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# Salary in the National Basketball Association

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# Salary in the National Basketball Association

## **Abstract**

This paper intends to analyze the association between NBA statistics and winning percentage and determine if that same relationship holds for player compensation and individual player statistics. To determine the associations, two separate multiple regressions are utilized during the NBA seasons, 2013-2014 and 2014-2015. This paper finds that teams are not effectively compensating players, with more analytical inclined front offices being more effective at compensating players.

## **Keywords**

NBA, Salary, Effective Allocation, Regression, and Statistics

## **Disciplines**

Business

## **SALARY IN THE NATIONAL BASKETBALL ASSOCIATION**

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**ABSTRACT**

This paper intends to analyze the association between NBA statistics and winning percentage and determine if that same relationship holds for player compensation and individual player statistics. To determine the associations, two separate multiple regressions are utilized during the NBA seasons, 2013-2014 and 2014-2015. This paper finds that teams are not effectively compensating players, with more analytical inclined front offices being more effective at compensating players.

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## INTRODUCTION

The National Basketball Association is a collection of thirty professional basketball teams in the United States and Canada. It is currently the third largest professional sports league in North America with approximately \$5 billion dollars in revenue.<sup>1</sup> Also, the National Basketball Association distributes a significant amount of salary to its players, which adds to the intrigue of the game. Each team had a salary cap \$63 million in 2014-2015, which is a soft limit of how much salary that a team can distribute to its roster before having to pay penalties.<sup>2 3</sup> With the sheer size and interest in the National Basketball Association, scholars and fans alike have an interest on the salaries of the National Basketball Association players.

The question of whether or not National Basketball Association players are paid enough has often been about the perspective according to scholars. Frank Scott, James Long and Ken Somppi (1985) say that the discussion was previously more qualitative in nature. In their study, Scott et al. found that fans and owners believed that National Basketball Association players were overpaid.<sup>4</sup> These fans appeared to believe that National Basketball Association players did not deserve their salaries because National Basketball Association players could be paid millions of dollars more than the average person.<sup>5</sup> While common fans believe that players were overpaid based on qualitative and relative examinations, economists disagree. Previously, with restrictions in labor markets like the lack of a free agency, National Basketball Association players may have been in fact underpaid like Major League Baseball players were. In fact, scholars like Gerald Scully (1974) have determined that players are paid less relative to the amount of money they brought to their teams in the 1970's. Scully compared the players' marginal revenue products with their actual salaries, which should be equal if baseball was perfectly competitive, and found there to be an imbalance.<sup>6</sup> Like the Major League Baseball, the removal of labor market

restrictions and addition of free agency has resulted in National Basketball Association players' salaries more closely reflecting their value to their teams, according to studies by Cassing and Douglass (1980).<sup>7</sup> Since scholars and fans have disagreed about the relative worth of players, it is important to note that there are differentiating factors that go into the calculation of a player's salary.

The idea that there is a constant tug and barter between players and owners about salary continues to be important even today. Bargaining agreements between players and owners are one of the main determinants of the size of the salary cap and ultimately how much players are paid. James R. Hill and Nicholas A. Jolly (2012) point to the 1998-1999 collective bargaining agreement as the year when there was an imposed a cap on individual salaries and team payrolls.<sup>8</sup> The impetus that dove the imposed cap on salaries was Kevin Garnett. Hill and Jolly say that because Kevin Garnett, in only his second year, signed a new contract that made him the fourth highest player in the National Basketball Association, there were subsequent escalations to salaries.<sup>9</sup> With growing salaries and costs, owners locked out the players and instituted the 1998-1999 collective bargaining agreement. Players were no longer considered underpaid; the team owners believed that the players were overpaid. One consequence of the collective bargaining agreement was that because premier players had an artificial cap on salaries, the distribution of player salary relative to skill no longer matched. In Hill and Jolly's research, they calculated the Theil and Gini, which serve to measure the economic inequality to analyze this issue. They found that the rookie scale in 1995 collective bargaining agreement with the introduction of the individual salary caps and the extension of the rookie scale in the 1998 collective bargaining agreement actually created a more uniform distribution of income.<sup>10</sup> This is an issue because now teams were paying players inefficiently. Neil Paine (2015) of Five Thirty

Eight also found this inefficiency. Paine compared the amount of wins a player added to the team and how much his salary was. He discovered that superstar players and rookies are paid far less than they deserve based on their skill levels while average rotation players were overpaid.<sup>11</sup> The constant pull and tug from new collective bargaining agreement drives one factor of the salary distribution.

Over the last decade or so, the quantitative shift has occurred in the National Basketball Association and in the basketball academic community, impacting the way people look at salaries. In 2006, the Massachusetts Institute of Technology Sloan Analytics Conference was created to discuss the role of analytics in sports. Quantitative research was one of the talking points about the importance for analyzing salaries. Now, the discussion revolves around how general managers assign value to players. Offensive statistics from box scores have typically had a higher correlation with how much a player is paid.<sup>12</sup> One of the possible reasons for this phenomenon that offensive statistics are more correlated with salary is how difficult it is to isolate an individual player's defensive impact. Kirk Goldsberry (2015) of Harvard University calls attention to this saying that previously it was difficult to analyze the defensive impact of a player with just traditional statistics unlike the more observable offensive statistics.<sup>13</sup> Nuoya Li (2014) of Clemson University analyzed offensive and defensive statistics of players in contract years, in which players are playing for a new contract. In her study, she found that while many offensive statistics such as points and assists are individually significant to salary, only blocks are individually significant to salary.<sup>14</sup> Other defensive statistics like steals and defensive rebounds are not individually significant in her research.<sup>15</sup> This indicates that there is a positive relationship between scoring points and passing out assists with increased salary but there is not necessarily a relationship with an increase in salary for steals. Adam Fromal (2015) similarly

finds that if players increase their offensive percentile they get paid more, but this is not the case if players increase their defensive percentile.<sup>16</sup> However, while Li and Fromal have found that offensive players have been compensated more for their observable statistics, not all scholars have agreed. Dan Rust, of University of Mississippi, found that certain defensive statistics, namely allowing points off post ups and pick and rolls are statistically significant to salary.<sup>17</sup> Currently, it seems that there are scholars who have found that offensive statistics do matter for players' salaries but other scholars also argue that teams still do take into consideration defensive statistics when determining salaries.

## **SIGNIFICANCE**

The premise for conducting this research is to shape the way people look at National Basketball Association salaries. Primarily, this research is conducted for the benefit of National Basketball Association front offices and general managers as they go through the decision making process for how to select free agents and to retain current players at what salary. Previously, they may have placed excessive emphasis on observable offensive box score statistics. With this research seeking to answer which player adds more expected wins, every general manager can more efficiently allocate their rosters. Specifically, after reading this research, teams gain knowledge on what specific statistics (offensive statistic, defensive statistic or a more holistic statistic encompassing both) lead to more wins. By doing so, general managers can easily compare players at the same position as well as against other positions. This is important as the salary cap makes it difficult for teams from spending as much as they want. Teams can be shrewd and spend their salary on two players that add more value to the team than one individual player at the same price. Furthermore, players, likewise, can use the research to gauge how much they are worth in free agency and through trade. The players' union is also

integrally related to the players' salaries, and they can use the research to effectively bargain with the league. Adam Silver, the commissioner, cares because he is face of the National Basketball Association. He has to plan accordingly to make the game as profitable for not only the owners but also placate the concerns of the players. Lastly, the research is interesting for other sport researchers and fans of the game who are enjoy looking at the quantitative complexities of free agency and trade transactions.

When reading the research paper, people will have many expectations on the quantitative aspects of the paper. Firstly, as this is targeted primarily for practical use and secondarily for academic use, people will expect to see the most relevant and recent data. They expect to see data that comes from the last few years as teams are developing more analytical front offices. As the paper will be finished in April of 2016, National Basketball Association front offices and players would expect a guide that covers the National Basketball Association 2016-2017 season. Furthermore, the more quantitative scholarly audience will expect to see statistically significant correlations that create the foundation of the research.

While there has been statistical analysis done on various determinants of salary, this research will also utilize those determinants to create a player salary guide that utilizes the most up to date traditional box score data and new statistical measures that is useful in determining current and future players' salaries. The paper will not only cover if there is a relationship with certain player statistics with how much they make, but also how to combine the different statistics into a practical tool to use in free agency and trade negotiations. Also, this research can continue to add to the discussion on what type of statistics, namely if new created comprehensive statistics like Win Share (a statistical measure created to take into consideration of traditional offensive and defensive box score statistics like points, assists, rebounds, blocks and steals) and

Real Plus-Minus (a statistical measure that takes into consideration for quality of teammates into a player's net point value while being on the court) have a greater impact on winning. This not only adds to the scholarly and academic discussion but also for general managers seeking to field a team.

## **HYPOTHESIS**

Through this research's analysis of previous studies, general managers and National Basketball Association teams seem to pay players more for observable offensive characteristics. Offensive statistics such as points per game may not be the best determinate for expected number of wins. The focus on paying players could be based more than just points, but rather defensive characteristics or a holistic advanced statistics that take into consideration the overall impact a player has on the court. The invention of more sophisticated analytical ratings such as Win Shares and Real Plus-Minus encompasses the overall impact a player has on the court and may show a greater correlation and statistically significant explanatory power with wins. If National Basketball Association general managers are not focusing on the right statistical determinants to increase winning, they are inefficiently allocating their salary cap on players.

## **FRAMEWORK**

The research is quantitative in nature and employs statistical analysis, primarily through regression to find the correlations between certain statistics and wins. The league wide data comes from a public source, Basketball Reference. Basketball Reference not only provided the Win/Loss records for all thirty teams but also the box score and more advanced statistics. For the 2013-2014 and 2014-2015 season, Basketball Reference provided the source for each team's PS/G, PA/G, FG, FGA, FG%, 3P, 3PA, 3P%, 2P, 2PA, 2P%, FT, FTA, FT%, ORB, DRB, TRB, AST, STL, BLK, TOV, PF (Table 1). Basketball Reference did not include the team's

accumulated advanced statistics, so to calculate the team's advanced statistics, the sum was taken from each of the team's players including PER, OWS, DWS, WS, OBPM, DBPM, BPM.

## **METHODOLOGY**

To narrow the large set of data down to statistics that are most associated to wins, this research applies a correlation cutoff (Table 2). With the narrowed down set of variables, this research completed a multiple regression of certain team statistics (X variable) with wins (Y variable) to determine if they are statistically significant by utilizing t-tests at the 95% and 99% confidence interval. The data for league consists of the 2013-2014 and 2014-2015 NBA seasons giving 60 total observations. The regression is completed on JMP statistical software. The application of regression and t-tests for significance are common theoretical frameworks that are utilized by scholars like Rust and Li.

After determining the team statistics that are statistically significant with winning, this research examines whether teams are compensating players according to those statistics. Using a similar process, a correlation cutoff is employed to narrow the data, which consists of the NBA 2014-2015 NBA season. Then conducting a multiple regression of certain player statistics (X variable) with salary (Y variable) and examining the statistics that are statistically significant at the 95% and 99% confidence interval. By doing so, the research is making an implicit assumption that teams only care about winning and that teams do not consider external basketball factors like sponsorship and viewership.

After finding the statistic with the highest statistically significant correlation to wins, this research builds a ratio that indicates how much a team should pay for a player. The formula that indicates how much a team should pay a player is  $\text{Player Statistic} * (\text{Total Salary}) / (\text{Total Statistic})$ . With each unit of individual player statistic, the player should be compensated by that ratio.

By calculating the efficient projected salary of players gives many interesting and practical results. This research is then able to analyze how efficient each team is at paying players. By sorting the players' salaries by their respective teams, the projected salary of the team can be calculated. The teams with the lowest actual salaries minus the projected salaries indicate an ability to not overpay players and perhaps an ability to find good players at cheap price. The teams with the highest actual salaries minus projected salaries are teams that overpay their players to the detriment of their teams.

## RESULTS

After narrowing down the data to statistics by correlations, only PS/G, FG%, 3P%, 2P%, Win Shares and DBPM have correlations of .6 after limiting variables due to possible collinearity (70%+ correlation with each other i.e. FG% and FGA). The multiple regression indicated that only Win Share is statistically significant at 99% confidence interval. 2P% and DBPM are statistically significant at the 95% confidence interval (Table 3).

If teams are truly compensating players based on their added win contribution, then the salaries should be associated with Win Shares and possibly 2P% and DBPM. However, after narrowing down the data to statistics that had correlations greater than .6 only left MP, FG, 2P, FTA, DRB, TOV and PTS (Table 4). Win Share and DBPM at the league level showed explanatory power for wins did not have explanatory power for player salaries. After completing the multiple regression of salary against MP, FG, 2P, FTA, DRB, TOV and PTS, only MP, DRB and TOV are statistically significant (Table 5).

Win Share has the most explanatory power for wins based on its .9 correlation with wins and being statistically significant at 99% confidence interval, so this research paper utilizes it as the factor for determining efficient salary. To utilize Win Share into a useable formula, this

research uses the total salary divided by the total Win Share, 1256 to get \$1.7 million/(Win Share), which means for every Win Share, a player is worth \$1.7 million per year. For example, a 2 Win Share player is worth \$3.4 million dollars per year in this current salary cap. Then applying this ratio throughout the NBA, each player will be paid accordingly. When the salary cap rises, teams can effectively annually adjust the ratio with new inputs for total salary cap and total Win Share. Teams then can utilize these projections to find undervalued players who are asking for less than the ratio says they deserve. Ideally finding a player that contributes more wins at a cheaper price.

The calculation of the projected salaries for players clearly showed that teams are not compensating players effectively. To define whether or not players were not fairly compensated, there needed to be a criterion for not only the absolute difference but also the percentage difference (Table 6). Using 2 million dollars as an overpayment minimum as well as being paid 25% more than the projected salary netted 95 players being overpaid. 2 million is a suitable amount as it puts into perspective the absolute amounts of money. Likewise, the 25% is a catch for players who make more significantly more than 10 million dollars, where 2 million is negligible. The top overpaid players by salary difference from projected and actual are Kobe Bryant, Amar'e Stoudemire, Carmelo Anthony, Derrick Rose and Joe Johnson (Table 7). There are 121 underpaid players who are being paid \$2 million dollars less than their projected salary and 25% less than their projected salaries. The players who are exceeding their contracts are Anthony Davis, Jimmy Butler, Stephen Curry, Rudy Gobert, Damian Lillard, and Draymond Green (Table 8). These players are producing more wins than their salary indicates they should. It's important to note that most of these underpaid players are being paid on their rookie deal or

second deal. They are going to be paid much more in the future, for example Anthony Davis signed a five year, \$145 million dollar contract.

After sorting players by team, teams are sorted by their effectiveness in paying players by Win Shares. Atlanta did the best in allocating pay, overpaying their players by only \$1,084,894. New York, Brooklyn and Los Angeles did the worst, overpaying their players by over \$30 million a year (Table 9). ESPN compiled a front office analytical ranking of NBA teams with four teams being all in on using analytics, eight teams being believers, nine being one foot in, six being skeptics on analytics and three being non believers. As expected, the more analytical the front office was based on ESPN's ranking, the better it did on this research's salary allocation projections. For example, all-in analytical offices average effectiveness is 10 but the non believers average effectiveness is 29 (Table 10). The all in and believers winning percentages are also higher than the one foot in, skeptics and non believers (Table 10).

## **CONCLUSION**

Based on the results, it seems clear that some teams are not efficiently paying their players. The first multiple regression indicated that 2P% and DBPM are both statistically significant for winning percentage at the 95% confidence interval, Win Share is statistically significant at the 99% confidence interval. However, the second multiple regression indicates that teams are paying players based on MP, DRB and TOV. While initially this research hypothesized that teams compensating more based on observable offensive statistics, it's actually not the case. The other takeaway is that teams are not compensating their players based on the statistics that are most associated with winning. With over 200 combined players that are either overpaid or underpaid, teams could do a better job scouting and analyzing players before giving contracts. What's interesting is that teams who are efficiently compensating their players based

on this research's model also tended to be ranked by ESPN as All-In and Believers of analytics. They also happen to have the better records in the NBA. This tends to indicate that the more analytical the front office is the more they subscribe to the type of analysis that this research conducted. With more teams implementing analytics into front offices, the inefficiencies should lessen. For now, this research is applicable to front offices looking to sign, trade and give contract extensions. To find underpaid players, it seems prudent to draft well and get players that perform in excess of what their salary dictates they should like Anthony Davis.

There are certain statistical issues that this research may have when analyzing salaries. There may be collinearity issues when looking at different statistics that may also have a relationship with each other. Also, this research has to recognize that by projecting players' Win Share, the focus is on a player's past performance, not necessarily their future performance. As there are always going to be difficulties making forecasts, by using past performance there is at least something that builds the foundation for the forecasts.

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<sup>1</sup> Stern Estimates NBA Revenue up 20 Percent to \$5B. 2012. *NBA.com*

<sup>2</sup> NBA Team Contracts & Payrolls. *Spotrac.com*.

<sup>3</sup> NBA - Salary Cap History. *Real GM*.

<sup>4</sup> Scott, F., E. L. James, and K. Somppi. 1985. Salary Vs. Marginal Revenue Product under Monopsony and Competition: The Case of Professional Basketball. *Atlantic Economic Journal*: 50-59.

<sup>5</sup> *Ibid.*

<sup>6</sup> Scully, G. 1974. Pay and Performance in Major League Baseball. *The American Economic Review*, no. 64.6.

<sup>7</sup> Cassing, J., and R. W. Douglas. 1980. Implications of the Auction Mechanism in Baseball's Free Agent Draft. *Southern Economic Journal*: 110.

<sup>8</sup> Hill, J. R. and N. A. Jolly. 2012. Salary Distribution and Collective Bargaining Agreements: A Case Study of the NBA. *Industrial Relations: A Journal of Economy and Society*: 342-63.

<sup>9</sup> *Ibid.*

<sup>10</sup> *Ibid.*

<sup>11</sup> Paine, N. 2015. No Matter How Much They Make, The Best Players In The National Basketball Association Are Vastly Underpaid. *Five Thirty Eight*.

<sup>12</sup> Li, N. 2014. The Determinants of the Salary in National Basketball Association and the Overpayment in the Year of Signing a New Contract. *Clemson University*.

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<sup>13</sup> Fromal, A. 2015 Defense Wins Titles, but Offense Pays. *Bleacher Report*.

<sup>14</sup> *Ibid.*

<sup>15</sup> *Ibid.*

<sup>16</sup> *Ibid.*

<sup>17</sup> Rust, D. 2014. An Analysis of New Performance Metrics in the National Basketball Association and Their Effects on Win Production and Salary. *University of Mississippi*

**APPENDIX**

1. Terms Definitions
2. Team Statistics' Correlation with Winning Percentage
3. Multiple Regression for League
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5. Player Multiple Regression
6. Sample Salary Calculations
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## 1. Terms Definitions

<b>Box Score Statistics</b>	<b>Advanced</b>
<p>W (Wins)  L (Losses)  FG (Field Goals Made)  FGA (Field Goals Attempted)  FG% (Field Goal Percentage Made)  3P (3 Point Field Goals Made)  3PA (3 Point Field Goals Attempted)  3P% (3 Point Field Goal Percentage Made)  2P (2 Point Field Goals Made)  2PA (2 Point Field Goals Attempted)  2P% (2 Point Field Goal Percentage Made)  FT (Free Throws Made)  FT (Free Throws Attempted)  FT (Free Throws Percentage Made)  ORB (Offensive Rebounds)  DRB (Defensive Rebounds)  TRB (Total Rebounds)  AST (Assists)  TOV (Turnovers)  STL (Steals)  BLK (Blocks)</p>	<p>PER (Per Minute Efficiency)  OWS (Offensive Win Share)  DWS (Defensive Win Share)  WS (Total Win Share)  OBPM (Offensive Box Plus/Minus)  DBPM (Defensive Box Plus/Minus)  BPM (Total Box Plus/Minus)</p>

## 2. Team Statistics' Correlation with Winning Percentage

Statistic	Correlation with Winning Percentage
PS/G	0.6
PA/G	-0.5
FG	0.6
FGA	-0.1
FG%	0.7
3P	0.5
3PA	0.4
3P%	0.6
2P	0.0
2PA	-0.4
2P%	0.7
FT	0.2
FTA	0.0
FT%	0.3
ORB	-0.3
DRB	0.5
TRB	0.2
AST	0.5
STL	0.1
BLK	0.3
TOV	-0.3
PF	-0.3
PER	-0.1
OWS	0.8
DWS	0.7
WS	0.9
OBPM	0.3
DBPM	0.6
BPM	0.5

### 3. Multiple Regression for League

Term	Estimate	Std Error	t Ratio	Prob>[t]	Significance
Intercept	-56.5	21.0	-2.69	0.0096	*
PS/G	0.0	0.2	0	0.9976	
FG%	-51.9	83.1	-0.63	0.5346	
3P%	70.0	42.7	1.64	0.1074	
2P%	134.9	62.5	2.16	0.0354	*
WS	0.7	0.1	9.02	<.0001	***
DBPM	0.1	0.1	2.04	0.0461	*

#### 4. Players Statistics' Correlation with Salary

Statistic	Correlation with Salary
Age	0.3
G	0.3
GS	0.5
MP	0.6
FG	0.6
FGA	0.6
FG%	0.2
3P	0.2
3PA	0.2
3P%	0.1
2P	0.6
2PA	0.6
2P%	0.2
FT	0.6
FTA	0.6
FT%	0.1
ORB	0.3
DRB	0.6
TRB	0.5
AST	0.4
STL	0.4
BLK	0.3
TOV	0.6
PF	0.4
PTS	0.6
PER	0.5
OWS	0.5
DWS	0.4
WS	0.5
WS/48	0.3
OBPM	0.4
DBPM	0.1
BPM	0.4

### 5. Player Multiple Regression

Term	Estimate	Std Error	t Ratio	Prob>[t]	Significance
Intercept	-15091	428275	-0.04	0.9719	
MP	-141356	49516	-2.85	0.0045	**
FG	-292547	2073891	-0.14	0.8879	
2P	375719	789910	0.48	0.6345	
FTA	-245081	523415	-0.47	0.6398	
DRB	721479	174180	4.14	<.0001	***
TOV	1077575	394514	2.73	0.0065	**
PTS	546253	634507	0.86	0.3897	

## 6. Sample Salary Calculations

Actual Salary	Projected Salary	Difference	%	Player	Salary
\$62,552	\$502,266	(\$439,714)	-703%	A.J. Price	
\$1,145,685	\$5,524,924	(\$4,379,239)	-382%	Aaron Brooks	<b>Underpaid</b>
\$3,992,040	\$1,674,219	\$2,317,821	58%	Aaron Gordon	<b>Overpaid</b>
\$1,855,320	\$0	\$1,855,320	100%	Adreian Payne	
\$12,000,000	\$14,565,708	(\$2,565,708)	-21%	Al Horford	
\$13,666,667	\$7,868,831	\$5,797,836	42%	Al Jefferson	<b>Overpaid</b>
\$1,276,061	\$4,520,392	(\$3,244,331)	-254%	Alan Anderson	<b>Underpaid</b>
\$3,034,356	\$2,846,173	\$188,183	6%	Alec Burks	
\$65,000	\$0	\$65,000	100%	Alex Kirk	
\$3,649,920	\$5,692,346	(\$2,042,426)	-56%	Alex Len	<b>Underpaid</b>
\$3,282,056	\$3,683,282	(\$401,226)	-12%	Alexey Shved	
\$981,084	\$5,357,502	(\$4,376,418)	-446%	Alexis Ajinca	<b>Underpaid</b>
\$981,084	\$5,524,924	(\$4,543,840)	-463%	Al-Farouq Aminu	<b>Underpaid</b>
\$862,000	\$2,176,485	(\$1,314,485)	-152%	Allen Crabbe	
\$1,063,384	\$2,009,063	(\$945,679)	-89%	Alonzo Gee	
\$23,896,658	\$6,027,189	\$17,869,469	75%	Amar'e Stoudemire	<b>Overpaid</b>
\$7,000,000	\$8,538,518	(\$1,538,518)	-22%	Amir Johnson	
\$9,704,595	\$3,181,017	\$6,523,578	67%	Anderson Varejao	<b>Overpaid</b>

### 7. Top 5 Overpaid Players

Actual Salary	Projected Salary	Difference	%	Player	Overpaid?
\$23,500,000	\$334,844	\$23,165,156	99%	Kobe Bryant	Overpaid
\$23,896,658	\$6,027,189	\$17,869,469	75%	Amar'e Stoudemire	Overpaid
\$22,458,000	\$4,855,236	\$17,602,764	78%	Carmelo Anthony	Overpaid
\$18,862,875	\$2,009,063	\$16,853,812	89%	Derrick Rose	Overpaid
\$23,180,790	\$6,864,299	\$16,316,491	70%	Joe Johnson	Overpaid

**8. Top 5 Underpaid Players**

<b>Actual Salary</b>	<b>Projected Salary</b>	<b>Difference</b>	<b>%</b>	<b>Player</b>	<b>Underpaid?</b>
\$5,607,240	\$23,439,070	(\$17,831,830)	-318%	Anthony Davis	Underpaid
\$2,008,748	\$18,751,256	(\$16,742,508)	-833%	Jimmy Butler	Underpaid
\$10,629,213	\$26,285,243	(\$15,656,030)	-147%	Stephen Curry	Underpaid
\$1,127,400	\$15,570,239	(\$14,442,839)	-1281%	Rudy Gobert	Underpaid
\$3,340,920	\$17,746,724	(\$14,405,804)	-431%	Damian Lillard	Underpaid

### 9. Team Salary Allocation Effectiveness

Team	Effectiveness	ESPN Ranking
ATL	1	Believers
PHO	2	One Foot In
UTA	3	One Foot In
POR	4	Believers
DET	5	Believers
PHI	6	All-In
DAL	7	All-In
SAS	8	All-In
BOS	9	Believers
DEN	10	Skeptics
OKC	11	Believers
LAC	12	Skeptics
MIL	13	One Foot In
MEM	14	Believers
ORL	15	One Foot In
CHA	16	One Foot In
GSW	17	Believers
TOR	18	One Foot In
SAC	19	One Foot In
HOU	20	All-In
CHI	21	Skeptics
NOP	22	Skeptics
WAS	23	Skeptics
CLE	24	Believers
MIN	25	Skeptics
IND	26	One Foot In
MIA	27	One Foot In
NYK	28	Non Believers
BRK	29	Non Believers
LAL	30	Non Believers

**10. Average Salary Allocation Effectiveness Wins versus ESPN Rankings**

ESPN Ranking	Average Effectiveness	Average Wins
All-In	10	45
Believers	11	50
One Foot In	15	38
Skeptics	19	38
NonBelievers	29	25

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