Points Above Replacement

A New NBA Metric to Evaluate Player Performance

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Abstract

In attempting to predict the score of an NBA game, players who are injured, suspended, or for any other reason not playing have a significant impact on said prediction. Baseball uses a statistic called Wins Above Replacement, or WAR, to tell how many wins a team would gain or lose if they replaced a certain player with one who is league average. The goal of this paper is to create a similar statistic, called Points Above Replacement, or PAR, that uses statistics from throughout the season to predict how many points a team gains or loses by missing a certain player, and thus having to replace him with one who is "league average". The statistic is standardized and adjusted by both position and value to a player's given team. The model roughly follows the calculation of WAR in baseball, assigning values to points created on offense and defense, as well as a positional and team adjustment. A comparison with the created metric along with other well-known advanced player metrics is done via a multiple regression.

Keywords

Analytics; Basketball; Player Value; Sports Data; Statistics;

1 Introduction

There exists many prediction models for NBA basketball, many with the purpose of anticipating the final score of a given game. However, the majority of these models use team average statistics to base their decisions. However, teams rosters can change every night, and do often. When star players are ruled out, players of lower quality take their minutes, and are expected to perform at a lower level. When lower level players do not play in a given game, star players are expected to play more minutes, which most likely will cause a slight uptick in performance. This reasoning is the cause for the creation of the new metric, PAR. PAR is based on the WAR statistic in baseball, which seeks to show player value based on average level. Many changes are constantly made to the statistic, however, and it is very subjective. Baumer et al. (2015) talks about how openWAR was concerned with issues of how WAR was previously calculated, such as accounting for uncertainty and reproductivity. Similarly, the measure of PAR seeks to add on to existing metrics by accounting for importance to a team, importance by position, and adjusting for amount of playing time. Points Above Replacement is a measure of how many points a team will gain or lose if a certain player does not play. The metric is created based on the last completed season, the 2020-2021 season, which was cut to 72 games, as opposed to 82, due to the COVID-19 pandemic.

This idea of Points Above Replacement is prefaced by many different statistical analyses that have been done over the years. Dehesa et al. (2019) discusses the different factors that influence player performance, and identifies different players' profiles in order to better analyze their contributions to their team. Similarly, PAR is mainly concerned with a player's value to the team they are currently on, rather than a function of the entire NBA, so that individual games can be predicted more accurately, and also so that individual teams can analyze the value of their roster, which is similar to the goal of the cited paper, and a part of where the influence was drawn.

Fearnhead and Taylor (2011) also tries to find a way to estimate NBA player ability. The analysis is based on splitting player value into offensive and defensive categories, then combining the two to get a total value. WAR is calculated very similarly, in that it assigns a value to all aspects of baseball, and then combines them (Fujita, 2022). PAR also assumes this method to create the metric, which will be discussed later. Another aspect of this analysis that PAR takes on is centering the data, so that the league average is 0, and all other data can be based around that. A key difference is that while this paper does break up the analysis by position, it only recognizes 3 different positions, while PAR looks at all 5 individual positions in the NBA.

No similar papers where a new NBA statistic to analyze individual points that a player adds to his team were found, but pieces of other NBA analytics were very influential in the creation of PAR. Similar to how openWAR sought to fix the typical WAR statistic, PAR seeks to stand out from other accepted advanced metrics, such as BPM and PER. Hamalian (2016) talks about the flaws that exist in PER, such as the lack of centering in the data, making the league average actually vary per season. The cited article also talks about how the pace statistic in PER ultimately does not do anything. Thus, PAR takes many of the same box-score statistics that PAR does, but seeks to center its data to form a season-by-season league average, and attributes a player's value to his team's total points and total minutes, rather than accounting for the pace of the team. There are similarities with PER that this article still believes are not efficient, and those shortcomings will be discussed further in later sections.

One of the main adjustments in PAR that occurs is that of a positional adjustment. Different positions have different requirements, so box score statistics need more analysis than meets the eye to really show a player's value. Piette et al. (2010) makes a point of this in the analysis of field goal percentage based on distance from the basket. Adjusting by positional need is a key aspect of PAR that was inspired by the metrics in the cited paper. Players in the NBA all have different skillsets, and different positions call for these specific skillsets in order for a team to be successful as a unit, which is a key point in the cited paper, as well as in PAR.

As previously stated, there were no other papers found in which a new NBA metric was attempted to be created, so the question is that of what PAR can add to previously accepted statistics. Position and team adjustments allow for a player's value to his specific team to be measured, giving a better expectation for their presence or absence. This is similar to how WAR is calculated, which takes into account a positional and league adjustment (Fujita, 2022). Adjusting to a position allows one to analyze a player based on what his position requires. The team adjustment is a function of how many minutes a player played throughout the entire season, and how many of their team's total points were scored by them. If a player plays a majority of his team's minutes, and scores a relatively high percentage of his team's points, he will be more valuable to his team, and his team will be hurt more by his absence in a game. The idea of how much an individual team will value an individual player is the key unique factor in PAR that causes it to stand out.

2 Data

All basic and advanced statistics from the 2020-2021 season were collected from the Basketball Reference website, as well as each team's total points throughout the course of the season (Basketball Reference, 2022). From the basic statistics, 4 metrics were created in order to calculate PAR. Offensive Points is a function of how many points a player will create on offense. While the coefficients vary by position, the statistics used are effective field goal percentage, three point percentage, free throw percentage, offensive rebounds, assists, points, and turnovers. Similarly, Defensive Points is a function of how many points a player helps prevent while his team is on defense. The coefficients also vary by position, but this metric is based on defensive rebounds, total rebounds, steals, blocks, and personal fouls.

The Positional Adjustment metric creates a coefficient of how valuable a player is to their individual team, and is based on how many minutes a player plays relative to their team, as well as how many points they score relative to their teams total points. The last statistic created is Points Per Win, which is based on the average amount of points a player will create in a game. This function is based on the sum of Offensive and Defensive Points, and is scaled to incorporate the total number of games, minutes, and players in a season. This statistic is very similarly calculated to Runs Per Win in the WAR statistic. Given that over the course of a 72 game season, all teams will play each other at least once, we assume a relatively equal distribution in terms of strength of schedule.

Advanced statistics for each player were also collected in order to perform a regression, to see how PAR compares with known and accepted metrics. Value Over Replacement Player, also known as VORP, was one of the metrics used, and is calculated with the help of Box Score Plus Minus, also known as BPM. These statistics also help give a relative estimate of a player's value compared to that of an average player, but they translate the statistic to a league average team as well. PAR does not do this, because it is concerned with how valuable a player is to his specific team, not throughout the entire league. If a player switched teams, his PAR value would most likely change, as his importance to one team may be more or less than it would to another. For simplicity, the team that a player played his most games on was taken into consideration for this metric.

Similarities to BPM, and therefore VORP, can be explained by many different factors. BPM centers data so that the league average is 0, and creates coefficients for factors based on a player's position and offensive role. While PAR is not concerned with offensive role, it does take into account position, and assumes that position, for the most part, is correlated with offensive role. Intentional usage of only universally available statistics allow for easy calculation as well as easy understanding for audiences. The key difference is that of playing time not being a factor in BPM and VORP, which is obviously a key factor in PAR (Myers, 2022).

Other statistics used include Player Efficiency Rating, a per-minute rating of player performance, and Win Shares, which estimates the number of wins a player creates for his team throughout the season. Due to all of these metrics' relative similarity to PAR, it is suggested that if they are highly correlated with PAR, it is a successful metric. However, we expect some differentiation between the metrics, as they all vary slightly in what they attempt to convey. The relative correlation between all these statistics shows that PAR is related to other advanced metrics analyzing player efficiency, but also that it introduces something new in basketball statistics.

3 Methods

The basic method for calculating the PAR method was based on how WAR is calculated in baseball, but also took influences from other advanced basketball statistics. WAR is based on Offensive and Defensive Runs, which are calculated subjectively via attributes of the game such as hitting, base running, fielding, and so forth (Fujita, 2022). The subjectivity is in the coefficients chosen to scale statistics which impact Offensive and Defensive Runs. Thus, there are actually an infinite different kinds of WAR in baseball, depending on which method of calculating Offensive and Defensive Runs is used. Similarly, PAR is created by calculating Offensive and Defensive Points statistics, to analyze how many points a player adds for his team, and how many he prevents the other team from scoring.

Using the basic offensive statistics of Effective Field Goal Percentage, Three Point Percentage, Free Throw Percentage, Offensive Rebounds, Assists, Points, and Turnovers, we assign a coefficient to them based on how important they are for a given position. Point guards are expected to pass more than centers, and a point guard's passing ability has more value to his team than a center, so more weight is placed on that statistic for point guards. This goes for all positions, and a coefficient matrix of a constant scale is created. That is to say, assists have a coefficient from point guards, shooting guards, small forwards, power forwards, and centers, respectively, of 4, 3.5, 3, 2.5, and 2.

The coefficient by position method is one similar to that of Box Plus Minus, another advanced NBA metric (Myers, 2022). The position a player was assigned for the calculation was the position where he played the most minutes throughout the 2020-2021 season. This coefficient method gives a clean scaling into the calculation of Offensive Points. Some statistics, such as Points and Effective Field Goal Percentage, are equally important, regardless of the position of a given player. Thus, these statistics have a constant coefficient that does not change. Once all coefficients were applied to all statistics, the sum was taken to give Offensive Points.

The exact same method was applied to the Defensive Points calculation, but used the basic defensive statistics of Defensive Rebounds, Total Rebounds, Steals, Blocks, and Personal Fouls. As turnovers and personal fouls are not desirable amongst players, the coefficients for these statistics is negative, which allows for a scale of not only the good a player does, but also what they do poorly. This coefficient method is similar to the Positional Adjustment metric applied in WAR calculation, which seeks to adjust a player's importance based on what is expected of their position.

The coefficients for each position are listed in Table 1. Coefficients are subjective, but were changed to have a constant scale by position, and create a PAR scale that lined up closely with other advanced metrics. This coefficient matrix could be looked at as an optimization problem, where coefficients by position are changed to achieve as high of a correlation with other advanced metrics as possible. However, a constant scale by position and a relatively high correlation to other metrics shows uniqueness in the statistic but also validity.

Table 1: Coefficients for Each Statistic in Offensive and Defensive Points

Statistic	Point Guard	Shooting Guard	Small Forward	Power Forward	Center
Effective FG Percentage	200	200	200	200	200
3 Point Percentage	300	275	250	225	200
Free Throw Percentage	100	90	80	70	60
Offensive Rebounds	1	1.5	2	2.5	3
Assists	4	3.5	3	2.5	2
Points	2	2	2	2	2
Turnovers	-5	-4.5	-4	-3.5	-3
Defensive Rebounds	2	2.5	3	3.5	4
Total Rebounds	3	3.25	3.5	3.75	4
Steals	5	4.5	4	3.5	3
Blocks	3	3.5	4	4.5	5
Personal Fouls	-3	-3	-3	-3	-3

The next step was creating a Team Adjustment statistic. As stated before, the PAR metric seeks to anticipate how valuable a player is to their given team, rather than as an average of the entire league. This gives more of an insight of how a team will fare without a certain player. We expect this statistic to change if a player were to switch teams. This is similar to the League Adjustment in WAR calculation, where a player's value is adjusted based on whether he plays in the American League or the National League. The Eastern and Western Conferences in the NBA have much less disparity compared to the MLB, and each conference plays each other much more frequently, so we instead change this to adjust a player's value to his specific team. The team assigned to a given player was the team where he played the most games during the 2020-2021 season. If a player had played an even amount of games for 2 separate teams, the team the player had played the most minutes for was assigned as his team.

The Team Adjustment statistic is then calculated by taking the total minutes a player was on the court during the entire season, and diving it by a constant of 3,456 (the maximum number of minutes a player could have played during the shortened season, 48 minutes per game multiplied by 72 games). Then, the percentage of points a player scored for his team (player's total points divided by team's total points throughout the season) was calculated, and the two results were multiplied together. As a player cannot play 100 percent of his team's minutes, or score 100 percent of his team's points, the result is a number between 0 and 1.

$$\frac{\text{Minutes Played}}{3456} \times \frac{\text{Points}}{\text{Team Total Points}}. \tag{1}$$

Creating the "Team Adjustment" statistic via Equation (1) has then successfully adjusted a player's statistics to his specific team.

A similar adjustment is also used in the calculation of Box Plus Minus, which is a key factor in calculating Value Over Replacement Player, two of the advanced metrics PAR will be compared against. The goal of this adjustment is to give less of a penalty to players who play a majority of their team's minutes, and score a majority of their team's points. This helps truly elite players stand out amongst the pack, as well as players who may not be the best of the best, but matter more to their team specifically than in the grand scheme of things.

Lastly, WAR implements a Runs Per Win statistic, which gives a basic idea of how many runs are needed for a win in the MLB. Similarly, a Points Per Win statistic is created for the NBA, which allows a scaling down of the PAR statistic. We calculate this via the combined Offensive and Defensive Points statistic for a player divided by the number of minutes he played, then adding 2,160 (72 games per season times 30 teams in the NBA, thus, the total number of chances to win throughout the season). This gives a basic metric of a players points created as a function of how many minutes he played, and allows us to even the metric out a bit more from star players to role players. This statistic serves as the denominator of our PAR calculation.

$$\frac{\text{Offensive Points} + \text{Defensive Points}}{\text{Minutes Played}} + 2160. \tag{2}$$

By creating the "Points Per Win" statistic, Equation (2) has thus scaled down the statistic based on how many points are in an average win, similar to Runs Per Win in WAR. The constant of 2,160 would change to 2,460 for an 82-game season, for a typical NBA season.

Finally, once all supporting statistics of PAR have been created, all that is left to do is combine them to achieve our PAR values for each player in the NBA. The formula for PAR is listed below.

$$\frac{(\text{Offensive Points} + \text{Defensive Points}) \times \text{Team Adjustment}}{\text{Points Per Win}}. \tag{3}$$

Equation (3) gives a good idea of how many points a player accounts for during a game, how important that is for his given team, and how important it is compared to all other players. The last step is to standardize this rough PAR statistic, so that the mean is 0, and the standard deviation is 1. Logically, this helps the idea of the metric in the sense that a perfectly league average player should have a PAR of 0, and his presence or absence from his team neither adds nor subtracts value. Thus, we have created a new NBA player metric, Points Above Replacement, PAR. All of the calculations, multiple regression, and graphs were created using R (R Core Team, 2022).

4 Results

First, the top 10 players in terms of PAR in the league will be analyzed. Then, the top 10 PAR values at each position will be evaluated.

Table 2: PAR Values from the Entire NBA

Rank	Player	Position	Team	PAR
1	Nikola Jokic	C	Denver Nuggets	7.69
2	Nikola Vucevic	C	Orlando Magic	6.55
3	Julius Randle	PF	New York Knicks	6.49
4	Luka Doncic	PG	Dallas Mavericks	4.61
5	Damian Lillard	PG	Portland Trail Blazers	4.47
6	Giannis Antetokounmpo	PF	Milwaukee Bucks	4.21
7	Stephen Curry	PG	Golden State Warriors	4.17
8	Russell Westbrook	PG	Washington Wizards	4.05
9	Jayson Tatum	SF	Boston Celtics	3.96
10	Domanatas Sabonis	PF	Indiana Pacers	3.21

As can be seen in Table 2, one player rises above all others in both PAR and VORP. That player is Nikola Jokic of the Denver Nuggets, and this "outlier" makes perfect sense, and helps show just how dominant his MVP season was. Not only did Jokic average 26.4 points, 10.8 rebounds, and 8.3 assists per game, he was doing it from the center position. Having a center that has the ability to perform in all aspects of the game, even those that his position does not require, proves his value to his team, which is why his value is so much higher in both the new PAR metric, and the accepted VORP metric. This logic applies to Nikola Vucevic, Julius Randle, Russell Westbrook, and Domanatas Sabonis as well. While they might not be considered the best at their position, or an extremely elite player in the NBA, they are very versatile players, that can do anything on the court, and thus they are rewarded with a high PAR value. This makes sense, as without these players, a lot of the statistics their team accumulates are gone, so while they may not have as much value in the grand scheme of the NBA, they were very much the most valuable players for their teams. Another key thing to note is that some players, such as LeBron James, have a lower PAR than expected, and this could be due to the fact that they played most frequently in a position that did not match their skill set. LeBron James played primarily as a point guard, but his skillset matches that of a small forward or power forward. Thus, his strengths are not adequately measured, as he is essentially being played "out of position".

Table 3: PAR Values from all Point Guards

Rank	Player	Team	PAR
1	Luka Doncic	Dallas Mavericks	4.61
2	Damian Lillard	Portland Trail Blazers	4.47
3	Stephen Curry	Golden State Warriors	4.17
4	Russell Westbrook	Washington Wizards	4.05
5	Trae Young	Atlanta Hawks	2.69
6	De'Aaron Fox	Sacramento Kings	1.94
7	Chris Paul	Phoenix Suns	1.93
8	Kyrie Irving	Brooklyn Nets	1.74
9	Dejounte Murray	San Antonio Spurs	1.64
10	Ja Morant	Memphis Grizzlies	1.45

Table 4: PAR Values from all Shooting Guards

Rank	Player	Team	PAR
1	Bradley Beal	Washington Wizards	3.17
2	Devin Booker	Phoenix Suns	2.74
3	Terry Rozier	Charlotte Hornets	2.59
4	Zach Lavine	Chicago Bulls	2.29
5	RJ Barrett	New York Knicks	2.28
6	Anthony Edwards	Minnesota Timberwolves	2.22
7	Jaylen Brown	Boston Celtics	1.87
8	Collin Sexton	Cleveland Cavaliers	1.85
9	Buddy Hield	Sacramento Kings	1.72
10	Norman Powell	Toronto Raptors	1.37

Table 5: PAR Values from all Small Forwards

Rank	Player	Team	PAR
1	Jayson Tatum	Boston Celtics	3.96
2	Khris Middleton	Milwaukee Bucks	2.39
3	Brandon Ingram	New Orleans Pelicans	2.13
4	Kawhi Leonard	Los Angeles Clippers	1.58
5	Paul George	Los Angeles Clippers	1.44
6	Michael Porter Jr.	Denver Nuggets	1.42
7	Jimmy Butler	Miami Heat	1.41
8	Bojan Bogdonavic	Utah Jazz	1.35
9	Mikal Bridges	Phoenix Suns	1.19
10	Jerami Grant	Detroit Pistons	1.14

Table 6: PAR Values from all Power Forwards

Rank	Player	Team	PAR
1	Julius Randle	New York Knicks	6.49
2	Giannis Antetokounmpo	Milwaukee Bucks	4.21
3	Domanatas Sabonis	Indiana Pacers	3.21
4	Zion Williamson	New Orleans Pelicans	3.07
5	Andrew Wiggins	Golden State Warriors	2.26
6	Demar Derozan	San Antonio Spurs	1.88
7	Tobias Harris	Philadelphia 76ers	1.87
8	Pascal Siakam	Toronto Raptors	1.72
9	John Collins	Atlanta Hawks	1.35
10	Harrison Barnes	Sacramento Kings	1.11

Table 7: PAR Values from all Centers

Rank	Player	Team	PAR
1	Nikola Jokic	Denver Nuggets	7.69
2	Nikola Vucevic	Orlando Magic	6.55
3	Rudy Gobert	Utah Jazz	3.10
4	Bam Adebayo	Miami Heat	2.78
5	Joel Embiid	Philadelphia 76ers	2.26
6	Clint Capela	Atlanta Hawks	2.25
7	DeAndre Ayton	Phoenix Suns	2.11
8	Jonas Valanciunas	Memphis Grizzlies	1.98
9	Karl-Anthony Towns	Minnesota Timberwolves	1.82
10	Kelly Olynyk	Miami Heat	1.39

PAR will also be compared with the 4 accepted advanced metrics that were used as regressors in the multiple regression on PAR. These include Player Efficiency Rating, Win Shares, Box Plus Minus, and Value Over Replacement Player.

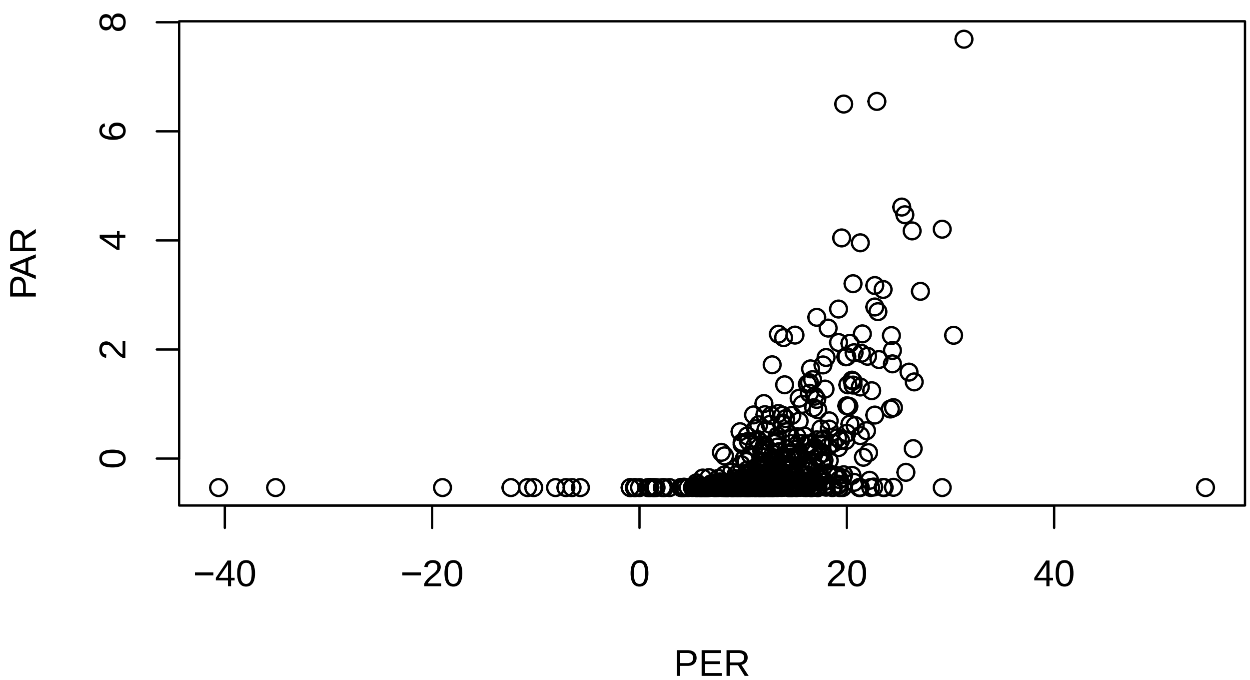

Figure 1: Player Efficiency Ratings (x) vs. Points Above Replacement (y)

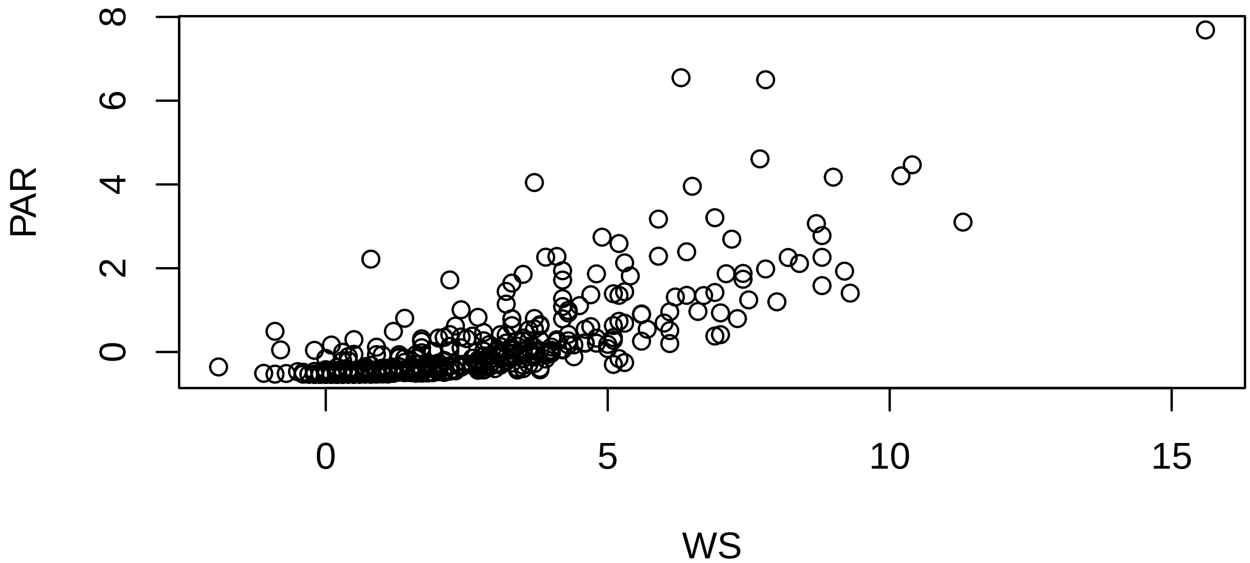

Figure 2: Win Shares (x) vs. Points Above Replacement (y)

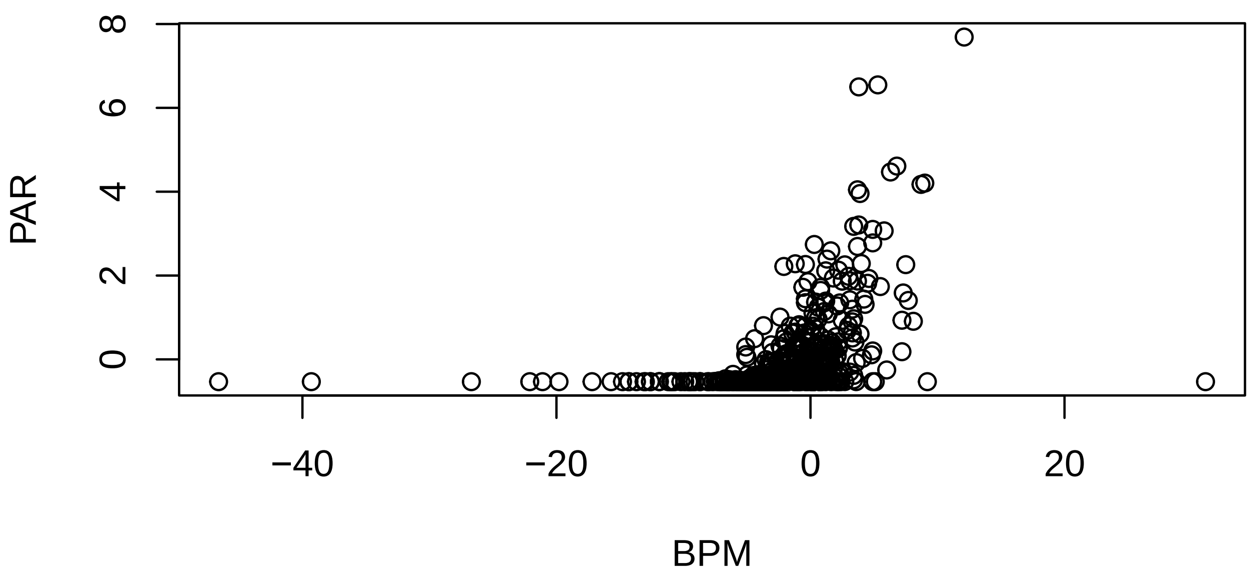

Figure 3: Box Plus Minus (x) vs. Points Above Replacement (y)

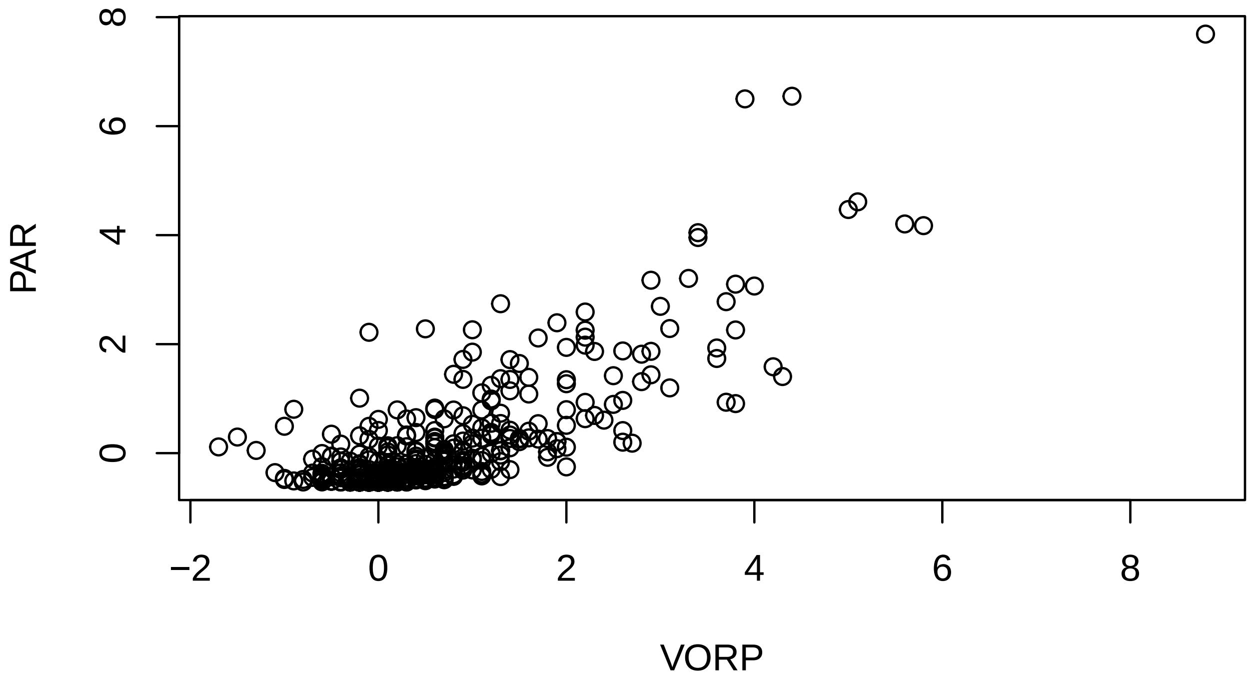

Figure 4: Value Over Replacement Player (x) vs. Points Above Replacement (y)

It can be seen in Figure 2 that the graphs of PAR and Win Shares, as well as PAR and Value Over Replacement Player in Figure 4 fit nicely, with a relatively positive and linear correlation. However, the graphs of PAR and Box Plus Minus in. Figure 3, as well as PAR and Player Efficiency Rating in Figure 1 appear to have less of a linear distribution. This can be attributed to the scaling methods of each statistic. Since Win Shares and Value Over Replacement Player follow a similar scale, with a minimum slightly below 0, and a maximum somewhere in the range of 10, the scales match, and each player's value of each metric fits similarly enough to form a linear distribution in both Figure 2 and Figure 4. However, Box Plus Minus ranges from -40 to above 20, so we see the graph of Figure 3 centered around 0, where the majority of players fall, and going almost straight upwards based on their PAR value. Player Efficiency Rating has a similar scale, so a similar effect is shown in Figure 1. In order to see how Points Above Replacement fits in terms of all of these accepted metrics, a multiple regression will be run, with the 4 accepted metrics as regressors, and with PAR as the independent variable.

Table 8: Multiple Regression on PAR

Variable	Estimate	Standard Error	P-Value
Intercept	-1.009	0.145	9.44×10^{-12}
PER	0.030	0.009	0.002
WS	0.121	0.024	4.75×10^{-7}
BPM	-0.057	0.013	1.27×10^{-5}
VORP	0.559	0.049	Less Than 2×10^{-16}

In Table 8 an adjusted R-squared value of 0.6974 is shown, along with an SER of 0.5501. The adjusted R-squared statistic is key, as it shows that 69.74 percent of variation in PAR can be explained by these other 4 accepted metrics. This shows a clear correlation between PAR and the metrics, but also shows that PAR has something unique to offer.

5 Discussion

Ultimately, the goal of this statistic is to allow a reader to gauge a player's value to his team based on a league average player. As previously stated, the metric is adjusted so that a league average player has a PAR value of 0. Based on all other players' PAR values, we can create a sort of "legend", a rough guideline for what a player's role will be based on the threshold his PAR value falls under.

Table 9: PAR Legend

Role	PAR
Benchwarmer	Less than -0.43
Role Player	-0.43 to 0.08
Starter	0.08 to 1.09
All-Star	1.09 to 1.94
Superstar	Greater than 1.94

This legend in Table 9 was calculated based on a quantile calculation of all PAR data. It is not an even distribution, as it is assumed that there are many more benchwarmers in the NBA than there are superstars. Thus, benchwarmers are defined as the bottom 50 percent of the league, as an NBA roster of about 15 players will only give 7 or 8 players significant minutes. Players between the 50th and 75th percentile are defined as role players, as they get significant minutes, but do not make an impact enough to be considered a solid starter. This is where a 'league average" player is expected to fall, as 0 is contained in this part of the legend, and 0 represents a league average player via this metric. Next, the 75th to 90th percentile are defined as starters, because only 5 players can start a game, and, more often than not, a team only has 3 or 4 players who are guaranteed starters. The 90th to 95th percentiles represent all-stars, as that is clearly a very prestigious area to be a part of. Lastly, it is assumed that only the top 5 percent of players in the league can be deemed "superstars", so they comprise the 95th to 100th percentile of the NBA. By this method, it is felt that a more realistic legend for PAR has been created as opposed to just breaking up the data evenly into 5 groups.

The concept of assigning value to a player based on how many points he contributes to his team is the main goal of this statistic. By taking the calculation of WAR from baseball, which is how many wins a player contributes to his team, and adjusting it for the sport of basketball, and points rather than wins, it is felt that the goal is successfully achieved. The scaling of the data around the mean allows a "replacement level" player to contribute exactly 0 points to his team, and the rest of the league is compared to that. The team adjustment is a key one as well, as, depending on what team a player plays for, his value will change, sometimes even drastically. Further research would need to be done, such as comparing PAR's estimation with actual point differentials when an entire roster aside from a certain player plays, but for the most part, the original goal of creating this statistic is achieved.

As can be seen from the Table 8, it is in relative agreement with many other accepted statistics, and even takes some ideas from the calculation of those statistics. However, at the same time, it is unique enough that it introduces a brand new outlook to the advanced metrics subject. Other statistics look for other ways to value a player, which is where the variation comes into play, but for the most part, elite players are valued as such through PAR, which is how it is known that the statistic holds.

There are a few limitations to discuss in the calculation of PAR. Firstly, the subjectivity in calculating the coefficients for Offensive and Defensive Points, as seen in Table 1, could be changed to any numbers to serve whatever purpose one is looking for. However, in baseball's WAR, this is the subjective part of the statistic that causes there to realistically be many different kinds of WAR, despite them all being the same statistic. The coefficients could be tweaked to serve a number of different purposes. Further tests could also be done to test the validity of PAR in practice. This could help a final score estimation model in the future for the purpose of season simulations, sports betting, and a number of other purposes. The sample size of 1 season makes this difficult, so calculations across multiple seasons, and future ones would help this discussion. However, PAR seems to provide a decent estimate of a player's value to his team, which is especially shown through its relation to VORP and BPM, which are the advanced metrics with goals that are most similar to that of PAR.

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Brian Krikorian plans to graduate in May 2022 from the University of Connecticut, with a Bachelor's of Science in Data Science, and a minor in Computer Science.