Positional Value in Soccer: Expected League Points Added above Replacement

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Abstract. Soccer is undeniably the most popular sport world-wide, but at the same time it is one of the least quantified. To date there is not a way to explicitly quantify the contribution of every player on the field to his team chances of winning. Successful sports metrics, such as the (adjusted) +/- that allows for division of credit among a basketball team’s players, fail to work in soccer due to severe co-linearities (i.e., the same players being on the field for the majority of the time). In this work, we develop a framework that can estimate the expected contribution of a soccer player to his team’s winning chances. In particular, using data from (i) approximately 20,000 games from 11 European leagues for 8 seasons, as well as, (ii) player ratings from FIFA, we estimate through a Skellam regression model the importance of every line in winning a soccer game. We consequently translate the model to expected league points added (per game) above a replacement player $eLPAR$. This model can be used as a guide for player transfer decisions, as well as, for transfer fees and contract negotiations among other applications. To showcase the applicability of $eLPAR$ we use market value data for approximately 10,000 players and we identify evidence that currently the market under-values defensive line players relative to goalkeepers. Finally, we discuss how our framework can be significantly enhanced using player tracking data, but also, how it can be used to obtain positional (and consequently player) value for American football, which is another sports where achieving division of credit has been proven to be hard to date.

1. Introduction. Soccer is undoubtedly the king of sports, with approximately 4 billion global following [28]. However, despite this huge global interest it still lags behind with respect to advanced quantitative analysis and metrics capturing teams’ and players’ performance as compared to other sports with much smaller fan base (e.g., baseball, basketball). Traditionally sports metrics quantify on-ball events. However, soccer epitomizes the notion of team sports through a game of space and off-ball movement. In soccer every player has possession of the ball an average of only 3 minutes [8], and hence, metrics that quantify on-ball events will fail to capture a player’s influence on the game.

Expected goals ($xG$) [18, 7] is probably the most prominent, advanced metric used in soccer today. $xG$ takes into account the context of a shot (e.g., location, number of defenders in the vicinity etc.) and provides us with the probability of a shot leading to a goal. $xG$ allows us to statistically evaluate players. For example, if a player is over-performing his expected goals, it suggests that he is either lucky or an above-average finisher. If this over-performance persists year-after-year then the latter will be a very plausible hypothesis. Nevertheless, while expected goals represent a straightforward concept and has been already used by mainstream soccer broadcast media, its application on evaluating players is still limited to a specific aspect of the game (i.e., shot taking) and only to players that actually take shots (and also potentially goalkeepers). A more inclusive version of $xG$, is the Expected Goal Chains ($xGC$) [21]. $xGC$ considers all passing sequences that lead to a shot and credits each player involved with the expected goal value for the shot. Of course, not all passes are created equally [20] and hence,

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xGC can over/under estimate the contribution of a pass to the final shot.

The last few years player tracking technology has started penetrating the soccer industry. During the last world cup in Russia, teams obtained player tracking data in real time [6]! The availability of fine-grained spatio-temporal data have allowed researchers to start looking into more detailed ways to evaluate soccer players through their movement in space. For example, Hoang et al. [16, 15] developed a deep imitation learning framework for identifying the optimal locations - i.e., the ones that minimize the probability of conceding a goal - of the defenders in any given situation based on the locations of the attackers (and the other defensive players). Fernandez and Bornn [8] also analyzed player tracking data and developed a metric quantifying the contribution of players in space creation as well as, this space’s value, while a nice overview of the current status of advanced spatio-temporal soccer analytics is provided by Bornn et al. [4]. Player tracking data will undoubtedly provide managers, coaches and players with information that previously was considered to be intangible, and revolutionize soccer analytics. However, to date all of the efforts are focused on specific aspects of the game. While in the future we anticipate that a manager will be able to holistically evaluate the contribution of a player during a game over a number of dimensions (e.g., space generation, space coverage, expected goals etc.), currently this is not the case - not to mention that player tracking technology is still slow in widespread adoption. Therefore, it has been hard to develop soccer metrics similar to Win Shares and/or Wins Above Replacement Player that exist for other sports (e.g., baseball, basketball etc.) [11, 25]. These - all-inclusive - metrics translate on field performance to what managers, coaches, players and casual fans can understand, relate to and care about, i.e., wins.

Our study aims at filling exactly this gap in the existing literature discussed above. The first step towards this is quantifying the positional values in soccer. For instance, how much more important are the middle-fielders compared to the goalkeeper when it comes to winning a game? In order to achieve this we use data from games from 11 European leagues as well as FIFA ratings for the players that played in these games. These ratings have been shown to be able to drive real-world soccer analytics studies [5] and they are easy to obtain\(^1\). Using these ratings we model the final goal differential of a game through a Skellam regression that allows us to estimate the impact of 1 unit of increase of the FIFA rating for a specific position on the probability of winning the game. As we will elaborate on later, to avoid any data sparsity problems (e.g., very few team play with a sweeper today), we group positions in the four team lines (attack, middle-field, defense and goalkeeping) and use as our model’s independent variables the difference on the average rating of the corresponding lines. Using this model we can then estimate the expected league points added above replacement (eLPAR) for every player. The emphasis is put on the fact that this is the expected points added from a player, since it is based on a fairly static, usually pre-season, player rating, and hence, does not capture the exact performance of a player in the games he played, even though the FIFA ratings change a few times over the course of a season based on the overall player’s performance. However, when we describe our model in detail it should become evident that if these data (i.e., game-level player ratings) are available the exact same framework can be used to evaluate the actual league points added above replacement from every player.

\(^1\)Data and code are available:https://github.com/kpelechrinis/eLPAR-soccer.
The contribution of our work is twofold:
1. We develop a pre-game win probability model for soccer that is accurate and well-calibrated. More importantly it is based on the starting lineups of the two teams and hence, it can account for personnel changes between games.
2. We develop the expected league points added above replacement (eLPAR) metric that can be used to identify positional values in soccer and facilitate quantitative (monetary) player valuation in a holistic way.

Section 2 describes the data we used as well as the regression model we developed for the score differential. Section 3 further details the development of our expected league points added above replacement using the Skellam regression model. In this section we also discuss the implications for the players’ transfer market. Finally, Section 4 discusses the scope and limitations of our current study, as well as, future directions for research.

2. Data and Methods. In this section we will present the data that we used for our analysis, existing modeling approaches for for the goal differential in a soccer game, as well as, the Skellam regression model we used.

2.1. Soccer Dataset. In our study we make use of the Kaggle European Soccer Database [1]. This dataset includes all the games (21,374 in total) from 11 European leagues\(^2\) between the seasons 2008-09 and 2015-16. For every game, information about the final result as well as the starting lineups are provided. There is also temporal information on the corresponding players’ ratings for the period covered by the data. A player’s \(p\) rating takes values between 0 and 100 and includes an overall rating \(r_p\), as well as sub-ratings for different skills (e.g., tackling, dribbling etc.). There are 11,060 players in totals and an average of 2 rating readings per season for every player. One of the information that we need for our analysis and is not present in the original dataset, is the players’ position and his market value. We obtained this information through FIFA’s rating website (www.sofifa.com) for all the players in our dataset.

The goals scored in a soccer game have traditionally been described through a Poisson distribution [17, 12], while a negative binomial distribution has also been proposed to account for possible over-dispersion in the data [19, 9]. However, the over-dispersion, whenever observed is fairly small and from a practical perspective does not justify the use of the negative binomial for modeling purposes considering the trade-off between complexity of estimating the models and improvement in accuracy [12]. In our data, we examined the presence of over-dispersion through the Pearson chi-squared dispersion test. We performed the test separately for the goal scored from home and away teams and in both cases the dispersion statistic is very close to 1 (1.01 and 1.1 respectively), which allows us to conclude that a Poisson model fits better for our data. Figure 1 depicts the two distributions for the goals scored per game for the home and away teams in our dataset.

Another important modeling question is the dependency between the two Poisson processes that capture the scoring for the two competing teams. In general, the empirical data exhibit a small correlation (usually with an absolute value for the correlation coefficient less than 0.05) between the goals scored by the two competing teams and the use of

\(^2\)English Premier League, Bundesliga, Serie A, Scotish Premier League, La Liga, Swiss Super League, Jupiler League, Ligue 1, Eredivisie, Liga Zon Sagres, Ekstraklasa.
Bivariate Poisson models has been proposed to deal with this correlation [13]. Simple put, 

\[(X, Y) \sim BP(\lambda_1, \lambda_2, \lambda_3),\] 

where:

\[
P(X = x, Y = y) = e^{-(\lambda_1 + \lambda_2 + \lambda_3)} \frac{\lambda_1^x \lambda_2^y}{x! y!} \sum_{k=0}^{\min(x,y)} \left(\begin{array}{c} x \\ k \end{array}\right) \left(\begin{array}{c} y \\ k \end{array}\right) k! \left(\frac{\lambda_3}{\lambda_1 \lambda_2}\right)^k
\]

The parameter \(\lambda_3\) captures the covariance between the two marginal Poisson distributions for \(X\) and \(Y\), i.e., \(\lambda_3 = \text{Cov}(X, Y)\). In our data, the correlation between the number of goals scored from the home and away team is also small and equal to -0.06. While this correlation is small, Karlis and Ntzoufras [13] showed that it can impact the estimation of the probability of a draw. However, a major drawback of the Bivariate Poisson model is that it can only model data with positive correlations [14]. Given that in our dataset the correlation is negative, and hence, a Bivariate Poisson model cannot be used, an alternative approach is to directly model the difference between the two Poisson processes that describe the goals scored for the two competing teams. With \(Z, X,\) and \(Y\) being the random variables describing the final score differential, the goals scored from the home team and the goals scored from the away team respectively, we clearly have \(Z = X - Y\). With \((X, Y) \sim BP(\lambda_1, \lambda_2, \lambda_3)\), \(Z\) has the following probability mass function [22]:

\[
P(z) = e^{\lambda_1 + \lambda_2} \left(\frac{\lambda_1}{\lambda_2}\right)^{z/2} \cdot I_z(2 \sqrt{\lambda_1 \lambda_2})
\]

where \(I_r(x)\) is the modified Bessel function. Equation (2.2) describes a Skellam distribution and clearly shows that the distribution of \(Z\) does not depend on the correlation between the two Poisson distributions \(X\) and \(Y\). In fact, Equation (2.2) is exactly the same as the distribution of the difference of two independent Poisson variates [22]. Therefore, we can directly model the
goal differential without having to explicitly model the covariance. Of course, the drawback of this approach is that the derived model is not able to provide estimates on the actual game score, but rather only on the score differential. Nevertheless, in our study we are not interested in the actual score but rather in the win/lose/draw probability. Hence, this does not pose any limitations for our work.

2.2. Skellam Regression Model. Our objective is to quantify the value of different positions in soccer. This problem translates to identifying how an one-unit increase in the rating of a player’s position impacts the probability of his team winning. For instance, if we substitute our current striker who has a FIFA rating of 79, with a new striker with a FIFA rating of 80, how do our chances of winning alter? Once we have this information we can obtain for every player an expected league points added per game over a reference, i.e., replacement, player (Section 3.1). This can then be used to obtain a more objective market value for players based on their position and rating (Section 3.2).

In order to achieve our goal we model the goal differential $Z$ of a game using as our independent variables the player/position ratings of the two teams that compete. Hence, our model’s dependent variable is the goal differential (home - away) of game $i$, $z_i$, while our independent variables are the positional rating differences of the two teams, $x_{i,\pi} = r_{p(h,\pi,i)} - r_{p(a,\pi,i)}$, $\forall \pi \in \Pi$, where $r_{p(h,\pi,i)}$ ($r_{p(a,\pi,i)}$) is the rating of the home (away) team player that covers position $\pi$ during game $i$ and $\Pi$ is the set of all soccer positions. One of the challenges with this setting is the fact that different teams will use different formations and hence, it can be very often the case that while one team might have 2 center backs and 2 wing backs, the other team might have 3 center backs only in its defensive line. This will lead to a situation where the independent variables $x_{i,\pi}$ might not be well-defined. While this could potentially be solved by knowing the exact formation of a team (we will elaborate on this later), this

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{soccer_positions.png}
\caption{For our analysis we grouped the various player positions to four distinct groups, namely, goalkeeping, attack, midfielders and defense.}
\end{figure}
is unfortunately a piece of information missing from our data. Nevertheless, even this could create data sparsity problems (e.g., formation/player combinations that do not appear often). Hence, we merge positions to four groups, namely, attacking line, middle-fielders, defensive line and goalkeeping. Figure 2 depicts the grouping of the positions we used to the four lines \( \Lambda = \{\lambda_D, \lambda_M, \lambda_A, \lambda_{GK}\} \). Note that this grouping in the four lines has been used in the past when analyzing soccer players as well [10]. The independent variables of our model are then the differences in the average rating of the corresponding lines. The interpretation of the model slightly changes now, since the independent variable captures the rating of the whole line as compared to a single position/player. Under this setting we fit a Skellam regression for \( Z \) through maximum likelihood estimation. In particular:

### Model 2.1: Final Goal Differential

We model the goal differential \( Z_i \) of game \( i \) using the following four co-variates:

- The difference between the average player rating of the defensive line of the two teams \( x_D \)
- The difference between the average player rating of the middle-fielders of the two teams \( x_M \)
- The difference between the average player rating of the attacking line of the two teams \( x_A \)
- The difference between the goalkeeper’s rating of the two teams \( x_{GK} \)

The random variable \( Z \) follows a Skellam distribution, where its parameters depend on the model’s covariates \( x = (x_D, x_M, x_A, x_{GK}) \):

\[
\begin{align*}
Z \sim & \text{Skellam}(\lambda_1, \lambda_2) \\
\log(\lambda_1) = & \mathbf{b}_1^T \cdot x \\
\log(\lambda_2) = & \mathbf{b}_2^T \cdot x
\end{align*}
\]

Table 1 shows the regression coefficients. It is interesting to note that the coefficients for the two parameters are fairly symmetric. \( \lambda_1 \) and \( \lambda_2 \) can be thought of as the mean of the Poisson distributions describing the home and visiting team respectively and hence, a positive relationship between an independent variable and the score differential for one team corresponds - to an equally strong - negative relationship between the same variable and the score differential. An additional thing to note is that an increase on the average rating of any line of a team contributes positively to the team’s chances of winning (as one might have expected).

Before using the model for estimating the expected league points added above replacement for each player, we examine how good the model is in terms of actually predicting the score differential and the win/draw/lose probabilities. We use an 80-20 split for training and testing of the model. We begin our evaluation by calculating the difference between the goal differential predicted by our model and the actual goal differential of the game [23]. Figure 3 (top) presents the distribution of this difference and as we can see it is centered around 0, while the standard deviation is equal to 1.6 goals. Furthermore, a chi-squared test cannot
| Variable | log($\lambda_1$) | log($\lambda_2$) |
|----------|------------------|------------------|
| Intercept | 0.37***          | 0.07***          |
|          | (0.012)          | (0.015)          |
| $x_D$    | 0.02***          | -0.03***         |
|          | (0.01)           | (0.002)          |
| $x_M$    | 0.02***          | -0.015***        |
|          | (0.01)           | (0.002)          |
| $x_A$    | 0.01***          | -0.01***         |
|          | (0.001)          | (0.001)          |
| $x_{GK}$ | 0.001            | -0.004**         |
|          | (0.001)          | (0.002)          |

N 21,374 21,374

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 1

Skellam regression coefficients

reject the hypothesis that the distribution is normal with mean equal to 0 and a standard deviation of 1.6.

However, apart from the score differential prediction error, more important for our purposes is the ability to obtain true win/loss/draw probabilities for the games. As we will see in Section 3.1 we will use the changes in these probabilities to calculate an expected league points added for every player based on their position and rating. Hence, we need to evaluate how accurate and well-calibrated these probabilities are. Figure 3 (bottom) presents the probability calibration curves. Given that we have 3 possible results (i.e., win, loss and draw), we present three curves from the perspective of the home team, that is, a home team win, loss or draw. The $x$-axis presents the predicted probability for each event, while the $y$-axis is the observed probability. In particular we quantize the data in bins of 0.05 probability range, and for all the games within each bin we calculate the fraction of games for which the home team won/lost/draw, and this is the observed probability. Ideally, we would like to have these two numbers being equal. Indeed, as we can see for all 3 events the probability output of our model is very accurate, that is, all lines are practically on top of the $y = x$ line. It is interesting to note, that our model does not provide a draw probability higher than 30% for any of the games in the test set, possibly due to the fact that the base rate for draws in the whole dataset is about 25%.

3. eELPAR and Market Value. We begin by defining the notion of a replacement player and developing eELPAR. We also show how we can use eELPAR to obtain objective player and transfer fee (monetary) valuations.

3.1. Replacement Player and Expected League Points Added. The notion of replacement player was popularized by Keith Woolner [27] who developed the Value Over Replacement Player (VORP) metric for baseball. The high level idea is that player talent comes at

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different levels. For instance, there are superstar players, average players and subpar player talent. These different levels come in different proportions within the pool of players, with superstars being a scarcity, while subpar players (what Woolner termed replacement players) being a commodity. This essentially means that a team needs to spend a lot of money if it wants to acquire a superstar, while technically a replacement player comes for free. Since a replacement player can be thought of as a free player, a good way to evaluate (and consequently estimate a market value for) a player is to estimate the (expected) contribution in wins, points etc. that he/she offers above a replacement player. One of the main contributions of Woolner’s work is to show that average players have value [25]! If we were to use the average player as our reference for evaluating talent, we would fail to recognize the value of average playing time. Nevertheless, replacement level, even though it is important for assigning economic value to a player, it is a less concrete mathematical concept. There are several ways that have been used to estimate this. For example, one can sort players (of a specific position) in decreasing order of their contract value and obtain as replacement level the talent at the bottom 20th percentile [24]. What we use for our study is a rule-of-thumb suggested from Woolner [26]. In particular, the replacement level is set at the 80% of the positional average rating. While the different approaches might provide slightly different values for a replacement player, they will not affect the relative importance of the various positions identified by the model. Figure 4 presents the distribution of the player ratings for the different lines for the last season in our dataset - i.e., 2015-16. The vertical green lines represent the replacement level for every position/line, i.e., 80% of the average of each distribution. As we can see all replacement levels are very close to each other and around a rating of 56. So the question now becomes how are we going to estimate the expected league points added above replacement (eLPAR) given the model from Section 2.2 and the replacements levels of each line. First let us define eLPAR more concretely:

Figure 3. Our model is able to predict the score differential as well as the win/loss/draw probabilities fairly accurate.
Definition 3.1: $eLPAR_p$

Consider a game between teams with only replacement players. Player $p$ substitutes a replacement player in the lineup. $eLPAR_p$ describes how many league points (win=3 points, draw = 1 point, loss = 0 points) $p$ is expected to add for his team.

Based on the above definition, $eLPAR_p$ can be calculated by estimating the change in the win/draw/loss probability after substituting a replacement player with $p$. However, the win probability model aforementioned does not consider individual players but rather lines. Therefore, in order to estimate the expected points to be added by inserting player $p$ in the lineup we have to consider the formation used by the team. For example, a defender substituting a replacement player in a 5-3-2 formation will add a different value of expected points as compared to a formation with only 3 center-backs in the defensive line. Therefore, in order to estimate $eLPAR_p$ we need to specify the formation we are referring to. Had the formation been available in our dataset we could have built a multilevel model, where each
A combination of position and formation would have had their own coefficients\textsuperscript{3}. Nevertheless, since this is not available our model captures the formation-average value of each line. In particular, $e\text{LPAR}_p$ for player $p$ with rating $r_p$ can be calculated as following:

1. Calculate the increase in the average rating of the line $\lambda \in \Lambda$ where $p$ substituted the replacement player based on $r_p$, formation $\phi$ and the replacement player rating for the line $r_{\text{replacement}, \phi, \lambda}$. 
2. Calculate, using the win probability model above, the change in the win, loss and draw probability ($\delta P_w$, $\delta P_d$ and $\delta P_l$ respectively) 
3. Calculate $e\text{LPAR}_p(\phi)$ as:

\begin{equation}
(3.1) \quad e\text{LPAR}_p(\phi) = 3 \cdot \delta P_w + 1 \cdot \delta P_d 
\end{equation}

It should be evident that by definition a replacement player has $e\text{LPAR} = 0$ - regardless of the formation - while if a player has rating better than a replacement, his $e\text{LPAR}$ will be positive. However, the actual value and how it compares to players playing in different positions will depend on the formation. In Figure 5 we present the expected league points added per game for players with different ratings (ranging from 50 to 99) and for different formations. While there are several different formations that a team can use, we chose 4 of the most often used ones.

One common pattern in all of the formations presented is the fact that for a given player rating goal keepers provide the smallest expected league points above replacement - which is in line with other studies/reports for the value of goal keepers in today’s soccer \cite{3}. It is also evident that depending on the formation the different positions offer different value. For example, a 4-5-1 system benefits more from an attacker with a rating of 90 as compared to a defender with the same rating, while in a 3-5-2 formation the opposite is true. It is also interesting to note that for a 4-4-2 formation, the value added above replacement for the different positions are very close to each other (the closest compared to the rest of the formations). This most probably is due to the fact that the 4-4-2 formation is the most balanced formation in soccer, and hence, all positions contribute equally to the team. To reiterate this is an expected value added, i.e., it is not based on the actual performance of a player but rather on static ratings for a player. Given that teams play different formations over different games (or even during the same game after in-game adjustments), a more detailed calculation of $e\text{LPAR}$ would include the fraction of total playing time spent by each player on a specific formation. With $T$ being the total number of minutes played by $p$, and $t_\phi$ the total minutes he played in formation $\phi$, we have:

\begin{equation}
(3.2) \quad e\text{LPAR}_p = \frac{1}{T} \sum_\phi t_\phi \cdot e\text{LPAR}_p(\phi) 
\end{equation}

The last row in Figure 5 presents the average $e\text{LPAR}$ for each position and player rating across all the four possessions (assuming equal playing time for all formations). As we can see

\footnote{And in this case we would also be able to analyze better the impact of positions within a line (e.g., value of RB/LB compared to CB).}
for the same player rating, a defender adds more expected league points above replacement, followed by an attacker with the same rating. A midfielder with the same rating adds only slightly less expected league points compared to an attacker of the same rating, while a goal keeper (with the same rating) adds the least amount of expected league points. A team manager can use this information to identify more appropriate targets given the team style play (formations used) and the budget. In the following section we will explore the relation

Figure 5. Expected league points added above replacement for different formations, player ratings and positions.
between the market value of a player and his eLPAR.

3.2. Positional Value and Player Market Value. In this section we will explore how we can utilize eLPAR to identify possible inefficiencies in the player’s transfer market. In particular, we are interested in examining whether the transfer market overvalues specific positions based on the eLPAR value they provide. Splitting the players in the four lines Figure 6 (left) presents the differences between the average market value - that is, the transfer fee paid from a team to acquire a player under contract - for each position. As we can see, on average, defenders are the lowest paid players! However, as aforementioned (Figure 5) for a given player rating, a defensive player provides the maximum eLPAR value. Nevertheless, what we are really interested in is the monetary value that a team pays for 1 expected league point above replacement per game for each player. Granted there is a different supply of players in different positions. For example, only 8.5% of the players are goal keepers, as compared to approximately 35% of defenders\(^4\), and hence, one might expect goalkeepers to be paid more than defenders. However, there is also smaller demand for these positions and hence, we expect these two to cancel out to a fairly great extend, at least to an extend that does not over-inflate the market values. Hence, we calculate the monetary cost the players market values imply that teams are willing to pay for 1 expected league point. Figure 6 (middle) presents the cost (in Euros) per 1 expected league point for different positions and as a function of the eLPAR they provide. An efficient market would have four straight horizontal lines, one on top of the other, since the value of 1 expected league point should be the same regardless of where this point is expected from. However, what we observe is that the market over-values significantly goal keepers (even though on average they are only the 3rd highest paid line), and this is mainly a result of their low eLPAR (the best goalkeeper in our dataset provides an eLPAR of just over 0.1 per 90 minutes). Furthermore, teams appear to be willing to pay a premium for expected league points generated by the offense as compared to points generated by the defense, and this premium increases with eLPAR. This becomes even more clear from the right plot in Figure 6, where teams are willing to pay multiples in premium for 1 expected league point coming from a goalkeeper with 88 FIFA rating as compared to the same contribution coming from a defender with 86 FIFA rating.

Player wages exhibit similar behavior (the ranking correlation between transfer/market value and a player’s wage is 0.94). Given that there is no salary cap in European soccer, teams can potentially overpay in general in order to bring in the players they want. Hence, across-teams comparisons might not be appropriate. However, within team comparison of contracts among its players is one way to explore whether teams are being rational in terms of payroll. In particular, we can examine the distribution of their total budget among their players, and whether this is in line with their positional values. Simply put, this analysis will provide us with some relative insight on whether teams spend their budget proportional to the positional and personal on-field value (i.e., FIFA rating) of each player. Let us consider two specific teams, that is, FC Barcelona and Manchester United. We will use the wages of the starting 11 players of the two teams (from the 2017-18 season) and considering the total budget \(B\) constant we will redistribute it based on the eLPAR of each player. Table

\(^{4}\)There is another approximately 35% of midfielders and 21% of attackers.
Figure 6. Even though goalkeepers are among the lowest paid players in soccer, they still are overpaid in terms of expected league points contributions. Defenders are undervalued when it comes to contributions in winning.

| Players    | FIFA Rating | Wage (€) | eLPAR   | eLPAR Wage (€) | eLPAR (4-4-2) | eLPAR Wage (4-4-2) (€) |
|------------|-------------|----------|---------|----------------|---------------|------------------------|
| M. Stegen  | 87          | 185K     | 0.106   | 97K            | 0.106         | 102K                   |
| S. Roberto | 82          | 150K     | 0.307   | 283K           | 0.285         | 276K                   |
| Pique      | 87          | 240K     | 0.359   | 330.5K         | 0.333         | 323K                   |
| S. Umtiti  | 84          | 175K     | 0.328   | 302K           | 0.304         | 295K                   |
| Jordi Alba | 87          | 185K     | 0.359   | 330.5K         | 0.333         | 323K                   |
| O. Dembele | 83          | 150K     | 0.268   | 246.5K         | 0.272         | 264K                   |
| I. Rakitic | 86          | 275K     | 0.295   | 272K           | 0.301         | 291K                   |
| s. Busquets| 87          | 250K     | 0.305   | 280.5K         | 0.31          | 300K                   |
| Coutinho   | 87          | 275K     | 0.305   | 280.5K         | 0.31          | 300K                   |
| L. Messi   | 94          | 556K     | 0.335   | 308K           | 0.292         | 283K                   |
| L. Suarez  | 92          | 510K     | 0.319   | 294K           | 0.278         | 269K                   |

Table 2

FC Barcelona wages and eLPAR-based projected wages.

2 presents the starting 11 for Barcelona, their FIFA rating and their wage\(^5\), while Table 3 presents the same information for Manchester United\(^6\). We have also included the formation-agnostic (i.e., average of the four most frequent formations aforementioned) eLPAR and the corresponding redistribution of salaries, as well as the same numbers for the default formation of each team (4-4-2 for Barcelona and 4-3-3 for Manchester United). The way we calculate the re-distribution is as following:

1. Calculate the fraction \( f_p = \frac{\text{eLPAR}_p}{\sum_{p=1}^{11} \text{eLPAR}_p} \) of total eLPAR that player \( p \) contributes to his team (eLPAR\(_{\text{total}} = \sum_{p=1}^{11} \text{eLPAR}_p \))

2. Calculate the eLPAR-based wage for player \( p \) as \( f_p \cdot B \)

As we can see there are differences in the wages projected when using eLPAR. Both teams

\(^5\)www.sofifa.com/team/241
\(^6\)www.sofifa.com/team/11

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Manchester United wages and ePAR-based projected wages.

| Players  | FIFA Rating | Wage (£) | ePAR | ePAR Wage (£) | ePAR (4-3-3) | ePAR Wage (4-3-3) (£) |
|----------|-------------|----------|------|---------------|--------------|------------------------|
| De Gea   | 91          | 295K     | 0.118| 79K           | 0.118        | 82K                    |
| A. Valencia | 83       | 130K     | 0.328| 214K           | 0.295        | 206.5K                 |
| C. Smalling | 81      | 120K     | 0.298| 200K           | 0.275        | 193K                   |
| V. Lindelof | 78      | 86K      | 0.265| 179K           | 0.246        | 172K                   |
| A. Young | 79          | 120K     | 0.276| 186K           | 0.255        | 179K                   |
| N. Matic | 85          | 180K     | 0.286| 193K           | 0.387        | 271K                   |
| A. Herrera | 83       | 145K     | 0.268| 181K           | 0.362        | 254K                   |
| P. Pogba | 88          | 250K     | 0.314| 212K           | 0.424        | 297K                   |
| J. Lingard | 81       | 115K     | 0.229| 155K           | 0.133        | 93.5K                  |
| R. Lukaku | 86       | 210K     | 0.27 | 183K           | 0.158        | 111K                   |
| A. Sanchez | 88      | 325K     | 0.287| 194K           | 0.168        | 118K                   |

Table 3

for example appear to overpay their goalkeepers based on their expected league points above replacement per 90 minutes. Of course, some players are under-valued, and as we can see these players are mainly in the defensive line. These results open up interesting questions for soccer clubs when it comes to budget decisions. Budget is spent for two reasons; (a) to win, as well as, (b) to maximize the monetary return (after all, sports franchises are businesses). The premium that clubs are willing to pay an attacker over a defender for the same amount of league points can be seen as an investment. These players bring fans in the stadium, increase gate revenue (e.g., through increased ticket prices), bring sponsors, sell club merchandise, etc. For example, even though attackers are approximately only 20% of the players’ pool, 60% of the top-selling jerseys in England during 2018 belonged to attackers [2]. Therefore, when we discuss the money spent from a team for a transfer (or a wage), winning is only one part of the equation. While teams with large budgets (like Manchester United and Barcelona) might be able to pay premiums as an investment, other teams in the middle-of-the-pack can achieve significant savings, without compromising their chances of winning. In fact, clubs with limited budget can maximize their winning chances, which is an investment as well (winning can bring in revenues that can then be used to acquire better/more popular players and so on). A club with a fixed transfer budget \( B \) can distribute it in such a way that maximizes the expected league points bought (even under positional constraints). For instance, with \( B = 10 \) millions and with the need for a center back and a goalkeeper, if we use the average market values for the two positions we should allocate 55% of the budget (i.e., 5.5 millions) for the goalkeeper and 45% of the budget for the defender. This will eventually get us about 0.315 expected league points per 90 minutes (a goalkeeper with a 77.5 FIFA rating and a defender with a 76.5 FIFA rating). However, if we allocate 2 millions for the goalkeeper and 8 millions for the defender this will get us around 0.34 expected league points (a goalkeeper with 74 FIFA rating and a defender with 79 FIFA rating), or simply put the team will have bought 1 expected
3.3. Fair Transfer Fees. In the last example above, the transfer fees mentioned are based on the current market transfer and most probably will still be an overpayment for the talent acquired. What basically one can achieve with an approach as the one described above is to optimize the team’s transfers based on the current market values. However, we can use our model and analysis to also estimate a fair (i.e., considering only a team’s winning chances) transfer fee for a player. For this we would need to know what 1M Euros is worth in terms of league points. To do so we will need the total transfer budget of teams and the total number of league points they obtained. For example, Figure 7 presents the relationship between a team’s transfer budget and the total points obtained for the 2017-18 Premier League. The slope of the linear fit is 0.44 ($R^2 = 0.71$), which means that 1M Euros in transfer budget is worth 0.44 Premier League points. Therefore for a player $p$ with $eLPAR_p$, who is expected to play $N$ games, a fair transfer fee is $N \cdot eLPAR_p$. For example, recently a transfer that was discussed a lot was that of goal keeper Danny Ward from Liverpool to Leicester. Based on Ward’s current rating (70) and his potential upside (78), the transfer fee should be between 4.6 and 6.7 million pounds, assuming he plays all 38 Premier League games next season (he is not currently expected to even start). However, Leicester paid 10 million pounds for this transfer [29]. Again there might be other reasons that Leicester was willing to pay 10 million pounds for Ward, and similar transfers can only be accurately - if at all - evaluated only after the players leaves/transfers from his new team. For instance, if Ward ends up playing 10 full seasons with Leicester his transfer fee can even be considered a steal. The same will be true if Leicester sells Ward for double this price within a couple of years. In general, estimating transfer fees is a much more complex task, but $eLPAR$ can facilitate these estimations by considering the on-pitch expected contributions of the player. We would like to emphasize here that the relationship between transfer budget and league points should be built separately for every league and for robustness more seasons need to be considered (appropriately adjusted for inflation).
4. Conclusions and Discussion. In this work our objective is to understand positional values in soccer and develop a metric that can provide an estimate for the expected contribution of a player on the field. We start by developing a win probability model for soccer games based on the ratings of the four lines of the teams (attack, midfield, defense and goalkeeper). We then translate this positional values to expected league points added above a replacement player $e_{LPAR}$ considering a team’s formations. We further show how this framework can be useful by analyzing transfer fees and players’ wages and relating them back to each player’s $e_{LPAR}$. Our results indicate that specific positions are over-valued when only considering their contribution to winning the game.

We believe that this study will trigger further research on the positional value in soccer. An immediate improvement over our current model is to consider the actual formation that the teams used (a piece of information missing in our current dataset). This will allow us to build a multilevel regression model where we will include covariates for more fine grained positions (e.g., center back, right back, center midfielder etc.). We can also include information about substitutions during a game (another piece of information not available to us). This will allow us to (a) obtain a weighted average for the average rating of a line based on the substitutions, and (b) a much more accurate estimate for a player’s total playing time. Furthermore, our current study is based on static player ratings obtained from FIFA. This only allows us to estimate the expected league points added over a replacement player. While these ratings capture the overall performance of a player during past season(s) and hence, it is still appropriate for estimating his monetary value, actual game ratings for players will allow us to estimate the actual league points added over replacement by a player over the course of a season. These game ratings for example can be composed through appropriate analysis of player tracking data, which at the least will provide us with information about how much time a combo-player (e.g., a left midfielder who can also play left wing/forward) played at each line. We will explore these directions as part of our future research, while we will also explore the applicability of a similar approach towards quantifying positional value for American Football (NFL). In particular, using player ratings from NFL Madden (in a similar way we use player ratings from FIFA), we can evaluate the contribution of 1 unit increase in the Madden rating of a player to the expected points added from a team’s play. This could be a significant step towards defining a metric similar to Wins Above replacement for NFL, and finally understanding the contribution of each position in winning.

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