# The Impact of the 2022-23 NBA Rule Change*

## Exploring the Relationship Between the New Transitional Foul Rule, Player Shooting Performance, and MVP Points

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Rule changes in professional basketball play a critical role in shaping both strategies and player performances. Specifically, the introduction of the transitional foul rule in the 2022-23 NBA season, which changes the way fouls are called during transition plays, could significantly affect players' shooting efficiency and their prospects for MVP awards. This paper examines the implications of this rule change, comparing player statistics between the 2022-23 and 2021-22 seasons. We find significant correlations between shooting efficiency and MVP points, highlighting the rule's influence on player recognition. This paper offers insights into the interplay between rule modifications, player performance, and individual accolades, underscoring the broader significance of adapting to regulatory shifts in professional sports.

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*Code and data are available at: https://github.com/AmieLiu/the-NBA-Rule-Change.git.

# 1 Introduction

In professional basketball, rule changes can reshape the game's landscape, altering strategies, player performances, and ultimately, the trajectory of teams' successes. The National Basketball Association (NBA), as the premier basketball league globally, often implements rule modifications to refine gameplay, increase scoring opportunities, and foster a more open and free-flowing style of basketball (Sorensen 2019). Under the new transitional foul rule in the 2022-23 NBA season, take fouls committed during transition scoring opportunities will result in one free throw and continued possession for the offended team (Reynolds 2022), encouraging defenders to make legitimate plays.

This paper analyzes the consequences of the 2022-23 NBA rule change, particularly its impact on player shooting performance and the dynamics of the Most Valuable Player (MVP) competition, comparing statistics with the previous season, 2021-22. Our estimand is to explore the relationship between player shooting performance and MVP points they won in these NBA seasons. We hypothesize that players who excel in transition offense may experience an increase in shooting efficiency as they capitalize on more fast-break opportunities without facing as many transition-take fouls, potentially leading to greater recognition in MVP voting due to the positive correlation between shooting efficiency and MVP consideration.

A clear gap exists in understanding the nuanced impacts of the new transitional foul rule on player performance and MVP considerations, especially when compared to the previous season. This paper seeks to fill this gap by thoroughly analyzing the statistical data from both the 2022-23 and 2021-22 NBA seasons to highlight the changes, continuities, and emerging trends over these times. To address this gap, we used the R programming language (R Core

Team 2023) to analyze shooting performance metrics, such as field goal percentage (FG%), three-point percentage (3P%), free throw percentage (FT%), as well as MVP voting points won from both seasons. Our findings reveal patterns in player shooting performance, MVP points accumulation, and the intertwined effects of the transitional foul rule… We discovered significant correlations between shooting efficiency and MVP points, with distinct variations observed between the two seasons.

Understanding the implications of the transitional foul rule in comparison to the previous season is crucial for stakeholders across the NBA landscape, from players and coaches to researchers and fans. By illuminating the intricate relationship between rule changes, player performance, and individual accolades, this paper contributes to a deeper understanding of the evolving dynamics within the league.

This paper is structured into three main sections: Data, Results, and Discussion. Section 2 Data explores sources and methodology. It includes various sources used for data collection, cleaning, and analyzing processes, drawing from the dataset. In Section 4 Results, we present our findings, focusing on data visualizations and analyses. Section 5 Discussion provides a comprehensive analysis of our research, highlights the implications for NBA basketball, the importance of limitations and considerations in our analysis, and identifies areas for future research. Section 6 Conclusion summarizes our main findings and the broader significance of our research.

# 2 Data

The data for this paper are obtained from Basketball Reference (Sports Reference LLC 2024c), which provides a wide range of basketball-related data that includes statistics, player and team information, game results, and more. The datasets used here are Sports Reference LLC (2024b) and Sports Reference LLC (2024a). These datasets include various statistics and information about NBA players who received votes for the MVP award, as well as their performance metrics for the 2022-23 and 2021-22 seasons. The data analysis involved using the R programming language (R Core Team 2023), along with the `tidyverse` (Wickham et al. 2019), `janitor` (Firke 2023), `knitr` (Xie 2014), `cowplot` (Wilke 2024), `broom` (Robinson, Hayes, and Couch 2023), and `rstanarm` (Brilleman et al. 2018) packages for data collection, cleaning, analysis, and statistical modeling. Within the `tidyverse` package (Wickham et al. 2019), I used `readr` (Wickham, Hester, and Bryan 2024), `dplyr` (Wickham et al. 2023), `tidyr` (Wickham, Vaughan, and Girlich 2023), and `ggplot2` (Wickham 2016) for reading CSV files, manipulating data, tidying data, and creating figures.

## 2.1 NBA 2021-22 and 2022-23 Seasons Top 10 MVP Data

Table 1 presents the performance metrics of NBA players who received votes for the Most Valuable Player (MVP) award in the 2022-23 season. It includes a total of 10 rows and five variables: ranking of the top 10 players (Rank), the total number of MVP points won by each player (MVP Points Won), FG% (Field Goal Percentage), TP% (Three-Point Percentage), and FT% (Free Throw Percentage).

Table 1: 2022-2023 season top 10 MVP table

| Rank | MVP Points Won | Field Goal Percentage | Three Points Percentage | Free Throw Percentage |
|---|---|---|---|---|
| 1 | 915 | 0.548 | 0.330 | 0.857 |
| 2 | 674 | 0.632 | 0.383 | 0.822 |
| 3 | 606 | 0.553 | 0.275 | 0.645 |
| 4 | 280 | 0.466 | 0.350 | 0.854 |
| 5 | 46 | 0.510 | 0.345 | 0.905 |
| 6 | 30 | 0.484 | 0.386 | 0.867 |
| 7 | 27 | 0.615 | 0.373 | 0.742 |
| 8 | 10 | 0.496 | 0.342 | 0.742 |
| 9 | 5 | 0.493 | 0.427 | 0.915 |
| 10 | 3 | 0.539 | 0.350 | 0.850 |

Field Goal Percentage indicates the efficiency of a player's shooting from the field, calculated as the ratio of successful field goals made to total field goal attempts. A higher field goal percentage suggests better shooting accuracy. Moreover, Three Points Percentage indicates the accuracy of a player's three-point shooting, measured as the percentage of successful three-point shots made out of total attempts. A higher three-point percentage reflects proficiency in long-range shooting. In addition, Free Throw Percentage represents the proficiency of a player in making free throws, calculated as the ratio of successful free throws made to total free throw attempts. A higher free throw percentage indicates better accuracy and consistency in free throw shooting.

Table 2 presents performance metrics of NBA players who received votes for the MVP award during the 2021-22 season. This dataset mirrors the structure of the previously mentioned dataset (see Table 1), providing insights into key performance indicators for players in the 2021-22 season.

Table 2: 2021-2022 season top 10 MVP table

| Rank | MVP Points Won | Field Goal Percentage | Three Points Percentage | Free Throw Percentage |
|---|---|---|---|---|
| 1 | 875 | 0.583 | 0.337 | 0.810 |
| 2 | 706 | 0.499 | 0.371 | 0.814 |
| 3 | 595 | 0.553 | 0.293 | 0.722 |
| 4 | 216 | 0.466 | 0.383 | 0.868 |

Table 2: 2021-2022 season top 10 MVP table

| Rank | MVP Points Won | Field Goal Percentage | Three Points Percentage | Free Throw Percentage |
|---|---|---|---|---|
| 5 | 146 | 0.457 | 0.353 | 0.744 |
| 6 | 43 | 0.453 | 0.353 | 0.853 |
| 7 | 10 | 0.493 | 0.344 | 0.761 |
| 8 | 4 | 0.437 | 0.380 | 0.923 |
| 9 | 2 | 0.493 | 0.317 | 0.837 |
| 10 | 1 | 0.504 | 0.352 | 0.877 |

## 2.2 Data Measurement

The measurement process quantifies real-world phenomena related to NBA player performance and translates them into dataset entries. We focused on performance metrics during the 2021-22 and 2022-23 seasons, including field goal percentage, three-point percentage, and free throw percentage. Data were collected from reputable sources like Sports Reference LLC (2024c). These raw data were then processed and cleaned to ensure accuracy and consistency. The selected variables were defined and operationalized. For example, field goal percentage was calculated as the ratio of successful field goals made to attempts. Similarly, three-point and free throw percentages were computed using standardized formulas. These measurements became dataset entries, with rows representing players and columns representing performance metrics.

## 2.3 Data Visualization

### 2.3.1 The distribution of MVP points won by top 10 players in the 2021-22 and 2022-23 seasons

Figure 1 illustrates the MVP points won by the top 10 NBA players in each of the 2022-23 and 2021-22 seasons. It clearly shows that the highest number of MVP points, which totaled 915, was given to the player who ranked 1st in the 2022-23 season. In contrast, the minimum point (1 point) was given to the player who ranked 10th in the 2021-22 season.

When examining the MVP points across the corresponding ranks in both seasons, players in seven out of the ten ranks during the 2022-23 season received more points than their counterparts in the same ranks during the 2021-22 season. The top ranks in the 2022-23 season (Rank 1, 3, 4) generally received more points than in the previous season. This might indicate a shift in voting behavior or a stronger consensus among voters regarding the leading candidates. Players at lower ranks (6-10) showed a relatively small variation in points, suggesting that while the top contenders might shift significantly in performance or perception, those at lower ranks maintain a more consistent level of recognition.

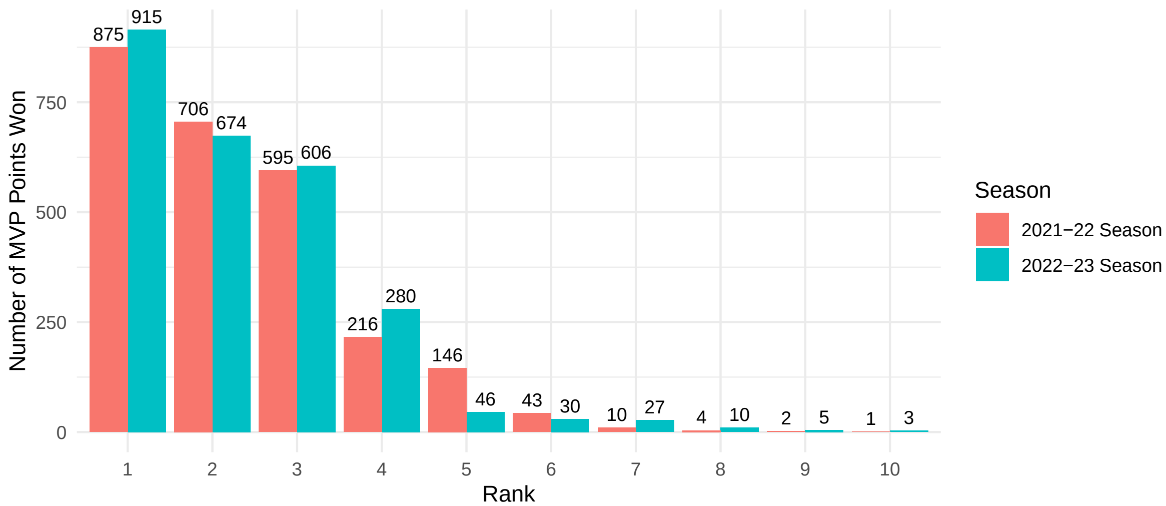


Figure 1: Number of MVP points won by each player from the top 10 rankings in the 2021-22 and 2022-23 seasons

### 2.3.2 Different shooting performances by top 10 players in the 2021-22 and 2022-23 seasons

Figure 2 provides a comparison of the shooting performances of the top 10 NBA players across 2022-23 and 2021-22 seasons, including Field Goal, Three-Point, and Free Throw percentages. Each metric is depicted with trend lines to illustrate the general trends across player ranks from 1 to 10.

The highest Field Goal Percentage observed was 0.632 in the 2022-23 season. In contrast, the lowest percentage was recorded at 0.437 in the 2021-22 season. The trend lines show that the 2022-23 season has higher percentages across the ranks compared to the previous season, despite a slight decline in percentage from the highest to the lowest ranked players in both seasons. This means there is an enhancement in field goal accuracy from the 2021-22 season to the 2022-23 season.

For the Three-Point Percentage, the highest was recorded at 0.427 in the 2022-23 season, while the lowest was also observed in the same season at 0.275. Interestingly, the trend line for 2022-23 shows a slight increase as player rank increases, unlike in 2021-22, where the trend line remains relatively flat across ranks. There is a marginal increase in three-point shooting percentages in the 2022-23 season

The scatter plot for Free Throw Percentage shows the highest performance at 0.923 in the 2021-22 season and the lowest at 0.645 in the 2022-23 season. Both seasons exhibit a slight upward trend in free throw efficiency from rank 1 to 10. The free throw percentage remains nearly constant in both seasons, with a minimal increase in the 2021-22 season.

# 3 Model

To explore the impact of the 2022-23 NBA transitional foul rule on player shooting performance and its subsequent effect on MVP voting, we constructed a linear regression model. The objective is to quantify the relationship between shooting performance metrics and MVP voting outcomes.

## 3.1 Model set-up

The dependent variable is MVP Voting Points and the independent variables are Field Goal Percentage (FG%), Three-Point Field Goal Percentage (3P%), and Free Throw Percentage (FT%). Each independent variable was chosen based on its potential influence on a player's performance under the conditions created by the new foul rule. We run the model in R (R Core Team 2023) utilizing the `rstanarm` package (Brilleman et al. 2018). Our model is constructed as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon$$

where:

- $Y$ is the MVP Voting Points. It is the dependent variable that represents the points a player receives in the MVP voting process.
- $X_1$ measures the FG% made out of attempts.
- $X_2$ measures the 3P% made out of attempts.
- $X_3$ measures the FT% made out of attempts.
- $\beta_0$ is the intercept of the regression model that represents the expected value of Total MVP Voting Points when all predictor variables (FG%, 3P%, FT%) are at zero.
- $\beta_1$ is the coefficient for FG%. It indicates how changes in a player's overall shooting efficiency from the field affect their MVP voting points.
- $\beta_2$ is the the coefficient for 3P%. This reflects the impact of three-point shooting efficiency on MVP voting.
- $\beta_3$ is the coefficient for FT%. This measures the influence of free throw shooting efficiency on MVP voting points.
- $\epsilon$ is the error term, representing the residual element not explained by the model. This captures the variability in MVP voting points not explained by shooting percentages alone.

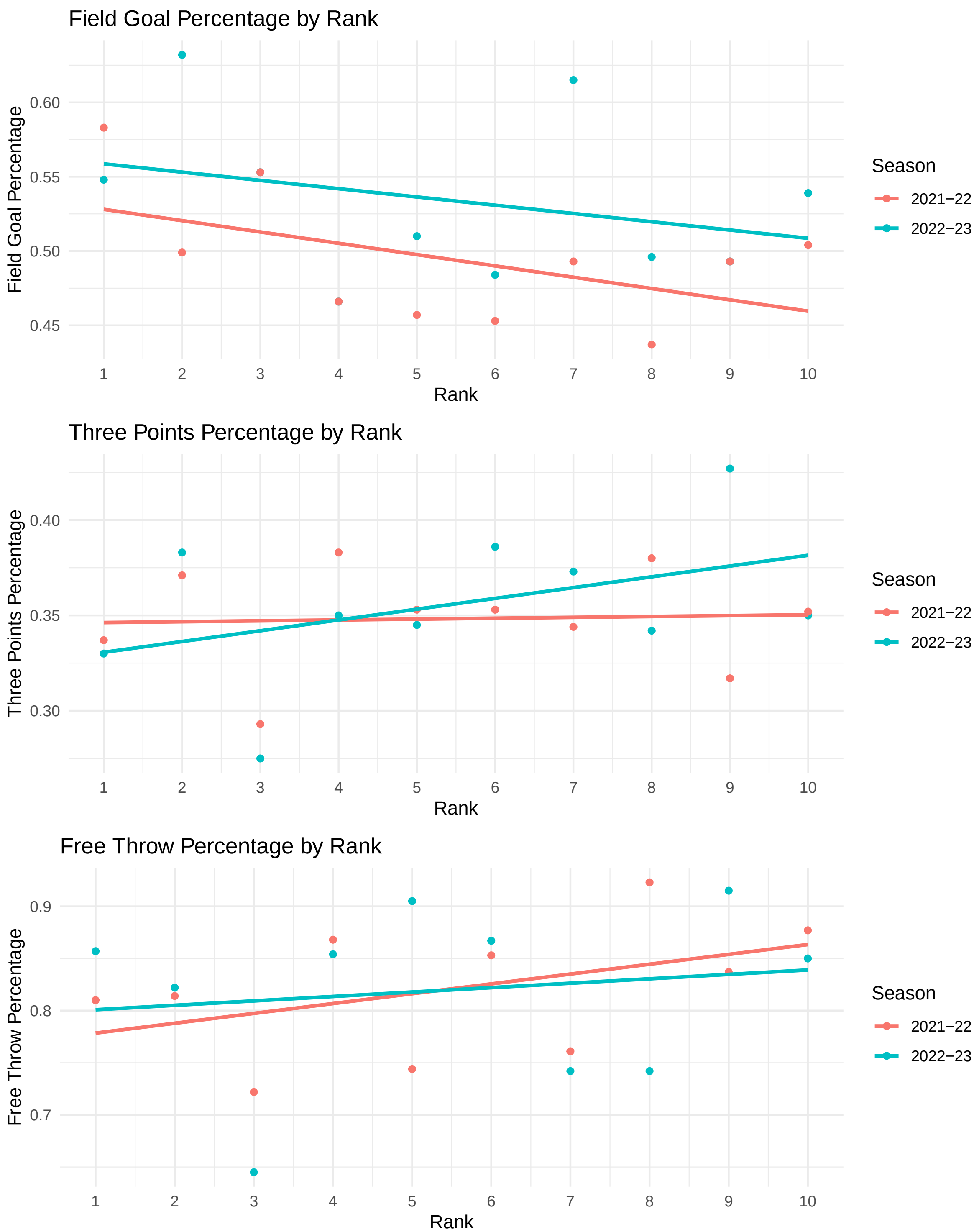


Figure 2: Different shooting percentage by each player from the top 10 rankings in the 2021-22 and 2022-23 seasons

### 3.1.1 Model justification

The selection of linear regression for our analysis suggests linear relationships between the shooting metrics and MVP voting points. We hypothesized that improvements in these shooting metrics, reflecting enhanced performance in transition plays free from take fouls, would correlate positively with higher MVP voting scores. The use of FG%, 3P%, and FT% as predictors is justified by their direct impact on game performance, which is critical in MVP considerations. Moreover, these metrics are commonly used in basketball analytics to assess player efficiency and effectiveness, making them relevant for evaluating the consequences of rule changes.

Statistical significance of the model coefficients will be tested using t-tests, where a p-value less than 0.05 will indicate significant influence of the predictor on MVP voting points. The overall fit of the model will be assessed by the R-squared value, which explains the proportion of variance in MVP points accounted for by the predictors.

# 4 Results

## 4.1 Summary of regression model results

Our results are summarized in Table 3 and Table 4. The estimate intercept is -920.99 with a high standard error of 1833.86 and high p-value of 0.63 (significantly greater than 0.05). The negative intercept might initially suggest a baseline negative effect, but considering high standard error and p-value, the intercept is not statistically significant. This means that the intercept does not provide reliable information about the baseline level of MVP points when shooting percentages are not accounted for.

Field Goal Percentage (FG%) has a positive coefficient, indicating that an increase in FG% will have an increase in MVP points. The estimate suggests that for each percentage point increase in FG%, MVP points increase by approximately 3432.88. However, the standard error of 2139, and the p-value of 0.160, which is above the significant level of 0.05, suggests that this relationship is not statistically significant at the conventional level. Thus, while FG% shows a positive impact on MVP points, this effect is not strong enough to be considered reliable within this model.

The coefficient for Three Points Percentage (3P%) is negative (-6037.23), suggesting that a higher 3P% correlates with fewer MVP points. It indicates a substantial decrease in MVP points for each percentage increase in 3P%. However, similar to FG%, the p-value of 0.140 indicates that this negative relationship is not statistically significant. The large standard error further points to high variability in the data, leading to uncertainty in the estimate.

For Free Throw Percentage (FT%), the regression model estimates a coefficient of 1828, which shows a positive relationship between FT% and MVP points. This suggests that higher FT%

could be associated with more MVP points. However, the p-value of 0.356 indicates that this effect is not statistically significant, which exceeds the commonly accepted 0.05 for declaring statistical significance. Moreover, the standard error (1828.51) is nearly equal to the estimate (1827.86), indicating low precision in the estimate. Consequently, there is considerable uncertainty around its effect on MVP points.

Table 3: Summary of regression model coefficients

| Term | Estimate | Std. Error | Statistic | p-value |
|---|---|---|---|---|
| (Intercept) | -920.99 | 1833.86 | -0.50 | 0.63 |
| Field Goal Percentage | 3432.88 | 2139.05 | 1.60 | 0.16 |
| Three Points Percentage | -6037.23 | 3553.44 | -1.70 | 0.14 |
| Free Throw Percentage | 1827.86 | 1828.51 | 1.00 | 0.36 |

Table 4 provides several important statistical metrics that help evaluate the overall fit and effectiveness of the regression model. The high Residual Standard Error of 314.30 suggests substantial unexplained variability, indicating the model's predictions can deviate significantly from actual values. While the Multiple R-squared value of 0.44 shows that the model explains about 44% of the variability in MVP points, the lower Adjusted R-squared of 0.17 indicates that the model's explanatory power significantly reduces when adjusted for the number of predictors, suggesting potential overfitting or irrelevance of some variables. Furthermore, the F-statistic of 1.60, which is relatively low, and p-value of 0.29 indicate that the model is not statistically significant, implying that the predictors do not reliably explain variations in MVP points.

Table 4: Summary of additional regression model metrics

| Metric | Value |
|---|---|
| Residual Standard Error | 314.30 |
| Multiple R-squared | 0.44 |
| Adjusted R-squared | 0.17 |
| F-statistic | 1.60 |
| p-value | 0.29 |

### 4.2 Observed versus predicted MVP points won

Figure 3 shows the observed MVP points (actual outcomes) against predicted MVP points (outcomes estimated by the model). The perfect predictions would result in all points falling exactly on the red dashed line, where the predicted values equal the observed values. However, as we can see, the data points are notably distant from this line, particularly at higher observed points. For instance, an observed value of 915 points in a predicted value of only 534.42. This significant deviation indicates that the model tends to underpredict MVP points for players with higher observed scores. In addition, for lower observed points, the model's performance is inconsistent. For instance, when the observed value is at 30, the predicted value is slightly negative (-5.09), which doesn't align with the possible range of MVP points. Conversely, an observed value of 3 has an inaccurate predicted value of 369.98. This means there is a potential issue of reliability and precision in the model's predictions for top-performing players.

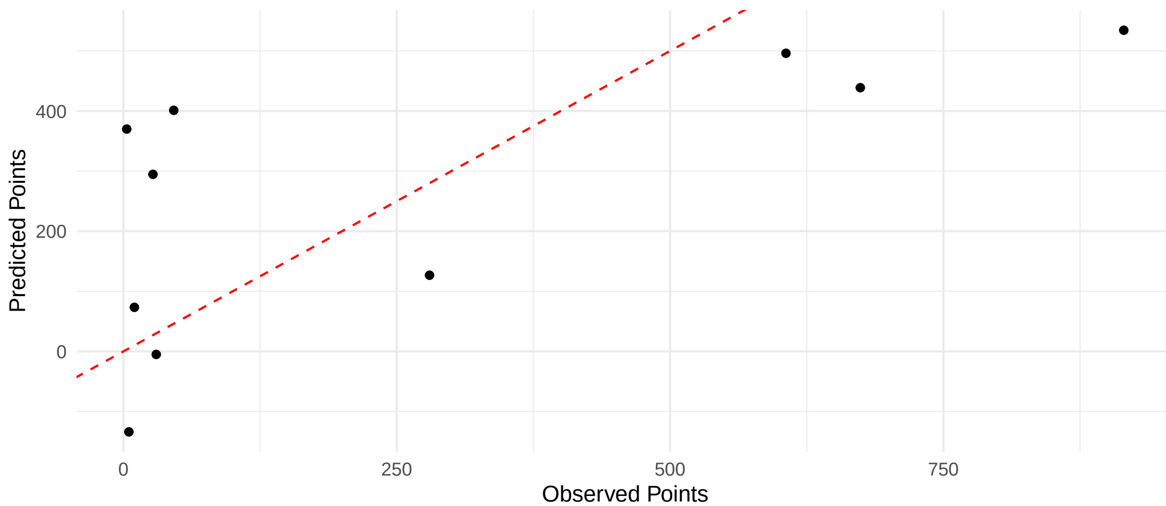


Figure 3: Observed vs. predicted values of MVP points won

# 5 Discussion

## 5.1 First discussion point

If my paper were 10 pages, then should be be at least 2.5 pages. The discussion is a chance to show off what you know and what you learnt from all this.

## 5.2 Second discussion point

## 5.3 Third discussion point

## 5.4 Weaknesses and next steps

Weaknesses and next steps should also be included.

## 6 Conclusion

## References


Brilleman, SL, MJ Crowther, M Moreno-Betancur, J Buros Novik, and R Wolfe. 2018. "Joint Longitudinal and Time-to-Event Models via Stan." https://github.com/stan-dev/stancon_talks/.

Firke, Sam. 2023. *Janitor: Simple Tools for Examining and Cleaning Dirty Data*. https://CRAN.R-project.org/package=janitor.

R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Reynolds, Tim. 2022. "Take-Foul Penalty, Score Changes Will Be Different in 2022-23 NBA Season." *NBA.com*. NBA.com. https://www.nba.com/news/take-foul-penalty-score-changes-will-be-different-in-2022-23-nba-season.

Robinson, David, Alex Hayes, and Simon Couch. 2023. *Broom: Convert Statistical Objects into Tidy Tibbles*. https://CRAN.R-project.org/package=broom.

Sorensen, Mike. 2019. "NBA Rules Have Adapted over the Years to Make the Game More Fun for Players, Fans." *Deseret News*. Deseret News. https://www.deseret.com/2019/2/21/20666425/nba-rules-have-adapted-over-the-years-to-make-the-game-more-fun-for-players-fans/.

Sports Reference LLC. 2024a. "2021-22 NBA Awards Voting." Basketball-Reference.com. https://www.basketball-reference.com/awards/awards_2022.html.

———. 2024b. "2022-23 NBA Awards Voting." Basketball-Reference.com. https://www.basketball-reference.com/awards/awards_2023.html.

———. 2024c. "Basketball Reference." Basketball-Reference.com. https://www.basketball-reference.com/.

Wickham, Hadley. 2016. *Ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. https://ggplot2.tidyverse.org.

Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D'Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. "Welcome to the tidyverse." *Journal of Open Source Software* 4 (43): 1686. https://doi.org/10.21105/joss.01686.

Wickham, Hadley, Romain François, Lionel Henry, Kirill Müller, and Davis Vaughan. 2023. *Dplyr: A Grammar of Data Manipulation*. https://CRAN.R-project.org/package=dplyr.

Wickham, Hadley, Jim Hester, and Jennifer Bryan. 2024. *Readr: Read Rectangular Text Data*. https://CRAN.R-project.org/package=readr.

Wickham, Hadley, Davis Vaughan, and Maximilian Girlich. 2023. *Tidyr: Tidy Messy Data*. https://CRAN.R-project.org/package=tidyr.

Wilke, Claus O. 2024. *Cowplot: Streamlined Plot Theme and Plot Annotations for 'Ggplot2'*. https://CRAN.R-project.org/package=cowplot.

Xie, Yihui. 2014. *Knitr: A Comprehensive Tool for Reproducible Research in R*. Edited by Victoria Stodden, Friedrich Leisch, and Roger D. Peng. Chapman; Hall/CRC. http://www.crcpress.com/product/isbn/9781466561595.