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## NBA Draft Pick Valuation

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### Recommended Citation

Parker, C. (2018). "NBA Draft Pick Valuation," *Summer Program for Undergraduate Research (SPUR)*.  
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## NBA Draft Pick Valuation

### Abstract

In this research paper, the discussion is targeted towards understanding the statistical analyses associated with the determining of draft pick success in the National Basketball Association. The three methodologies in question are Player Efficiency Rating and standard statistical categories, Roland Beech's Rating System, and Win Shares. Through the discussion of these three separate methods, the research aims to give a holistic assessment of which study is the most likely to predict a player's success post-draft. Through the paper, the ideas presented before, during, and after research are discussed with an emphasis on educating the reader on the field of predictive analytics and the role it plays in sports business. In its conclusion, the paper summarizes not that one methodology is superior to the others, but that the most conclusive method is one where all three approaches are analyzed and combined.

### Keywords

draft, NBA, predictive analytics, sports statistics

### Disciplines

Business

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In this research paper, the discussion is targeted towards understanding the statistical analyses associated with the determining of draft pick success in the National Basketball Association. The three methodologies in question are Player Efficiency Rating and standard statistical categories, Roland Beech's Rating System, and Win Shares. Through the discussion of these three separate methods, the research aims to give a holistic assessment of which study is the most likely to predict a player's success post-draft. Through the paper, the ideas presented before, during, and after research are discussed with an emphasis on educating the reader on the field of predictive analytics and the role it plays in sports business. In its conclusion, the paper summarizes not that one methodology is superior to the others, but that the most conclusive method is one where all three approaches are analyzed and combined.

### **Introduction**

To put in context the research conducted by this study and the analyses associated with it, it is important to take into account the history of the current National Basketball Association (NBA) draft system. The draft system, regardless of format and league, is in place to allow teams to acquire talent from both college and international sources to improve the organization or gain leverage to acquire more draft picks in either the current draft or future drafts. The current system or draft lottery was set in place in 1985 to allow the teams that did not make the playoffs the chance at the 1<sup>st</sup> overall pick in the draft. More specifically, the first three picks are determined from the lottery system where the worst of the teams that missed the playoffs are given the most ping pong balls, at 250 out of a total of 1000. Each team is given a smaller amount until all 14 teams are assigned to a percentage chance of winning. After the first three picks are determined, the remaining teams are filled in reverse win-loss order. However, starting in 2019, the worst three teams will have 14% odds at the first pick and the lottery will increase to the first four spots and the same fill-in method outlined before.

### **Role of Predictive Analytics**

Where this study and subsequent analysis comes into play is in the realm of predicting the success of NBA draftees after they join their respective teams after the draft. With this being said, there were a variety of approaches this research discusses later that will delve more in depth about the progression of questions asked and the steps put in place to best answer them.

The initial research question that was proposed prior to the research being conducted was "How can an NBA team be sure they pick the right player at their relative draft spot?" Being extremely broad, this question allowed the research to go in whatever direction the data took it in. Prior to the data collection portion that will be discussed in the latter sections, let's dive into the brainstorming process that occurred prior to establishing what precise direction the research would go in.

The first idea developed in the preliminary process of this research was the creation of an algorithm that would have imputable scales for each team. A team would be able to put in desired points, rebounds, assists, etc. for a desired position and receive an index. From there, they could use this index number to

evaluate the current talent pool, both professionally and from college, in order to pick or sign the closest match to their needs. For example, if the New York Knicks need a point guard (an actual need), they can use the index to compare NBA averages at the position. They could then find the corresponding index number among the draft board and pick accordingly to draft the player that best fits this need.

Another idea that was developed was to find percentile ranks for each player in each statistical category prior to their draft. Then, the most important attributes are scaled and create an index in that way. Then a team would compare this index to current players and compute average player index for each position. From there, other factors could be added into the index such as difficulty of college conference, international league, or high school level.

### **Player Efficiency Rating and Standard Statistical Analysis**

Upon engaging in research in the all-inclusive statistic or Player Efficiency Rating (PER) developed by John Hollinger, one must dive into the conventional statistical categories and how that plays a role in the draft process. From the DraftExpress site, analysis was conducted for curves regarding the first overall pick. Historically, the first overall pick's points per game, assists per game, and rebounds per game can be mapped by the curves,  $y = 0.23x^2 + 930.99x - 1463212.43$ ,  $y = 0.08x^2 + 186.41x - 329353.99$ , and  $y = 0.67x^2 + 1114.9x - 2160779.76$  respectively. With this data, it became more tangible the trends that players picked first overall exhibit in their standard career statistics. In addition to the obvious upward trends in recent years, DraftExpress included the curve for player efficiency rating as  $y = 0.69x^2 + 1396.49x - 255329743$  which exhibited similar trends to the first three metrics outlined. From there the research question was posed: how can we compare overall player efficiency ratings where the results are directly reflected in the players relative ability levels? Displayed below is the PER for each drafted 2018 player prior to their draft:

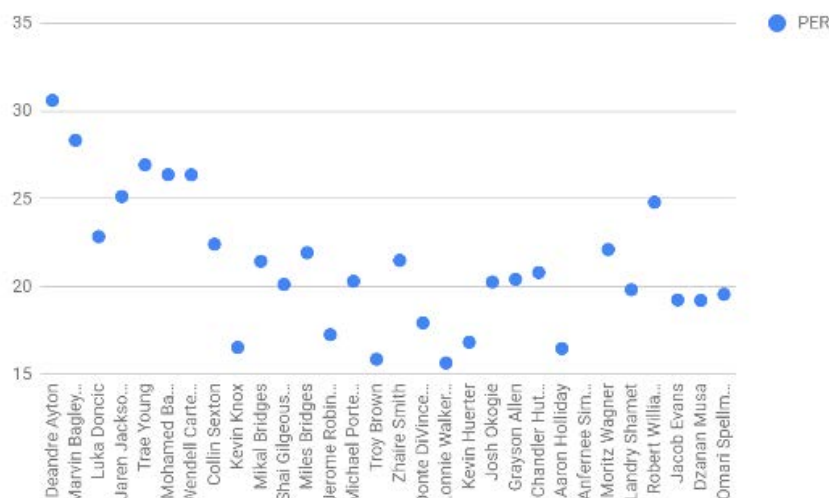


Figure 1.1

The graph displays an approximately standard curve of values, with the progression of the PER generally decreasing as the picks go on. However, a couple of points draw interest due to the position in which they occur on the scatterplot. For example, Deandre Ayton's PER being greater than 30 is remarkable due to the average center's drafted PER of 17.1. To put that into more perspective, LeBron James and James Harden (2018 Most Valuable Player) finished with PERs below 30, so if this is any indication of Ayton's dominance, this could be a great transition into the NBA and a terrific pick for the Phoenix Suns.

Another PER that goes against the trend of the scatterplot is Robert Williams' PER of about 25. Similar to Ayton, this number, and especially his lower pick in the first round, might be a steal for the Boston Celtics considering their relatively low draft position.

From this initial diagnosis of player efficiency rating came the question: how can we determine value in late first round picks? Building off of the discussion regarding Robert Williams, possibly an analysis of trends in PER over a multi-year period could allow for the measurement of the percentage change of the statistic. Therefore, a researcher would be able to statistically model a player's growth over a four-year span and make more accurate predictions regarding the year after graduation. Unfortunately, the modern draft system has become more centered around players taking one year in college to gain visibility and subsequently jumping into the pool rather than the traditional graduation of college and joining the draft class after. This highlights a restriction not only on PER analysis, but on analysis of college basketball trends in general because one year tends to not be a big enough sample size for statistical modeling. Finally, a restriction that applies directly to PER is the statistic's scope. When the metric was developed by John Hollinger of Basketball Reference, the statistician hoped to create an all-inclusive statistic that would allow research, such as this study, to accurately analyze player contribution to their team. The major shortcoming of the statistic is not what it includes but what it does not. PER fails to include all statistics on the defense side of the ball, which usually results in the best offensive players accruing the best rating, whereas players who are defensively active players may fall short because their statistic is not taken into account. All in all, PER is a sound way to look at a player's contribution to the team and a possible solution to draft player success.

### **Roland Beech's Expected Performance**

Another important progression of this research was an analysis of statistician Roland Beech's player valuation system. As per his model, he uses a rating system that consists of an extremely simplistic combination of basic stats to model players efficiency. The system is as follows:

$$\text{Rating} = (\text{Points/Game}) + (\text{Rebounds/Games}) + (\text{Assists/Game})$$

From this system Beech allocates the following categories of players based on the numerical value of their rating:

Star Player: Rating >20

Solid Player:  $15 < \text{Rating} < 19.9$

Role Player:  $10 < \text{Rating} < 14.9$

Deep Bench:  $5 < \text{Rating} < 9.9$

Complete Bust: Rating <5

From this rating, one could run some extremely preliminary graphs to see the percentage of each pick having one of these five categories of players. Attached below is such a graph, which was generated on Microsoft Excel:

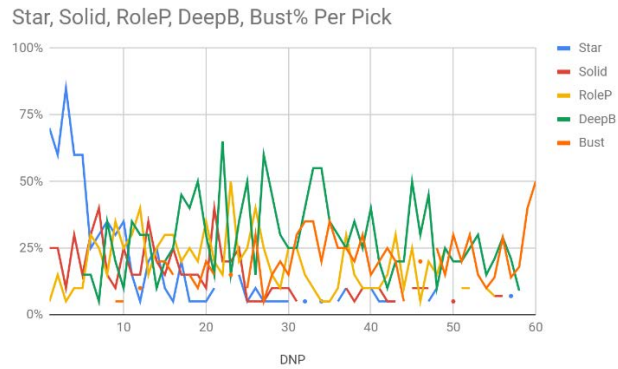


Figure 1.2

From this model, one could extract some of the most notable features that could be applied to later analyses. The most notable feature is the fact that the Star Player Rating is higher for the third pick than the second pick. In addition to that, the third pick has a higher points per game and assists per game than the second pick. From this, one could begin to deduce that the third pick may be equally valuable or possibly more than the second pick, which could justify a team to trade down for a pick and additional assets. Along the same vein, the third pick performed higher in assists per game, had a higher Star Player Rating and had an equivalent Role Player Rating as the first overall pick. From these two comparisons, the ideology that having the first pick is the primary strategy might be tainted and the instances in the past where teams have traded down for the third pick (Boston trading down from the 1<sup>st</sup> to the 3<sup>rd</sup> pick in 2017) and have had incredible success. In order to make more conclusive generalizations, more models are needed to make a more wholistic determination.

### Win Shares Analysis

The last and majority of the conclusions of this research comes from the analysis of the statistic Win Shares and Win Shares per 48 minutes. The most current version that was analyzed here was Offensive Win Shares, which is calculated by

$$\frac{(\text{Points Produced}) - 0.92(\text{League Points per Possession})(\text{Offensive Possessions})}{0.32(\text{League Points per Game})\left(\frac{\text{Team Pace}}{\text{League Pace}}\right)}$$

From there the statistic Win Shares per 48 minutes is Win Shares divided by 48 to account for varying minutes that players play over the course of a season. From a basic analysis from R, one can begin to compare the variances between the first couple draft slots in order to see how relatively spread out the Win Shares per 48 minutes (WS/48) are compared to each other. From this analysis, the hope was to see if a pick could be more predictable in the WS/48 statistic.

By using R, the WS/48 for the first and second pick were compared to show that the ratio between the variances was 1.073. In context, this means that the spread of the first pick's results was higher than that of the second. This is interesting considering the fact that scouts believe that the first pick is always more valuable than the second. If a team is looking for a safer pick with a more predictable range of values, the second pick may possibly be their answer, but if one is willing to risk a higher WS/48 value the first may prove more valuable. With this methodology in mind, the second pick has a higher variance than the third pick, but the third pick has a lower variance than the fourth pick. In comparison to the first three picks, the fourth pick has the highest variance, which could incentivize a team to trade up into the top three to avoid the volatility of the fourth pick.

From this analysis, the research hints to the fact of a team's preferences and whether they are willing to use the data driven analytics or the "hunches" that scouts use to grade players. All in all, Win Shares is the most comprehensive formula for a player's value to their team and when the spread of a pick's Win Shares are taken into account, teams could use the data to understand the value of each pick.

### **Conclusion**

This study has touched on a few key approaches to looking at statistical analyses in the NBA draft. From the application of the Player Efficiency Rating and standard statistical categories, one could conclude that for current NBA players, this could be a significant barometer of skill level and ability, but due to the varying levels of basketball prior to the NBA, these may not be the most conclusive. Along this vein, Roland Beech's rating system was excellent to compare the role a player would play in a system, but its simplicity is a possible pitfall for its ability to be applicable. Finally, the analysis of WS/48 was the most promising due to its ability to compare the spread of a player's contribution relative to their draft pick. However, some players exhibit traits that may not show up on the statistics sheet. Due to careful picking of these three methods for comparison, one could conclude that the best measure to forecast a draft player's success is not to look at one study, but to examine all three of these systems in order to make a holistic evaluation prior to submitting the pick to commissioner Adam Silver.

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