What do NBA fans look for in their favorite small forwards?

Abstract

The purpose of our project is to analyze data concerning small forwards in the NBA to determine what fans value most when deciding what players they believe are the best. We concluded that fans weigh positive statistics more than they weight negative statistics such as losses. Currently, the metric that is known for predicting public opinion is known as the Player Efficiency Rating (PER). We wanted to use our analysis to create our own metric for predicting whether or not a player would be rated into the top ten and compare our metrics predictive results to the PER's. Our metric outperformed the PER when comparing how many players each metric predicted would be in the top ten in a number of different small forward rankings, not only just the <u>ranker.com</u> from which we based our metric.

Introduction

In preparation for conducting our data analysis, we gathered information from ranker.com which provided us with a ranked list of the top 50 small forwards in the NBA generated by a public opinion poll. We used this ranked list as a baseline for our data analysis. We then referred to data from nba.com regarding twelve different statistics on these fifty players. Our goal was to compare the data from the NBA to the public opinion poll to get a better understanding as to what specific statistics fans value most when deciding who they believe is the best player.

Methods

For our data analysis, we utilized small forward data from the NBA from the 2013/2014 season until the 2018/2019 season. We decided on the year range by going as far back as we could while still having data on at least 40% of the players. We collected NBA data for the top 50 small forwards according to ranker.com. In order to prepare the data for analysis, we created separate tables for each statistic where each column was a season, the indices were the players, and the data was the player's statistic for the season in question. Next, we averaged each of the players' statistics across all the seasons. We then separated each table into two

categories: top 10 players and non-top 10 players based on the ranker.com public opinion poll. After separating the data, we ran 12 2-sample t-tests (one for each statistic) where our null hypothesis was that there would be no difference between the means of the top 10 and the means of the non-top 10 small forwards, and our alternative hypothesis was that there is a significant difference between the means of the top-10 and the means of the non-top 10. After running the t-tests, we used the pvalues to make our own formula to determine who are the best small forwards. We named our formula "Player Rank Metric (PRM)." Our formula includes only the statistics found to be significant by their p-values. We then obtained z-scores of all 12 statistics' means for each player (normalized the data) and used the z-scores for our PRM formula. In our metric, each statistic is weighted according to the power of its p-value and either added or subtracted based on whether its a positive or a negative statistic. After trying many different weights based on p-value, we found this method to be the cleanest and most predictive. After calculating the scores for each player using our PRM formula to determine our own "top 10" list, we compared our top 10 list to the player efficiency ranking (PER) to determine how many of our top 10 predictions were actually in the top 10 versus theirs. Our final step was to determine whether our statistic had been overfit to ranker.com data or whether it had predictive potential for other rankings as well. In order to determine this, we compared how many we predicted correctly versus how many the PER predicted correctly with respect to other ranking websites (hoopshype, sportskeeda, and nba).

Player Rank Metric (PRM):

(Assists * 3) + (Points * 6) + (Rebounds * 4) + (Steals * 3) + (Blocks * 2) + (Field Goal % * 2) - (Turnovers * 4) + (Wins * 3) + (Minutes Played * 8)

Results

T-test results

The t-tests revealed that assists, points, rebounds, steals, blocks, field goal percentage, turnovers, wins, and minutes played are all significant factors in deciding whether or not a player is high-ranked. The measures we found that are not significant are three-pointers made, personal fouls, and losses.

| | P-Values | | | |
|------------------|----------|--|--|--|
| Field Goals Made | 3.66E-01 | | | |
| Assists | 1.69E-03 | | | |
| Points | 7.08E-06 | | | |
| Rebounds | 8.09E-05 | | | |
| Steals | 4.31E-03 | | | |
| Blocks | 1.67E-02 | | | |
| Field Goal % | 1.58E-02 | | | |
| Personal Fouls | 2.76E-01 | | | |
| Turnovers | 1.15E-04 | | | |
| Wins | 1.05E-02 | | | |
| Losses | 2.23E-01 | | | |
| Minutes Played | 2.71E-08 | | | |

PRM vs. PER Results



| Player by PRM Rank | PRM Score | Ranker.com Rank | Player by PER Rank | PER Score | Ranker.com Rank |
|--------------------------|-----------|-----------------|--------------------|-----------|-----------------|
| 1. LeBron James | 46.145097 | 1 | 1. Luka Doncic | 32.66 | - |
| 2. Kevin Durant | 43.576912 | 3 | 2. LeBron James | 27.67 | 1 |
| 3. Ben Simmons | 36.886762 | 8 | 3. Kawhi Leonard | 25.65 | 2 |
| 4. Giannis Antetokounmpo | 36.704295 | 4 | 4. Jimmy Butler | 23.8 | 6 |
| 5. Jimmy Butler | 33.048807 | 6 | 5. Paul George | 22.43 | 5 |
| 6. Kawhi Leonard | 31.317335 | 2 | 6. Gordon Hayward | 22.26 | 10 |
| 7. Paul George | 20.273832 | 5 | 7. Brandon Clarke | 22.15 | - |
| 8. Jayson Tatum | 18.836382 | 7 | 8. Brandon Ingram | 22.11 | 9 |
| 9. Tobias Harris | 18.150992 | - | 9. Andrew Wiggins | 19.86 | - |
| 10. Khris Middleton | 11.190536 | - | 10. Moritz Wagner | 19.71 | - |

Discussion and Conclusions

Our metric is designed to line up, generally, with how players are perceived by the general population. Our t-tests suggest that people do not care very much about the number of three-pointers a small-forwards make, the number of personal fouls small-forwards make, and the number of losses a small-forward has. In considering what it means to be a high-ranked basketball player, the most interesting one of these is losses. One might assume that watching a player lose might affect the ranking of their individual performance in comparison to other players, but it does not appear to be a significant factor. However, watching a player win is a significant factor in determining whether a player is good or not. Because of the significance of wins in the determination of a high ranking player, our data suggests players on good teams, players that win more, get ranked as better, even if they, individually, are no different from another player.

According to our formula, the most important factors in the determination of a high-ranking player are minutes played, points scored, rebounds, turnovers, assists, steals, wins, blocks, and field goal percentage in order. By using these factors we were able to perform better against the existing metric, Player Efficiency Rating (PER), closely aligned with public perception of players. The formula for PER uses many advanced statistics to calculate how much a player contributes to their team minus how much they take away from the team. By performing better on every list tested, we revealed that even in the age of sports analytics, people are likely still judging players on basic stats. One of the factors in PER is the number of missed field goals and missed free throws, however these don't appear in our formula. This along with losses and personal fouls suggests when people rank players they do not care about the bad things they do, only the positives. This is something that would be interesting to pursue further through a different kind of statistical test.

Another line of inquiry would be to extend our metric to other positions and see if it works just as well or if it would need to be adjusted by position. If they are not the same, could we create a new metric using the same methodology? Perhaps because the way we created our metric was by weighing the most significant factors the heaviest. An area of improvement would be to include all small forwards in the nba. The small forwards we analyzed were all on one list, which determined who was analyzed.

Ultimately our analysis suggests a lot about how people perceive players when ranking them, even when ranked by experts. The most significant conclusion is that people may not care about the pitfalls of a particular player or how many mistakes they make, only how many positive statistics they add to their stat sheet.

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