Total Team Spending and Profitability Results in a Higher League Ranking in the English Premier League*

An Analysis of Economic Predictors on League Rank in the 2023-2024 Season

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This paper uses a linear regression model to predict English Premier League teams rank in the standings based on three explanatory variables: match attendance, total payroll, and market value. Utilizing R's lm function, this paper analyzes the relationship between these variables and teams total points accumulated during the English Premier League 2023-2024 season. Findings suggest that each explanatory variable significantly influences a team's league position (total points), highlighting the association between team success and team wealth.

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*Code and data are available at: https://github.com/Bellamaclean7/English_Premier_League_Economic_Predictors_on_League_Rank_2023-2024_Season.git.

1 Introduction

Established in 1992, the English Premier League comprises twenty clubs that compete annually, embarking on a 38 week season, each striving not only for the championship but also to avoid relegation. The English Premier League is the wealthiest football league globally, producing a total revenue of €10.5 billion as of the end of the 2022/2023 season (Premier League 2023a). Since the league began in 1992, only seven teams have come out victorious, with three of the seven teams only winning once (Leicester City 2015/16, Blackburn Rovers 1994/95 and Liverpool 2019/20) (Premier League 2023b).

In the context of sports economics, understanding the economic factors that contribute to a team's success within such a wealthy league whose only ever had seven teams rise to the top may aid in understanding why teams like Manchester United (13 league titles), Manchester City (7 league titles), Chelsea (5 league titles), and Arsenal (3 league titles) continue to dominant the standings.

This paper seeks to address a critical gap in existing research, which has often focused on immediate sporting outcomes rather than the underlying economic drivers that may predict long-term performance in the league standings and aid in understanding why only all a small number of teams have been able to win the English Premier League. Using a linear regression model, this analysis will predict English Premier League teams rank in the standings based on three economic explanatory variables: home matchday attendance, total payroll, and market value. Utilizing R's lm function, this paper analyzes the relationship between these variables and teams total points accumulated up to Matchday 33 during the English Premier League 2023-2024 season.

The findings reveal significant insights: while all three variables showed a positive correlation with team success, market value emerged as the most potent predictor, suggesting that financial strength translates more effectively into on-field success than previously understood.

The remainder of the paper is structured as follows. Section 2 describes the data collection phase and methodology. Section 3 details the model's construction and theoretical underpinnings, as well as model predictions. Section 4 presents the results of the regression analysis, and Section 5 discusses the implications of the findings, as well as weaknesses and next steps.

2 Data

Data was collected and analyzed using the statistical programming software R (R Core Team 2023), with additional support from `tidyverse` (Wickham et al. 2023c), `ggplot2` (Wickham 2023), `dplyr` (Wickham et al. 2023a), `readr` (Wickham et al. 2023b), `KableExtra` (Zhu 2023), `knitr` (Xie 2023), `rstanarm` (Team 2023), and `corrplot` (Wei and Simko 2023).

The analysis dataset used for this paper is comprised of five datasets that were compiled during the data cleaning process. The first dataset, Table 1, contains every teams average home matchday attendance for the 2023-2024 season, which was collected from Football Web Pages (2023). The second dataset, Table 2, contains every teams current market value, which was collected from Transfermarkt (2023a). The third dataset, Table 3, contains the current total payroll for each team in the English Premier League, and was collected from Spotrac (2023a). The fourth dataset, Table 4, contains the total amount spent in transfer fees prior to the start of the 2023-2024 season for each team in the English Premier League, and was collected from Spotrac (2023b). The final dataset, Table 5, contains the total points earned by each team in the English Premier League during the 2023-2024 as of Matchday 33, and was retrieved from Transfermarkt (2023b).

Table 1: The dataset containing average home matchday attendance for each team in the English Premier League during the 2023-2024 season.

Team	Home Matchday Attendance
Manchester City F.C.	53,194
Manchester United F.C.	73,523
Arsenal F.C.	60,213
Chelsea F.C.	39,626
Liverpool F.C.	54,672
Aston Villa F.C.	41,783
Tottenham Hotspur F.C.	61,524
West Ham United F.C.	62,463
Newcastle United F.C.	52,158
Everton F.C.	39,063
Crystal Palace	24,797
Nottingham Forest F.C.	29,356
Fulham F.C.	24,290
Brighton & Hove Albion	31,517
AFC Bournemouth	11,085
Brentford F.C.	17,081
Burnley F.C.	21,168

Wolverhampton Wanderers F.C.	31,291
Sheffield United F.C.	30,269
Luton Town F.C.	11,113

Table 2: The dataset containing the current market value of each team in the English Premier League.

Team	Market Value
Manchester City F.C.	£1.27B
Manchester United F.C.	£734M
Arsenal F.C.	£1.12B
Chelsea F.C.	£928M
Liverpool F.C.	£921M
Aston Villa F.C.	£646M
Tottenham Hotspur F.C.	£777M
West Ham United F.C.	£447M
Newcastle United F.C.	£638M
Everton F.C.	£345M
Crystal Palace	£405M
Nottingham Forest F.C.	£370M
Fulham F.C.	£338M
Brighton & Hove Albion	£505M
AFC Bournemouth	£353M
Brentford F.C.	£426M
Burnley F.C.	£265M
Wolverhampton Wanderers F.C.	£340M
Sheffield United F.C.	£144M
Luton Town F.C.	£125M

Table 3: The dataset containing the current total payroll for each team in the English Premier League.

Team	Active Players	Forwards	Midfielders	Defensemen	Goalkeepers	Total
Manchester City F.C.	24	£27,300,000	£91,052,000	£63,440,000	£9,620,000	£191,412,000
Manchester United F.C.	26	£47,780,000	£58,500,000	£63,955,000	£10,400,000	£180,635,000
Arsenal F.C.	25	£43,160,000	£63,460,000	£48,306,000	£11,180,000	£166,106,000
Chelsea F.C.	28	£23,764,000	£59,540,000	£59,800,000	£6,240,000	£149,344,000
Liverpool F.C.	24	£41,912,000	£39,780,000	£42,380,000	£11,440,000	£135,512,000
Aston Villa F.C.	26	£25,220,000	£32,710,000	£40,200,000	£14,040,000	£112,170,000
Tottenham Hotspur F.C.	26	£34,060,000	£36,240,000	£24,270,000	£8,580,000	£103,150,000
West Ham United F.C.	23	£12,948,000	£42,900,000	£29,120,000	£9,828,000	£94,796,000
Newcastle United F.C.	28	£16,180,000	£37,180,000	£28,184,000	£6,240,000	£87,784,000
Everton F.C.	24	£18,486,000	£28,715,000	£23,552,000	£7,280,000	£78,033,000
Crystal Palace	29	£9,100,000	£26,780,000	£28,860,000	£8,080,000	£73,210,000
Nottingham Forest F.C.	28	£18,850,000	£16,120,000	£21,840,000	£7,020,000	£63,830,000
Fulham F.C.	24	£15,210,000	£21,476,000	£19,970,000	£5,980,000	£62,636,000
Brighton & Hove Albion	29	£22,230,000	£16,770,000	£18,000,000	£3,380,000	£60,380,000
AFC Bournemouth	24	£10,400,000	£10,998,000	£12,740,000	£4,004,000	£43,342,000
Brentford F.C.	30	£8,840,000	£13,260,000	£13,260,000	£3,900,000	£39,260,000

Burnley F.C.	31	£9,308,000	£12,480,000	£10,192,000	£3,120,000	£36,140,000
Wolverhampton Wanderers F.C.	20	£11,440,000	£8,840,000	£13,000,000	£2,270,000	£35,550,000
Sheffield United F.C.	28	£7,358,000	£8,190,000	£11,518,000	£4,290,000	£31,876,000
Luton Town F.C.	27	£6,110,000	£9,360,000	£4,290,000	£2,990,000	£23,940,000

Table 4: The dataset containing the total amount spent in transfer fees prior to the start of the 2023-2024 season for each team in the English Premier League.

Team	Total Transfer Fees
Manchester City F.C.	£151,100,000.00
Manchester United F.C.	£121,700,000.00
Arsenal F.C.	£226,600,000.00
Chelsea F.C.	£449,100,000.00
Liverpool F.C.	£172,000,000.00
Aston Villa F.C.	£97,400,000.00
Tottenham Hotspur F.C.	£231,300,000.00
West Ham United F.C.	£135,800,000.00
Newcastle United F.C.	£145,200,000.00
Everton F.C.	£37,500,000.00
Crystal Palace	£67,800,000.00
Nottingham Forest F.C.	£93,870,000.00
Fulham F.C.	£298,900,000.00
Brighton & Hove Albion	£107,350,000.00
AFC Bournemouth	£87,070,000.00
Brentford F.C.	£67,850,000.00
Burnley F.C.	£107,050,000.00
Wolverhampton Wanderers F.C.	£44,000,000.00
Sheffield United F.C.	£41,850,000.00
Luton Town F.C.	£7,600,000.00

Table 5: The dataset containing the total points earned by each team in the English Premier League during the 2023-2024 as of Matchday 30.

Team	Points
Manchester City F.C.	73
Arsenal F.C.	71
Liverpool F.C.	71
Aston Villa F.C.	63
Tottenham Hotspur F.C.	60
Newcastle United F.C.	50
Manchester United F.C.	50
West Ham United F.C.	48
Chelsea F.C.	47
Brighton & Hove Albion	44
Wolverhampton Wanderers F.C.	43
Fulham F.C.	42
AFC Bournemouth	42
Crystal Palace	33
Brentford F.C.	32

Everton F.C.	27
Nottingham Forest F.C.	26
Luton Town F.C.	25
Burnley F.C.	20
Sheffield United F.C.	16

The datasets were then combined during the cleaning process to create one master dataset for analysis. The merging process was conducted on the common column `team`, ensuring that data from each dataset corresponding to a specific team was consolidated into a single row within the analysis dataset. This methodology allowed for a unified view of each team's `matchday attendance`, `market value`, `total team points`, `total payroll`, and `total transfer spending`, facilitating a multifaceted analysis of team performance and financial metrics.

As part of the data cleaning process, specific columns containing numeric values but stored as character strings—due to the inclusion of commas as thousands separators and currency symbols—were converted to their appropriate numeric data types. This conversion involved stripping the character columns 'average_home_matchday_attendance', 'total_wage_bill', and 'transfer_fees' of non-numeric characters (i.e., commas and the pound sterling symbol) and then casting them to integer or numeric types as contextually appropriate, as well as applying the same scaling methods to each variable. This step was essential for enabling quantitative analysis of these variables.

Furthermore, to streamline the dataset and focus the analysis on key variables of interest, certain columns deemed extraneous to the core analytical objectives were removed. These included detailed payroll information per position (`forwards`, `midfielders`, `defensemen`, `goalkeepers`) and the column `active.players`. The removal of these columns served to reduce the dataset's complexity, facilitating a more focused and manageable analysis of the relationships between team performance metrics and financial expenditures.

The resulting dataset for analysis is shown in Table 6.

Table 6: The dataset containing the total points earned by each team in the English Premier League during the 2023-2024 as of Matchday 33.

Team	Home Matchday Attendance	Market Value	Points	Total Payroll	Total Transfer Fees
Manchester City F.C.	53194	1.27000	73	0.191412	0.15110
Manchester United F.C.	73523	0.73425	50	0.180635	0.12170
Arsenal F.C.	60213	1.12000	71	0.166106	0.22660
Chelsea F.C.	39626	0.92830	47	0.149344	0.44910
Liverpool F.C.	54672	0.92140	71	0.135512	0.17200
Aston Villa F.C.	41783	0.64620	63	0.112170	0.09740
Tottenham Hotspur F.C.	61524	0.77730	60	0.103150	0.23130
West Ham United F.C.	62463	0.44660	48	0.094796	0.13580
Newcastle United F.C.	52158	0.63770	50	0.087784	0.14520
Everton F.C.	39063	0.34540	27	0.078033	0.03750
Crystal Palace	24797	0.40470	33	0.073210	0.06780

Nottingham Forest F.C.	29356	0.36965	26	0.063830	0.09387
Fulham F.C.	24290	0.33800	42	0.062636	0.29890
Brighton & Hove Albion	31517	0.50510	44	0.060380	0.10735
AFC Bournemouth	11085	0.35280	42	0.043342	0.08707
Brentford F.C.	17081	0.42608	32	0.039260	0.06785
Burnley F.C.	21168	0.26510	20	0.036140	0.10705
Wolverhampton Wanderers F.C.	31291	0.33970	43	0.035550	0.04400
Sheffield United F.C.	30269	0.14375	16	0.031876	0.04185
Luton Town F.C.	11113	0.12510	25	0.023940	0.00760

The analysis dataset has 6 columns:

1. The `Team` column, which denotes the name of each football club in the English Premier League.
2. The `Home Matchday Attendance` column, which denotes the average number of spectators attending home matches of the football club. This helps understand the club's popularity, fan base size, and infrastructure.
3. The `Market Value` column, which represents the total market value of the team in billions of pounds. It indicates the financial strength and quality of the club.
4. The `Points` column, which represents the total points a team has accumulated over the season in the league. Points are awarded based on wins and draws.
5. The `Total Payroll` column, which details the total annual wages paid by the club to its players, given in pounds. It reflects the financial commitment of the club towards its playing squad.
6. The `Total Transfer Fees` column, which denotes the total amount spent by the club on transfer fees in pounds during the transfer window for the given year. It indicates the club's investment in new players for the season.

From here I began examining the relationships between English Premier League teams' league performance (expressed in points accumulated) and various financial indicators during the 2023-2024 season. The following four graphs (Figure 1, Figure 2, Figure 3, and Figure 4) present a scatter plot paired with a linear regression trend line to evaluate the correlation between league points and each key economic metric presented in Table 6.

In Figure 1, Figure 2, Figure 3, and Figure 4, each point point on the graph represents a team, plotted with their total points on the x-axis and their average home attendance on the y-axis. The trend line in Figure 1 demonstrates a positive correlation between team performance and matchday turnout. The correlation coefficient of 0.683116662462212 indicates a positive association with moderate correlation, where teams with higher league points tend to have a higher home matchday attendance. Figure 2 linear regression trend line suggests a correlation between a team's financial expenditure on payroll and their success in the league. A correlation coefficient of 0.788682340622421 reflects a positive relationship, implying that teams with higher payrolls may be more likely to accumulate greater league points. Figure 3 demonstrates a pronounced upward trend represented by the linear regression line, with a correlation coefficient of 0.88165690596531, indicative of a strong positive relationship. This suggests that

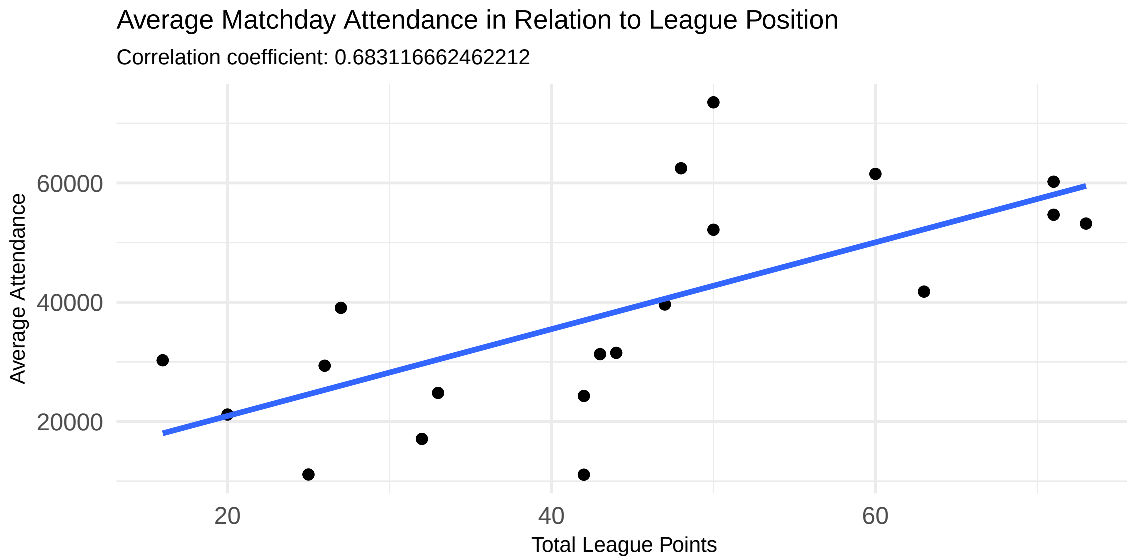


Figure 1: Scatter plot illustrating the relationship between total league points and average matchday attendance during the 2023-2024 season.

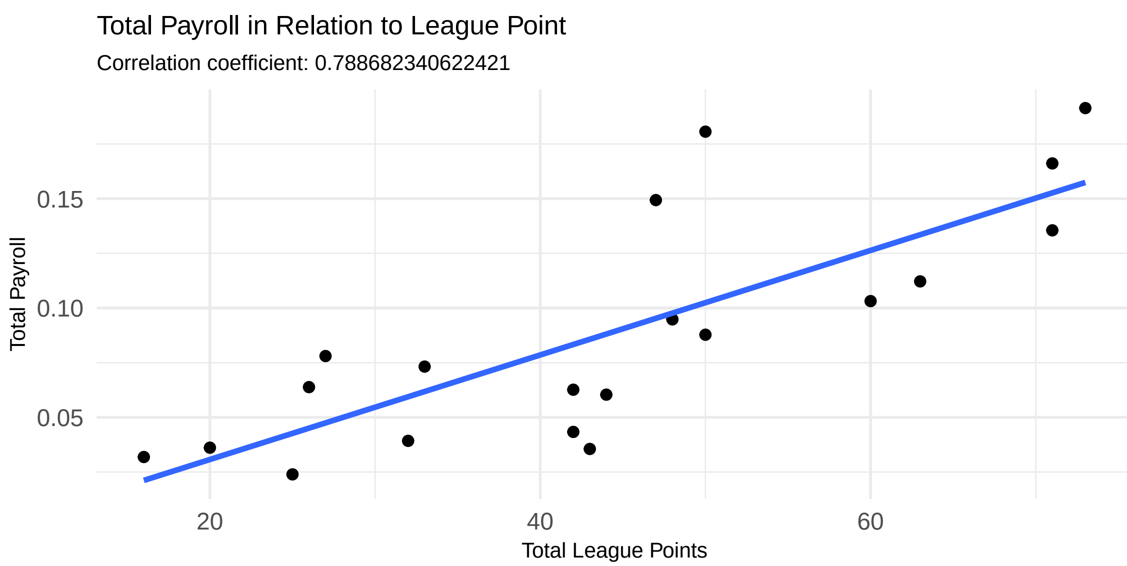


Figure 2: Scatter plot depicting the association between total league points and the total payroll for teams in the 2023-2024 season.

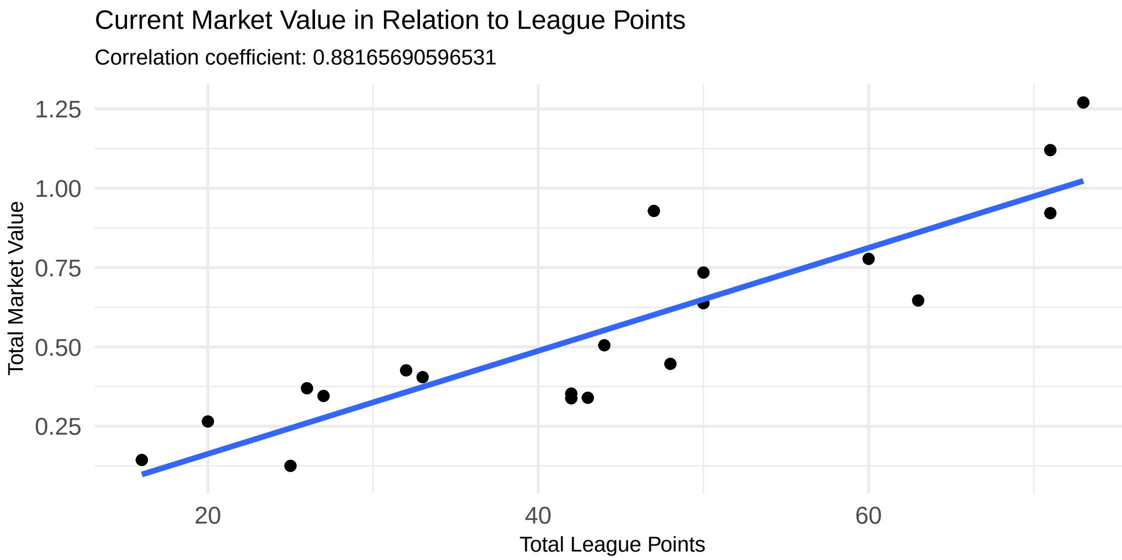


Figure 3: Scatter plot demonstrating the correlation between the current market value of teams and their accumulated league points for the 2023-2024 season.

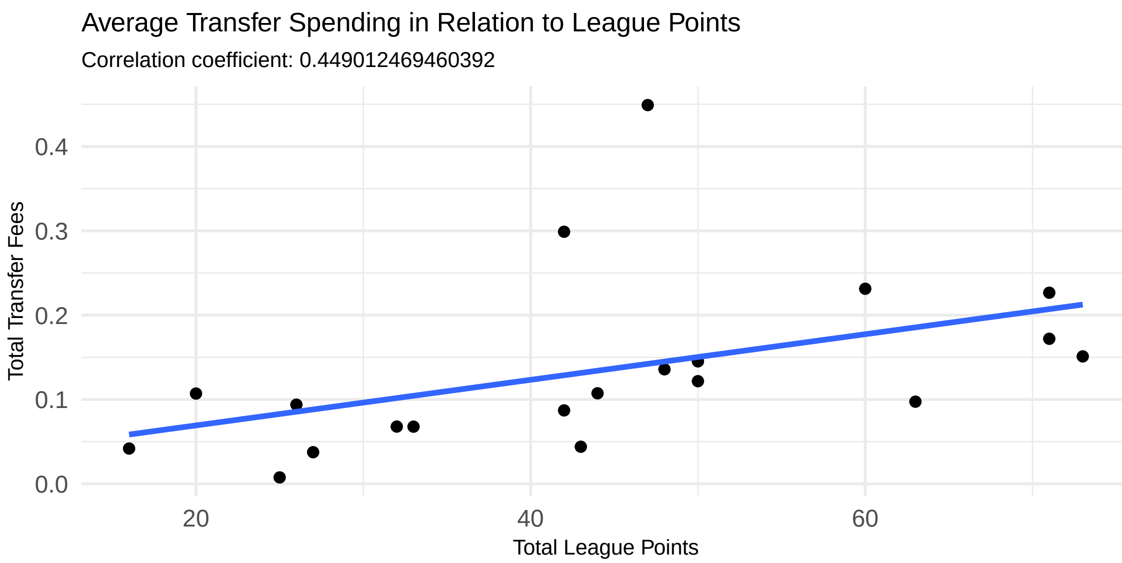


Figure 4: Scatter plot illustrating the relationship between teams total transfer spending and their corresponding league points for the 2023-2024 season.

teams with higher market values tend to amass more league points, underlining a potential link between financial strength and on-field success. Figure 4 trend line indicates a moderate positive correlation, with a correlation coefficient of approximately 0.449012469460392. This suggests that higher league points tend to coincide with increased transfer spending, although the relationship is not strongly linear.

When running simple linear regression with `Points` ~ `Each Dependent Variable`, you're looking at the relationship between each variable in isolation with `Points`. The positive trend and strong correlation coefficients found in Figure 1, Figure 2, Figure 3 when analyzed in isolation with `Points`, suggests that as `Market Value`, `Total Payroll`, and `Average Matchday Attendance` of a team increases (independently from each other), so do the points accumulated.

3 Model

3.1 Linear Regression

A linear regression model is a statistical model for linear relationships between variables given by

$$Y_i = \beta_0 + \beta_1 X_{i,1} + \beta_2 X_{i,2} + \ldots + \beta_p X_{i,p} + \varepsilon_i \quad \text{for } i = 1, \ldots, n. \tag{1}$$

As shown in equation (1) a linear regression model has the following components:

- Y_i: The dependent variable for the i^{th} observation. This is the response variable that is trying to be predicted or explained, dependent on the corresponding explanatory variables $X_{i,1}, X_{i,2}, \ldots, X_{i,p}$.
- β_0: The intercept of the regression line. It represents the expected value of Y_i when all the independent variables (X) are equal to 0.
- $\beta_1, \beta_2, \ldots, \beta_p$: The coefficients of the model. Each β_j (for $j = 1, \ldots, p$) represents the expected change in Y_i for a one-unit change in the j^{th} independent variable, $X_{i,j}$, holding all other variables constant.
- $X_{i,1}, X_{i,2}, \ldots, X_{i,p}$: The independent variables (also called predictors or explanatory variables) for the i^{th} observation. These variables are used to predict the value of the dependent variable.
- ε_i: The error term for the i^{th} observation. It represents the difference between the observed value of the dependent variable and the value predicted by the model. It's assumed to be randomly distributed with a mean of 0.

- $i = 1, \ldots, n$: This indicates that the equation applies to each observation in the dataset, from the first ($i = 1$) to the n^{th} (the last observation), where n is the total number of observations.

3.2 Model set-up

$$\begin{aligned} \text{pts}_i = \beta_0 + \beta_1 \times \text{average\_home\_matchday\_attendance}_i \\ + \beta_2 \times \text{total\_wage\_bill}_i + \beta_3 \times \text{market\_value}_i + \varepsilon_i \end{aligned} \tag{2}$$

Equation (2) can be explained as follows:

- pts_i: The dependent variable for the i^{th} observation. This is the outcome variable that the model is trying to predict or explain, which in this context could represent points (or any other metric of success) associated with each observation.
- $\beta_1, \beta_2, \beta_3$: The coefficients of the model. Each of these coefficients represents the expected change in pts_i for a one-unit increase in their respective independent variable, assuming all other variables are held constant.
  - β_1 is associated with $\text{average\_home\_matchday\_attendance}_i$, indicating how changes in home matchday attendance are expected to affect pts_i.
  - β_2 corresponds to total_wage_bill_i, reflecting the impact of the total wage bill on pts_i.
  - β_3 is linked with market_value_i, showing how the market value is predicted to influence pts_i.

3.3 Model justification

The linear regression model given by Equation (2), derived from the foundational principles of linear regression outlined in Equation (1), provides a transparent mechanism to quantify the impact of various economic factors on the total points accumulated by EPL teams (a direct correlation to team rank in league standings). The model will aid in gaining insights into how attendance, total payroll, and market value could affect performance metrics. The model is operationalized using the `lm` function in `R`. A strong positive relationship is expected between the dependent variable (`Points`) and three independent variables (`Home Matchday Attendance`, `Total Payroll`, and `Market Value`). The higher the three independent variables are, the more points that should be accumulated by a team.

3.4 Model Prediction

A positive relationship is hypothesized between the dependent variable (`Points`) and the three independent variables (`Home Matchday Attendance`, `Total Payroll`, and `Market Value`). The underlying assumption is that higher values for these independent variables should correlate with an increased number of points earned by a team. Such a correlation would suggest that greater fan engagement (as reflected in matchday attendance), higher investment in player talent (as indicated by the payroll), and a more substantial market presence (denoted by market value) are all strategic levers that could lead to better performance in the league.

4 Results

Table 7 shows the table of the coefficients after running the linear model summary.

Table 7: Summary of Linear Model Coefficients

	Estimate	StdError	tValue	Pr
(Intercept)	14.0159614	4.6112152	3.039537	0.0078076
average_home_matchday_attendance	0.0002593	0.0001778	1.458001	0.1641895
total_wage_bill	-139.8905906	113.2953089	-1.234743	0.2347529
market_value	58.6176203	15.3445374	3.820097	0.0015074

Note: Residuals: Min 1Q Median 3Q Max -10.8121 -6.0644 -0.9837 5.1376 15.9644

Residual standard error: 8.261 on 16 degrees of freedom Multiple R-squared: 0.8057, Adjusted R-squared: 0.7693 F-statistic: 22.12 on 3 and 16 DF, p-value: 6.159e-06

The results from the linear regression model indicate a strong relationship between points earned by English Premier League teams and variables such as average home matchday attendance, total wage bill, and market value. The model explains a significant portion of the variability in points, with an R^2 value of 0.8057, suggesting that about 80.57% of the variation in team points can be accounted for by these three predictors. Market value is particularly impactful, as indicated by a statistically significant positive coefficient ($p = 0.00151$), suggesting that higher market values are associated with higher points. Conversely, the coefficient for the total wage bill is negative, though not statistically significant, hinting that higher wage bills might not necessarily translate into better performance. This is somewhat surprising, however, results could stem from market value being such a strong predictor that it is overshadowing the impactfulness of total wage bill. Attendance shows a positive but non-significant impact on points. The model's residuals indicate some deviation from perfect prediction, with values ranging from -10.81 to 15.96, suggesting variability that the model doesn't capture. Overall, the significant p-value for the model (6.159e-06) confirms the effectiveness of these predictors in forecasting league points and therefore the confirmation to move forward in the analysis.

Table 8 shows the actual and predicted performance of English Premier League teams for the 2023-2024. Each row of the table corresponds to a different team and lists three key pieces of information: the team's name, their actual points accumulated in the league as of Matchday 33, and their predicted points, which are calculated based on variables such as home attendance, total payroll, and market value. The teams are sorted by their actual points in descending order, showcasing the teams with higher performance at the top of the table.

Table 8: Actual vs Predicted Points for English Premier League Teams Based on Home Attendance, Total Payroll, and Market Value, Sorted by Current League Ranking in Descending Order

Team	Points	Predicted Points
Manchester City F.C.	73	75
Arsenal F.C.	71	72
Liverpool F.C.	71	63
Aston Villa F.C.	63	47
Tottenham Hotspur F.C.	60	61
Manchester United F.C.	50	51
Newcastle United F.C.	50	53
West Ham United F.C.	48	43
Chelsea F.C.	47	58
Brighton & Hove Albion	44	43
Wolverhampton Wanderers F.C.	43	37
Fulham F.C.	42	31
AFC Bournemouth	42	32
Crystal Palace	33	34
Brentford F.C.	32	38
Everton F.C.	27	33
Nottingham Forest F.C.	26	34
Luton Town F.C.	25	21
Burnley F.C.	20	30
Sheffield United F.C.	16	26

Figure 5 compares actual league points as of Matchday 33 of the 2023-2024 English Premier League season to predicted league points. Points predicted by the linear regression model are plotted alongside the points actually obtained by the teams to evaluate the models accuracy. The teams are arranged on the x-axis in descending order of their actual points, and two sets of bars represent the actual (in blue) and predicted (in red) points for each team, allowing for a direct side-by-side comparison between the models predictions and real-world outcomes.

Table 9 presents a comparative analysis of the rankings of English Premier League teams, juxtaposing their actual standings against their predicted standings. The prediction is derived from Equation (2) that incorporates variables such as home attendance, total payroll, and market value. Each row in the table features a rank number, followed by the actual team

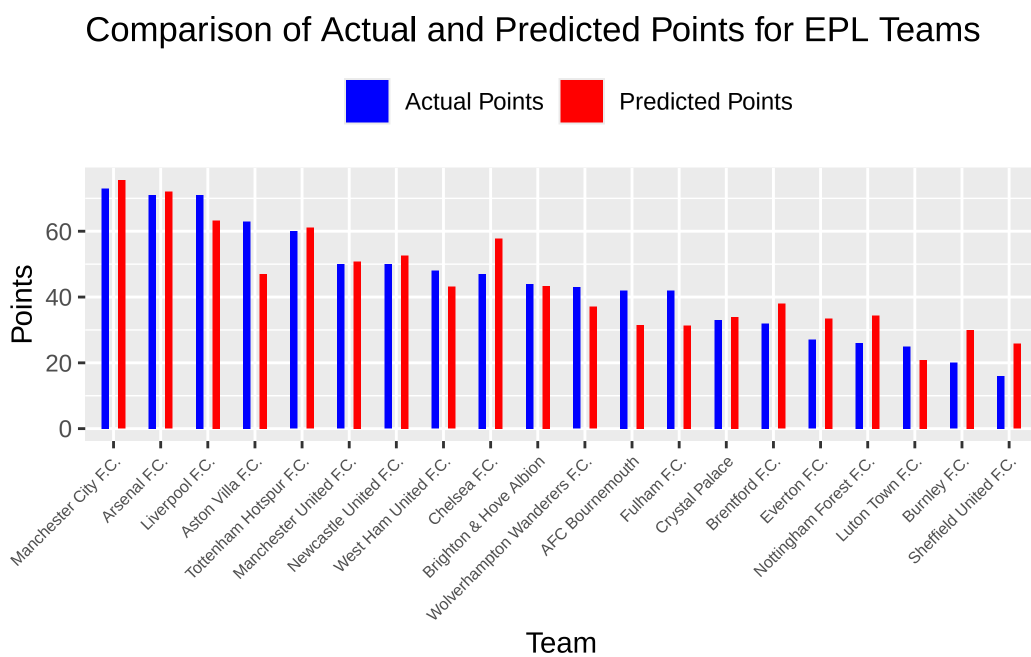


Figure 5: A double bar graph comparing the actual and predicted points for teams in the English Premier League.

standing corresponding to that rank, and the predicted team standing that would occupy the same rank based on the model's calculations. This layout allows for a direct comparison of where teams are predicted to stand based on certain metrics versus where they actually stand in the league, highlighting the model's accuracy and identifying discrepancies between expected and actual performances.

Table 9: Actual Rank vs Predicted Rank Based on Home Attendance, Total Payroll, and Market Value for English Premier League Teams

Rank	Actual Standings	Predicted Standings
1	Manchester City F.C.	Manchester City F.C.
2	Arsenal F.C.	Arsenal F.C.
3	Liverpool F.C.	Liverpool F.C.
4	Aston Villa F.C.	Tottenham Hotspur F.C.
5	Tottenham Hotspur F.C.	Chelsea F.C.
6	Manchester United F.C.	Newcastle United F.C.
7	Newcastle United F.C.	Manchester United F.C.
8	West Ham United F.C.	Aston Villa F.C.
9	Chelsea F.C.	Brighton & Hove Albion
10	Brighton & Hove Albion	West Ham United F.C.
11	Wolverhampton Wanderers F.C.	Brentford F.C.

12	Fulham F.C.	Wolverhampton Wanderers F.C.
13	AFC Bournemouth	Nottingham Forest F.C.
14	Crystal Palace	Crystal Palace
15	Brentford F.C.	Everton F.C.
16	Everton F.C.	AFC Bournemouth
17	Nottingham Forest F.C.	Fulham F.C.
18	Luton Town F.C.	Burnley F.C.
19	Burnley F.C.	Sheffield United F.C.
20	Sheffield United F.C.	Luton Town F.C.

The top-performing teams are generally predicted quite accurately, with only slight deviations in rankings regarding the top 10 teams. The top three teams for both actual and predicted are identical. The results also correctly predict the worst teams in the league, accurately predicting the three teams at the bottom of the table, however, in a slightly different order then their actual rank. Although the model does accurately predict the weaker teams in the league, it is evident that the model expected more points to be accumulated by these teams then the actual points accumulated. Figure 6 visualizes the results of Table 9 in a scatter plot.

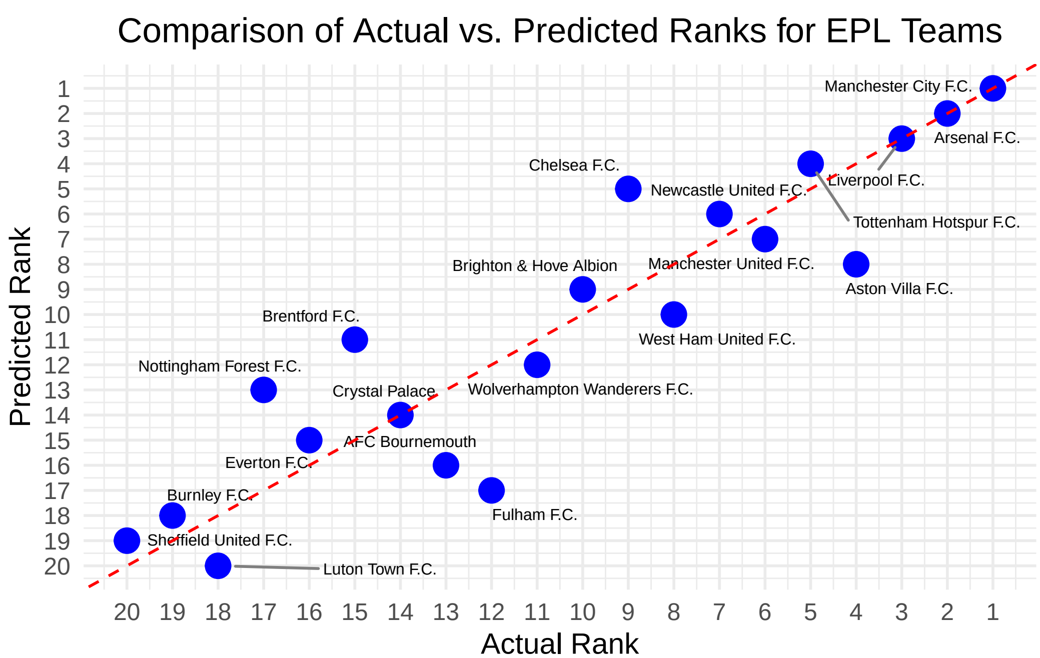


Figure 6: A scatter plot comparing actual and predicted rankings of English Premier League (EPL) teams.

5 Discussion

The application of predictive analytics in football is an expanding field that can provide a competitive edge to clubs. This study aimed to correlate financial factors with team success highlighting the potential of data-driven decision-making in enhancing a team's competitive performance. The significant correlation between a team's market value and league points serves as evidence of the tangible benefits that can be gained from predictive analytics and understanding the significance of team wealth in professional sports.

The data presented in Section 4 indicates a strong positive correlation between the predicted points, which take into account factors such as home attendance, payroll, and market value, and the actual points achieved by the teams in the English Premier League. As of Matchday 33, Most teams appear to be performing within a close range of their predicted outcomes, suggesting that the model used for predictions is fairly accurate or that most teams are performing as expected given their financial inputs.

The results of the regression analysis underscore the substantial role that economic factors play in the performance of English Premier League teams. The robust association between market value and league points, in particular, confirms the prevailing notion that financial strength translates into competitive success. The unexpected negative coefficient for the total wage bill is one of the most interesting aspect of this analysis. While not statistically significant, the correlation raises questions about the efficiency and return on investment of high player salaries. It hints that simply spending more on player wages does not guarantee better outcomes, highlighting the complexity of financial management in football.

5.1 Analyzing Chelsea F.C.'s Underachievement

Within the predictions lies a couple outliers, with Chelsea F.C. being the most notable. Chelsea's actual points stand at 47, while the model predicted they would have achieved 58 points by Matchday 33. This discrepancy of 11 points is significant and suggests that Chelsea F.C. is underperforming relative to its financial status. As a club known to have a substantial payroll and high market value, and a significant fan base, which are indicators of a team's wealth and resources available for acquiring talent, the expectation would be for Chelsea to secure a position closer to the top of the table.

This outlier status of Chelsea F.C. draws attention and could prompt stakeholders to conduct a deeper analysis into why the club is not meeting the expectations set by its financial prowess. It raises questions about the efficacy of the investments made by the club and whether financial power is translating into performance on the pitch as anticipated.

Chelsea F.C.'s lower-than-expected league points despite its significant financial outlay exemplifies the multifaceted nature of football performance. The discrepancy between predicted and actual points for Chelsea F.C. is one of the largest among all teams, prompting a closer look at factors beyond the economic predictors used in this study. It serves as a reminder that team cohesion, tactical decisions, and possibly non-quantifiable elements such as team spirit and injuries can heavily influence results. As such, Chelsea F.C.'s example could be a launching pad for exploring the non-economic dimensions that interplay with financial resources to shape the success of a football club.

5.2 Analyzing Fulham F.C.'s Overachievement

Despite having relatively modest financial metrics compared to the league's top spenders, Fulham F.C. managed to outperform the projections. Fulham's actual points stand at 42 (12th place), while the model predicted they would have achieved only 31 points (17th place) by Matchday 33. This suggests that Fulham F.C. is outperforming relative to their financial status.

This suggests that their are ways in which other areas of the game besides financial metrics lead to higher league rankings. This could include effective management, coaching, and perhaps strong team cohesion that transcends financial capabilities. Perhaps Fulham's management has excelled this season in areas such as player development, game strategy, and optimizing team dynamics. Management strategies and the coaching staff's ability to maximize player potential and tactical execution on a budget far less then their more successful counterparts could aid other clubs in understanding how to maximize results while minimizing expenditures.

5.3 Weaknesses and Next Steps

While the linear regression model has demonstrated predictive strength, its limitations must be acknowledged. The study's primary limitation, though intentional, is its exclusive focus on financial predictors to forecast English Premier League performance. While such economic indicators are significant, they represent only a fraction of the factors that influence football outcomes. The model does not account for the strength of the coaching staff, the psychological state of players, injuries, weather conditions during matches, and other situational factors that could affect performance on a match-to-match basis. Furthermore, the analysis does not take into account the total payroll of coaching and managing staff, it strictly looks at players.

Another limitation is the scope of the study, which is restricted to the current season. This narrow time frame does not allow for the analysis of trends or the examination of the persistence of the identified relationships across different seasons. Football is a dynamic sport where teams' fortunes can fluctuate drastically from year to year; hence, a multi-season approach would most likely yield more robust insights.

The sample size, constrained to the current teams in the Premier League for a single season, poses a further limitation. The relatively small dataset may not capture the full variability and could potentially overestimate or underestimate the effects of the predictors. Larger datasets that span perhaps all four division/tiers of English football might provide a more comprehensive view of the financial dynamics at play.

This report primarily focuses on the immediate financial aspects of team success. However, there is increasing evidence that investments in English Premier League teams youth academies and development programs are crucial for long-term success. These potential benefits make a strong case for channeling financial resources into nurturing young talent as a strategic move for long term success within a club. Next steps could include analyzing the investment strategies and financial power present in youth development programs and could add a new dimension to understanding English Premier League teams success.

Appendix

A Model details

A.1 Model Summary

```
Call:
lm(formula = pts ~ average_home_matchday_attendance + total_wage_bill +
    market_value, data = analysis_data)

Residuals:
     Min       1Q   Median       3Q      Max
-10.8121  -6.0644  -0.9837   5.1376  15.9644

Coefficients:
                                 Estimate Std. Error t value Pr(>|t|)
(Intercept)                     1.402e+01  4.611e+00   3.040  0.00781 **
average_home_matchday_attendance  2.593e-04  1.778e-04   1.458  0.16419
total_wage_bill                -1.399e+02  1.133e+02  -1.235  0.23475
market_value                    5.862e+01  1.534e+01   3.820  0.00151 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 8.261 on 16 degrees of freedom
Multiple R-squared:  0.8057,    Adjusted R-squared:  0.7693
F-statistic: 22.12 on 3 and 16 DF,  p-value: 6.159e-06
```

A.2 Posterior predictive check

Figure 7 Conduct a simulation-based approach to assess how well the model can predict new data. First new datasets were created by adding randomly sampled residuals (differences between observed and model-predicted values) to the fitted values from the model. Sampling residuals allows me to include the natural variability and error structure of the model in the simulated data. I do this many times (1000 simulations), each time generating a full set of predicted points based on your model but incorporating different sampled residuals. Then calculate the mean and quantile intervals (e.g., 95% confidence intervals) for these simulated points. These statistics are used to see how the simulated data (predictions) compare against the actual data. Mean of simulations represents the average predicted points from all simulations for each team. Confidence intervals give a range where you expect the true value of the teams points to fall, based on the models predictions and its inherent uncertainty. The final step involves plotting the actual points against the mean of the simulated points for each team. This visualization checks model validity. If the model is good, most actual points should lie within the plotted confidence intervals of the simulated means. It also assesses prediction accuracy. The closer these points lie along the diagonal line (where actual equals predicted), the better your model is at accurately predicting the points.

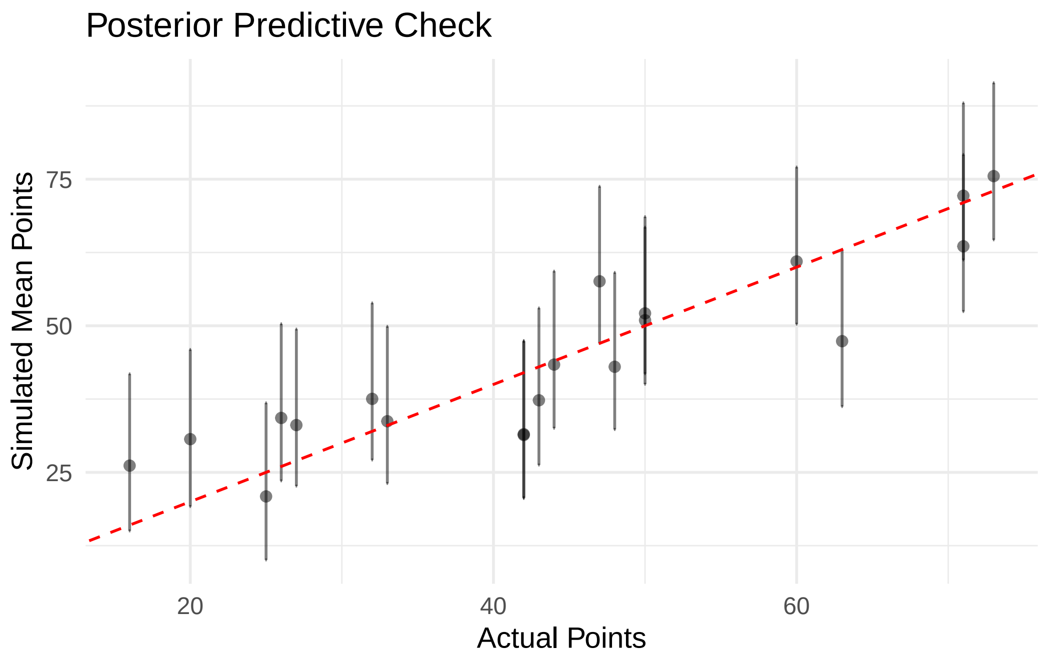
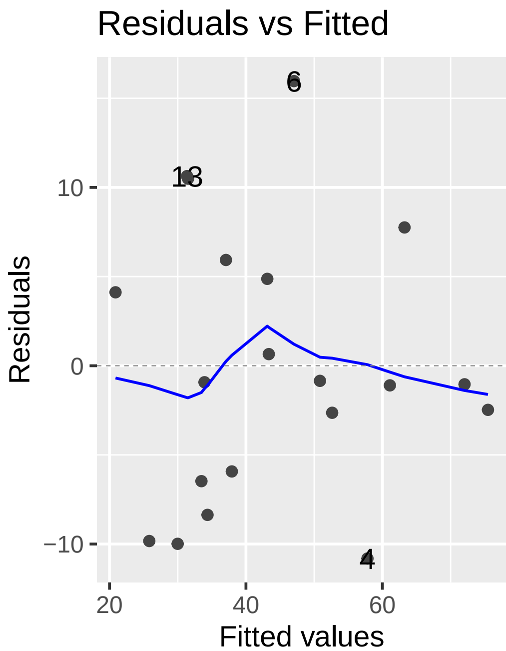
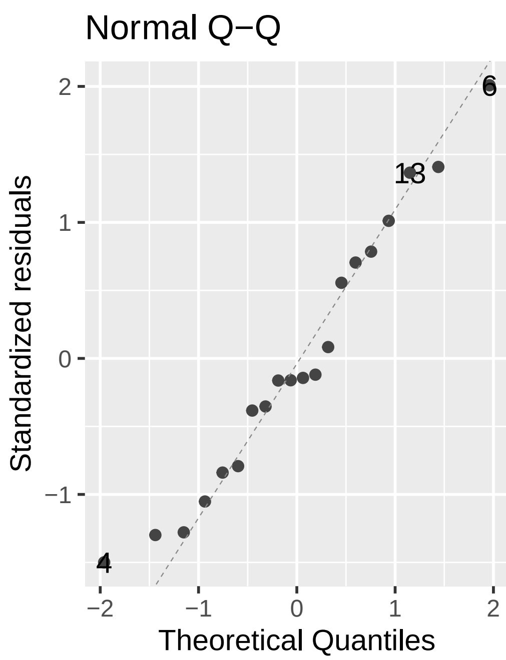
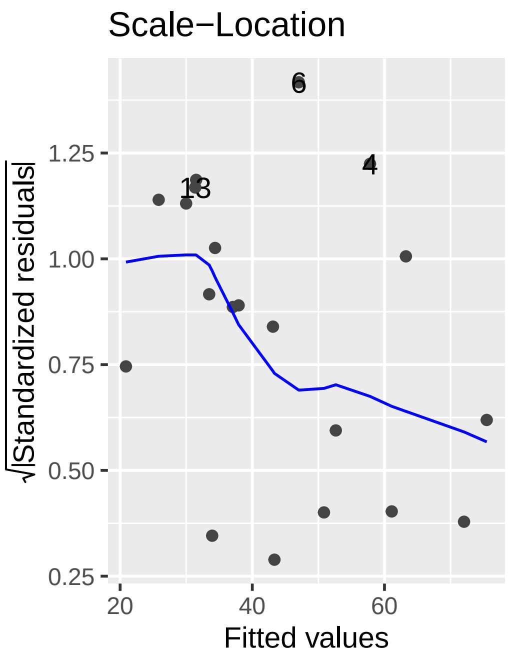


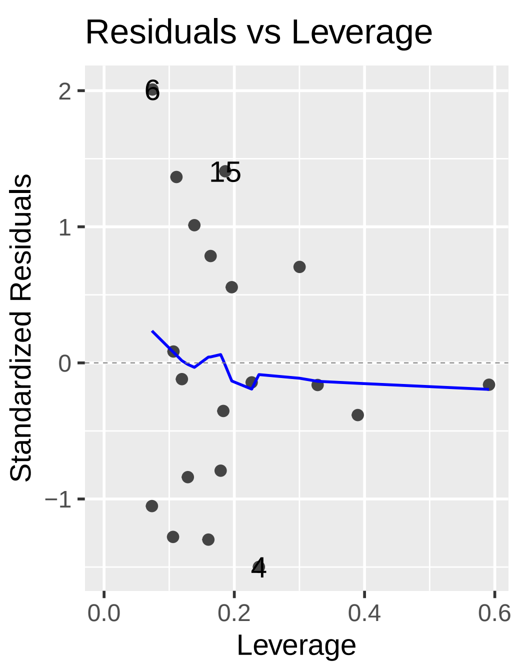
Figure 7: Conducting a simulation-based approach to assess how well the model can predict new data.

A.3 Diagnostics










```
    Durbin-Watson test

data:  model
DW = 2.3214, p-value = 0.6851
```

```
alternative hypothesis: true autocorrelation is greater than 0


    Anderson-Darling normality test

data:  residuals(model)
A = 0.30059, p-value = 0.5471

average_home_matchday_attendance                  total_wage_bill
                        2.956659                         9.710251
                    market_value
                        6.572163


    Durbin-Watson test

data:  model
DW = 2.3214, p-value = 0.6851
alternative hypothesis: true autocorrelation is greater than 0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```

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