

Research Paper: NBA Strategies for Player Acquisition

Introduction

The NBA has been trending to become a position-less league (Mudric, 2019). Players are having to refine all aspects of their game as a result and organizations are devising analytics strategies to identify players that will work in their system. The NBA analytics revolution is causing teams to focus more on player efficiency than traditional size focus for a position. Recently, the Houston Rockets traded away Clint Capela and now their tallest player in the starting lineup is 6'7" (Woike, 2020). There have been a few attempts at identifying players who have a complete all-around game. These metrics categorize both a player's presence and efficiency on the court, which are both imperative in determining upgrades in a lineup. This is the basis of our research in player acquisition strategies in which we simply look at the complete portfolio of players. One specific technique that we will examine is lineup optimization. The theory being that if we understand our current optimized lineup, we can either target free agency with player upgrade in mind or target players to build around the optimized lineup. This would help to create a strategy for going into free agency. The next strategy we look to examine is how to cluster the position-less league. For that, we will walk through Principal Components Analysis and perform a clustering analysis of free agents in the NBA. This is helpful to understand where the layout of the free agency market is and to identify voids in the current roster. The next strategy, is to examine free agent's shooting composition as to see where their shooting is most efficient. The evolution of the game has forced more attempts beyond the arc or easy shots under the hoop. Daryl Morey's economic vision of shooting has changed the league, in fact most mid-range shots average 0.85 points per attempt, which in theory would force someone to get to the foul line instead (Goldsberry, 2019). In terms of economics, nothing matters more of player

acquisition strategy than cost of acquisition. Our research will also show some strategies around player acquisition with regards to salaries.

Methods/Literature Review:

Player Efficiency Metrics

The first strategy in player acquisition is determine “player win score”, which was created by Dave Berri to produce a more sensible approach to providing linear weights to production on the NBA court (Berri takes this follow a step further in a complex calculation called Wins Produced but for now we’ll focus on player win score). The formula is as followed:

Player win score = points + rebounds + steals + 0.5(assists) + 0.5(blocked shots) – FG attempts - turnovers - 0.5(FT attempts) - 0.5(personal fouls).

Given we don’t know the formula for Wins Produced, we can use Win Score to approximate a player’s relative effect on the court. Players like Giannis Antetokounmpo (former MVP) leads the NBA with a player win score of 17.7 games, which if the Bucks do not re-sign will fall down to being a mid-level team in the East with 18 games lost because of one person’s production. The Lakers have two double digit win-scores in their starting lineup with Anthony Davis (8th in the league) and LeBron James (16th in the league) who account for 27 games in their production. That’s more than half the team’s western conference leading wins. Identifying players on smaller market teams with higher player win score at a smaller value can be a particularly appealing strategy for teams. For example, Richaun Holmes has a player win score of 11.1 games at the age of 29. Given that Lakers have an expiring contract of 34-year-old Dwight Howard (8.3 player win score) and another aging center in Javale McGee (age of 32, 6.95), Holmes could be a nice target to replace both players in the lineup. Holmes is a perfect undervalued example, given he was drafted by the 76ers during the “Process” era and sent to Kings as part of a strategy to

stockpile picks. There's an argument that he's outplayed given his situation of playing for struggling teams. Add him to a thriving lineup with James/Davis, you could yield higher production. Another metric to consider is the NBA efficiency rating also known as TENDEX created by Dave Heeren. The formula is the following:

$$\text{Efficiency per game} = (\text{points per game}) + (\text{rebounds per game}) + (\text{assists per game}) + (\text{steals per game}) + (\text{blocked shots per game}) - (\text{turnovers per game}) - (\text{missed FG per game}) - (\text{missed FT per game})$$

Heeren created the statistic to reward players for positive production and hinder them for negative production. It's one of the first statistics to look at efficiency. However, it is pretty simplistic as it doesn't apply linear weights as shown prior. It's basically a simple aggregator of box score stuffers. The top efficiency per game for 2020 free agent class are all All-Stars: Giannis Antetokounmpo, Anthony Davis, and Rudy Gobert. All of which have high amounts of minutes per game. This is a helpful baseline statistic to understand since it has evolved greatly over time into other efficiency metrics such as PER (created by John Hollinger), Game Score Ratings, WINVAL, Box Score Plus/Minus, and VORP. Box Score Plus/Minus is a similar rating but has a true zero to show their added effect relative to not being on the court. That is to say, if a player has a negative box score plus/minus, it would be suggested they may bring down other players. In examining the free agency class, players like Mitchell Robinson and Daniel Theis have a similar if not better BPM than Rudy Gobert but at a fraction of the price. At a nearly +6 rating, they should be considered to be having "All-NBA" like seasons. One simple observation is that a majority of the high-ranking BPM Free Agent players are C/PF who likely handle the ball less. These players are likely playing with high production offensive players. Players like Steven Adams ranks high playing with the likes of Chris Paul and Shai Gilgeous-Alexander who are effective at creating offense and high percentage shots. This could be a strategy for a team

that has an effective ball-handler in search of someone to convert on their ability to pass. As mentioned previously, VORP is one of the more developed metrics at determining a player's production when replaced (similar to WAR in baseball). VORP stands for Value Over Replacement Player or average above the median producing player. This metric aims to primarily calculate a relative effect of a player on that lineup. Mitchell Robinson at 21 has a VORP of 2.2, which is slightly lower than Gobert's 3.2. This is important for teams looking to capitalize on players to pair with stars and not break the bank (Robinson's salary is a fraction of Gobert's). The point of understanding the efficiency metrics is to get one comparison for a portfolio of on-court production, which is helpful in identifying players to acquire.

Another strategy to look at is utilizing Linear Programming in optimizing the lineup based on a production metric and certain constraints such as salary. Optimizing lineups is a concept Fangraphs brought about (Petti, 2012) in creating value in every hitting position for baseball. Hans Man used machine learning and efficiency metrics to build a team based on minutes production (Man, 2017). However, we've yet to see LP models in reference to building NBA rosters. For this, we identified player win score as an effective metric for determining a player's relative effect based on linear weights. For the Lakers, we optimized their current season roster and saw that a lineup of Avery Bradley, Anthony Davis, LeBron James, Kyle Kuzma, and Javale McGee would yield 41 wins, which is interesting since this combination has only been on the court at the same time for only 7 minutes this season (Appendix B). Given this, their free agency strategy would likely be to retain Anthony Davis to keep their optimized lineup together. For the construction of the linear model, we used the constraints that the starting lineup should exceed no more than 75% of the NBA salary cap of \$115M next summer (in hopes to fill out the rest of the roster). We also set the following lineup constraints:

#1 = PG

#2 = SG
 #3 = SG/SF/PF
 #4 = PF
 #5 = PF/C

This lineup allows us to be flexible in two positions given the position-less league. This lineup optimization lineup is also helpful to understand when we substitute a player into the mix, if that changes the optimal lineup. We subsequently ran two tests for lineup optimization. One included all available free agents in combination of our current roster and the other strictly gave the #1 to LeBron James and the #4 to Anthony Davis to represent a very real scenario. In both scenarios, we didn't find a solution that was feasible, which would indicate that the player acquisition strategy should be set to finding players to fill out the rest of the roster based on our player profile deficiencies and to find players at production values (such as Richaun Holmes or Mitchell Robinson).

Player Clustering & Principal Components Analysis

Another strategy for player acquisition is to look at grouping free agents based on clusters in order to determine the different types of players available on the market. As mentioned earlier, the NBA is becoming a position-less league so assessing free agents based on positions limits a team's ability to understand a player's true value. Haider Hussain used Principal Components Analysis (PCA) along with K-means clustering to come up with 9 groups of players. Data was collected from 2011-2018 on each player because 2011, according to Hussain, was when position less basketball started to take form. Patel et al. (2017) used t-Distributed Stochastic Neighbor Embedding (t-SNE) and PCA along with K-means and found 4 groups of players with similar playing styles. They also looked at NBA teams and how players on those teams match the clusters that they came up with to see if there were any correlations between the clusters and winning teams.

For this analysis, the *sklearn* module is used to do a PCA and then a cluster analysis. Data was retrieved from basketballreference.com. A list was gathered of the potential free agents for 2020-21 summer and noted down their playerIds on basketballreference.com. A crawler was then set up in Python using *BeautifulSoup* library and *urllib.request* module to get per game season and career averages and the table was parsed for a player's career for further analysis. Using a PCA K-means, we identified 4 different clusters. PCA helped to reduce 26 features to 3 principal components in order to help to parse out their clusters. Below are the results of the cluster analysis on the free agents:

| Player | Position | Cluster |
|-----------------------|----------|---------|
| Daniel Theis | C | 0 |
| Ers Kanter | C | 0 |
| Nemanja Bjelica | PF | 0 |
| Richaun Holmes | C | 0 |
| Anthony Davis | C | 1 |
| DeMar DeRozan | SG | 1 |
| Giannis Antetokounmpo | PF | 1 |
| LaMarcus Aldridge | PF | 1 |
| Brandon Ingram | SF | 2 |
| Gordon Hayward | SF | 2 |
| Kyle Lowry | PG | 2 |
| Andre Drummond | C | 3 |
| Mitchell Robinson | C | 3 |
| Rudy Gobert | C | 3 |
| Steven Adams | C | 3 |

The first cluster can be characterized as “backup big men”. These are big men who can come off the bench and give you 6-10 points per game (PPG) and 4-7 Rebounds per game (RPG). The second cluster are your “superstars” and these are your players who can put up 19-24 PPG and average 32-34 min. The third cluster are your “role players” who get you roughly 14-16 PPG and shoot beyond the arc. The last cluster is your “mid-level big men” who can get you around 8-14 PPG along with 6-14 RPG.

Looking at our current roster, Anthony Davis, set to be a free agent at the end of the 2019-2020 season, is averaging the most PPG and RPG placing him in the “superstar” cluster. We could also use another big man that was characterized in the last cluster as “mid-level big men” who can get you around 8-14 PPG and 6-14 RPG. DeMarcus Cousins was supposed to fill that role but due to injuries that was not a reality this season.

Shooting Heatmaps

In addition to Richaun Holmes, Chris Boucher has been identified as potential targets in next summer’s class. Our next step was to acquire their shot data to see how their shooting patterns might fit in with the rest of the team and would fill the team needs. The shot data was acquired for all of the players examined through the ballR package in R that allows a user to select a player, season, and several different types of shot charts that can then be edited in a variety of different ways. One hypothesis is that Richaun Holmes and Chris Boucher would have high efficiency given their position. Goldsberry’s article of How Mapping Shots in the NBA Changed it Forever would suggest that both Holmes convert at a rate 50-60% assuming they are positioned at a lower post for higher conversion. High converting big men are often overlooked in today’s shooting centric NBA. For example, Boban Marjanovic has the highest Points per Shot Attempt of All-Time at 1.62 (Herring, C. 2018) yet he as of 2018, he had yet to play 1,000 minutes in 3 seasons.

In order to test this hypothesis that Richaun Holmes and Chris Boucher would have high efficiency given their position, and to see the amount of these high efficiency shots that they were taking, their shot charts were examined. The first chart that is seen as Appendix C below is a Hexagonal shot chart for Richaun Holmes for the 2019-2020 season and shows the frequency

of his field goal attempts by location and how he compares to the league average for that respective part of the court.

As can be seen from this Hexagonal shot chart, Richaun Holmes is a typical backup big man who does most of his work near the basket. He will not bring as much value as a big man who could stretch the floor by taking 3-point shots. However, he does shoot well above average in the “paint” and has somewhat extended range to at least the elbows of the court. Additionally, he shoots very well from the line for a big man, over 80% so far this year, so those shots near the paint will help to draw fouls and his high free throw shooting percentage will help the team capitalize on those fouls.

The next visualization, found in Appendix D below, of his Richaun Holmes’ shooting shows is the heat map of his most common shot locations with high frequency shot locations shown in lighter colors and low frequency shot locations shown in darker colors. This visualization is again for the 2019-2020 season that Richaun Holmes has spent with the Sacramento Kings. As can be seen from this heatmap, the vast majority of the shots that Richaun Holmes has taken so far this season have been at the basket. This heat map helps to illustrate even more clearly than the Hexagonal shot chart the frequency of shots that Richaun Holmes takes at the rim. The most valuable shots in basketball are dunks, free throws, and three pointers, so acquiring a player that will help with both dunks and free throws would be very valuable to a contending Lakers team.

The other player whose shot selection was examined was Chris Boucher of the Toronto Raptors. Appendix E below shows the Hexagonal shot chart for Chris Boucher this season. As can be seen from this chart, Chris Boucher is a typical new age big man, who has a number of shots near the rim and also beyond the three-point line. His field goal percentage near the rim is

not quite as good as Richaun Holmes, but he makes up for this by helping to space the floor more with his three-point shot selection. In particular, this is a valuable skill to have when paired with LeBron James, who has the ability to give everyone he plays with open looks from the 3-point line.

The next shot chart, in Appendix F below, shows Chris Boucher's shot heat map, with the frequency of his shot locations shown. What this heat map helps to show is that the majority of Chris Boucher's shots come close to the rim and it looks like he also has a floater or hook shot in his game from the bright spot that is slightly below the restricted area. However, this heat map also helps to show that the number of 3s that he takes is less than as it appears on the Hexagonal shot chart, but again this is something that can be changed and improved by playing on a Lakers team with LeBron James.

Approaching Player Valuation Models

After determining the players that we are going to be targeting in the upcoming off-season, examining their production statistics and shot charts, the next step is to figure out exactly how much to offer them in free agency or in a trade. Thus far, we've identified the Lakers should acquire a back-up big man. For player valuation modeling, we will also examine Malik Beasley (role player) in addition to Chris Boucher for upcoming summer. The data that was used to perform this analysis was also pulled from ballR. We combined current NBA salaries with the current season's statistics like PER, VORP, usage percentage, and other metrics to project future cost of acquisition.

Before launching into this analysis, the way that NBA salaries are determined needs to be examined. The NBA marketplace is not exactly one where a player's value is reflected in the salary that they command. There are many examples in recent years of players that have taken significantly less than the maximum amount that they could earn in free agency in order to sign

with teams that would enable them to compete for a championship. For example, in 2010, the Miami Heat were able to acquire LeBron James, and Chris Bosh because James, Bosh, and Wade all agreed to take smaller deals in order to fit under the salary cap. Unlike major league baseball, where there is no salary cap and a player's value are more accurately reflected in their salary, the NBA has a somewhat hard cap that forces teams to become creative when they want to sign multiple star players. In fact, the most recent CBA has made it harder for teams to do so, and has incentivized star players who were drafted by a franchise to then resign with original franchise for more money and an extra year.

In order to perform this analysis, the model was trained on players that were not in the last year of their current deals, as those players who are in the last year are more likely to be on a deal that is less reflective of their value. There are a number of different ways that this could be looked at, but ultimately there are a variety of factors to be considered and limiting the data in such a way appears to be an effective means to approximate value. Once the data was limited to players who are not on the last year of their current deal, the model was run on the players' VORP, usage percentage, age, and average minutes played per game to predict the value of their contract. A summary of the model is included below:

```
Call:
lm(formula = value ~ vorp + usgpercent + age.x + mp.x, data = train)

Residuals:
    Min       1Q   Median       3Q      Max
-17027348 -3302786   52243  3186662 13898394

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -35813819  4665843  -7.676 3.46e-12 ***
vorp         1710321   579656   2.951 0.00376 **
usgpercent    567328   118806   4.775 4.76e-06 ***
age.x        1037043   171242   6.056 1.40e-08 ***
mp.x          356061    79167   4.498 1.51e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5977000 on 130 degrees of freedom
Multiple R-squared:  0.7104,    Adjusted R-squared:  0.7015
F-statistic: 79.73 on 4 and 130 DF,  p-value: < 2.2e-16
```

Once this model was trained, a dataset of those players on the last year of their current deal was created to predict their upcoming value. What this model found was that Richaun

Holmes, Malik Beasley, and Chris Boucher are expected to see value increases this upcoming free agency. Below is a table that includes the values of their current salary for the 2019-2020 season and their predicted value for this year:

| <u>Player Name</u> | <u>2019-2020 Salary</u> | <u>Predicted Value</u> |
|--------------------|-------------------------|------------------------|
| Chris Boucher | \$1,985,289 | \$9,125,334 |
| Malik Beasley | \$3,895,424 | \$8,211,125 |
| Richaun Holmes | \$5,005,350 | \$12,183,930 |

Based on their statistics this year, it would seem that Richaun Holmes would be the more valuable player but Chris Boucher does have a good deal of upside and could probably be had at a value much lower than the \$9,125,334 that was predicted by the basic linear regression model.

Recommendations

Based on the analysis from this project on the 2020 NBA free agent class, **we recommend resigning Anthony Davis to a long-term extension.** As discussed earlier in the report, Anthony Davis ranks 8th in the league in win-scores and when combined with LeBron James account for 27 games in their production. This would be a huge loss in terms of the number of games the Los Angeles Lakers win next season if Anthony Davis is not signed. Based on the cluster analysis, Anthony Davis falls into the “superstar” cluster in the free agent class along with Giannis Antetokounmpo, DeMar DeRozan, and LaMarcus Aldridge. Failing to resign Anthony Davis would mean we would have to potentially look into another superstar of the same caliber which may be difficult due to salary cap restrictions and players commitment to their current team in resigning.

We also recommend signing Richaun Holmes and not resigning either Dwight Howard or Javale McGee for next season. As mentioned earlier, Richaun Holmes has a player win score

of 11.1 games and is only 29 years of age whereas Dwight Howard is 34 with a player win score of 8.3 and Javale McGee is 32 with a player win score of 6.95. **Also, given the fact that we waived DeMarcus Cousins and are still considering resigning him for next season, we recommend going after either Mitchell Robins or Daniel Theis.** These are both good potential replacements for Cousins and can be acquired at a fraction of the price of someone like Rudy Gobert who is also available this summer. As discussed earlier, these two players have a similar if not better BPM than Rudy Gobert and Mitchell Robinson has a VORP of 2.2 which can help complement our two stars without breaking the bank.

Overall all of the examples of lineup creation & optimization, PCA, charting shot selection, salary forecasts, and efficiency metrics are all strategies and tactics to deploy in targeting free agents for a given team. We realize there are a lot of limitations in our models such as variables not included. However, given the uncertainties of salary cap structure in the future, it is important for teams to identify their current efficiencies and deficiencies in order to assign proper player valuations in creating a player acquisition strategy.

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https://stats.nba.com/lineups/advanced/?Season=2019-20&SeasonType=Regular%20Season&TeamID=1610612747&sort=GP&dir=1&CF=GROUP_NAME*E*Bradley:GROUP_NAME*E*James:GROUP_NAME*E*Davis:GROUP_NAME*E*McGee:GROUP_NAME*E*Kuzma

Appendices

Appendix A - Player Win Score Tables

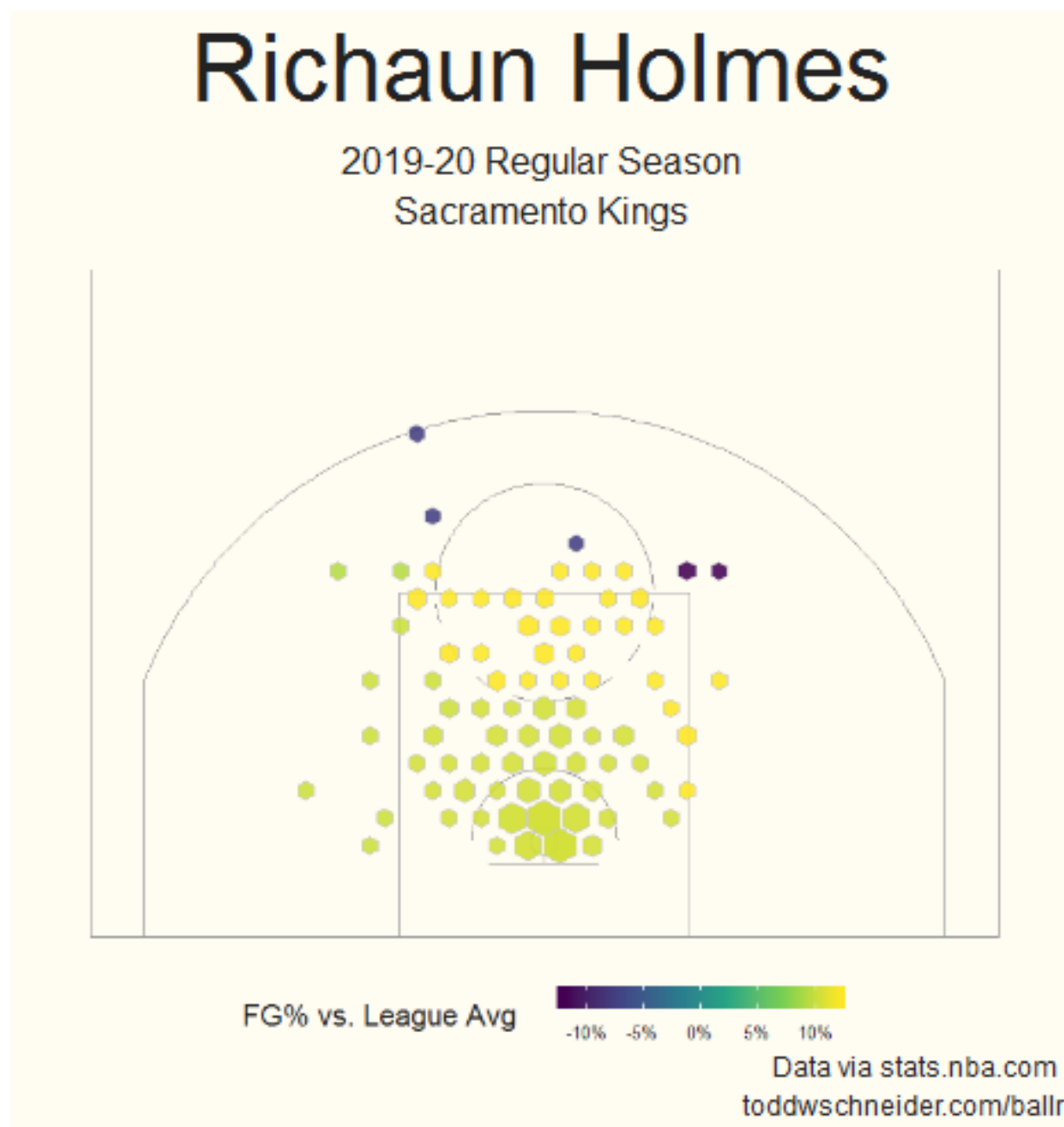
Laker's 2019/20 season player win score

| player <chr> | pos <chr> | age <dbl> | mp <dbl> | plyr_win_score <dbl> |
|--------------------------|---------------------|---------------------|--------------------|--------------------------------|
| Kostas Antetokounmpo | PF | 22 | 1.7 | 0.45 |
| Avery Bradley | SG | 29 | 23.5 | 2.45 |
| Kentavious Caldwell-Pope | SG | 26 | 25.3 | 3.55 |
| Alex Caruso | PG | 25 | 18.3 | 2.65 |
| Quinn Cook | PG | 26 | 11.4 | 1.10 |
| Troy Daniels | SG | 28 | 11.4 | 1.15 |
| Anthony Davis | PF | 26 | 34.6 | 14.85 |
| Jared Dudley | SF | 34 | 8.1 | 1.25 |
| Danny Green | SG | 32 | 25.0 | 4.70 |
| Talen Horton-Tucker | SG | 19 | 2.5 | 0.50 |
| Dwight Howard | C | 34 | 19.7 | 8.30 |
| LeBron James | PG | 35 | 34.9 | 12.60 |
| Kyle Kuzma | PF | 24 | 24.6 | 3.70 |
| JaVale McGee | C | 32 | 16.8 | 6.95 |
| Zach Norvell | SG | 22 | 2.5 | 0.00 |
| Rajon Rondo | PG | 33 | 20.9 | 4.35 |

Appendix B - Lineup Optimization

| player <chr> | pos <fctr> | age <dbl> | mp <dbl> | plyr_win_score <dbl> | value <dbl> | plyr_win_rank <int> |
|------------------------|----------------------|---------------------|--------------------|--------------------------------|-----------------------|-------------------------------|
| Avery Bradley | SG | 29 | 23.5 | 2.45 | 5005350 | 336 |
| Anthony Davis | PF | 26 | 34.6 | 14.85 | 28751774 | 8 |
| LeBron James | PG | 35 | 34.9 | 12.60 | 39219566 | 16 |
| Kyle Kuzma | PF | 24 | 24.6 | 3.70 | 3562178 | 254 |
| JaVale McGee | C | 32 | 16.8 | 6.95 | 4200000 | 96 |

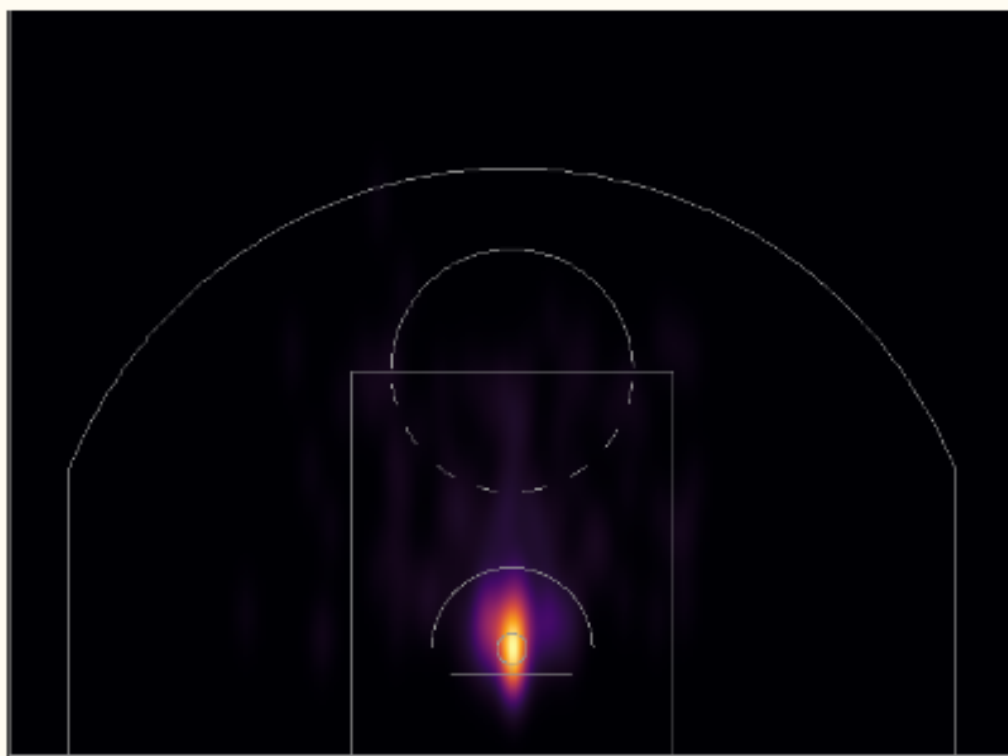
Appendix C - Richaun Holmes Hexagonal Shot Chart



Appendix D - Richaun Holmes Heat Map

Richaun Holmes

2019-20 Regular Season
Sacramento Kings



Shot Frequency



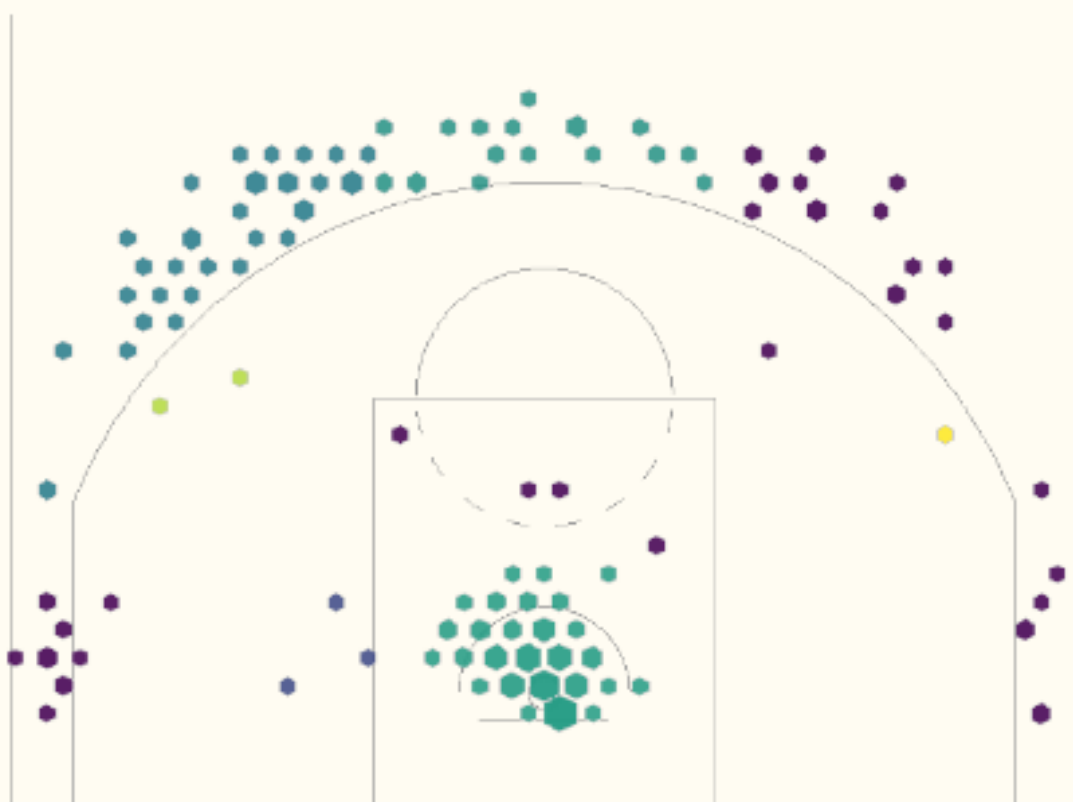
Data via stats.nba.com
toddwschneider.com/ballr

Appendix E -Chris Boucher Hexagonal Shot Chart

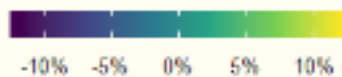
Chris Boucher

2019-20 Regular Season

Toronto Raptors



FG% vs. League Avg

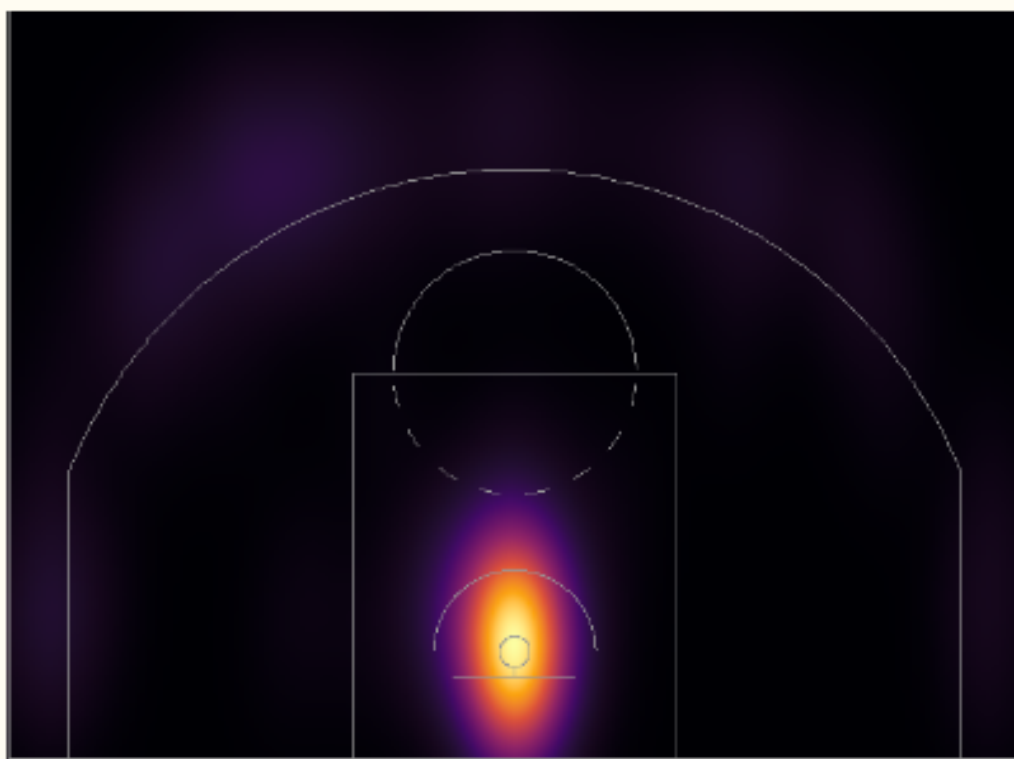


Data via stats.nba.com
toddschneider.com/ballr

Appendix F - Chris Boucher Heat Map

Chris Boucher

2019-20 Regular Season
Toronto Raptors



Shot Frequency



Data via stats.nba.com
toddwschneider.com/ballr