A Descriptive Model for NBA Player Ratings Using Shot-Specific-Distance Expected Value Points per Possession

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Abstract

This paper develops a player evaluation framework that measures the expected points per possession by shot distance for a given player while on the court as either an offensive or defensive adversary. This is done by modeling a basketball possession as a binary progression of events with known expected point values for each event progression. For a given player, the expected points contributed are determined by the skills of his teammates, opponents and the likelihood a particular event occurs while he is on the court. This framework assesses the impact a player has on his team in terms of total possession and shot-specific-distance offensive and defensive expected points contributed per possession. By refining the model by shot-specific-distance events, the relative strengths and weaknesses of a player can be determined to better understand where he maximizes or minimizes his team's success. In addition, the model's framework can be used to estimate the number of wins contributed by a player above a replacement level player. This can be used to estimate a player's impact on winning games and indicate if his on-court value is reflected by his market value.

1 Introduction

In any sport, evaluating the performance impact of a given player towards his or her team's chance of winning begins by identifying key performance indicators [KPIs] of winning games. The identification of KPIs begins by observing the flow and subsequent interactions that define a game. In general, any game can be described and played out as an ordered process of events or actions with varying subsequent reactions that yield a unit of value, most often represented as points scored. In basketball, the corresponding game flow is complex with dynamic interdependent player-to-player interactions making it difficult to asses a player's impact during a game. Current basketball player evaluation methods such as ESPN's proprietary Real Adjusted Plus-Minus (RAPM) and John Hollinger's PER incorporate a variety of information to address the underlying complexity of the game to value players, most notably through net points scored or box score statistics [PTS, REBS, AST, TO, etc.]. However, one of the limiting factors of these methodologies is that they attempt to measure the impact of a player on a macro scale by considering an observation period stretching multiple possessions, if not entire games.

Fundamentally, basketball games are played on a possession-by-possession basis and the eventual result of a basketball game is predicated on each team's possession efficiency. Teams that are more efficient offensively and defensively than their opponents will score more points, allow fewer points and win games. Possession efficiency is comprised of player actions on the court and the relative value is dependent on how a player influences the likelihood that certain events occur, specifically high-yield point events. For example, consider a Golden State Warriors regular season possession against the New Orleans Pelicans where forward Draymond Green sets a high ball-screen on teammate Steph Curry's defender that opens up an uncontested three-point basket for Curry. If this event were to repeatedly occur, Green's value would increase because more points would be expected per possession while he is on the court. Based on this observation, the model proposed in this paper asserts that a player's value should be measured according to the number of points per possession he contributes to his team by specifically taking into account the likelihood that certain events occur while he is on the court. How a player influences the events on the court will subsequently impact the expected number of points a team scores on a possession. Therefore, the amount of possessions that a player puts himself or his teammates, directly or indirectly, in position to produce high-yield point events should correspond to the value he brings to his team.

The model's framework is inspired by previous work by Joseph Kuehn in his paper, "Accounting for Complementary Skill Sets when Evaluating NBA Players' Values", presented at the 2016 MIT Sloan Sports Analytics Conference. Although conceptually similar, the model framework in this paper differs from Kuehn's work primarily in terms of intent and depth. While Kuehn uses his model to evaluate the impact that a player is likely to be associated with certain actions, its corresponding spillover effects on teammates and resultant substitutability, the model proposed in this paper limits the evaluation framework to metrics of points contributed per possession in terms of overall and shot-specific-distance events in terms of offensive and defensive contributions with the assumption a player has average teammates and is playing against an average set of opponents. This will be used to evaluate the overall and specific strengths and weaknesses of players and their relative corresponding value amongst peer players by using expected points as a metric of comparison.

2 Data

The data used for the model is play-by-play data from the 2015 – 2016 NBA season obtained from NBAstuffer.com. Due to time constraints on the project, the data used is from games played between October 20, 2015 to May 1, 2016, which includes all regular season games plus the first week of 2016 NBA playoffs. Each game split within the data can be categorized as an end of an event progression that can occur during a possession, list the five offensive and defensive players on the court and the distance of the shot attempt if applicable, among other items. Only players who were recorded to have been in all possible events were evaluated in the model. In addition, player information about position, team affiliation, minutes played per game and salary were gathered from ESPN.com and Basketball-Reference.com.

3 Model Structure

The player evaluation model is built upon an event progression tree that breaks down a basketball possession into subsets of binary events. As described in Section 3.1, for each event progression, the model sets an expected point value based on the outcome of the progression of events. The likelihood any event occurs on the court is determined by the player, teammates and opponent's skills, detailed further in Section 3.2 and 3.3. In total, the expected points per possession is the probability that each subsequent event occurs during a possession multiplied by the expected number of points. Although constructed similarly to RAPM, the model proposed in this paper differs from RAPM because it measures event likelihood and the corresponding impact on points scored as opposed to the differential in points scored while a player is on the court[1].

3.1 Descriptive Binary Tree Model

For a given possession, the model describes all possible actions and events that can occur using binary representation. The choice to use a binary tree was by design and meant to match the mathematical binomial Rasch model that is used to measure the probability that a given event occurs while a player is on the court that includes adjustments for teammates and opponents' skills. As illustrated in Figure 1 of the Appendix, the model breaks down a possession using binary splits. During a given possession, the five offensive players can either create a non-shooting foul or a non-foul event, such as turnover or shot attempt. In the case of a non-shooting foul, if the offensive team is not in the bonus, the possession continues from an out-of-bounds pass otherwise they are awarded two free-throw attempts. A non-foul event can either result in a turnover, which ends the possession, or a shot attempt. A shot attempt can either be a two-point or a three-point attempt. For both distances, the shot attempt can either be missed or made and for both outcomes it can either result in a no-foul or a foul event. If the shot attempt is missed and there is no foul, the possession continues if the offensive team secures the rebound otherwise it ends. If there is a foul on the missed shot, the offensive team is awarded either two or three free-throws. If the shot is made and there is no foul, the possession ends otherwise a foul on a made shot awards the offensive one additional free-throw attempt.

The tree models all free-throw shooting events as independent of the previous event. For example, the model treats a free-throw that occurred after a non-shooting foul the same as after a shooting foul event. In addition, instead of dissecting the free throw events by all possible missed-made shot combinations, the model uses the league average free throw percentage[2] and measures the probability that the last free throw is made or missed. If missed, the possession continues if the offensive team secures the rebound otherwise the possession ends.

In total, the binary tree models twenty-three possible outcomes during an NBA possession. For each outcome, there is an associated expected points returned. For example, if a player attempts a three-point basket, makes the shot and is not fouled, the expected points is three. If the possession ends in an offensive rebound, the expected points is the summation of any previously accumulated points and the average expected points per possession. As shown in Figure 1 of the Appendix, possession continuation events are designated with green boxes, end possession events are designated with red boxes and the expected points are designated with yellow boxes.

3.2 Non-Shot-Specific-Distance Player Model

Using the binary tree outlined in Section 3.1, the probability that a given event occurs is dependent on the skills of the player, his teammates and the opponents. As stated in Section 1, a player can influence the frequency of events on the court either directly or indirectly by putting himself or his teammates in position to commit actions that yield high expected points scored. The influence a player has on altering the likelihood that an events occurs impacts the expected points per possession and therefore indicates the relative value he brings to his team.

Given a branch split in the possession event tree, the probability that an event occurs during a possession is described using a binomial Rasch model that measures the probability with the following logistic function:

Equation (1)
$$P(y_{\gamma_i} = 1) = \frac{e^{\eta_{\gamma_i}}}{1 + e^{\eta_{\gamma_i}}}$$

where γ represents an event in the tree for the i^{th} player, where η is equivalent to:

Equation (2)
$$\eta_{\gamma_i} = \alpha_\gamma + \left(\sum_{j=1}^{5} \beta_{O_{\gamma_{ij}}} + \sum_{j=1}^{5} \delta_{D_{\gamma_{ij}}}\right) + \varepsilon_\gamma$$

where α represents the intercept, β represents the offensive, δ represents the defensive skills of the i^{th} and j^{th} player and ε represents the Gaussian error. Together, Equation 1 and Equation 2 provide the mathematical model that describes the probability that a given event occurs on the court with the i^{th} player playing with average teammates against average opponents. By measuring the probabilities of events in the possession event tree shown in Figure 1 of the Appendix, the expected points per possession for all possible event progressions can be calculated by multiplying each probability in a given event progression together with the known expected points of that sequence.

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[1] One of the primary inputs for ESPN's RAPM model.
[2] League average free-throw percentage was 75.7% during the 2015 – 2016 season.

3.3 Shot-Specific-Distance Player Model

The shot-specific-distance player model hypothesizes that a player performs better towards his strengths and one way this can be observed is through the distance of shot attempt events. By adapting the binary tree model described in Section 3.1 and the non-shot-specific-distance model outlined in Section 3.2 (Equation 1 and 2), the expected points per possession given a known shot distance for a player can be determined. In the context of Figure 1 from the Appendix, the shot-specific-distance player model assumes the progression of events during a possession results in a shot attempt, which eliminates the probabilistic impact of non-shooting events on the expected points per possession. In this case, the binary tree used to model a specific shot attempt distance is a subset of the comprehensive tree described in Section 3.1.

The shot-specific-distance player model divides a basketball court up into six different shot ranges and is shown within the context of a basketball court in Figure 3.3.1. In total, there are five two-point and one three-point ranges taken into consideration. Although the three-point shot attempt can be categorized into distance ranges, doing so for this model did not provide any additional insight for evaluating players as the majority of three-point shots are taken within the same range at about 24 to 26 feet from the basket. As a result, all three-point events were considered to be from one distance range.

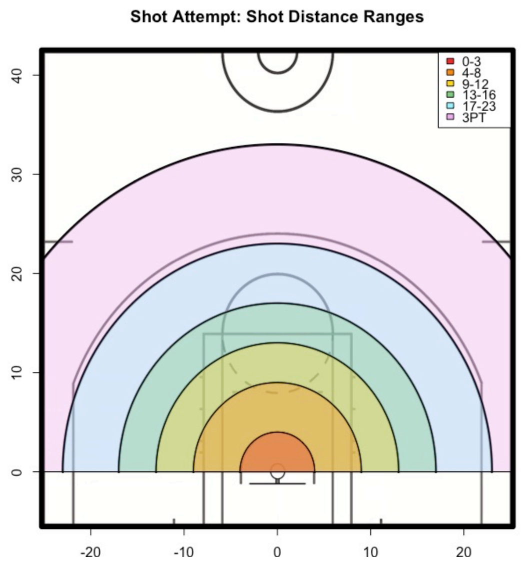

Figure 3.3.1: Shows the shot-specific-distance range breakdown within the context of an NBA court.

The possession event tree used for a two-point shot attempt and three-point shot attempt are shown in Figure 2 and Figure 3 of the Appendix respectively. The most notable difference between the two event trees is the level in which the tree assesses the probability that a shooting foul occurs. Since, the play-by-play data used for the model does not assign distances to missed two-point attempts that draw a foul, it is impossible to classify these events by shot-distance without the assistance of SportVU data. As a result, the original configuration of the two-point shot attempt sub-tree was redefined to consider the probability of a foul event before assessing whether the shot was missed or made. The reconfigured tree shown in Figure 2 of the Appendix accounts for shot-specific distance on the left side of the tree while generalizing the frequency of a foul event based on all two-point shot attempt distances on the right side. Since the model categorizes all three-point shot attempts equal regardless of distance, the three-point sub-tree was not altered from the original event tree and is shown in Figure 3 of the Appendix.

Given a branch split from either shot-specific-distance possession event tree, the probability that an event occurs is modeled using Equation 1 above, however, η in this case is equivalent to:

Equation (3) $$\eta_i = \alpha + \theta_{R1} + .. + \theta_{R6} \left(\sum_{j=1}^{5} \beta_{O_{\gamma\_R1_{ij}}} + \sum_{j=1}^{5} \delta_{D_{\gamma\_R1_{ij}}}\right) + \ldots + \left(\sum_{j=1}^{5} \beta_{O_{\gamma\_R1_{ij}}} + \sum_{j=1}^{5} \delta_{D_{\gamma\_R1_{ij}}}\right) + \epsilon_i$$

where α represents the intercept, θ represents the coefficient for a given shot range, β represents the offensive, δ represents the defensive skills of the i^{th} and j^{t} player and ε represents the Gaussian error. The notation R_1 to R_6 denotes the range of the shot attempt with R_1 representing the closest and R_6 representing the farthest range from the basket.

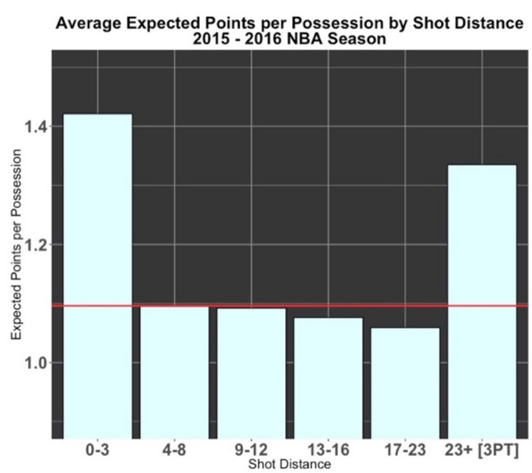

Figure 3.3.2: Shows the 2015 - 2016 league average expected points per possession for a shot attempt given a location on the court. The red line is the average expected points per possession regardless of a shot attempt event.

Figure 3.3.2 above shows the league average expected points per possession by shot attempt distance for the 2015 – 2016 season. As indicated by the results, for a lineup with five average players competing against five average opponents, the highest expected return in points scored per possession came when shots were taken within three feet of the basket. From this range, teams increased the possession point expectancy by 0.327 points[3]. The least valuable shot attempt came from shots taken between 17 to 23 feet from the basket where teams saw a decrease of 0.035 points from the average. In general, as the shot distance extends away from the basket, the point expectancy diminishes until the shot extends beyond the three-point line. At this distance, the additional increase in value from two to three points makes a three-point attempt the second most valuable range despite its distance. An interesting observation to note, the model's results support the philosophy of Daryl Morey, general manager of the Houston Rockets, coined "Moreyball", which states that scoring efforts should be focused on attempts near that basket and behind the three-point line because of their high point expectancy value while long distant two-point shot attempts should be avoided because of their low point expectancy value.

3.3.4 Adjusting Expected Points for Playing Time

Without adjustment, the expected points per possession unrealistically assumes that a player plays the entire duration of the game. To adjust the model, a player's expected points per possession is factored using the following equation:

Equation (4)
$$\mathrm{EVP_i} = \frac{\mathrm{MPG_i}}{48} * \left[\mathrm{EVP_i} - \mathrm{EVP_{Average}}\right] + \mathrm{EVP_{Average}}$$

where $\mathrm{EVP_i}$ represents the expected points per possession for the i^{th} player, $\mathrm{MPG_i}$ represents the average minutes played per game for the i^{th} player and $\mathrm{EVP_{Average}}$ represents the league average expected points per possession. The adjustment described in Equation 4 gives a more realistic estimate of the expected points per possession for a player.

4 Non-Shot-Specific-Distance Results

Figure 4.1 shows the results of the model in terms of overall offensive, defensive and net-expected points per 100 possessions. By plotting each player by their offensive point expectancy (y-axis) and defensive point expectancy (x-axis), a player's relative skills and strengths between offensive and defensive impact can be compared. In addition, each player is mapped based on his net-expected points per 100 possessions which is measured by the difference between his offensive and defensive point expectancy while on the court. Players that create a net-positive impact on score differential will be green while players that create a net-negative impact will be orange. As mentioned in Section 3.3, the league average expected points per 100 possessions is 109.5 points. As will be discussed in further detail in Section 6, a replacement level player led-offensive team and defensive team was valued to score 107.7 points and allow 111.1 points per 100 possessions respectively.

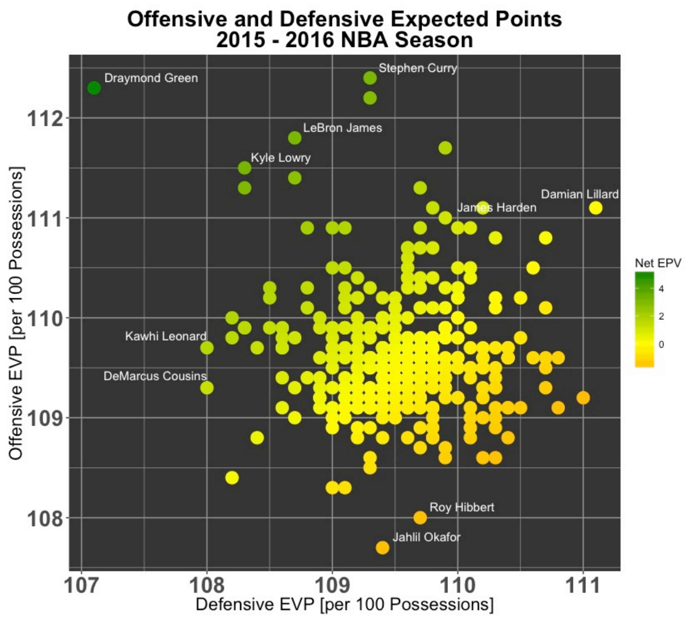

Figure 4.1: Plots offensive against defensive expected points per 100 possessions for each player in the model, colored by net point differential.

Table 4.1: A complimentary value table for Figure 4.1. To see full top and bottom 15 rankings see Appendix Tables 1 - 6.

Player	$\mathrm{EPV_{OFF}}$	$\Delta_{\mathrm{Average}}$	$\mathrm{EPV_{DEF}}$	$\Delta_{\mathrm{Average}}$	$\mathrm{EPV_{NET}}$
Draymond Green	112.3	2.8	107.1	-2.5	5.2
Steph Curry	112.4	2.9	109.3	-0.2	3.1
LeBron James	111.8	2.3	108.7	-0.9	3.1
Klye Lowry	111.5	2.0	108.3	-1.3	3.2
Damian Lillard	111.1	1.6	111.1	1.6	0.0
James Harden	111.0	1.5	109.9	0.4	1.1
Kawhi Leonard	109.7	0.2	108.0	-1.6	1.7
DeMarcus Cousins	109.3	-0.2	108.0	-1.6	1.3
Roy Hibbert	108.0	-1.6	109.7	0.2	-1.7
Jahlil Okafor	107.7	-1.8	109.4	-0.1	-1.7

[3] The average expected points per possession regardless of a shot attempt was 1.094 points for the 2015 – 2016 season.

Players plotted in the upper half of Figure 4.1 are considered above average to exceptional offensive impact players. This group is led by the model's best offensive player, Steph Curry, who had an expected 112.4 points per 100 possessions or 2.9 points above a league average player. Players plotted on the left are valued as above average to exceptional defensive impact players. This group is led by the model's best defensive player, Draymond Green, slightly above well-known defensive stalwarts Kawhi Leonard and DeMarcus Cousins, at 107.1 points allowed per 100 possessions or 2.4 points below a league average player. Players that are plotted in the upper-left quadrant of Figure 4.1 are considered the best overall players with the highest net-expected points while on the court. This group is led by the model's best overall impact player, Draymond Green, who contributed a positive 5.2 points per 100 possessions while on the court. Tables 1 – 6 of the Appendix detail the full top and bottom 15 players by category.

5 Shot-Specific-Distance Results

As outlined in Section 3.3, the shot-specific-distance player model is based on the assumption that a possession leads to a shot attempt and examines the resultant expected points given a known distance on the attempt. The shot-specific-distance model proposes that the relative strengths of a given player can be observed by shot-distance. As a result, the model's purpose is to identify players that excel in specific scenarios or roles given a shot attempt event, which is the most common event that occurs during a possession. Tables 5.1 and 5.2 below describe the top three offensive and defensive players in the model by shot attempt distance. Tables 7 – 16 of the Appendix detail the top and bottom 10 offensive and defensive players for each two-point shot attempt distance while Tables 17 – 26 show the top and bottom 10 offensive and defensive players by position for a three-point shot attempt.

Table 5.2: Shows the top three offensive players by two-point shot attempt distance. See Tables 7 – 11 of the Appendix for full top and bottom 10 offensive players by two-point shot attempt distance.

0 - 3		4 - 8		9 - 12		13 - 16		17 - 23	
Player	**EPV_{OFF}**	**Player**	**EPV_{OFF}**	**Player**	**EPV_{OFF}**	**Player**	**EPV_{OFF}**	**Player**	**EPV_{OFF}**
Russell Westbrook	1.446	Joe Johnson	1.115	Damian Lillard	1.107	Kevin Durant	1.103	Russell Westbrook	1.080
James Harden	1.444	Thaddeus Young	1.113	Kyle Lowry	1.105	Russell Westbrook	1.095	Harrison Barnes	1.077
Draymond Green	1.442	Serge Ibaka	1.113	Russell Westbrook	1.105	Serge Ibaka	1.093	Kyrie Irving	1.077

Table 5.2: Shows the top three defensive players by two-point shot attempt distance. See Tables 12 – 16 of the Appendix for full top and bottom 10 defensive players by two-point shot attempt distance.

0 - 3		4 - 8		9 - 12		13 - 16		17 - 23	
Player	**EPV_{DEF}**	**Player**	**EPV_{DEF}**	**Player**	**EPV_{DEF}**	**Player**	**EPV_{DEF}**	**Player**	**EPV_{DEF}**
C.J. McCollum	1.403	Stephen Curry	1.082	Marcin Gortat	1.072	Klay Thompson	1.061	Brook Lopez	1.046
Robert Covington	1.403	Danny Green	1.082	Kyle Lowry	1.077	Gary Harris	1.062	DeAndre Jordan	1.046
Rudy Gobert	1.408	Chris Paul	1.082	John Wall	1.079	Kevin Durant	1.064	Ian Mahinmi	1.046

5.1 Valuing Three-Point Defensive Impact Players

The fastest growing movement in the NBA is a shift in style of play towards "small ball". Small-ball consists of lineups that are guard orientated with interior post players that are skilled three-point shooters that can spread the court on offense by placing a demand on taking three-point shot attempts. Initiated by the Phoenix Suns in the mid-2000's, the style of play has become widespread throughout the league with the reigning NBA champion Golden State Warriors demonstrating a mastery of the style of play. Highlighted previously in Section 3.3, Figure 3.3.2, the three-point shot attempt is a worthwhile investment as it provides a significant boost in expected points scored per possession by 0.236 points over an average possession. In an effort to minimize the impact of small-ball lineups, general managers have placed a premium on players that can provide a defensive impact on three-point shot attempts. Without capable players on the court that can provide an impact any small-ball defensive scheme is limited in its effectiveness.

Table 5.3: Shows the top and bottom three defensive players by position for three-point shot attempts. See Tables 17 – 26 of the Appendix for full top and bottom 10 offensive and defensive players by position for three-point shot attempts.

	PG	SG	SF	PF	C
Top	Deron Williams	Arron Afflalo	Kawhi Leonard	Draymond Green	Andre Drummond
Top	Elfrid Payton	Kyle Korver	Paul George	Kevin Love	DeMarcus Cousins
Top	Goran Dragic	Wesley Matthews	Rudy Gay	Luol Deng	Ian Mahinmi
Bottom	Jameer Nelson	Dion Waiters	Maurice Harkless	Mirza Teletovic	Karl-Anthony Towns
Bottom	Ish Smith	Bradley Beal	Jeff Green	Thomas Robinson	Nikola Jokic
Bottom	John Wall	Jamal Crawford	C.J. Miles	Zach Randolph	Dwight Howard

One significant feature of the shot specific model is its ability to provide insight into which players are most impactful at given shot distances. In this case, the model is used to evaluate players by their defensive three-point impact by position with the top and bottom three players shown in Table 5.3. The results do not indicate that these players are exceptionally good or bad in one-on-one defensive matchups at this distance, but that while they are on the court, their teams perform exceptionally well or poorly against the three-point shot attempt. Tables 17 – 21 of the Appendix detail the top and bottom offensive three-point players by position while Tables 22 – 26 detail the top and bottom defensive three-point players by position.

5.2 Assessing the Strengths and Weaknesses of the Cavaliers' "Big Three"

In addition to identifying player strengths in specific scenarios described in Section 5.1, the relative impact a player has can also be compared amongst peer players by examining their point expectancy impact across the six shooting ranges. For example, this assessment can be done for teammates to compare how their relative strengths and weaknesses coalesce together and as a small case study is done for the Cleveland Cavaliers' top three players: Kevin Love, Kyrie Irving and LeBron James.

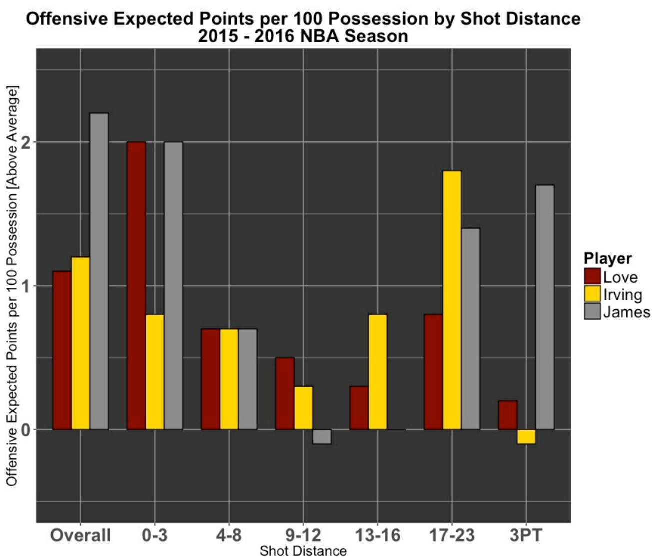

Figure 5.2.1: Shows the offensive expected points per 100 possessions for Kevin Love, Kyrie Irving and LeBron James above the league average.

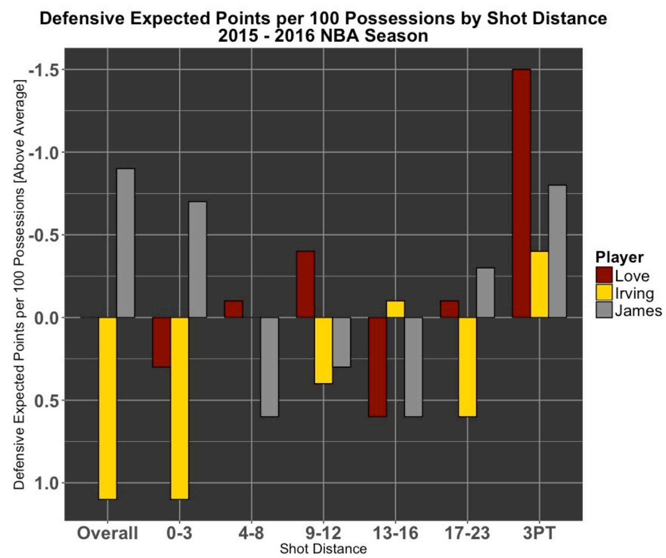

Figure 5.2.2: Shows the defensive expected points per 100 possessions for Kevin Love, Kyrie Irving and LeBron James below the league

Figures 5.2.1 and 5.2.2 show the offensive and defensive points expected per 100 possessions above the league average for Love, Irving and James while they are on the court assuming average teammates playing against average opponents. Offensively, James provides the most impact, specifically when shots are taken close to the basket and from three-point distance, which could be attributed to James' physical ability to score close to the basket or draw off-ball defenders towards James allowing him to pass out to open perimeter shots. Irving and Love are both above average offensive impact players, but their skills complement each other well. Love excels close to the basket while Irving excels from mid to deep ranged two-point attempts. Defensively, James provides the greatest overall impact specifically close to the basket while Love is an exceptional three-point defensive impact player. The most glaring observation is Irving's poor defensive impact play, especially when shots are taken within 12 feet of the basket. Although James provides a significant boost from this range, both Love and Irving's below average impact defensive skills in this range could prove to be their largest weakness where as their greatest strength is in defending long distance shots. Irving's average overall net-point expectancy could also explain why the Cavaliers did not see a significant boost in wins while Irving was the primary player before James returned to Cleveland in 2014.

6 Wins Above Replacement

With expected points contributed on offense and allowed on defense per possession, a players estimated wins produced in substitution of a replacement level player (WAR) can be computed using Bill James win expectancy formula adjusted by Daryl Morey for basketball. A replacement level player is a player that any team can acquire at any point during the season and are typically players that play on 10-day contracts, receive minimal playing time or are not part of the regular rotation. By estimating the number of wins produced by a player, their on-court expected points contributed per possession can be additionally translated into wins.

6.1 Method of Calculation

In this model, replacement level players were considered to have the worst expected points per possession offensively and defensively because of the data filtering process outlined in Section 3, which removed players from the model that did not participate in all possession outcomes. The method used to calculate the WAR of a player considers the points scored and allowed per possession by the specific player, an average level player, a replacement level player and the average number of minutes that the specific player plays per game. Daryl Morey's basketball win expectancy equation below is then used to calculate the expected winning percentage for a team with that player on the court.

Equation (5)
$$\mathrm{win\%_{Player\ i}} = \frac{\mathrm{P_{s_i}}^{13.91}}{\mathrm{P_{s_i}}^{13.91} + \mathrm{P_{a_i}}^{13.91}}$$

where $\mathrm{win\%_{Player\ i}}$ is the win-lost percentage for a given player, P_s is the points scored per game, P_a is the points allowed per game and 13.91 is the statistically acceptable coefficient to predict win-lost percentages in basketball determined by Morey. For each player the points scored is a combination of the factored points scored per possession while a player was on the court and the points scored while he was off the court assuming an average set of teammates, specifically described as:

Equation (6)
$$\mathrm{P_{s_i}} = \frac{\mathrm{MPG_i}}{48} * 100\mathrm{Poss} * \mathrm{EPV_{OFF_i}} + \left[1 - \frac{\mathrm{MPG_i}}{48}\right] * 100\mathrm{Poss} * \mathrm{EPV_{OFF_{AVG}}}$$

Equation (7)
$$\mathrm{P_{a_i}} = \frac{\mathrm{MPG_i}}{48} * 100\mathrm{Poss} * \mathrm{EPV_{DEF_i}} + \left[1 - \frac{\mathrm{MPG_i}}{48}\right] * 100\mathrm{Poss} * \mathrm{EPV_{DEF_{AVG}}}$$

where MPG is the average minutes per game for $\mathrm{player_i}$, EPV is the expected points per possession scored on offense or allowed on defense and is multiplied by 100 possessions[4]. For each player, the corresponding winning percentage can be calculated using Equation 5 and then applied to Equation 8 to measure the total number of wins a player contributes above a replacement level player over 82 game season.

Equation (8)
$$\mathrm{WAR_i} = \left[\mathrm{win\%_i} - \mathrm{win\%_{replacement}}\right] * 82$$

6.2 Player WAR with Respect to Compensation

Shown below in Figure 6.2.1 is each player's calculated WAR value plotted against their 2015 – 2016 salary obtained from ESPN.com. In addition, each player's point is colored based on the total net expected points contributed per possession. As expected, there is a positive correlation between a player's net-EPV value and their WAR value. Players in the upper-half have the highest while player's in the bottom-half of the plot have the lowest WAR values. Players that provide the most value per dollar spent to their team lie in the upper-left quadrant while players who are worth the least per dollar spent are in the bottom-right quadrant of the figure.

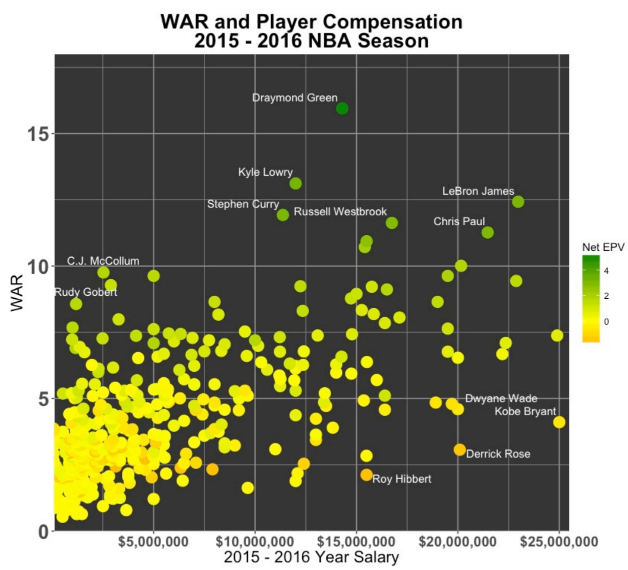

Figure 6.2.1: Plots players WAR against player salary for the 2015 – 2016 season. Each plot is colored based on net-point expectancy. Table 27 of the Appendix shows the top and bottom 25 WAR players.

[4] Considered the average amount of possessions in an NBA game during the 2015 – 2016 season.

Despite valued as the overall best player, Draymond Green is still considered undervalued by his market value despite recently signing a large contract extension with the Golden State Warriors during the 2015 off-season. As expected, consistent All-NBA caliber players such as LeBron James and Chris Paul are reasonably compensated for their impact on winning. Players such as Kobe Bryant, Derrick Rose and Roy Hibbert are considered overpaid for their on-court impact and represents a dubious financial investment by their respective teams or these players have experienced a decline in their on-court impact from when they initially signed their contract. It should be noted that because the NBA collective bargaining agreement specifies pay scales based on player experience, players such as C.J. McCullum and Rudy Gobert, both on rookie contracts, are limited in their compensation. It should be expected that once their rookie contract expires, they should be actively seeking to receive \$12 – \$15 million dollar contracts per year to fairly compensate for their value.

7 Conclusion

This paper develops a player evaluation framework that measures the expected value points per possession by shot-specific distance for a given player while on the court as either an offensive or defensive adversary. The model allows for insight into how a player impacts the game in terms of offensive and defensive contributions, but also based on specific shot distances. The model provides insight, but also establishes a springboard to understand why certain players excel or struggle in certain aspects of a basketball possession. For example, the model identified that a Kyrie Irving-led defensive team struggles when shot attempts are taken within 12 feet of the basket, which encourages further evaluation in these specific scenarios to understand why this might be the case (i.e. poor pick-and-roll defense). In addition to player insights, the model also creates a framework for translating player contributions on the court into winning games, which provides an additional metric to value a player's worth that can be used to identify the market value of players and whether they are under or over-valued by teams.

Moving forward, the model can be further improved if it follows a similar path to Joseph Kuehn's work in "Accounting for Complementary Skill Sets when Evaluating NBA Players' Values", presented at the 2016 MIT Sloan Sports Analytics Conference. His work takes into account the impact specific teammates have on the likelihood that certain actions occur on the court. Currently as it stands, the model presented in this paper measures player expected points per possession assuming four average teammates playing against five average opponents, which is not reflective of the true situations players are in on the court. Understanding specific player complimentary skill sets within the context of given shot attempt distances or sequences of events becomes valuable in assessing how a player would fit on another team, especially within the context of a given style of play philosophy, team weaknesses or specifically where players can improve their skills and minimize weaknesses. As described, an advanced version of this model would be beneficial for team building, matchup and player evaluations.

8 Appendix

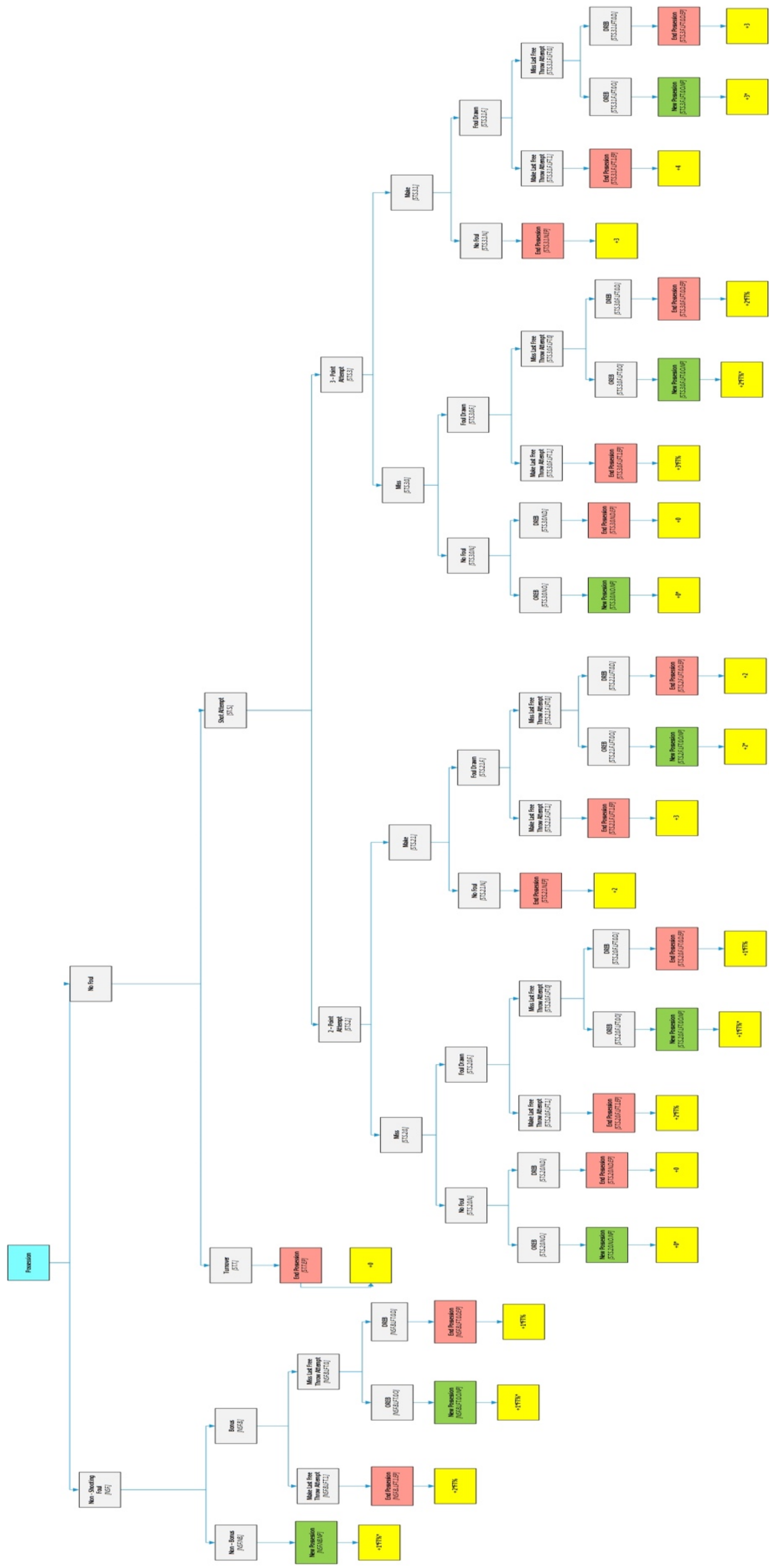

Figure 1: Event progression tree for the non-shot-specific-distance player model. A possession can be broken down into 23 different end results and is described in Section 3.1.

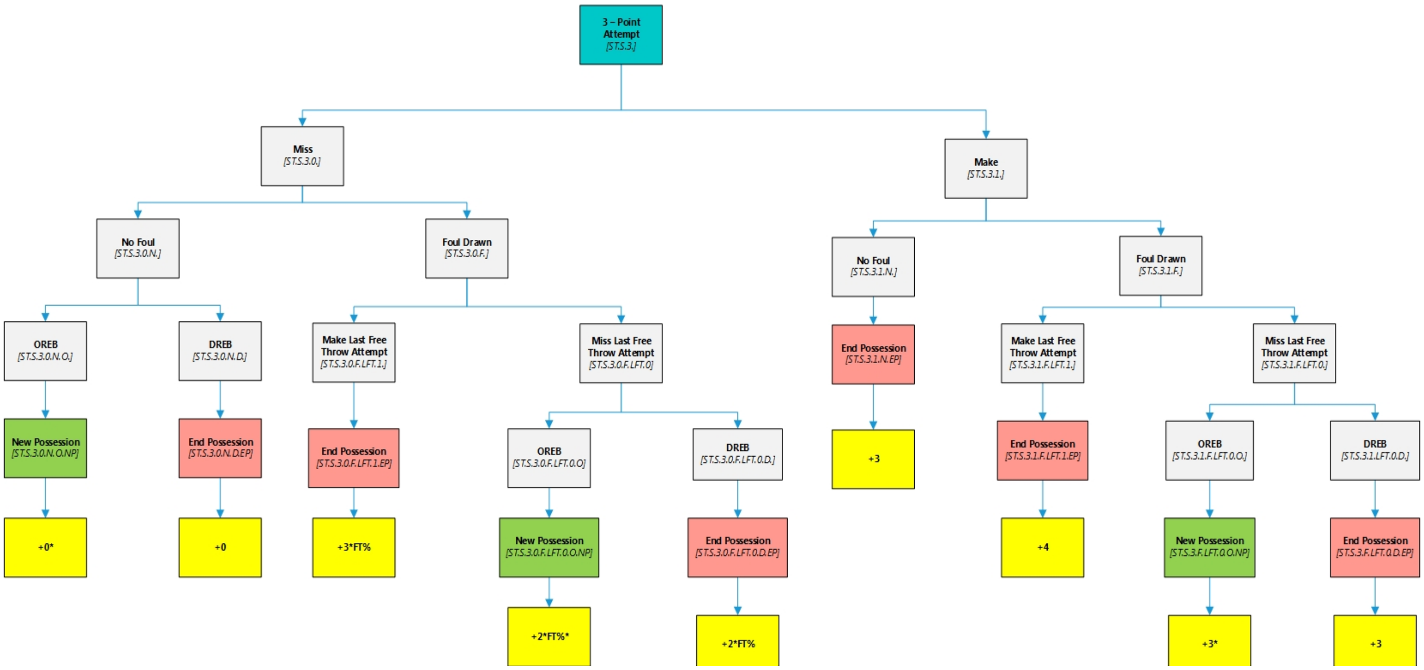

Figure 2: Event progression tree for the shot-specific-distance player model for a known two-point basket. A two-point shot attempt is broken up into 5 different ranges as diagrammatically shown in Figure 3.3.1.

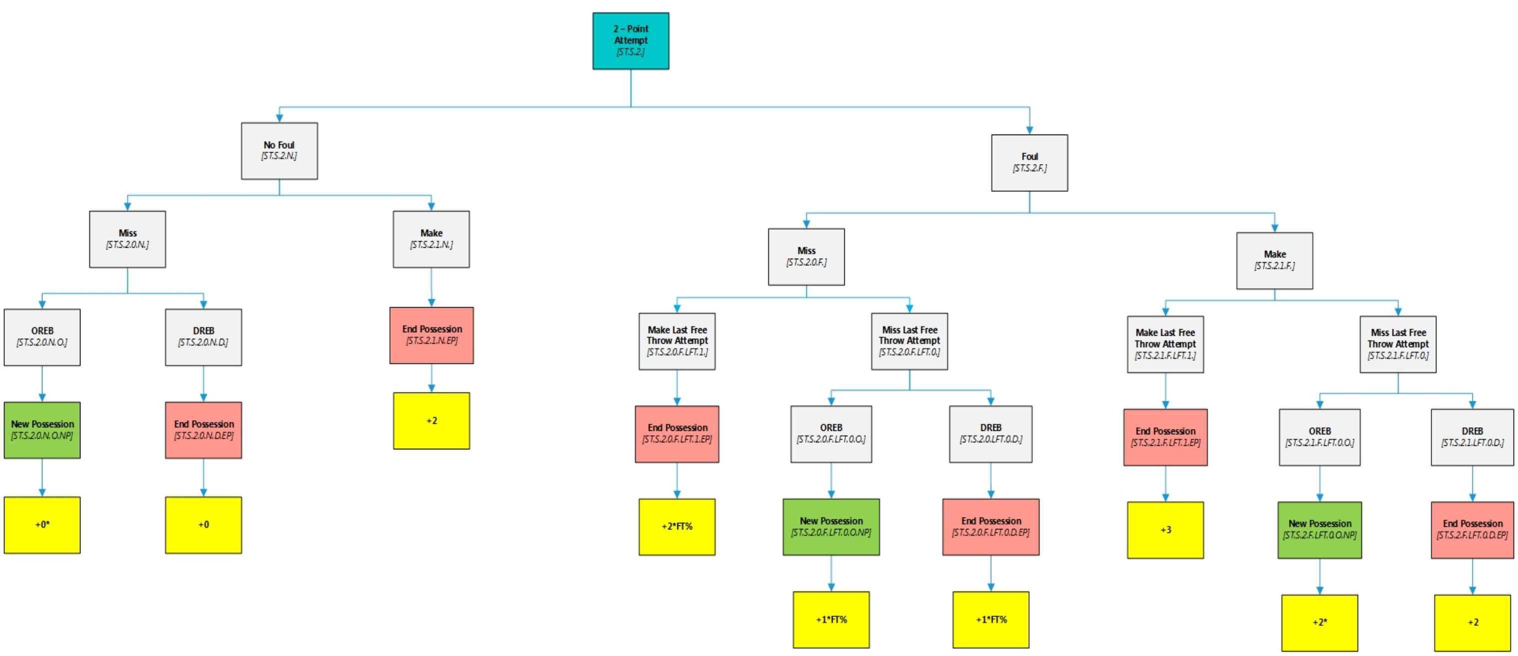

Figure 3: Event progression tree for the shot-specific-distance player model for a known three-point shot attempt. A three-point shot attempt consists of a single range stretching from the three-point line and beyond, distance varies based on location on court.

Tables 1 – 3: Shows the top - 15 offensive, defensive and net-expected points per 100 possessions players in the non-shot-specific-distance model. The offensive and defensive ratings are compared to the league average of 109.5 points per 100 possessions. The league average for net-expected points in 0.

Top – 15 Offensive EPV		
Player	EPV	$\Delta_{Average}$
Stephen Curry	112.4	2.9
Draymond Green	112.3	2.8
Russell Westbrook	112.2	2.7
LeBron James	111.8	2.3
Kevin Durant	111.7	2.2
Kyle Lowry	111.5	2.0
Klay Thompson	111.4	1.9
Carmelo Anthony	111.3	1.8
Chris Paul	111.3	1.8
Damian Lillard	111.1	1.6
Kentavious Caldwell-Pope	111.1	1.6
Wesley Matthews	111.1	1.6
James Harden	111.0	1.5
DeAndre Jordan	110.9	1.4
Gordon Hayward	110.9	1.4

Top – 15 Defensive EPV		
Player	EPV	$\Delta_{Average}$
Draymond Green	107.1	-2.5
DeMarcus Cousins	108.0	-1.6
Kawhi Leonard	108.0	-1.6
Brook Lopez	108.2	-1.3
Rudy Gobert	108.2	-1.3
Tim Duncan	108.2	-1.3
Chris Paul	108.3	-1.3
Kyle Lowry	108.3	-1.3
Marcus Morris	108.3	-1.3
Robert Covington	108.3	-1.3
Ian Mahinmi	108.4	-1.1
Justise Winslow	108.4	-1.1
C.J. McCollum	108.5	-1.1
Danny Green	108.5	-1.1
Kristaps Porzingis	108.5	-1.1

Top – 15 Net EPV	
Player	EPV
Draymond Green	5.2
Kyle Lowry	3.2
Stephen Curry	3.1
LeBron James	3.1
Chris Paul	3.0
Russell Westbrook	2.9
Klay Thompson	2.7
Gordon Hayward	2.1
DeAndre Jordan	1.9
Matthew Dellavedova	1.8
C.J. McCollum	1.8
Kevin Durant	1.8
Tim Duncan	1.8
Danny Green	1.7
Kawhi Leonard	1.7

Tables 4 – 6: Shows the bottom - 15 offensive, defensive and net-expected points per 100 possessions players in the non-shot-specific-distance model. The offensive and defensive ratings are compared to the league average of 109.5 points per 100 possessions. The league average for net-expected points in 0.

Bottom – 15 Offensive EPV		
Player	EPV	$\Delta_{Average}$
Ian Mahinmi	108.8	-0.8
Jerami Grant	108.8	-0.8
Luis Scola	108.8	-0.8
Kevin Martin	108.7	-0.8
Ty Lawson	108.7	-0.8
Blake Griffin	108.6	-1.0
Ersan Ilyasova	108.6	-1.0
Marco Belinelli	108.6	-1.0
Wayne Ellington	108.6	-1.0
Tyson Chandler	108.5	-1.1
Brook Lopez	108.4	-1.1
Marc Gasol	108.3	-1.3
Nerlens Noel	108.3	-1.3
Roy Hibbert	108.0	-1.6
Jahlil Okafor	107.7	-1.8

Bottom – 15 Defensive EPV		
Player	EPV	$\Delta_{Average}$
Shabazz Muhammad	110.4	0.9
Arron Afflalo	110.5	1.0
Jerryd Bayless	110.5	1.0
Karl-Anthony Towns	110.5	1.0
Darren Collison	110.6	1.1
Markel Brown	110.6	1.1
Devin Booker	110.7	1.2
J.J. Barea	110.7	1.2
Kyrie Irving	110.7	1.2
Will Barton	110.7	1.2
Zach LaVine	110.7	1.2
Bojan Bogdanovic	110.8	1.3
Jordan Clarkson	110.8	1.3
Julius Randle	111.0	1.5
Damian Lillard	111.1	1.6

Bottom – 15 Net EPV	
Player	EPV
Derrick Williams	-1.3
Nik Stauskas	-1.3
Jabari Parker	-1.3
Michael Beasley	-1.3
Wayne Ellington	-1.3
Andrea Bargnani	-1.4
Devin Booker	-1.4
Jerryd Bayless	-1.4
Derrick Rose	-1.6
Marco Belinelli	-1.6
Ersan Ilyasova	-1.7
Jahlil Okafor	-1.7
Jordan Clarkson	-1.7
Roy Hibbert	-1.7
Julius Randle	-1.8

Data Processing

Data analysis was not a direct process and required a multi-step effort that was completed strictly through R using four modules to collect, process and synthesize the data for analysis. Starting with a raw data file of all play-by-play splits for the 2015 – 2016 season, the four modules allowed final analysis by completing the following tasks:

1) Tag Data – Each play-by-play split was categorized based on the criteria to fit any of the twenty-three possible progression end-event splits shown in Figure 1 of the Appendix. The categorization used key identifiers such as shot, missed, turnover and foul from the data to classify ~408,000 of ~608,000 total splits in the dataset.

2) Sort Player Role – Each categorized play-by-play split sorted the home and away players on the court into offensive and defensive roles given the content of the end-event category. Additional information including shot distance, player responsible and team among others were kept.

3) Calculate Branch Split Beta and Probability Values – By representing the possession event tree in an array using the identifier code of each event, the beta values for each player for every split could be calculated by traversing the tree using recursion and the relevant substring of the end-event code.

4) Calculate Expected Points for Each Branch Progression – Mimicking a Huffman Encoding scheme to classify left branch nodes as 0 and right branch nodes as 1, the beta values could be transformed into probabilities for each split and then used to calculate the expected points for a given event progression for every player in the model.

Tables 7 – 11: Shows top and bottom 10 offensive expected points per possession players in the shot-specific-distance model. The offensive ratings are separated by distance and values are compared to the average expected points per possession for that

Top – 10 Offensive Players				**Table 7**	**Bottom – 10 Offensive Players**			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Russell Westbrook	OKC	1.446	0.025	**0 - 3**	Ramon Sessions	WAS	1.413	-0.008
James Harden	HOU	1.444	0.023		Norris Cole	NOP	1.413	-0.008
Draymond Green	GSW	1.442	0.021		Roy Hibbert	LAL	1.412	-0.009
Goran Dragic	MIA	1.442	0.021		Omer Asik	NOP	1.412	-0.009
Kevin Love	CLE	1.441	0.020		Derrick Rose	CHI	1.412	-0.009
LeBron James	CLE	1.441	0.020		Arron Afflalo	NYK	1.412	-0.009
Avery Bradley	BOS	1.440	0.019		Mike Conley	MEM	1.411	-0.010
Klay Thompson	GSW	1.440	0.019		Jameer Nelson	DEN	1.409	-0.012

Top – 10 Offensive Players				**Table 8**	**Bottom – 10 Offensive Players**			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Joe Johnson	BRK	1.115	0.020	**4 - 8**	Al Horford	ATL	1.085	-0.010
Thaddeus Young	BRK	1.113	0.019		Eric Bledsoe	PHO	1.085	-0.010
Serge Ibaka	OKC	1.113	0.019		Marco Belinelli	SAC	1.085	-0.010
Courtney Lee	CHO	1.111	0.016		Blake Griffin	LAC	1.084	-0.010
Victor Oladipo	ORL	1.110	0.015		Isaiah Canaan	PHI	1.084	-0.011
Brandon Bass	LAL	1.109	0.014		Jerami Grant	PHI	1.084	-0.011
Omri Casspi	SAC	1.108	0.014		Alex Len	PHO	1.083	-0.012
Nikola Vucevic	ORL	1.108	0.014		Matt Barnes	MEM	1.082	-0.013

Top – 10 Offensive Players				**Table 9**	**Bottom – 10 Offensive Players**			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Damian Lillard	POR	1.107	0.015	**9 - 12**	Hassan Whiteside	MIA	1.084	-0.008
Kyle Lowry	TOR	1.105	0.013		Blake Griffin	LAC	1.083	-0.009
Russell Westbrook	OKC	1.105	0.012		Victor Oladipo	ORL	1.083	-0.009
Danilo Gallinari	DEN	1.104	0.012		Wayne Ellington	BRK	1.083	-0.009
Eric Bledsoe	PHO	1.104	0.012		Elfrid Payton	ORL	1.083	-0.009
Serge Ibaka	OKC	1.104	0.011		Jahlil Okafor	PHI	1.081	-0.011
Jerryd Bayless	MIL	1.103	0.011		Marcin Gortat	WAS	1.081	-0.011
Dion Waiters	OKC	1.102	0.010		Kawhi Leonard	SAS	1.080	-0.012

Top – 10 Offensive Players				**Table 10**	**Bottom – 10 Offensive Players**			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Kevin Durant	OKC	1.103	0.027	**13 - 16**	Wayne Ellington	BRK	1.066	-0.011
Russell Westbrook	OKC	1.095	0.019		Marcus Smart	BOS	1.065	-0.011
Serge Ibaka	OKC	1.093	0.017		Marcin Gortat	WAS	1.065	-0.011
Gordon Hayward	UTA	1.093	0.016		Jordan Clarkson	LAL	1.065	-0.012
Isaiah Thomas	BOS	1.090	0.014		Monta Ellis	IND	1.064	-0.012
Allen Crabbe	POR	1.088	0.012		Brook Lopez	BRK	1.064	-0.012
Enes Kanter	OKC	1.088	0.012		Jahlil Okafor	PHI	1.063	-0.014
Jimmy Butler	CHI	1.087	0.011		D'Angelo Russell	LAL	1.062	-0.014

Top – 10 Offensive Players				**Table 11**	**Bottom – 10 Offensive Players**			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Russell Westbrook	OKC	1.080	0.021	**17 - 23**	Jahlil Okafor	PHI	1.047	-0.012
Harrison Barnes	GSW	1.077	0.018		Tyson Chandler	PHO	1.047	-0.012
Kyrie Irving	CLE	1.077	0.018		Elfrid Payton	ORL	1.047	-0.012
Kevin Durant	OKC	1.076	0.017		Michael Carter-Williams	MIL	1.047	-0.012
Serge Ibaka	OKC	1.076	0.017		Jordan Hill	IND	1.047	-0.012
Carmelo Anthony	NYK	1.075	0.015		Jabari Parker	MIL	1.046	-0.013
LeBron James	CLE	1.073	0.014		Marcus Smart	BOS	1.046	-0.013
Karl-Anthony Towns	MIN	1.072	0.013		Nerlens Noel	PHI	1.046	-0.014

Tables 12 – 16: Shows top and bottom 10 defensive expected points per possession players in the shot-specific-distance model. The defensive ratings are separated by distance and are compared to the average expected points per possession for that distance

Top – 10 Defensive Players				Table 12	Bottom – 10 Defensive Players			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
C.J. McCollum	POR	1.403	-0.019		Rudy Gay	SAC	1.436	0.015
Robert Covington	PHI	1.403	-0.018		Darren Collison	SAC	1.437	0.015
Rudy Gobert	UTA	1.408	-0.013		Julius Randle	LAL	1.437	0.016
LaMarcus Aldridge	SAS	1.408	-0.013	**0 - 3**	Hollis Thompson	PHI	1.437	0.016
Tony Snell	CHI	1.408	-0.013		Rajon Rondo	SAC	1.437	0.016
Andrew Bogut	GSW	1.409	-0.012		Zach LaVine	MIN	1.438	0.017
Serge Ibaka	OKC	1.409	-0.012		Jabari Parker	MIL	1.438	0.017
Amir Johnson	BOS	1.410	-0.012		Jordan Clarkson	LAL	1.439	0.017

Top – 10 Defensive Players				Table 13	Bottom – 10 Defensive Players			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Stephen Curry	GSW	1.082	-0.013		Goran Dragic	MIA	1.104	0.009
Danny Green	SAS	1.082	-0.013		Devin Booker	PHO	1.104	0.009
Chris Paul	LAC	1.082	-0.012		Jordan Clarkson	LAL	1.105	0.010
Kemba Walker	CHO	1.083	-0.012	**4 - 8**	Bojan Bogdanovic	BRK	1.105	0.010
Nikola Vucevic	ORL	1.083	-0.012		Greg Monroe	MIL	1.105	0.010
LaMarcus Aldridge	SAS	1.083	-0.011		Ersan Ilyasova	ORL	1.105	0.011
Jimmy Butler	CHI	1.084	-0.011		Bradley Beal	WAS	1.107	0.013
Kristaps Porzingis	NYK	1.084	-0.011		Nik Stauskas	PHI	1.108	0.013

Top – 10 Defensive Players				Table 14	Bottom – 10 Defensive Players			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Marcin Gortat	WAS	1.072	-0.020		Avery Bradley	BOS	1.099	0.007
Kyle Lowry	TOR	1.077	-0.015		Isaiah Thomas	BOS	1.099	0.007
John Wall	WAS	1.079	-0.013		Jrue Holiday	NOP	1.099	0.007
C.J. McCollum	POR	1.080	-0.012	**9 - 12**	Greg Monroe	MIL	1.099	0.007
Kevin Durant	OKC	1.080	-0.012		Al Jefferson	CHO	1.100	0.008
Marcus Morris	DET	1.081	-0.011		Ramon Sessions	WAS	1.100	0.008
Bismack Biyombo	TOR	1.082	-0.011		Jerryd Bayless	MIL	1.100	0.008
Terrence Ross	TOR	1.082	-0.010		Giannis Antetokounmpo	MIL	1.102	0.010

Top – 10 Defensive Players				Table 15	Bottom – 10 Defensive Players			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Klay Thompson	GSW	1.061	-0.015		Paul George	IND	1.085	0.009
Gary Harris	DEN	1.062	-0.014		Ramon Sessions	WAS	1.085	0.009
Kevin Durant	OKC	1.064	-0.013		Danilo Gallinari	DEN	1.085	0.009
Draymond Green	GSW	1.064	-0.012	**13 - 16**	Patrick Patterson	TOR	1.086	0.009
Thaddeus Young	BRK	1.064	-0.012		Giannis Antetokounmpo	MIL	1.086	0.010
Nicolas Batum	CHO	1.064	-0.012		Kentavious Caldwell-Pope	DET	1.086	0.010
Zach Randolph	MEM	1.064	-0.012		Hollis Thompson	PHI	1.086	0.010
DeAndre Jordan	LAC	1.065	-0.011		Darren Collison	SAC	1.087	0.011

Top – 10 Defensive Players				Table 16	Bottom – 10 Defensive Players			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Brook Lopez	BRK	1.046	-0.013		Kemba Walker	CHO	1.068	0.009
DeAndre Jordan	LAC	1.046	-0.013		P.J. Hairston	MEM	1.068	0.009
Ian Mahinmi	IND	1.046	-0.013		Giannis Antetokounmpo	MIL	1.068	0.009
George Hill	IND	1.046	-0.013	**17 - 23**	Harrison Barnes	GSW	1.069	0.010
Draymond Green	GSW	1.047	-0.013		Nik Stauskas	PHI	1.069	0.010
Jeremy Lin	CHO	1.048	-0.011		Evan Fournier	ORL	1.069	0.010
Alonzo Gee	NOP	1.048	-0.011		Mike Conley	MEM	1.069	0.010
Hassan Whiteside	MIA	1.048	-0.011		Marc Gasol	MEM	1.071	0.011

Tables 17 – 21: Shows top and bottom 10 offensive points per possession players in the shot-specific-distance model from three-point distance. The offensive ratings are separated by position and compared to the average expected points for a three-point shot.

Top – 10 Offensive Players				Table 17	Bottom – 10 Offensive Players			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Stephen Curry	GSW	1.370	0.035	PG	Greivis Vasquez	MIL	1.329	-0.006
Russell Westbrook	OKC	1.351	0.016		Langston Galloway	NYK	1.329	-0.006
Kyle Lowry	TOR	1.351	0.016		George Hill	IND	1.327	-0.008
Damian Lillard	POR	1.350	0.015		Ramon Sessions	WAS	1.327	-0.008
Patrick Beverley	HOU	1.350	0.014		Ty Lawson	HOU	1.326	-0.009
John Wall	WAS	1.346	0.011		Isaiah Thomas	BOS	1.325	-0.010
Shaun Livingston	GSW	1.345	0.010		D'Angelo Russell	LAL	1.325	-0.011
Patty Mills	SAS	1.344	0.009		Goran Dragic	MIA	1.324	-0.012

Top – 10 Offensive Players				Table 18	Bottom – 10 Offensive Players			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Klay Thompson	GSW	1.355	0.020	SG	Lou Williams	LAL	1.330	-0.005
Khris Middleton	MIL	1.349	0.014		Gerald Green	MIA	1.329	-0.006
DeMar DeRozan	TOR	1.348	0.013		Austin Rivers	LAC	1.329	-0.006
Kentavious Caldwell-Pope	DET	1.347	0.012		Tim Hardaway Jr.	ATL	1.329	-0.006
Monta Ellis	IND	1.347	0.011		Arron Afflalo	NYK	1.328	-0.007
J.R. Smith	CLE	1.346	0.011		Jordan Clarkson	LAL	1.328	-0.007
Rodney Hood	UTA	1.344	0.009		O.J. Mayo	MIL	1.325	-0.010
Dion Waiters	OKC	1.344	0.009		Gary Harris	DEN	1.324	-0.011

Top – 10 Offensive Players				Table 19	Bottom – 10 Offensive Players			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Andre Iguodala	GSW	1.354	0.019	SF	Jae Crowder	BOS	1.326	-0.009
Carmelo Anthony	NYK	1.354	0.019		Justise Winslow	MIA	1.326	-0.009
LeBron James	CLE	1.352	0.017		Matt Barnes	MEM	1.325	-0.010
Kawhi Leonard	SAS	1.350	0.015		Alonzo Gee	NOP	1.325	-0.010
Paul George	IND	1.348	0.013		Chandler Parsons	DAL	1.324	-0.011
Doug McDermott	CHI	1.347	0.012		Paul Pierce	LAC	1.324	-0.011
Al-Farouq Aminu	POR	1.345	0.010		Kent Bazemore	ATL	1.324	-0.011
P.J. Tucker	PHO	1.344	0.009		Rudy Gay	SAC	1.324	-0.011

Top – 10 Offensive Players				Table 20	Bottom – 10 Offensive Players			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Draymond Green	GSW	1.359	0.024	PF	Julius Randle	LAL	1.330	-0.005
Lavoy Allen	IND	1.353	0.018		Luol Deng	MIA	1.330	-0.005
Tristan Thompson	CLE	1.352	0.016		Darrell Arthur	DEN	1.330	-0.006
Thaddeus Young	BRK	1.348	0.013		Charlie Villanueva	DAL	1.328	-0.007
Patrick Patterson	TOR	1.347	0.012		Josh Smith	DET	1.327	-0.008
Serge Ibaka	OKC	1.346	0.011		Aaron Gordon	ORL	1.326	-0.009
Derrick Favors	UTA	1.345	0.010		Lance Thomas	NYK	1.326	-0.010
LaMarcus Aldridge	SAS	1.344	0.008		Amir Johnson	BOS	1.322	-0.013

Top – 10 Offensive Players				Table 21	Bottom – 10 Offensive Players			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Enes Kanter	OKC	1.353	0.018	C	Miles Plumlee	MIL	1.330	-0.005
Jordan Hill	IND	1.350	0.015		Myles Turner	IND	1.330	-0.005
Joakim Noah	CHI	1.347	0.012		Karl-Anthony Towns	MIN	1.329	-0.006
Dwight Howard	HOU	1.347	0.012		Alex Len	PHO	1.329	-0.007
Festus Ezeli	GSW	1.345	0.010		Andrew Bogut	GSW	1.328	-0.008
Gorgui Dieng	MIN	1.345	0.010		Brook Lopez	BRK	1.327	-0.008
Tyson Chandler	PHO	1.343	0.008		Roy Hibbert	LAL	1.327	-0.008
Jonas Valanciunas	TOR	1.343	0.008		Al Jefferson	CHO	1.326	-0.009

Tables 22 – 26: Shows top and bottom 10 defensive points per possession players in the shot-specific-distance model from three-point distance. The defensive ratings are separated by position and compared to the average expected points for a three-point shot.

Top – 10 Defensive Players				Table 22	Bottom – 10 Defensive Players			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Deron Williams	DAL	1.317	-0.018		T.J. McConnell	PHI	1.345	0.009
Elfrid Payton	ORL	1.320	-0.015		Damian Lillard	POR	1.345	0.010
Goran Dragic	MIA	1.324	-0.011		J.J. Barea	DAL	1.345	0.010
Stephen Curry	GSW	1.325	-0.011	**PG**	Trey Burke	UTA	1.345	0.010
Tony Parker	SAS	1.326	-0.010		Devin Harris	DAL	1.345	0.010
George Hill	IND	1.326	-0.009		Jameer Nelson	DEN	1.346	0.011
Reggie Jackson	DET	1.326	-0.009		Ish Smith	PHI	1.347	0.012
Giannis Antetokounmpo	MIL	1.326	-0.009		John Wall	WAS	1.349	0.014

Top – 10 Defensive Players				Table 23	Bottom – 10 Defensive Players			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Arron Afflalo	NYK	1.318	-0.017		Allen Crabbe	POR	1.343	0.008
Kyle Korver	ATL	1.321	-0.015		Gary Neal	WAS	1.344	0.009
Wesley Matthews	DAL	1.321	-0.014		C.J. McCollum	POR	1.344	0.009
Danny Green	SAS	1.322	-0.013	**SG**	Austin Rivers	LAC	1.345	0.010
Klay Thompson	GSW	1.323	-0.012		Markel Brown	BRK	1.347	0.012
Jeremy Lamb	CHO	1.328	-0.007		Dion Waiters	OKC	1.348	0.013
Monta Ellis	IND	1.328	-0.007		Bradley Beal	WAS	1.349	0.014
Evan Turner	BOS	1.329	-0.006		Jamal Crawford	LAC	1.351	0.015

Top – 10 Defensive Players				Table 24	Bottom – 10 Defensive Players			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Kawhi Leonard	SAS	1.322	-0.013		Andre Iguodala	GSW	1.340	0.005
Paul George	IND	1.324	-0.011		Paul Pierce	LAC	1.340	0.005
Rudy Gay	SAC	1.324	-0.011		P.J. Tucker	PHO	1.341	0.005
Joe Johnson	BRK	1.324	-0.011	**SF**	Derrick Williams	NYK	1.341	0.006
Nicolas Batum	CHO	1.324	-0.011		P.J. Hairston	MEM	1.341	0.006
Marcus Morris	DET	1.325	-0.010		Maurice Harkless	POR	1.342	0.007
Tony Snell	CHI	1.327	-0.009		Jeff Green	LAC	1.342	0.007
LeBron James	CLE	1.327	-0.008		C.J. Miles	IND	1.344	0.009

Top – 10 Defensive Players				Table 25	Bottom – 10 Defensive Players			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Draymond Green	GSW	1.32	-0.02		Dirk Nowitzki	DAL	1.339	0.004
Kevin Love	CLE	1.32	-0.02		Luis Scola	TOR	1.340	0.004
Luol Deng	MIA	1.32	-0.01		Larry Nance Jr.	LAL	1.340	0.005
Thaddeus Young	BRK	1.32	-0.01	**PF**	Chris McCullough	BRK	1.340	0.005
Derrick Favors	UTA	1.33	-0.01		Quincy Acy	SAC	1.341	0.006
Chris Bosh	MIA	1.33	-0.01		Mirza Teletovic	PHO	1.342	0.007
Kristaps Porzingis	NYK	1.33	-0.01		Thomas Robinson	BRK	1.342	0.007
Paul Millsap	ATL	1.33	-0.01		Zach Randolph	MEM	1.343	0.008

Top – 10 Defensive Players				Table 26	Bottom – 10 Defensive Players			
Player	Team	EPV	$\Delta_{Average}$		Player	Team	EPV	$\Delta_{Average}$
Andre Drummond	DET	1.318	-0.017		Timofey Mozgov	CLE	1.339	0.004
DeMarcus Cousins	SAC	1.319	-0.016		Ryan Hollins	MEM	1.339	0.004
Ian Mahinmi	IND	1.323	-0.012		Chris Andersen	MEM	1.339	0.004
Andrew Bogut	GSW	1.324	-0.012	**C**	Gorgui Dieng	MIN	1.339	0.004
Tim Duncan	SAS	1.324	-0.011		Jonas Valanciunas	TOR	1.339	0.004
Zaza Pachulia	DAL	1.325	-0.010		Karl-Anthony Towns	MIN	1.339	0.004
Omer Asik	NOP	1.327	-0.008		Nikola Jokic	DEN	1.341	0.006
Jordan Hill	IND	1.328	-0.007		Dwight Howard	HOU	1.342	0.007

Table 27: Shows the top - 25 and bottom - 25 players in terms of wins above a replacement level player (WAR). In addition to the WAR value, the dollars spent by a team for one additional win above a replacement level player is calculated. Players with green values are considered good value while players with red values are considered bad value for their team.

Top – 25 WAR Players

Player	Team	WAR	$ per Additional Win
Draymond Green	GSW	15.95	$896,551.72
Kyle Lowry	TOR	13.12	$914,634.15
LeBron James	CLE	12.43	$1,848,028.96
Stephen Curry	GSW	11.93	$953,125.40
Russell Westbrook	OKC	11.63	$1,439,743.59
Chris Paul	LAC	11.27	$1,904,941.97
Klay Thompson	GSW	10.94	$1,416,819.01
Gordon Hayward	UTA	10.72	$1,437,459.89
Kevin Durant	OKC	10.01	$2,013,848.35
C.J. McCollum	POR	9.76	$258,725.41
Marcus Morris	DET	9.63	$519,210.80
DeAndre Jordan	LAC	9.63	$2,024,922.12
Carmelo Anthony	NYK	9.44	$2,423,199.15
Kentavious Caldwell-Pope	DET	9.28	$311,612.07
Nicolas Batum	CHO	9.24	$1,324,215.37
James Harden	HOU	9.22	$1,708,941.21
Kawhi Leonard	SAS	9.12	$1,809,210.53
Khris Middleton	MIL	8.95	$1,675,977.65
DeMarcus Cousins	SAC	8.78	$1,677,544.87
Paul Millsap	ATL	8.65	$2,196,531.79
George Hill	IND	8.65	$924,855.49
Rudy Gobert	UTA	8.57	$137,208.87
Jimmy Butler	CHI	8.34	$1,829,736.21
Serge Ibaka	OKC	8.31	$1,486,161.25
John Wall	WAS	8.19	$1,935,525.03

Bottom – 25 WAR Players

Player	Team	WAR	$ per Additional Win
Walter Tavares	ATL	1.22	$819,672.13
Tibor Pleiss	UTA	1.22	$2,459,016.39
Chris Kaman	POR	1.21	$4,132,231.40
Cory Jefferson	PHO	1.16	$318,965.52
Jeff Ayres	LAC	1.13	$166,150.44
Chris Copeland	ORL	1.13	$973,451.33
Andrew Goudelock	HOU	1.13	$177,522.12
Eric Moreland	SAC	1.11	$761,314.41
Shayne Whittington	IND	1.09	$775,283.49
James Michael McAdoo	GSW	1.08	$782,462.04
Jarell Eddie	WAS	1.05	$534,967.62
Cameron Bairstow	CHI	1.02	$828,489.22
Jorge Gutierrez	CHO	0.98	$193,877.55
Joel Anthony	DET	0.94	$2,659,574.47
Bryce Cotton	PHO	0.9	$254,070.00
Erick Green	DEN	0.87	$114,942.53
Russ Smith	MEM	0.81	$1,008,002.47
Anthony Bennett	MIN	0.79	$4,620,253.16
Aaron Harrison	CHO	0.79	$664,674.68
Pat Connaughton	POR	0.77	$681,938.96
Sasha Kaun	CLE	0.74	$1,756,756.76
Luis Montero	POR	0.65	$807,835.38
Mitch McGary	OKC	0.64	$2,286,000.00
Jordan Mickey	BOS	0.64	$1,875,000.00
Jimmer Fredette	SAS	0.54	$940,205.56