An Analysis of Nationality Bias in the English Premier League

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Abstract

In association football, there is a well known idea that how a player is rated by the media, fans, coaches, clubs and more is heavily influenced by the player's nationality. One of the most infamous cases of this is the so-called "English Tax," the idea that English players are generally overrated, especially in the English Premier League (EPL). In this paper, we do an analysis of nationality bias in the EPL using statistical data from FBRef and FIFA ratings. We found that nationality does have an effect on how a player is rated, although, surprisingly, we found that English players are underrated as compared to players from traditional "footballing nations." The footballing nations include such countries as Brazil, Argentina, France, Spain, and other similar nations with quality players and international success. There are several possible explanations for our conclusions, and future research would be needed to explore those ideas. The study of nationality bias has several applications in football, including player recruitment, scouting, coaching, and match preparation.

Introduction

The English Premier League (EPL) is considered the best association football league in the world, with players from all over the world signing for some of the biggest clubs in the world. In the English Premier League, there is an idea that players are often unfairly rated based on their nationality. The most prominent example of this being the infamous "English Tax," where English players are considered by the public to be overrated by the media and fans.

My research aims to find differences between statistical and subjective analysis for players in the EPL, and whether these differences are impacted by player nationality.

One of the biggest challenges in doing analysis on subjective analysis is finding data that accurately measures how a player is rated by the media and fans. One of the most widely used datasets for overcoming this challenge are the player ratings from the video game EA Sports FIFA. FIFA's ratings are subjectively created by over 9,000 data-reviewers, which makes the ratings a really good measure of how a player is subjectively rated.

Another challenge is determining how good a player is based on their statistics. Because football is such a complex game, often players can be really good but they might not have great statistics. For example, a hard working, positionally good midfielder can greatly improve their team, but this won't show up in individual statistics. On the contrary, a player who looks really good in their statistics might actually be harming their team. Think about a goal scoring forward where all they do is score goals. They don't press, they aren't involved in the buildup, and they don't have a very high work rate. This player would look really good in statistics because of all the goals and attacking they do, but in reality their team might play better without them. To overcome this challenge, I chose to do analysis on one specific attribute: shooting. In essence, shooting is the easiest attribute to rate. How good a player is at shooting is directly related to shooting statistics, such as goals and expected goals, much more than how good a player is at passing is related to passing stats. Shooting is the attribute most accurately measured by statistics, and so is the best attribute to consider when comparing subjective and objective analysis.

I conducted an analysis comparing statistical shooting data with the EA Sports FIFA shooting rating to determine if there is nationality bias in the EPL, and, if so, what countries or regions are over or underrated. Specifically, I wanted to determine if the idea that English players are overrated has any basis in objective analysis.

Methods

Data Collection

I collected data from two sources. The first set of data was in-game statistical data from the English Premier League from the website FBref. I used the worldfootballR package in R to collect data from the 2017/18 season to the 2020/21 season. For the second set of data, I collected ratings from EA Sports FIFA. To do this, I downloaded the FIFA ratings from datasets on Kaggle. I downloaded the data from FIFA 17 to FIFA 22.

Data Tidying

I selected the columns from the dataset that related to player shooting in both the FIFA datasets and the in-game dataset. Next, I combined the datasets. I combined the FIFA datasets into one FIFA dataset. I then combined the FIFA dataset with the in-game dataset by player name. First, I matched the datasets by the players' full names. Of the players who were not matched, I matched by first initial and last name. Next, I matched by first name and last name. Then, I matched by only last name. Of the players who were still not matched, I manually created a csv file with their FIFA names and the in-game dataset names. I combined the datasets with the matched names I manually created.

Nationality Grouping

I grouped the nationalities of players into groups based on geography and how much of a "footballing nation" they are. I separated the nationalities into 9 groups: FootballingNations, Tier2, England, UK, OtherEurope, OtherAmericas, Africa, Asia, and Other. The FootballingNations were determined with an algorithm based on the number of World Cups won, success at the past 5 World Cups, number of World Cups made, FIFA World Rankings, and my own personal opinions based on my past experiences. Tier2 used the same algorithm, but is composed of the teams a tier lower than the FootballingNations. England is only English players, while UK is Welsh, Scottish, and Northern Irish players. OtherEurope is composed of players from Europe not in FootballingNations, Tier2, England or UK. OtherAmericas is composed of players from Central and South America from countries not in FootballingNations or Tier2. Africa is African players. Asia is Asian players, not including Turkey, which I put into OtherEurope. Other is composed of players from countries which do not fit into the above categories, which came out to be the USA, Australia, and New Zealand.

Modeling

We modeled the FIFA shooting ratings using the in-game statistical data. We compared the English players to the players in each of the other nationality groups, as well as all the other players combined. For each comparison, we used a matching procedure, matching based on FIFA shooting rating. We then used a random forest model to predict the FIFA shooting rating. We then conducted a t-test to determine the statistical significance of the difference between the two groups in the comparison. We ran each comparison 1000 times because of the randomness introduced by the matching procedure.

Results

After running each nationality group comparison with England, we had 1000 estimates for each comparison. Each estimate is the estimated difference in the mean of the residuals in the comparison, with the difference being subtracted in the order of nationality group minus England. Thus, a positive estimate means the players in the nationality group are generally rated higher than English players, while a negative estimate means the nationality group players are rated lower than English players.

We can see the differences by nationality group in Figure 1. Rest is a comparison between English players and non-English players of any nationality. FootballingNations, Rest, OtherEurope, Tier2, and Asia were the groups we found rated higher than England. OtherAmericas and Africa are rated roughly the same as England, while the UK and Other are rated lower than England. However, because of the small sample sizes (Table 1), only the FootballingNations and Rest comparisons are anywhere near significant at $p = 0.05$ (Figure 2). The p-values are from a t-test comparing the two nationality groups, if the nationality group has an effect on shooting rating.

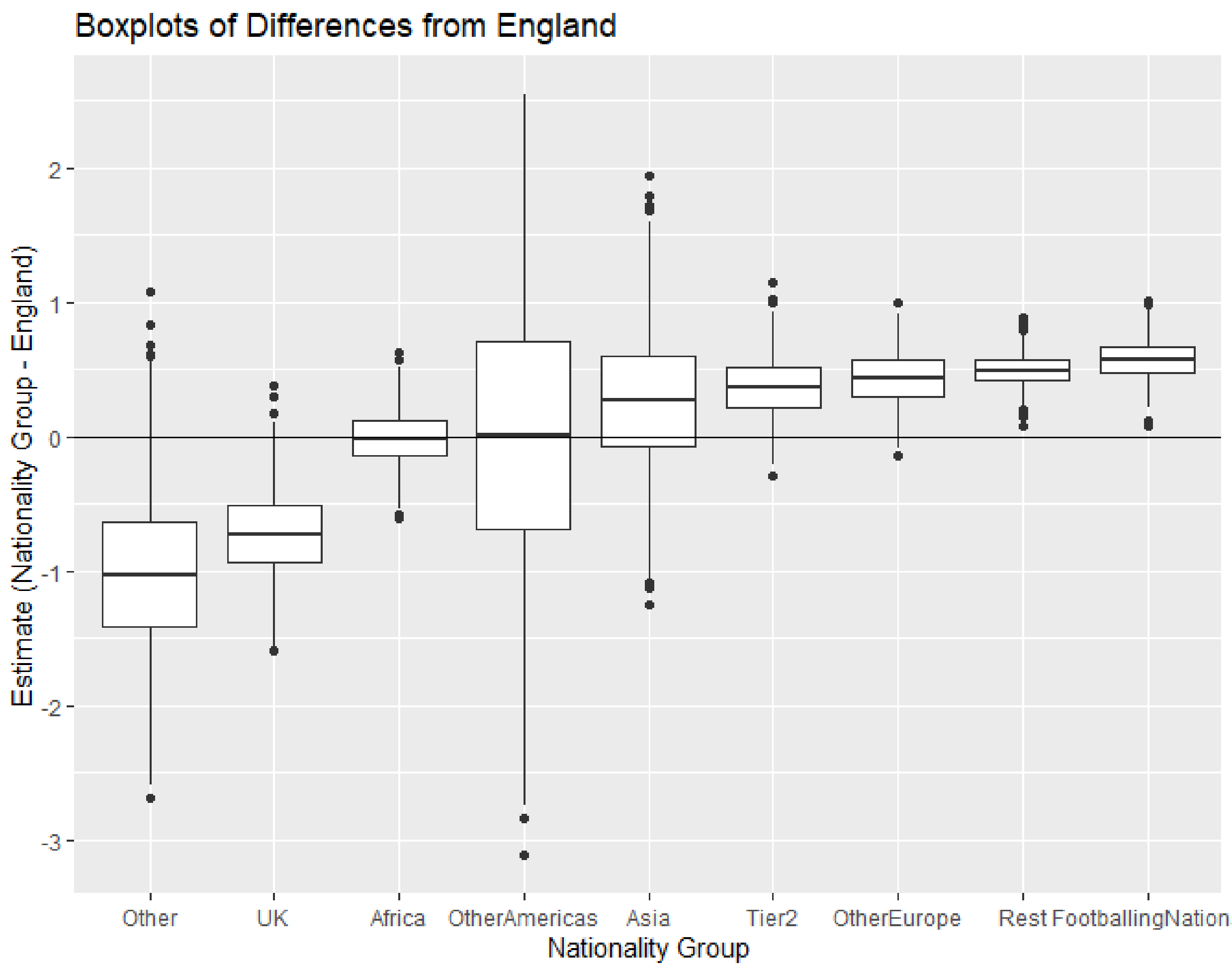

Figure 1 *Boxplots of the differences in mean residuals by nationality group, calculated in the order Nationality Group - England. A reference line is shown at 0.*

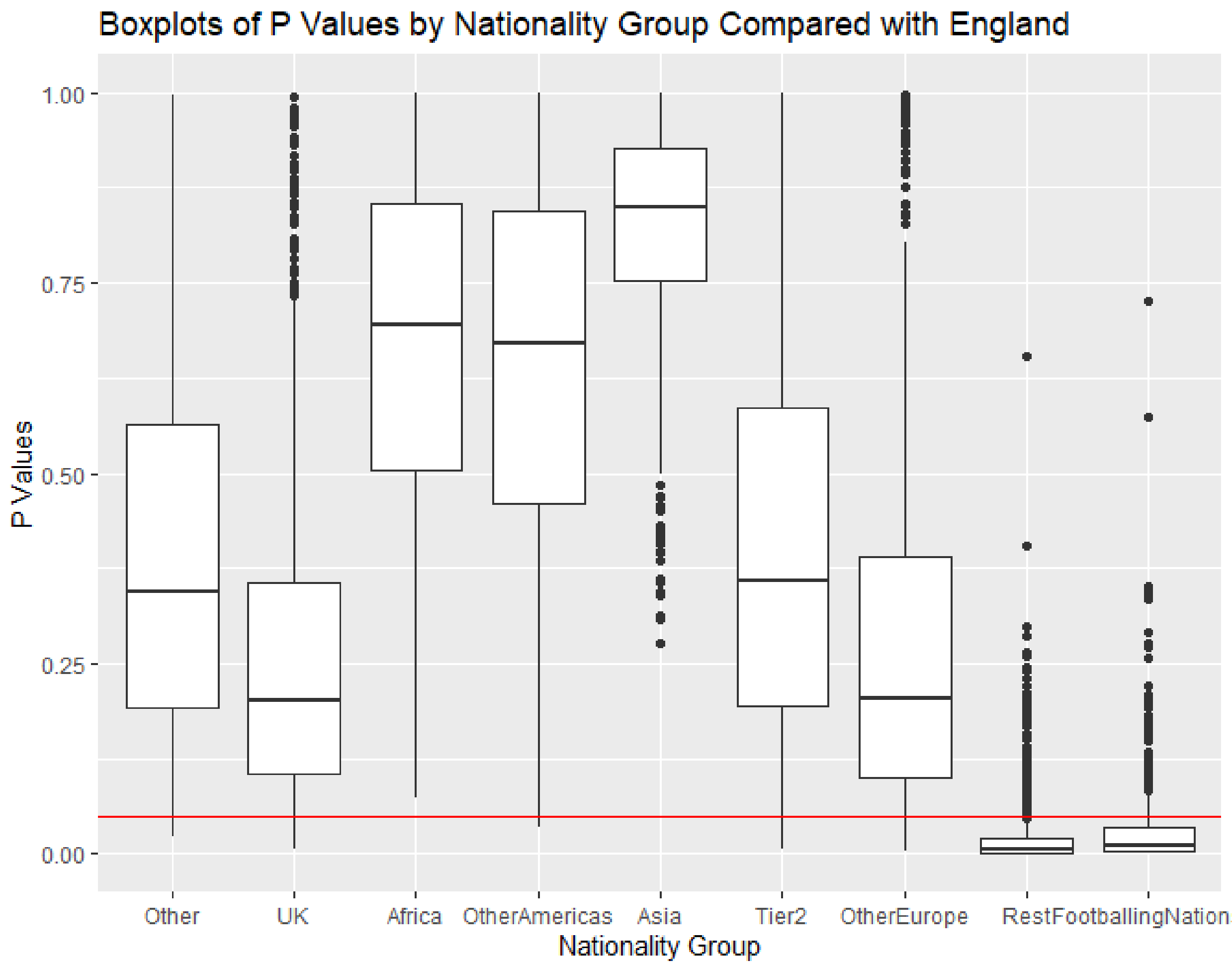

Figure 2 *Boxplots of the p-values for each nationality group comparison. A reference line is at the standard significance level of 0.05.*

Group	Count
England	511
Footballing Nations	355
Other Europe	131
Africa	126
Tier2	93
UK	70
Other Americas	17
Other	16
Asia	15

Table 1 *Shows the number of player seasons for each nationality group.*

Figures 3 and 4 show the p-values for each of the 1000 matching simulations in a histogram. For the FootballingNations, 81.4% or simulations yielded a significant p-value, with a mean p-value of 0.0312. For the Rest comparison, 91% of simulations yielded a significant p-value, with a mean of 0.0192.

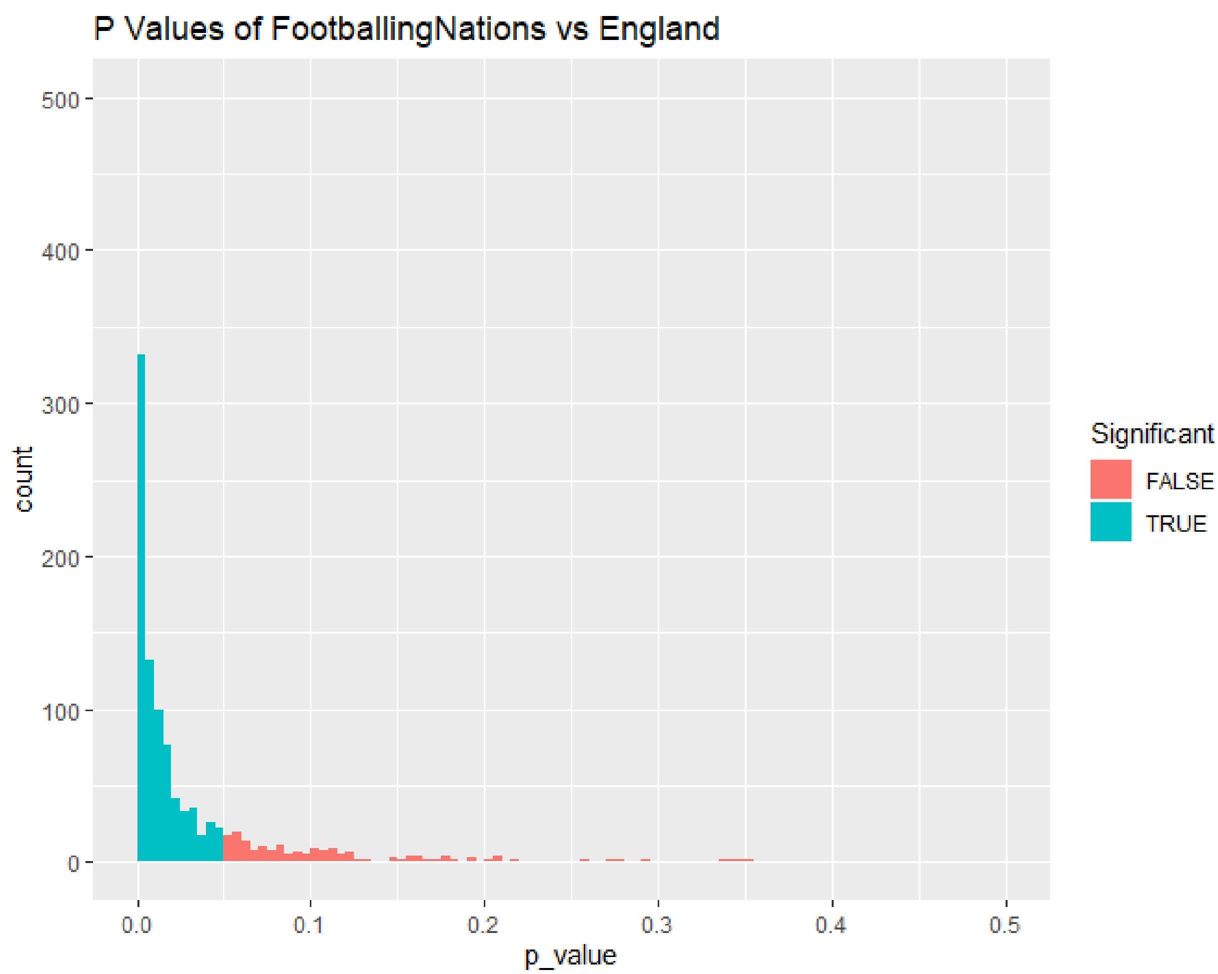

Figure 3

Shows the p-values of the FootballingNations vs England comparison. Blue is p-values that are significant, while red is p-values that are not.

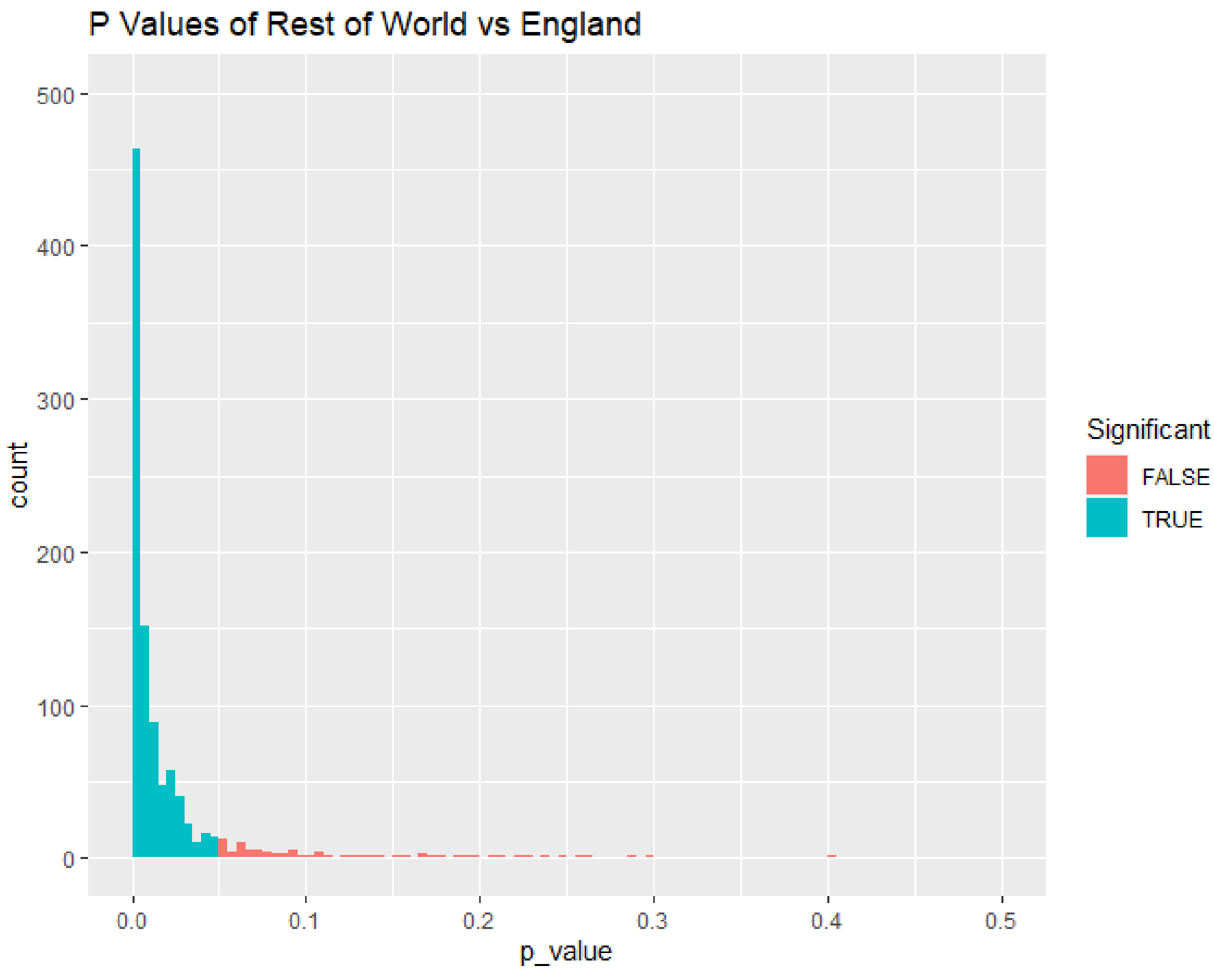

Figure 4

Shows the p-values of the Rest of World (Rest) vs England comparison. Blue is p-values that are significant, while red is p-values that are not.

Discussion

The goal of our research was to determine whether there was nationality bias in the English Premier League, specifically, whether English players were overrated. Our results support the existence of nationality bias players are rated, because there is a noticeable difference in residuals for the different nationalities as compared with England (Figure 1). However, because of the small sample sizes due to the relative lack of players outside of England and the Footballing Nations, only two of the comparisons with England were deemed to be statistically significant. Those comparisons were between England and the rest of the world, and England and the Footballing Nations. In addition, contrary to our hypothesis, English players were not overrated in the EPL compared to worldwide players. In fact, we found the opposite, that English players are underrated.

The first part of our hypothesis was found to be correct, there is indeed nationality bias in the EPL. Two of the comparisons of nationalities were significant, while the comparisons that did not have small sample sizes and could well be significant with enough data. There was correlation between nationality and rating for the non-significant comparisons, and further research could show these correlations significantly.

There are several possible explanations for why our results differed from the second part of our hypothesis, about the “English Tax.” First, our research was based on in-game shooting shooting statistics and shooting ratings. Thus, it could be the case that English players are underrated at shooting, and not underrated overall. English players are generally considered more physical and less technical than their worldwide counterparts, which could explain our results.

Another possible explanation for our results is our use of FIFA ratings. It is possible that FIFA ratings underrate English players, while the English media, fans, and clubs overrate the players. We used FIFA ratings as a proxy for the general perception of how good a player is, which might be inaccurate. Because FIFA is a worldwide organization, it is possible that they are immune to the "English Bias," at least, more so than the English media and fans, which could account for our results.

A third possible explanation for our results is the number of squad players that were used in our analysis. Squad players generally do not play as much in the Premier League, so our model likely was not very effective in rating them. In addition, because some squad players do not have much first team experience, their FIFA ratings could be based more on their demographics, including their nationality. For relatively unknown players, FIFA might revert to common perceptions of players including nationality, which would compound the first point that English players are generally more physical and less technical. Take the example of two young players who have not played very much with the same overall FIFA rating, with one being English and the other being Brazilian. The Brazilian player is possibly rated higher than the English player in shooting, because of the general perception that English players are physical and Brazilians are technical. It is important to note that their overall ratings are the same, the attributes that are changing are their individual attributes, such as shooting and physical strength.

In addition, our model could be missing something that would explain the results. No model is perfect, and it is possible that our model is missing something important that would explain the results. And finally, the last explanation is that maybe English players are rated fairly or indeed underrated in the EPL, and the entire idea of the "English Tax" is a myth.

It is likely that the differences in our results and hypothesis are due to a combination of the above explanations, and not one single factor contributes to the difference. These explanations could also be generalized to all potential comparisons, not necessarily comparisons with England.

Further research is needed to create stronger evidence for the existence of nationality bias, and to further analyze the “English Tax.” One potential study for further research is to use a different attribute from shooting, for example passing, to find evidence for nationality bias outside of shooting. Another potential study could examine nationality bias using ratings other than FIFA ratings, which could include match ratings, individual awards such as the Ballon d’Or, or other video game datasets such as Football Manager. Other research could be conducted in leagues outside of the EPL, including women’s leagues, to see if similar patterns emerge worldwide.

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