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 found no statistically significant correlations between shooting efficiency and MVP points. 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 no statistically significant relationships between shooting efficiency and MVP points in the 2022-23 NBA season.

This paper is structured into four main sections: Data, Model, Results, and Discussion. Section 2 Data explores sources, methodology, measurement, and data visualization. It includes various sources used for data collection, cleaning, and analyzing processes, drawing from the dataset. Section 3 Model describes the statistical model employed in our analysis. In Section 4 Results, we present our findings, focusing on comprehensive analyses obtained from the model. Section 5 Discussion provides a summary of our research, highlights the implications for NBA basketball, the importance of limitations and considerations in our analysis, and identifies areas for future 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), `readr` (Wickham, Hester, and Bryan 2024), `dplyr` (Wickham et al. 2023), `tidyr` (Wickham, Vaughan, and Girlich 2023), and `ggplot2` (Wickham 2016) are used 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
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

Table 2: 2021-2022 season top 10 MVP table

Rank	MVP Points Won	Field Goal Percentage	Three Points Percentage	Free Throw Percentage
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.

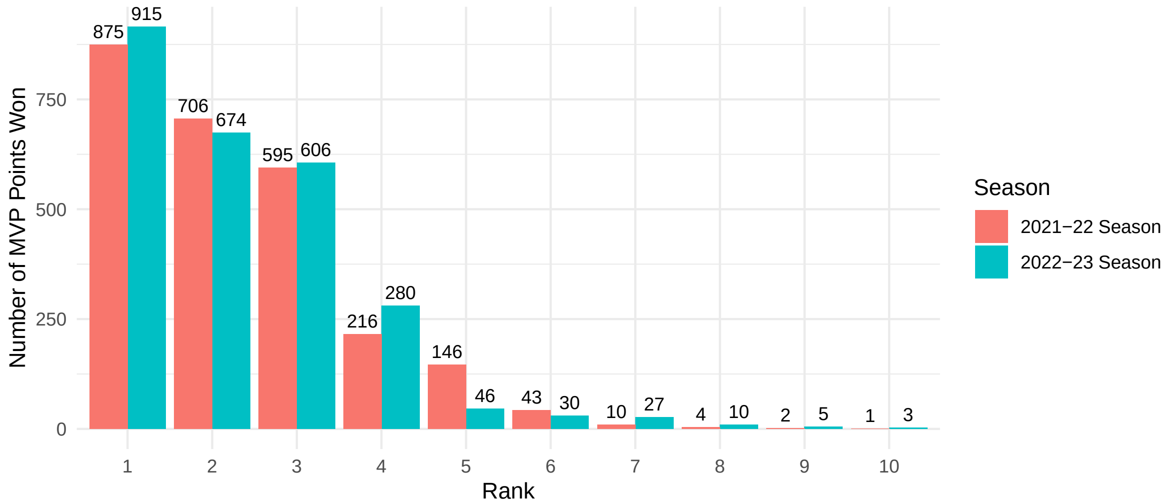

Figure 1: Number of MVP points won by each player from the top 10 rankings in the 2021-22 and 2022-23 seasons

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.

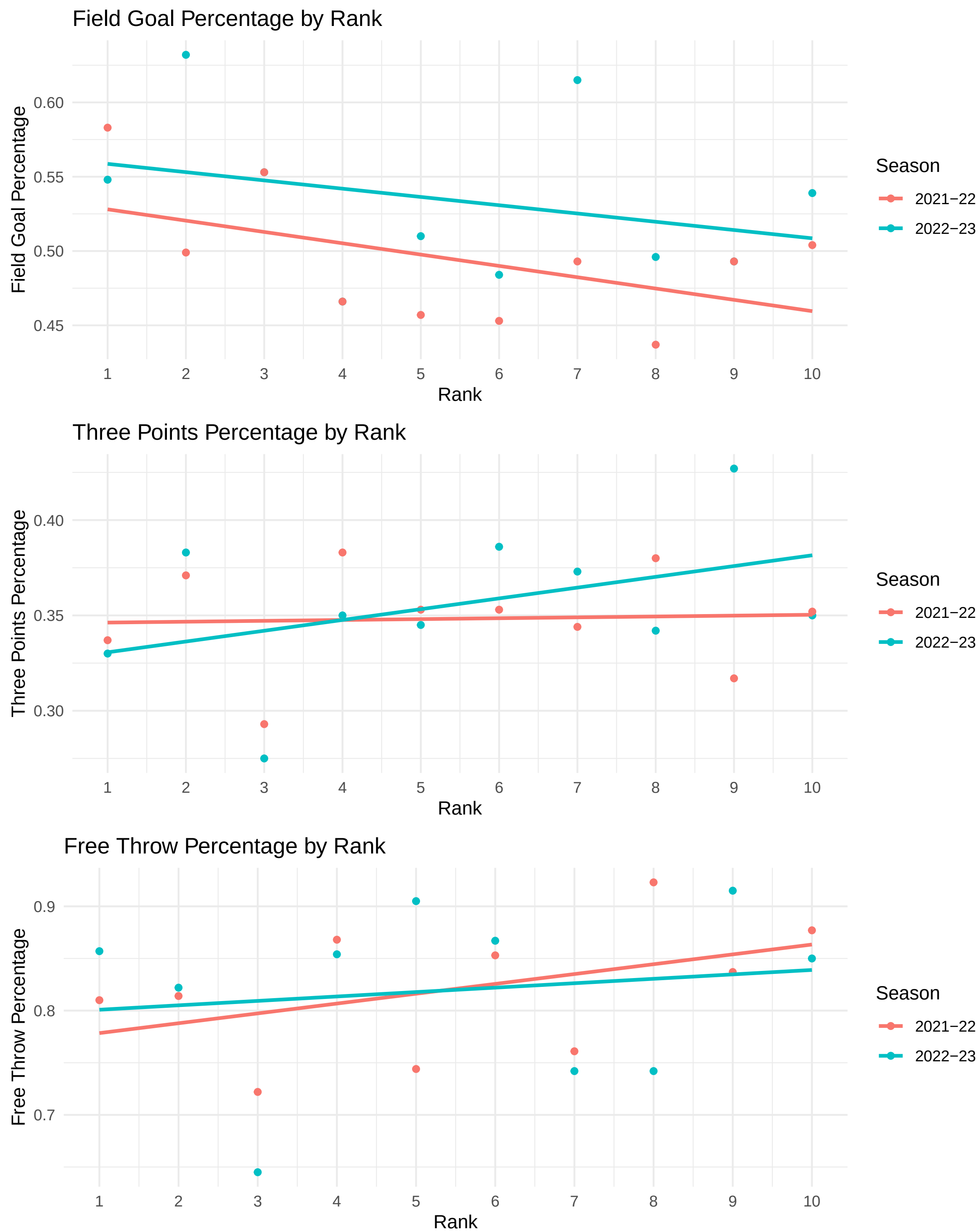

Figure 2: Different shooting percentage by each player from the top 10 rankings in the 2021-22 and 2022-23 seasons

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.
- β_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.
- β_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.
- β_2 is the the coefficient for 3P%. This reflects the impact of three-point shooting efficiency on MVP voting.
- β_3 is the coefficient for FT%. This measures the influence of free throw shooting efficiency on MVP voting points.
- ϵ 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.

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 indicates that the observed MVP points and the predicted MVP points are not well aligned. Specifically, the model's predictions deviate significantly from the actual outcomes.

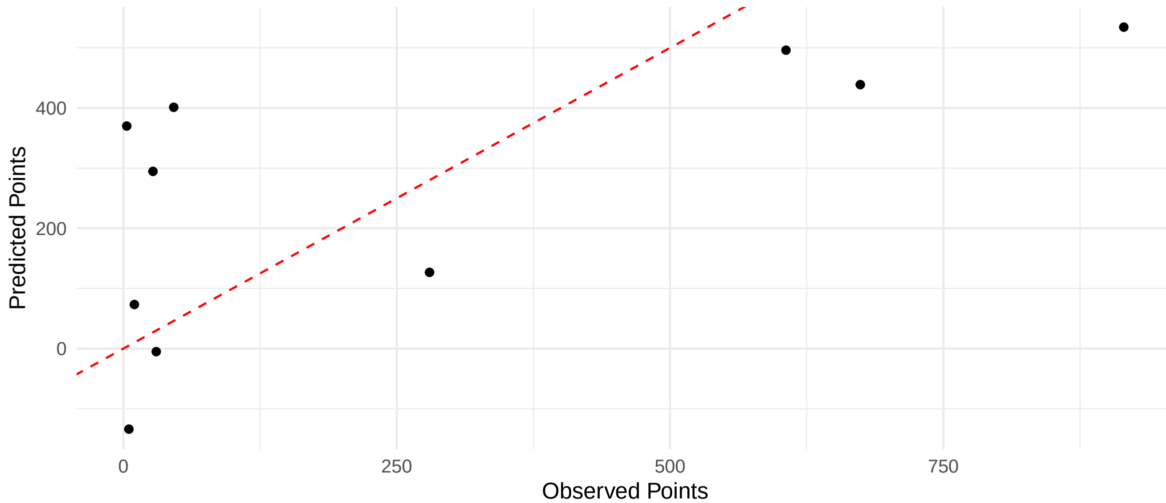

Figure 3: Observed vs. predicted values of MVP points won

5 Discussion

5.1 Summary of key findings

The primary objective of this paper is to analyze the consequences of the 2022-23 NBA transitional foul rule on player shooting performance and MVP points won. The methodology involves collecting and analyzing data from the NBA seasons of 2021-22 and 2022-23, sourced from Sports Reference LLC (2024c). We compare player shooting performance across these two seasons to visualize the data, illustrating trends between the seasons. The key variables analyzed include FG%, 3P%, FT%, and MVP points. There's a shift in MVP points distribution, with top-ranked players in the 2022-23 season generally receiving more points compared to the previous season, suggesting potential changes in voter perception or player performance (see Figure 1).

To further examine the relationship between shooting performance metrics and MVP voting outcomes, a linear regression model is constructed. This model uses MVP points as the dependent variable and shooting percentages (FG%, 3P%, FT%) as independent variables. The use of linear regression allows for quantifying the potential impact of shooting performance on MVP voting, considering the influence of the transitional foul rule. However, the results show that there are no significant findings about relationships between shooting percentages and MVP points (see Table 3 and Table 4).

5.2 The psychological impacts of the new NBA's transitional foul rule change on players

To understand the implications of the NBA's transitional foul rule change, it is essential to consider its psychological impacts on players, akin to the effects observed with strategic timeouts. As discussed by Goldschmied, Raphaeli, and Morgulev (2023), strategic timeouts are often employed to disrupt a player's performance during critical moments of a game. While they are intended to disrupt a player's rhythm and impair performance, they often fail to achieve their intended effect (Goldschmied, Raphaeli, and Morgulev 2023). Instead, players may adapt and focus more intensely. Similarly, with the new transitional foul rule in the NBA, players might initially experience disruptions in their game strategy but adapt quickly to optimize performance under the new conditions. This adaptability is evident in the lack of significant changes in the Three-Point Percentage (3P%) and Free Throw Percentage (FT%) among the top players (Figure 2).

Furthermore, the transitional foul rule could increase players' confidence during fast-break situations because they know that unnecessary contact could result in significant penalties for the opposing team. This may lead to a more fluid approach to offensive transitions, enhancing both individual and team scoring efficiency. It also allows players to play the game more freely and focus more on their performance rather than feeling defensive pressure. This trend is indicated by Figure 2, which shows an observable increase in the FG% of the top 10 players in the 2022-23 season compared to the previous season. The transitional foul rule in the NBA not only modifies the game's structural dynamics but also has profound psychological effects on players, influencing how players strategize and execute during games. As they adapt to these new changes, the overall impact on performance metrics and psychological resilience becomes a fascinating aspect of professional basketball dynamics.

5.3 Potential biases in the MVP voting process

The inherent biases could affect the MVP voting process when evaluating the implications of the NBA's transitional foul rule changes. Although shooting percentages statistical metrics provide quantitative measures of player performance, there is no significant relationship between a player's shooting performance and MVP points won, as shown by Figure 3. Therefore, this means that other factors influence the allocation of MVP points, which may involve subjective judgment.

The MVP voting process is conducted by a total of 100 sportswriters and broadcasters chosen by the NBA from the United States and Canada (Restrepo 2024). Although these panelists are responsible for assessing player performances over the season (Restrepo 2024), their subjective opinions and personal biases could affect their voting choices. Caudill, Mixon, and Wallace (2014) highlights similar biases in referee decisions, providing a parallel to potential biases in MVP voting. The research suggests that well-known NBA players often receive favorable calls, particularly during crucial moments in playoff games (Caudill, Mixon, and Wallace 2014). This observation about referee bias can be extended to the MVP voting process. As referees may show favoritism towards star players, MVP voters can also be influenced by a player's fame, media visibility, or the prevailing narrative about their season performance. This bias can result in equally deserving but less prominent players not receiving comparable recognition in the MVP voting process. The MVP voting process not only reflects statistical performance but is also shaped by the subjective interpretations and biases of the voting panel.

5.4 Weaknesses and next steps

Although our analysis aims to explore the relationships between the NBA rule change, shooting performance metrics, and MVP points, it is important to acknowledge potential weaknesses that arise. These weaknesses include the limited scope of variables considered, the size of the datasets, statistical significance, and the subjectivity in MVP voting. In our findings, we did not observe a statistically significant relationship between MVP points and a player's shooting performance. This suggests that factors beyond shooting efficiency, such as scores, defensive contributions, team success, and player injuries, also influence MVP considerations. The exclusion of these variables may limit the depth and comprehensiveness of the analysis. In addition, our analysis is based on data from the 2022-23 and 2021-22 NBA seasons, which may not provide a sufficiently large sample size to draw definitive conclusions. Therefore, expanding the time frame to include data from a longer period, such as 10 years, could enhance the robustness of our key findings. This can allow us to comprehensively understand the impact of rule changes on player performance and MVP points. Moreover, the MVP voting process is subjective and may be influenced by the personal biases of the voting panel. This subjectivity leads to uncertainty in the interpretation of MVP points outcomes.

To deepen our understanding of the factors influencing MVP points and the effects of rule changes in the NBA, future research is needed. Firstly, a broader range of player performance metrics beyond shooting percentages is necessary to grasp the player's overall impact on the game. Secondly, understanding the correlation between team success and individual player performance in MVP considerations is essential, as MVP voting considers a player's contribution to their team's success. Thirdly, extending the time frame of datasets to identify long-term trends in MVP voting and player performance is necessary to track the evolution of player recognition over time. Finally, exploring the composition and dynamics of the MVP voting panel, including individual biases, preferences, and voting patterns, will facilitate a deeper understanding of their influence on MVP outcomes. This investigation can encompass demographic factors, geographic biases, and media narratives that may impact voting decisions.

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/.

Caudill, Steven B., Franklin G. Mixon, and Scott Wallace. 2014. "Life on the Red Carpet: Star Players and Referee Bias in the National Basketball Association." *International Journal of the Economics of Business* 21 (2): 245–53. https://doi.org/10.1080/13571516.2014.903110.

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

Goldschmied, Nadav, Mike Raphaeli, and Elia Morgulev. 2023. "'Icing the Shooter' in Basketball: The Unintended Consequences of Time-Out Management When the Game Is on the Line." *Psychology of Sport and Exercise* 68 (May): 102440. https://doi.org/10.1016/j.psychsport.2023.102440.

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

Restrepo, Andy. 2024. "How Does MVP Voting Work in the NBA? Who Has a Vote?" *AS*. https://en.as.com/nba/how-does-mvp-voting-work-in-the-nba-who-has-a-vote-n/.

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.