,18	6,18	8	15	5,33%	4,59%
Mgladbach	45	47,31	2,31	2,31	8	8	5,33%	5,59%
Schalke	43	46,37	3,37	3,37	10	11	5,09%	5,48%
Frankfurt	42	50,68	8,68	8,68	11	5	4,98%	5,99%
Leverkusen	41	49,63	8,63	8,63	12	6	4,86%	5,87%
Augsburg	38	34,81	-3,19	3,19	13	16	4,50%	4,11%
Hamburg	38	31,51	-6,49	6,49	13	17	4,50%	3,72%
Mainz	37	46,47	9,47	9,47	15	9	4,38%	5,49%
Wolfsburg	37	46,38	9,38	9,38	15	10	4,38%	5,48%
Ingolstadt	32	42,54	10,54	10,54	17	12	3,79%	5,03%
Darmstadt	25	26,47	1,47	1,47	18	18	2,96%	3,13%

		SDs	HICB	xHICB
Average Diff. Points vs. xPts	6,32	3,11	108,35	106,07

Groups	Avg. Diff	SDs
Upper	5,86	1,88
Middle	6,34	2,04
Lower	7,72	2,48

Figure 1. Exemplary table retrieved and determined from xG data, containing actual points, xPts, differences, absolute differences, ranks and xranks, average differences between points & xPts (and standard deviations) for the whole league and across tiers.

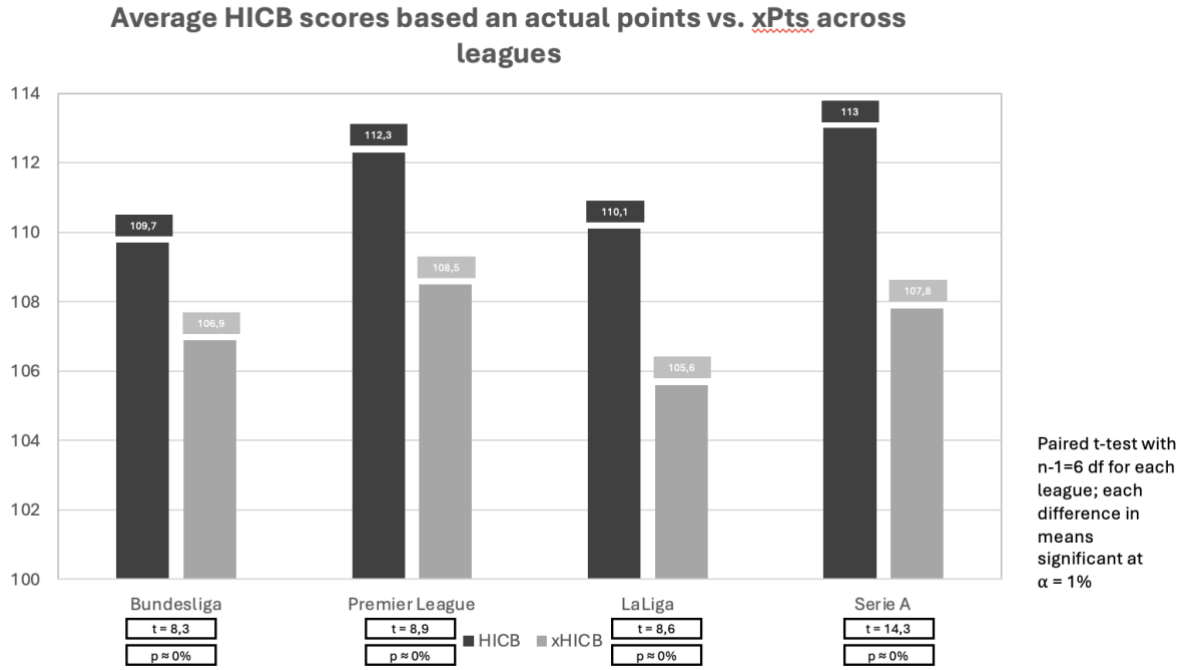

Figure 2. average HICB scores actual points vs. xPts over the last 7 seasons & t-stat + p-value for paired t-test

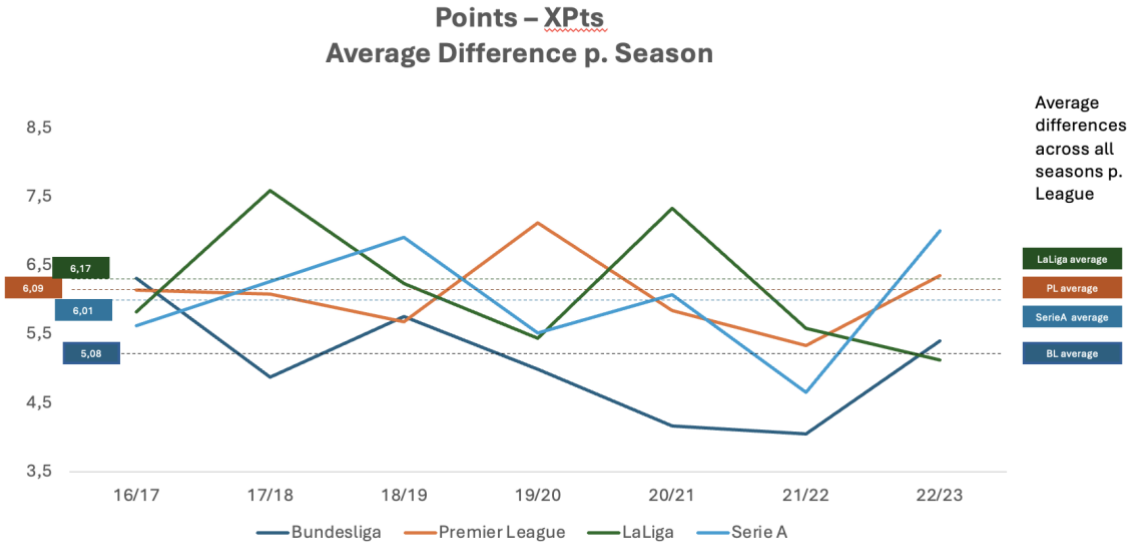

Figure 3. Graph comparing development of the average differences between points and xPts over the last 7 seasons between Bundesliga, Premier League, LaLiga, Serie A.

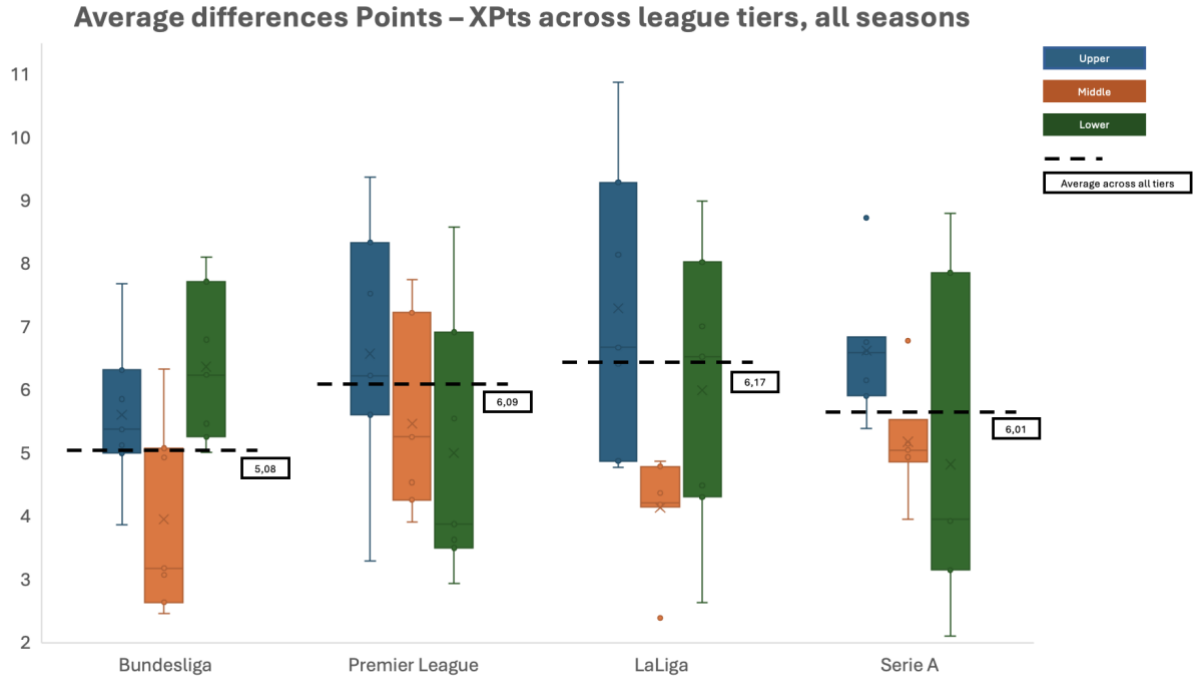

Figure 4. Boxplots comparing the average differences between points and xPts within tiers over the last 7 seasons between Bundesliga, Premier League, LaLiga, Serie A.

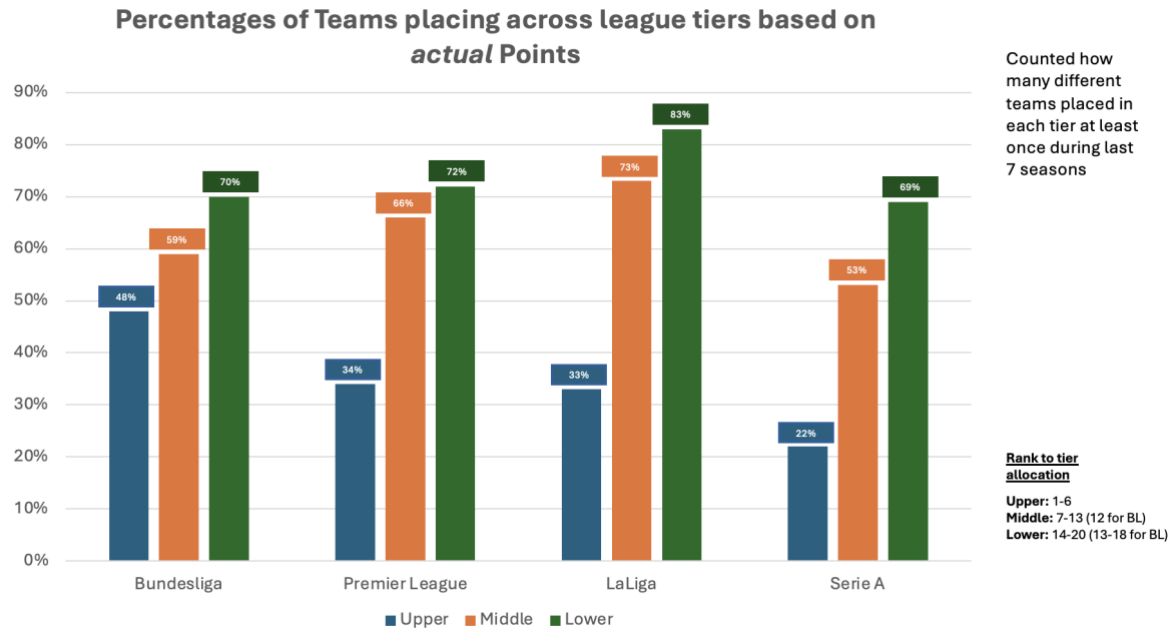

Figure 5. Bar chart comparing the percentage of teams that have participated in the Bundesliga/Premier League/LaLiga/Serie A which have ended in the different tiers based on actual points.

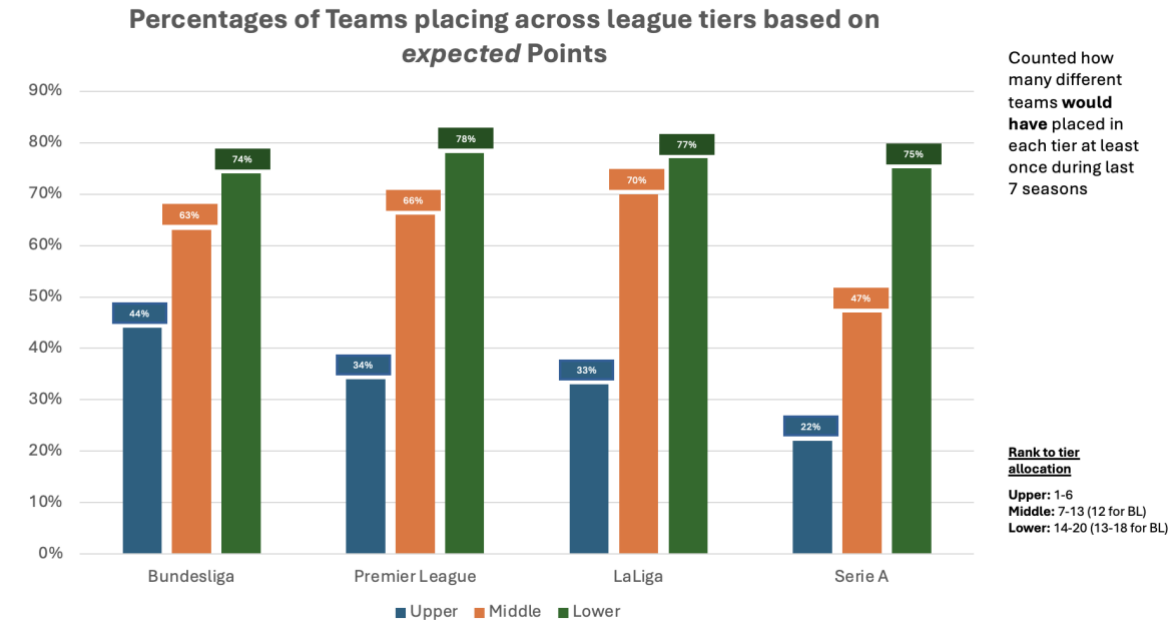

Figure 6. Bar chart comparing the percentage of teams that have participated in the Bundesliga/Premier League/LaLiga/Serie A which have ended in the different tiers based on xPts.

	actual			expected		
	upper	*middle*	*lower*	*upper*	*middle*	*lower*
Bayern Munich	7	0	0	7	0	0
RB Leipzig	7	0	0	6	1	0
Borussia Dortmund	7	0	0	7	0	0
Hoffenheim	3	4	0	3	3	1
Cologne	1	2	3	1	3	2
Hertha Berlin	1	3	3	0	4	3
Freiburg	2	3	2	1	1	5
Werder Bremen	0	4	2	0	2	4
Mgladbach	2	5	0	3	4	0
Schalke	1	2	3	1	2	3
Frankfurt	2	5	0	4	2	1
Leverkusen	6	1	0	6	1	0
Augsburg	0	1	6	0	2	5
Hamburg	0	0	2	0	0	2
Mainz	0	4	3	0	5	2
Wolfsburg	2	3	2	2	4	1
Ingolstadt	0	0	1	0	1	0
Darmstadt	0	0	1	0	0	1
Hannover	0	0	2	0	0	2
Stuttgart	0	2	3	0	3	2
Dusseldorf	0	1	1	0	0	2
Nuremberg	0	0	1	0	0	1
Paderbon	0	0	1	0	0	1
Union Berlin	2	2	0	1	3	0
Bielefeld	0	0	2	0	0	2
Bochum	0	1	1	0	1	1
Furth	0	0	1	0	0	1
	13	**16**	**19**	**12**	**17**	**20**
	48%	**59%**	**70%**	**44%**	**63%**	**74%**

Figure 7. Table of counts, showing how often each team ended in each tier & counting how many different teams ended in each tier, Bundesliga.

	actual			expected		
	upper	*middle*	*lower*	*upper*	*middle*	*lower*
Juventus	7	0	0	7	0	0
Roma	5	2	0	7	0	0
Napoli	6	1	0	7	0	0
Atalanta	5	2	0	7	0	0
Lazio	6	1	0	3	4	0
AC Milan	7	0	0	4	3	0
Inter	6	1	0	7	0	0
Fiorentina	0	6	1	0	6	1
Torino	0	5	2	0	6	1
Sassuolo	0	7	0	0	6	1
Sampdoria	0	4	3	0	5	2
Cagliari	0	2	4	0	0	6
Udinese	0	7	0	0	6	1
Chievo	0	1	2	0	1	2
Bologna	0	5	2	0	4	3
Genoa	0	2	4	0	2	4
Crotone	0	0	3	0	0	3
Empoli	0	0	4	0	1	3
Palermo	0	0	1	0	0	1
Pescara	0	0	1	0	0	1
SPAL	0	0	3	0	1	2
Verona	0	3	2	0	3	2
Benevento	0	0	2	0	0	2
Parma Calcio	0	1	2	0	0	3
Frosinone	0	0	1	0	0	1
Brescia	0	0	1	0	0	1
Lecce	0	0	2	0	1	1
Spezia	0	0	3	0	0	3
Salernitana	0	0	2	0	0	2
Venezia	0	0	1	0	0	1
Monza	0	1	0	0	1	0
Cremonese	0	0	1	0	0	1
	7	**17**	**22**	**7**	**15**	**24**
	22%	**53%**	**69%**	**22%**	**47%**	**75%**

Figure 8. Table of counts, showing how often each team ended in each tier & counting how many different teams ended in each tier, Serie A.

Teams	Sum of Differences	cumulated ranks	nr. of seasons	avg. Rank
Bayern Munich	-27,53	7	7	1,00
Borussia Dortmund	-23,27	16	7	2,29
RB Leipzig	-1,7	23	7	3,29
Leverkusen	2,02	39	7	5,57
Union Berlin	-18,37	26	4	6,50
Hoffenheim	-6,02	53	7	7,57
Mgladbach	7,46	54	7	7,71
Frankfurt	10,38	57	7	8,14
Freiburg	-30,78	62	7	8,86
Wolfsburg	4,69	66	7	9,43
Mainz	19,02	82	7	11,71
Cologne	27,24	71	6	11,83
Hertha Berlin	6,28	83	7	11,86
Werder Bremen	-2,77	72	6	12,00
Schalke	12,29	73	6	12,17
Bochum	-1,97	25	2	12,50
Stuttgart	23,6	63	5	12,60
Dusseldorf	-1,92	27	2	13,50
Augsburg	0,94	96	7	13,71
Hamburg	1,1	30	2	15,00
Hannover	4,79	30	2	15,00
Bielefeld	-10,9	31	2	15,50
Ingolstadt	10,54	17	1	17,00
Darmstadt	1,47	18	1	18,00
Nuremberg	16,12	18	1	18,00
Paderbon	8,67	18	1	18,00
Furth	8,48	18	1	18,00

Figure 9. table based on average ranks Bundesliga, showing summed differences between points and xPts.

Teams	Sum of Differences	cumulated ra	nr. of season:	avg. Rank
Manchester City	-12,8	10	7	1,43
Liverpool	-44,33	21	7	3,00
Manchester United	-34,37	28	7	4,00
Chelsea	6,21	31	7	4,43
Tottenham	-46,24	34	7	4,86
Arsenal	-44,85	39	7	5,57
Wolverhampton	-9,46	47	5	9,40
Leicester	11,5	66	7	9,43
Newcastle	-24,77	63	6	10,50
West Ham	-6,87	75	7	10,71
Everton	2,07	77	7	11,00
Brentford	9,26	22	2	11,00
Aston Villa	-4,14	49	4	12,25
Crystal Palace	22,57	87	7	12,43
Bournemouth	-1,77	64	5	12,80
Brighton	40,51	78	6	13,00
Burnley	-14,9	82	6	13,67
Sheffield	2,26	29	2	14,50
Southampton	49,48	102	7	14,57
Stoke	11,46	30	2	15,00
Leeds	8,25	45	3	15,00
Watford	28,63	78	5	15,60
Fulham	9,26	47	3	15,67
Swansea	-5,2	32	2	16,00
Nottingham	-2,95	16	1	16,00
West Brom	16,14	49	3	16,33
Hull	-3,27	18	1	18,00
Huddersfield	13,45	36	2	18,00
Cardiff	3,45	18	1	18,00
Middlesbrough	9,25	19	1	19,00
Sunderland	8,24	20	1	20,00
Norwich	15,16	40	2	20,00

Figure 10. table based on average ranks Premier League, showing summed differences between points and xPts.

Teams	Sum of Differences	cumulated ranks	nr. of season:	avg. Rank
Barcelona	-46,42	12	7	1,71
Real Madrid	-43,35	13	7	1,86
Atletico Mad	-72,08	17	7	2,43
Sevilla	-25,82	37	7	5,29
Real Socieda	8,55	47	7	6,71
Villareal	7,2	48	7	6,86
Real Betis	-14,8	61	7	8,71
Valencia	-1,41	64	7	9,14
Girona	10,77	28	3	9,33
Athletic Club	28,73	66	7	9,43
Getafe	13,45	65	6	10,83
Osasuna	3,8	57	5	11,40
Celta Vigo	17,45	89	7	12,71
Eibar	25,12	64	5	12,80
Espanyol	6,36	77	6	12,83
Granada	-3,08	53	4	13,25
Cadiz	-1,9	40	3	13,33
Alaves	-2,35	83	6	13,83
Vallecano	16,05	42	3	14,00
Mallorca	1,85	43	3	14,33
Levante	6,19	74	5	14,80
Malaga	15,58	31	2	15,50
Leganes	26,6	64	4	16,00
Elche	-2,25	49	3	16,33
Las Palmas	12,16	33	2	16,50
Valladolid	3,6	66	4	16,50
Deportivo	35,32	34	2	17,00
Almeria	-0,84	17	1	17,00
Gijon	2,86	18	1	18,00
Huesca	23,19	37	2	18,50

Figure 11. table based on average ranks LaLiga, showing summed differences between points and xPts.

Teams	Sum of Differences	cumulated ranks	nr. of seasons	avg. Rank
Juventus	-70,4	14	7	2,00
Roma	-5,25	36	7	5,14
Napoli	-35,18	23	7	3,29
Atalanta	10,44	34	7	4,86
Lazio	-50,79	33	7	4,71
AC Milan	-37,68	31	7	4,43
Inter	-17,63	22	7	3,14
Fiorentina	26,36	67	7	9,57
Torino	-0,74	77	7	11,00
Sassuolo	1,83	71	7	10,14
Sampdoria	2,98	88	7	12,57
Cagliari	-3,25	88	6	14,67
Udinese	28,84	87	7	12,43
Chievo	16,49	47	3	15,67
Bologna	10,58	86	7	12,29
Genoa	43,71	92	6	15,33
Crotone	7,25	54	3	18,00
Empoli	1,77	63	4	15,75
Palermo	4,52	19	1	19,00
Pescara	23,05	20	1	20,00
SPAL	10,63	50	3	16,67
Verona	25,26	64	5	12,80
Benevento	8,84	38	2	19,00
Parma Calcic	6,1	43	3	14,33
Frosinone	10,94	19	1	19,00
Brescia	8,14	19	1	19,00
Lecce	11,12	34	2	17,00
Spezia	9,18	47	3	15,67
Salernitana	-7,88	32	2	16,00
Venezia	1,29	20	1	20,00
Monza	-5,16	11	1	11,00
Cremonese	5,56	19	1	19,00

Figure 12. table based on average ranks Serie A, showing summed differences between points and xPts.

EXEMPLARY

	2022/23 Points	xPts	Diff	abs. Diff	Rank	xRank
Bayern Munich	71	71,99	0,99	0,99	1	1
RB Leipzig	66	67,51	1,51	1,51	3	2
Borussia Dortmund	71	64,69	-6,31	6,31	1	3
Hoffenheim	36	32,97	-3,03	3,03	12	16
Cologne	42	49,67	7,67	7,67	11	6
Hertha Berlin	29	34,33	5,33	5,33	18	15
Freiburg	59	47,33	-11,67	11,67	5	7
Bochum	35	32,16	-2,84	2,84	14	17
Mgladbach	43	44,29	1,29	1,29	10	11
Werder Bremen	36	40,48	4,48	4,48	12	13
Frankfurt	50	51,5	1,5	1,5	6	5
Leverkusen	50	52,59	2,59	2,59	6	4
Augsburg	34	30,23	-3,77	3,77	15	18
Schalke	31	38,76	7,76	7,76	17	14
Mainz	46	45,15	-0,85	0,85	9	10
Wolfsburg	49	47,23	-1,77	1,77	8	9
Union Berlin	62	42,32	-19,68	19,68	4	12
Stuttgart	33	47,31	14,31	14,31	16	8
				5,41	3,11	
				6,32	2,03	
				3,18	1,02	
				6,80	2,18	

Across all seasons

avg. Diff	avg. SD
5,08	3,19
5,61	1,80
3,96	1,27
6,37	2,03

Figure 13. Exemplary table retrieved and determined from xG data, containing the same data as Figure 1 and additional data on avg. differences and SDs over all seasons.

	actual			expected		
	upper	*middle*	*lower*	*upper*	*middle*	*lower*
Chelsea	6	1	0	6	1	0
Tottenham	5	2	0	4	3	0
Manchester City	7	0	0	7	0	0
Liverpool	7	0	0	7	0	0
Arsenal	5	2	0	4	3	0
Manchester United	7	0	0	6	1	0
Everton	0	5	2	0	6	1
Southampton	0	2	5	0	4	3
Bournemouth	0	3	2	0	2	3
West Brom	0	1	2	0	2	1
West Ham	1	4	2	0	5	2
Leicester	2	4	1	2	4	1
Stoke	0	1	1	0	1	1
Crystal Palace	0	4	3	1	4	2
Swansea	0	0	2	0	0	2
Burnley	0	2	4	0	2	4
Watford	0	1	4	0	2	3
Hull	0	0	1	0	0	1
Middlesbrough	0	0	1	0	0	1
Sunderland	0	0	1	0	0	1
Newcastle	1	5	0	1	1	4
Brighton	1	1	4	2	2	2
Huddersfield	0	0	2	0	0	2
Wolverhampton	1	4	0	2	1	2
Cardiff	0	0	1	0	0	1
Fulham	0	1	2	0	0	3
Sheffield	0	1	1	0	1	1
Aston Villa	0	2	2	0	3	1
Norwich	0	0	2	0	0	2
Leeds	0	1	2	0	2	1
Brentford	0	2	0	0	2	0
Nottingham	0	0	1	0	0	1
	11	**21**	**23**	**11**	**21**	**25**
	34%	**66%**	**72%**	**34%**	**66%**	**78%**

Figure 14. Table of counts, showing how often each team ended in each tier & counting how many different teams ended in each tier, Premier League.

	actual			expected		
	upper	*middle*	*lower*	*upper*	*middle*	*lower*
Real Madrid	7	0	0	7	0	0
Barcelona	7	0	0	7	0	0
Atletico Madrid	7	0	0	7	0	0
Sevilla	5	2	0	5	2	0
Villareal	4	2	1	5	2	0
Real Sociedad	5	2	0	4	3	0
Athletic Club	0	6	1	3	3	1
Espanyol	0	4	2	0	2	4
Alaves	0	2	4	0	1	5
Eibar	0	4	1	1	3	1
Malaga	0	1	1	0	1	1
Valencia	2	4	1	2	4	1
Celta Vigo	0	5	2	0	4	3
Las Palmas	0	0	2	0	0	2
Real Betis	4	1	2	0	6	1
Deportivo	0	0	2	0	2	0
Leganes	0	1	3	0	2	2
Gijon	0	0	1	0	0	1
Osasuna	0	4	1	0	3	2
Granada	1	1	2	0	1	3
Levante	0	1	4	0	1	4
Girona	0	2	1	0	2	1
Getafe	1	2	3	1	3	2
Vallecano	0	2	1	0	2	1
Huesca	0	0	2	0	1	1
Valladolid	0	1	3	0	0	4
Mallorca	0	1	2	0	1	2
Cadiz	0	1	2	0	0	3
Elche	0	1	2	0	0	3
Almeria	0	0	1	0	0	1
	10	**22**	**25**	**10**	**21**	**23**
	33%	**73%**	**83%**	**33%**	**70%**	**77%**

Figure 15. Table of counts, showing how often each team ended in each tier & counting how many different teams ended in each tier, LaLiga.