Optimizing Shot Choice in the NBA in Late-Game Situations While Down 2

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Abstract

This project aims to quantify the decision-making process behind shooting a two or a three with the last possession of the game while down two in the NBA. Using ESPN play-by-play and box-score data extracted using the HoopR package in R, we develop two models, a Regularized Rasch Model which predicts the odds of making a two or three pointer for a given possession using offensive and defensive strengths, and a Bradley-Terry Model to predict overtime performance. Combining the two models, we then find the winning probabilities of shooting a two or shooting a three and determine the optimal action by taking the higher winning probability result. Applying this model on previous shots in the NBA, we find that teams should shoot the three pointer 20.8% more than they empirically did, and that teams that did follow the decision of our model won 30.77% of the time, compared to teams who did not, who only won 26.07% of the time. In these results, we find a potential inefficiency in decision-making in these situations where teams are not shooting three-pointers as much as they should.

1 Introduction

On November 27, 2022, in a game between the Brooklyn Nets and the Dallas Mavericks, when down 112 - 110, a Ben Simmons steal allowed for Kevin Durant to tie the game with a dunk with 8.8 seconds left, forcing overtime. While the play kept the Brooklyn Nets alive, the Mavericks slowly pulled away in overtime, beating the Nets 129 - 125 after overtime.

While the play undoubtedly benefited the Nets and allowed them to continue the game, the decision to go for a two pointer raises an interesting question about decision-making when down two on the last possession of the game. Teams can either play more conservatively by going for a much more efficient two-pointer in an attempt to force overtime and continue the game, or attempt a less efficient three-pointer and try to win the game outright, without having to go to overtime.

With these shots having the potential to change the outcome of the game, it is important for teams to choose the decision that maximizes the winning probability. In looking at this choice, this work aims to develop a statistical framework to determine whether teams should shoot a three or two when down two on that team's last possession of the game.

1.1 Previous Work

This work aims to fill a gap in current knowledge as there is not much previous public literature dealing specifically with this type of question. While Christmann et. al[1] analyzes late-game situations in NBA games, their work takes a more general look, evaluating a multitude of plays in late-game situations instead of the decision to go for two or three while specifically while down two.

However, similar work has been done in the NFL, looking specifically at the decision to go for a two-point conversion while down eight points. This choice is similar to the go for two or go for three problem this work tackles, as there is a choice between playing more conservatively and kicking the extra point, making it a seven point game and allowing the team to tie the game with another touchdown and extra point or going for a two-point conversion, creating a six point game, potentially allowing the team to win the game with another touchdown, or tie the game if the first two-point conversion is missed with another two-point conversion attempt. While there is not very much published literature on this problem, there is a heavy informal debate on whether a team should go for a two-point conversion, without a definitive answer[2][3].

2 Data

This work uses play-by-play data as well as box-score data from ESPN through the HoopR R Package. Through this package, we found every single non-free throw shooting attempt starting from the 2009 - 2010 season until the 2023 - 2024 season as of April 15, 2024. We chose the 2009 − 2010 season as our cutoff as the ESPN play-by-play data becomes more unreliable before that seasons. Using the box-score data, we also found the winner and loser of the game for each shot. In addition, we removed all shots that were over 30 feet from the basket to exclude high hoping, long-distance shots which are more desperation heaves than drawn up shots.

2.1 Data Wrangling

For our shots of interest, we look to find shots which are part of a drawn-up play and a deliberate action to either choose a three or two, and because of the potential for offensive rebounding, we cannot simply take the last shot that a team down two would take as with an offensive rebound on a three point attempt, which would have been the deliberate play, could miss, resulting in a rebound and a two-point attempt that is not part of the original, drawn-up play.

For this reason, we first define a possession as a sequence of events in our play-by-play data with one team continually holding on to the ball. We then find all last possessions of regulation of a team who is at that time down two points. Using this last possession, we define the first shot attempt of that possession as the shot of interest to ensure that we get as close as possible to the drawn-up shot attempt. Following all data wrangling, we get a dataset of 1080 shots, where a team was down two with their last possession of regulation.

3 Exploratory Data Analysis

Our initial data analysis begins with a visualization of the shots attempted. We want to understand the distribution of shots both inside and beyond the arc. To increase readability, we only choose to show the most recent 4 seasons as our dataset (only for the graph itself, not for further analysis):

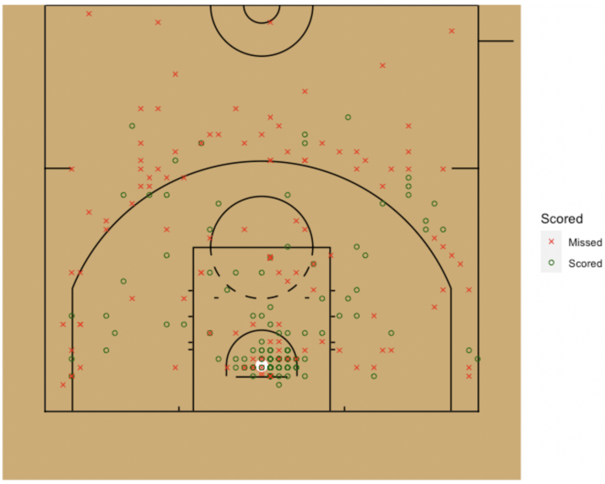

Figure 1: All shots attempted when down 2 in the last possession of the game from the 2020 - 2021 season to the 2023 - 2024 season

Over the course of the 15-year period our analysis looks at, 3-point shots on the last possession had a 17.0% field goal percentage, and 2-point shots on the last possession yielded a 16.9% field goal percentage. Of course, this is before any further data cleaning was done, such as removing 3-point shots further than

28-feet away, which we overall define as "chucks" and eliminate from the dataset due to the unlikely nature that these shots are plays drawn-up by a team and due to the likelihood that such shots in desperation if a play fails. Our analysis aims to determine team strategy for drawing up plays that leads to 2- and 3-point opportunities, which explains why we eliminate these long-range attempts.

Additionally, our dataset does not include an indicator for whether a shot is a 2- or a 3-point attempt. However, as the dataset included the x- and y-coordinates for each shot relative to center court, we manually calculated each attempt based on the calculated equation for 3-point arc. The x-coordinates are the coordinates in feet from one basket to the other, whereas the y-coordinates are the coordinates in feet from side to side. Starting from the basket itself, any shot that is 23.75 feet away or further from the basket must always be a three pointer. Due to the way an NBA 3-point arc is created, any shot that is 22 feet or further away from the basket in the y-direction is also considered a 3-pointer, as the line is closer to the basket near the baseline. These are the parameters we use to estimate whether a shot is a 2- or 3-point attempt.

By viewing a select few of these shots via the NBA website, we confirm that for the vast majority of shots, our equation yields the proper denotation for deciding 2-point versus 3-point attempts.

4 Methodology

4.1 Modeling Overtime Performance

To model overtime performance, we use Bradley-Terry models based on the data for each team within each season from the 2009 - 2010 season to the 2023 - 2024 season. Our initial assumption in modeling overtime performance came from the fact that there was no significant difference between the probability that a team that tied the game would win in overtime and the probability of the team that gave up a game-tying shot would win in overtime. Below are the exact results of this analysis:

$$\begin{aligned} P(Win\ \ if\ \ Tying\ \ Game) &= 0.502 \\ P(Win\ \ if\ \ on\ \ Receiving\ \ End\ \ of\ \ Game\ \ Tying\ \ Shot) &= 0.497 \end{aligned}$$

The Bradley-Terry models we create come from utilizing the win-loss logistic version of that model. In essence, the Bradley-Terry model comes in two versions: one that models outcomes based on point differential, and one that models based on only the binary outcome of the game. We utilize the second version, as our main interest in this analysis is finding the predicted outcome of the overtime period in a binary sense. After regressing the coefficients for each team based on each game's outcome, we found βs for each team. Specifically, β_0 is the overall home-court advantage, β_h is the home team's coefficient, and β_a is the away team's coefficient. We then find η for use in our model in the following manner for each game i:

$$\eta_i = \beta_0 + \beta_{h_i} - \beta_{a_i}$$

Utilizing these calculated ηs, we find the probability of the home team winning each game i in the following manner:

$$z_i = \frac{e^{\eta_i}}{1 + e^{\eta_i}}$$

We calculate Bradley-Terry models for each season based on the final standings after all games have been played, and end up with 15 unique Bradley-Terry models with all of these coefficients. These Bradley-Terry models are used to estimate the probability of each team winning in over time, as we assume playing an overtime period is analogous to starting a game from scratch and playing a new 5 minute-long game.

4.2 Shot Probability Model

To model shot probability, we use a Regularized Rasch Model which uses a linear regression with cross-validation to account for smaller sample sizes. Through this regression, we use two independent variables, the offensive adversary, which is the player who shoots the ball, and the defensive adversary, which is the team that is defending the shot, and we use a binary indicator of whether the shot went in or not as our response variable. We then use one-hot encoding, giving us a matrix where each row is a shot and each column is a shooter or defensive team, where there is a 1 if either the shooter or defensive team was involved in the shot and a 0 if not, to format the data for model training.

Through this regression, we can quantify both the shooting ability of each player and defensive abilities of each team using the coefficients as a result of the regression, and we can then model the probability of a shot scoring as, where each β is the corresponding coefficient and β_0 is the intercept,

$$P(Shot) = \beta_{Shooter} + \beta_{Defense} + \beta_0$$

We simply sum the coefficients instead of using a logistic function like we do in applying the Bradley-Terry Model in Section 4.2 as our response variable is already constrained within 0 or 1, so our probabilities are accurately modeled by the sum, as opposed to our Bradley-Terry Model, where the sum of the coefficients best describes the predicted score differential, where a logistic function is needed to fit that differential into a probability from 0 to 1.

To train our model, we use a collection of every single non-free throw shot taken in the NBA from the 2009 - 2010 season to the 2023 - 2024 season as described Section 2.1. We use all shots, instead of considering certain types of shots in clutch situations, as we assume, based on the works of Solomov et. al[4], that clutch is a product of noise and that players do not suddenly increase or decrease their shot-making ability in last-minute, game-changing situations, like the shots that we are attempting to model.

Through this assumption, we are able to gain a much large sample size using all shots, gaining a sample size of $n = 3455695$ as opposed to shots in clutch situations, where if we use the NBA's definition of clutch shots, which are shots in the final five minutes of the fourth quarter or overtime where the score is within five points[5], we get a sample size of $n = 156433$.

In addition, if we were to use clutch shots only, we would get strengths for much less players, as players who have shot in the NBA might have not shot in clutch time, making applying our model less flexible to potential future usage. We also have a higher risk of overfitting, as a player might have 200 shots but only 4 clutch shots, one of which is a shot that we are trying to predict, giving us a situation where we are training on 4 shots total, where 25% of our data is the shot that we a trying to model, as opposed to training on 200 shots total, where only 0.5% of our data is the shot that we are trying to model.

Since shooting and defensive ability obviously varies between seasons and in two point and three point shooting attempts, we develop two models for each season, one modeling two point shooting and defensive strengths, and the other one modeling three point shooting and defensive strengths, giving us a total of 32 different Rasch Models which are applied to our shots of interest.

5 Results

Putting our two models, we can determine the odds of winning for both attempting a two or a three as

$$P(Win \mid Three\ Point\ Attempt) = P(Three\ Pointer\ Scoring)$$
$$P(Win \mid Two\ Point\ Attempt) = P(Two\ Pointer\ Scoring)P(OT\ Win)$$

Putting these probabilities together, a team should attempt a three pointer if $P(Win \mid Three\ Point\ Attempt) > P(Win \mid Two\ Point\ Attempt)$ and a team should attempt a two pointer if $P(Win \mid Three\ Point\ Attempt) \leq P(Win \mid Two\ Point\ Attempt)$[1].

In calculating the odds of winning when one takes a two point attempt, we assume that the odds of winning in overtime is adequately independent of the fact that a team shot a game-tying two to send the game into overtime. In essence, we suppose that there is momentum from the fact that a team scored that game-tying two that would not effect performance in overtime, allowing us to essentially treat overtime as a completely new game. This assumption is supported by the fact that, in our dataset, $P(Win\ OT \mid Two\ Pointer)$ and $P(Lose\ OT \mid Two\ Pointer)$ are almost equal as explained in Section 4.1.

[1]We include the equality in this formula to include the very low-likelihood of both percentages being the equal, opting for the more conservative choice. However, in this unlikely event, we feel that the decision to go for a two or three would then become a stylistic choice.

Applying these probabilities to our original dataset of shots while down 2, we found that teams should have shot the three pointer 59.8% of the time, as opposed to the original 39% found in Section 3. In analyzing decision-making we also found that teams that followed the decision made by our model had a winning percentage of 30.77%($n = 520$) as opposed to teams that did not follow the decision made by our model won only 26.07%($n = 560$) of the time.

6 Discussion

Through this framework, we are able to potentially highlight an inefficiency in shot decisions while down 2 in the NBA. As seen in Section 5, we found that teams should have shot the three-pointer 20.8% more than they did previously, and that teams that did follow the decision of our model won 4.07% more than teams that did not follow the decision of our model, meaning that teams should shoot three pointers more frequently than they do previously.

This finding is obviously not a blanket statement, as since our Rasch Model relies on shooting and defensive abilities, decision-making still relies heavily on the shooting abilities of the team, as the decision to shoot a two or three still depends on the a team's two and three point shooting abilities as well as the defensive ability of the other team. However, it still remains notable that teams are not shooting the three-pointer when down two as much as, in the model's eyes, much as they should.

This result is somewhat surprising, especially with the relatively low three-point percentage of these shots of interest as found in Section 3, but we account some of this difference to be a result of the removal of hopeful long distance shots with very little time left, which would obviously have a much lower field goal percentage than a traditional percentage shot, but there is a significant probability that this difference is a result of other variables that our model fails to account for, like time left, where it is obviously more difficult to shoot a three pointer with 2 seconds left as compared to 20 seconds left.

6.1 Limitations and Future Work

Because of the relative simplicity of both our Bradley-Terry and Rasch Models, our model fails to account for, as stated above, variables like the amount of time left when the play begins and whether the play began on an in-bound or a rebound. These variables undoubtedly affect decision-making and shot-making probabilities but since our Rasch Model only considers strength of shooting and defense, these variables are not considered.

Furthermore, in analyzing defensive strengths, since we did not have rosters in our data, our model only considers the total strength of the defensive team and not each individual player's defensive strength. These strengths come from a team's defensive performance over the entire season and might be different in a last possession situation. For example, for the Minnesota Timberwolves, their calculated strength would be over a myriad of rosters, including and not including their star defender, Rudy Gobert. However, in an endgame situation, Gobert would most likely be on the floor, meaning that our defensive strengths would be an underestimate of the Timberwolves players' defensive strength that are on the floor at that time.

It is also important to note that treating overtime as a completely new game and clutch as a result of noise might not be perfect assumptions, as variables such as fatigue and altitude might have an effect on overtime performance, and it might not be completely fair to assume overtime as a new game. For the assumption for clutch, it is still a highly debated topic about the existence of clutch, meaning that it might not be completely accurate to train our Rasch Model on all shots, as opposed to only on clutch shots.

Another avenue for future exploration would be utilizing a Markov chain-based approach with respect to the number of seconds left in the game at the beginning of the possession, as our model does not discriminate between a shot taken with 12 seconds left during an inbound play versus one taken with 1.5 seconds left. A team with 1.5 seconds left might want to draw up a 2-point shot more often because it is easier to get the ball inbounded inside the 3-point arc with so few seconds left due to the defense's risk-averse approach of potentially allowing a 2-point shot with no risk of automatically losing the game without an overtime period. However, a team with 12 seconds left may be able to draw up a more complex play that yields to a three point attempt simply due to time. Using a markov chain, we could distinguish these differences based on clumping shots into clusters based on the amount of time left in the game at the beginning of the possession.

Additionally, since we do not know who will be taking a hypothetical three-pointer instead of the actual two-pointer or vice-versa, we assume that the person shooting the two-pointer will also shoot the hypothetical three-pointer, but this assumption does not necessarily hold when dealing with strong two-point shooters who play mostly in the paint, like centers, who might not be very great three point shooters.

To mitigate these limitations, it might be worth looking at another models which can better predict shot probability and win probability while including these external variables. For shot probability, a model similar to an expected goals model in soccer, which could consider shot distance, defensive coverage, and time left would most likely yield more accurate results than our Rasch Model, while for our overtime model, it might be worth adapting a win-probability model while including variables like player load.

A final potential area to develop this model as a tool for teams to use to determine whether to shoot a two or three when drawing up a play. Instead of analyzing past shots, one could develop a shot probability model and overtime model using data up to the game of interest, running the model and finding win probabilities with various potential shooters on two-pointers and three-pointers when drawing up a play to maximize the odds of winning when down 2.

7 Conclusion

While utilizing a team-based model for predicting both overtime outcomes and 2- and 3-point shot efficiencies has drawbacks in not analyzing the specific lineups on the court, teams overall use similar clutch lineups across games due to wanting their 5 best players to be in the game in such situations. To illustrate the use for such a model, we give an example below:

With how competitive the 7-10 spots in the Western Conference were in 2023-24 season, using a strategy that overall improves team performance by 4.07% could be the difference between a team being in 7-8 play-in game versus the 9-10 play-in game, even if such a difference results in a single win increase for that team. Considering that the Eastern Conference champion from the 2022-23 season was the Miami Heat, who lost their first play-in game before winning their second chance and gaining an 8th seed playoff berth, such a small change in strategy could have a ballooning effect on a team's season outcome and could be the difference between a coach being fired and retaining his position in the off-season.

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