Star Player Bias in the NBA: A Quantile Regression Approach

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Abstract:

This paper examines the impact of an NBA player's salary on the number of fouls drawn by them in a season. NBA referees have complete discretion in making calls of whether a player does or does not commit a foul in game, with decisions susceptible to bias, favoring certain players with more fouls called in their favor than another player. The study uses salary to determine a player's value, using a panel dataset of all players from the 2015-16 NBA season through the 2018-19 NBA season for salary and game statistics. The impact of salary is determined using a quantile regression approach. The focus on the significance of salary on fouls drawn. The results show statistically significant evidence of star-player bias by NBA referees. Players with higher salaries can expect to receive a greater number of foul calls drawn per 48 minutes of play than players receiving a lower salary.

JEL Classification: C21, D03, Z20

Keywords: Quantile Regression, Referee Bias, Basketball, Panel Dataset

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1.0 INTRODUCTION

Referees, the arbitrators of rules in sports, often have the sole discretion to determine when a play or sequence in a game violates a rule and requires a penalty or foul to be assessed and when it does not. Due to the fast-paced nature and lenient interpretation of rules in the NBA, referees in NBA games often have significant discretion in determining when a play warrants a foul or not. This has led to a significant focus on referee bias when referees show favoritism or rely on another factor unaffiliated with the play in question to help them make a judgement call. Referee bias can result from a number of factors, referees may be biased against players based on race, nationality, or height. Referees may favor home teams, teams with better records, or the team losing in a game.

This study aims to examine the relationship between a player's salary and the number of fouls that player draws per 48 minutes of game play, the length of an NBA game. If a positive relationship between the dependent variable, the foul drawn rate, and the variable of interest, salary, is significant it will help teams develop better strategy by exploiting the inherent bias of the referees. Highly paid players would be incentivized to play more aggressively because they are more likely to receive foul calls in their favor on questionable plays and lower paid players would have to adjust to a less aggressive style of play to avoid toss-up call situations that would fall against them. A significant positive relationship would also increase the perceived value of better free throw shooters because if these players are paid higher salaries, they are likely to receive more fouls drawn, and by consequence get more free throw attempts. So, better free throw shooters are more likely to convert these attempts into points, resulting in greater on-court production.

This paper was developed from the previous literature on the topic of star player bias but differs in two keyways. First, the variable of interest in this study is salary which is distinct from the previous research on the topic that often use all-star selections as a determinant of star player status. This research also uses a quantile regression approach to examine the relationship between salary and foul rate. This regression method has been tested before in the field of sports economics but has not been utilized in the research of star-player bias.

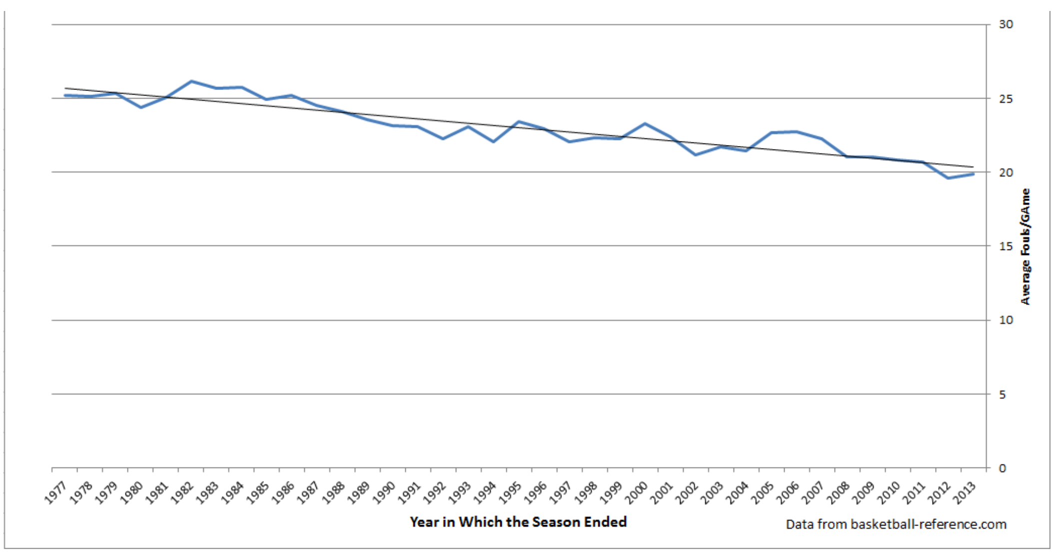
The following section of this paper, Section 2, examines the trends of fouls and salaries in the NBA. Section 3 then provides a review of the previous literature on this issue. Section 4 spells out the data and empirical model and Section 5 discusses the results of the quantile regression approach. Finally, Section 6 draws conclusions from the results and overall analysis of the data.

2.0 NBA Statistics & Trends

On February 3rd, 2021 Paul George, an NBA all-star playing for the Los Angeles Clippers told reporters he felt "absolutely disrespected" that he was only sent to the free throw line once in his game against the Brooklyn Nets that night. That night George did not explicitly mention his all-star as a reason for why he should receive more attempts at the free throw line, but the implication had been made and a debate among media pundits, players, and NBA officials ensued. Some feeling that George's plays were toss up calls that could have been fairly assessed against either team, or others who see George's star player caliber status as a reason to have more foul calls in his favor.

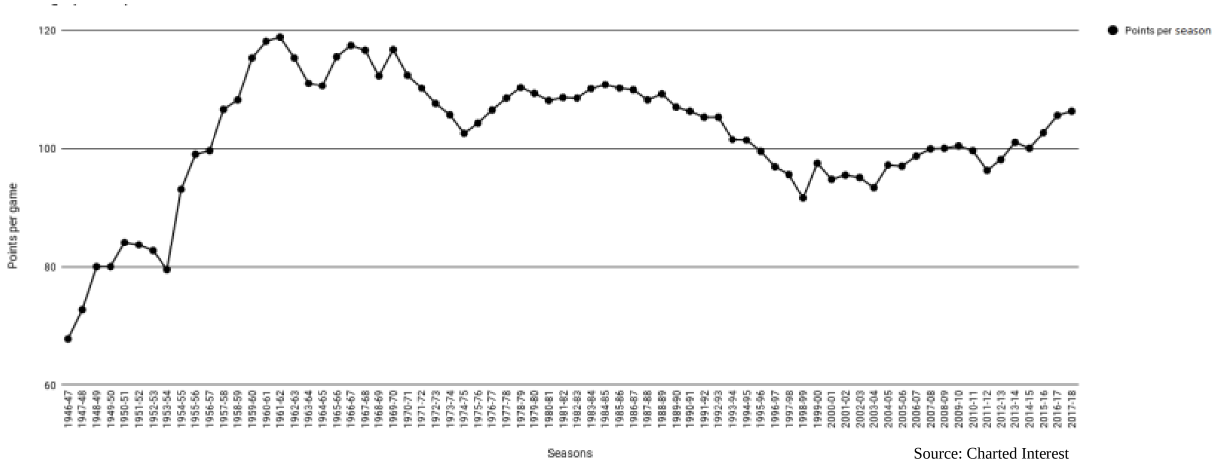
Ask almost any NBA fan and they will agree with the statement that referee bias exists in the NBA, particularly in favor of star players. Many around the league believe referees favor the highest paid, most noteworthy, all-stars by calling a greater number of fouls in their favor, either calling a foul drawn on offense or not calling a foul against while on defense. These excess fouls drawn are what Peter Li refers to as, "superstar calls".

Figure 1: Average Fouls Called per Game in the NBA (1977-2013)



According to Figure 1 from basketball-reference.com and displayed on the chart above, the number of fouls called on average in the NBA has been decreasing on a per game basis since the late 1970's. This trend has coincided with a multi-decade drop in the average points per game in the NBA until the early 2000's when average points per game began to rise again. These results are displayed in Figure 2. Average points per game as of the 2017-18 NBA season remain significantly below the levels of scoring seen in the 60's, 70's, and 80's. This would mean as points remain flat and fouls decrease, each foul becomes even more critical to the outcome of a game.

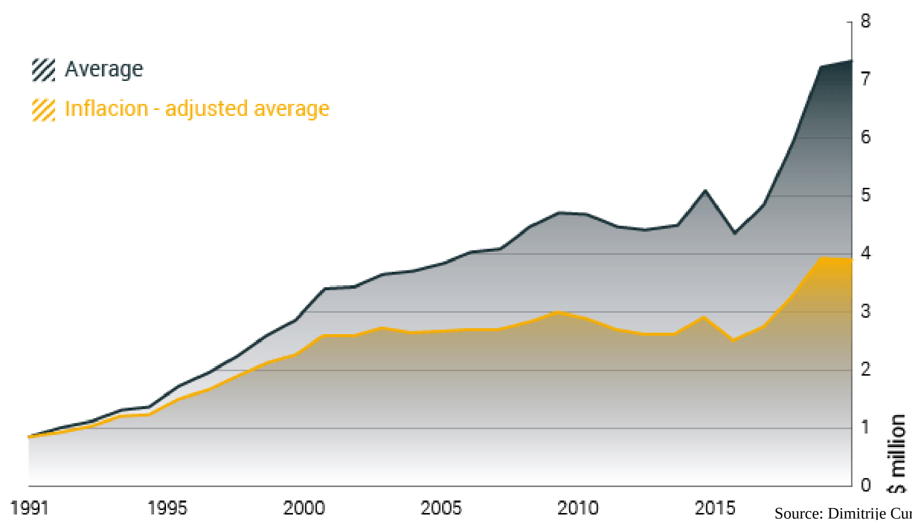
Figure 2: Average Points per Game in the NBA (1947-2018)



Source: Charted Interest

While the number of fouls called and points scored over the past 30 – 40 seasons appears to be dropping in correlation with each other, salaries have exploded in the NBA. According to Figure 3 the average league increased from approx. $1 million in the 1991 season to over $8 million by the 2019 season. In inflation adjusted terms the average league salary quadrupled during the 28-year span.

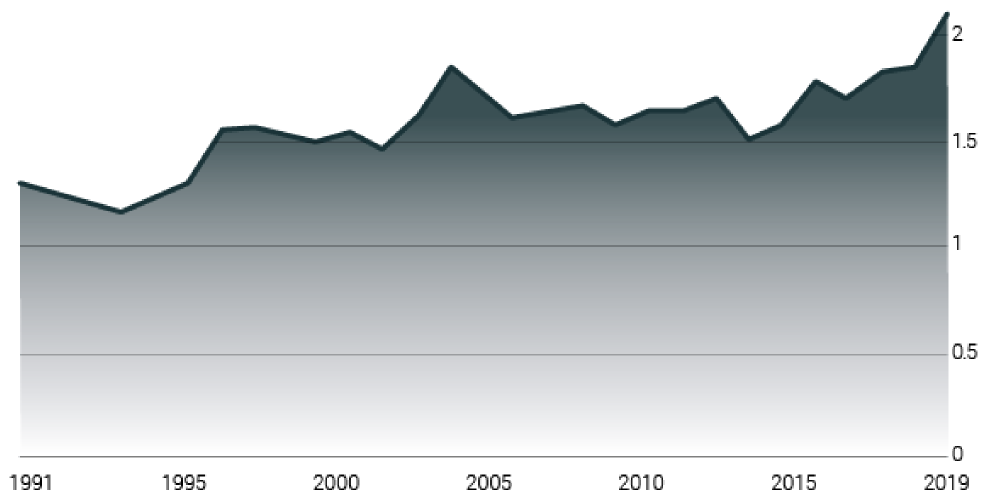
Figure 3: Average NBA Player Salary (1991-2019)



Source: Dimitrije Curcic

During the same span of time, as salaries boomed in the NBA the ratio of average to median player salary also began to rise. This ratio is a barometer for the gap between highly paid players and lower to mid-tier level teammates. As the ratio rose it reflected increasing salaries at the top of the of the league's income earners that was outpacing the growth of the rest of the league's players. By 2019 the ratio was over 2, the average salary in the NBA was more than double the median salary in the league that year. The historical trend of the ratio is displayed in Figure 4.

Figure 4: Average / Median Salary Ratio NBA (1991-2019)



Source: Dimitrije Curcic

While the NBA has seen a drop in fouls called per game and points scored per game over their historical timeline and the average salary in the NBA has increased substantially with a greater share of the pie going to the league's top earners, surprisingly, these players have been playing less. According to Sam Quinn of CBS Sports the average minutes per game by All-NBA players has dropped by 4 minutes per game in the last 15 years. That translates to a loss of over 300 minutes over the course of an 82-game season. These trends point to potential important relationships between salaries, players, and their impact on the game.

3.0 LITERATURE REVIEW

Referee bias in sports is a thoroughly researched topic with studies across many different sports, spread throughout the world. Referee Bias can take on many different forms, though often manifests itself in the number of fouls called for or against a player or team. Price & Wolfers (2010) examined bias by referees based on race. They find own-race race bias from referee crews to be statistically and practically significant, even when controlling for player and referee- fixed effects. Price & Wolfers (2010) also specify a foul rate in the model to adjust for the differences in minutes among players.

Referee bias in the NBA has not only been investigated on the basis of race and ethnicity, but also, other factors like which team is home (Lehman & Reifman 1987 and Price, Remer & Stone 2012), player's height (Gift & Rodenberg 2014), and a player's star power or marketability (Caudill, Mixon & Wallace 2014). Elite players have long been suspected of receiving preferential treatment in the NBA by referees. Caudill, Mixon & Wallace (2014) tested this hypothesis on a dataset of players in the 2011 NBA playoffs. Star players were determined to have received an all-star selection in either the current or previous season, or both. The authors compared the free throw attempts per minute in the final quarter of the game to attempts per minute in the preceding three quarters. The authors then examine the ratio of all-star players with significantly positive excess free throw calculations to non-all-stars with excess free throws. They find a statistically significant difference between all-star and non-all-star players with respect to excess free throw attempts, suggesting evidence of referees making biased calls to protect the leagues star players. Gift & Rodenberg (2014) examined the Napoleon Complex in the NBA, a bias by shorter refereeing crews to give more fouls to taller players. The authors determined a bias against taller players did exist using an OLS with fixed effects and the dependent variable of a player's foul rate.

Referee bias in favor of star players exists not only in the NBA but also in other sports leagues around the world. Erikstad & Johansen (2020) examined the existence of referee bias in the Norwegian Premier League. The authors utilized a Chi-squared test to examine if a successful team received more penalties in their favor compared to an unsuccessful team. The results showed bias in favor of successful teams did exist.

Quantile regression approach has been utilized in previous literature in sport, including football (Keefer 2013), baseball (Fort, Lee & Oh 2019), and golf (Kahane 2010). The method is often utilized in examining issues with salary in sport due to its advantages handling nonnormality issues from skewness or outliers, player fouls drawn rate follows a similar skewed distribution to salary. Scully (1974) was the first to employ the quantile regression method in a sport related field when he examined the marginal revenue and value of players in the MLB.

4.0 DATA AND EMPIRICAL METHODOLOGY

4.1 Data

The data used in this study consists of season observations from 4 NBA seasons from 2015-2016 to 2018-2019. Data on player position and statistics, including in-game performance data, was provided by Basketball-Reference.com. Player annual salary data was provided by ESPN. Players participating on “two-way contracts”, contracts allowing players to participate as a part-time member of the roster, were not included in the dataset due to the artificially low contract salary they receive. A description of the variables used can be found in the appendix. The summary statistics of the data are presented in Table 1:

Table 1: Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Salary	2,069	5,874,250	6,879,225	4,608	3.75e+07
Age	2,069	26.469	4.279	19	42
Center	2,069	0.2020	0.4016	0	1
GS	2,069	23.033	27.655	0	82
PTS	2,069	489.923	461.901	0	2818
DBPM	2,069	-0.1376	1.999	-29.1	42.7
FGA	2,069	398.045	357.326	0	1941
ThreePA	2,069	130.157	144.042	0	1028
TOV	2,069	62.648	59.848	0	464

Table 2 contains the correlation table to examine for potential collinearity and high correlation among the variables.

Table 2: Correlation Statistics

Variables	*Salary*	*Age*	*Center*	*GS*	*PTS*	*DBPM*	*FGA*	*ThreePA*	*TOV*
Salary	1.0000								
Age	0.2454	1.0000							
Center	0.0125	-0.0223	1.0000						
GS	0.5528	0.0249	-0.0301	1.0000					
PTS	0.5878	0.0100	-0.0630	0.7958	1.0000				
DBPM	0.0822	0.0538	-0.0143	0.0951	0.0478	1.0000			
FGA	0.5692	0.0055	-0.0660	0.7961	0.9898	0.0291	1.0000		
ThreePA	0.4115	0.0662	-0.0845	0.5715	0.7559	-0.0255	0.7805	1.0000	
TOV	0.5366	-0.0001	-0.0963	0.7507	0.9041	0.0805	0.9017	0.6478	1.0000

4.2 Empirical Model

The model was developed from previous literature, using variables included in earlier research by Price & Wolfers (2010) and Caudill, Mixon & Wallace (2014) which examined referee bias in the NBA. The model is adapted to use salary as a proxy for star-player status and a quantile regression approach previously used in Kahane (2010) and Keefer (2013) due to the skewness of the dependent variable. The model is specified below:

Model (1): $Foul\_Drawn\_Rate_{it} = \beta_0(\theta) + \beta_1\, Salary_{it}(\theta) + \beta_2\, Age_{it}(\theta) + \beta_3\, Starts_{it}(\theta) + \beta_4\, Points_{it}(\theta) + \beta_5\, DBPM_{it}(\theta) + \beta_6\, FGA_{it}(\theta) + \beta_7\, 3PFGA_{it}(\theta) + \beta_8\, TO_{it}(\theta) - \beta_9\, Center_i(\theta)) + \varepsilon_{\theta it}$

The dependent variable in the model, $Foul\_Drawn\_Rate_{it}$, measures the number of fouls a player draws per 48 minutes played for player i in season t. The variable is calculated by dividing the number of fouls drawn by a player each season by the number of total minutes played and then multiplying that result by 48. This approach balances the dataset to control for players receiving significant different amount of playing time, a similar per minute adjustment has been used in previous research on star-player bias by Caudill, Mixon & Wallace (2014).

There are nine independent variables in the model which were gathered from two sources, ESPN and basketball-reference.com. A description of the variables and their respective sources is included in the appendix as Appendix A. The first variable is $Salary_{it}$, the independent variable of interest; this variable is used as proxy for star-player status, it measures the total compensation a player i received after the conclusion of season t. Age_{it} represents the age, in years, of player i in season t. $Starts_{it}$ represents the number of games a player i starts in season t. $Points_{it}$ represents the number of total points scored by player i in season t. $DBPM_{it}$ is a defensive index calculated using player defensive statistics, such as blocks, steals and fouls to estimate the number of points above average a team can expect to score when player i is on the court. FGA_{it} represents the number of field goals player i attempts in season t. $3PFGA_{it}$ represents the number of three-point field goals a player i attempts in season t. TO_{it} represents the number of turnovers a player i commits in season t. $Center_i$ represents a binary variable which takes on the value of 1 if the player's listed primary listed position is center and 0 otherwise. Finally, $\varepsilon_{\theta it}$ represents the error term in the model.

5.0 EMPIRICAL RESULTS

Table 3 contains the results of the three quantile regressions specified. Results were gathered for the 25th, 50th, and 75th quantiles. A standard OLS regression including all of the variables in the original model was also specified to compare with the quantile regression results.

Table 3. Quantile Regression Results

	Standard OLS *Fouls_Drawn_Rate*	25th Quantile *Fouls_Drawn_Rate*	50th Quantile *Fouls_Drawn_Rate*	75th Quantile *Fouls_Drawn_Rate*
Salary	1.17e-08*	9.74e-09*	1.06e-08**	1.83e-08**
	(2.56)	(2.39)	(2.67)	(3.26)
Age	-0.0203***	-0.0197***	-0.0217***	-0.0246***
	(-3.45)	(-3.76)	(-4.26)	(-3.41)
Center	-0.0990	-0.0425	-0.0836	-0.0943
	(-1.70)	(-0.82)	(-1.65)	(-1.32)
GS	-0.0114***	-0.00702***	-0.00982***	-0.0129***
	(-8.02)	(-5.53)	(-7.94)	(-7.35)
PTS	0.00629***	0.00478***	0.00641***	0.00687***
	(16.62)	(14.19)	(19.54)	(14.77)
DBPM	-0.0191	-0.0214*	-0.0346***	-0.0509***
	(-1.59)	(-2.00)	(-3.32)	(-3.44)
FGA	-0.00602***	-0.00409***	-0.00609***	-0.00670***
	(-11.67)	(-8.90)	(-13.60)	(-10.56)
ThreePA	-0.00298***	-0.00290***	-0.00299***	-0.00325***
	(-10.71)	(-11.71)	(-12.41)	(-9.50)
TOV	0.00363***	0.00444***	0.00422***	0.00377**
	(3.83)	(5.26)	(5.13)	(3.23)
Season Controls	✓	✓	✓	✓
Team Controls	✓	✓	✓	✓
N	2069	2069	2069	2069

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results show evidence of star-player bias does exist in the NBA. The variable of interest, *Salary*, appears significant in all of the quantile regressions as well as the OLS regression. The variable becomes more significant at higher quantiles, only significant at the 5% level of significance for the 25th quantile but significant at the 1% level for the 50th and 75th quantile regression estimations. While the variable of interest is statistically significant the very low magnitude of salary means the practical significance of the relationship is small. For example, in the 75th quantile regression a player who receives a $10 million increase in salary would expect to receive an extra 0.183 fouls drawn per 48 minutes played. However, the results still show star-player bias exists and this would be consistent with the previous literature by Caudill, Mixon & Wallace (2014) which also found evidence of star-player bias in the NBA.

Interpreting the results shows the impact of salary also increases at the higher quantile levels. The 75th quantile regression has salary with nearly double the impact on fouls drawn than the impact in the 25th quantile. Most of the controls also were highly significant across all of the regressions estimated with the exception of *Center* which was not statistically significant in any of the models, so player position does not affect a player's fouls drawn rate. The variable *Age* was statistically significant and negative, this is due to potential a decrease of aggressive playing style as players gets older due to primarily the increased injury risk as players age. Many variables had high levels of correlation and as expected, were all highly significant. These variables were included despite their high levels of correlation because they measured player performance and while they did not measure the same factors of player performance, they were expected to correlate significantly regardless.

Ultimately a number of factors appear to have a statistically significant impact on the number of fouls a player draws, and the controls were highly significant with the correct anticipated signs. The variable of interest provides statistically significant evidence of star-player bias by referees in the NBA and the effect of this bias increases at the higher quantile levels. As a player's salary rises the number of fouls they receive also increases, so the highly paid star-players receive a greater number of fouls called in their favor than their lower paid counterparts.

6.0 CONCLUSION

The aim of this study was to determine if star-players in the NBA benefited from referee bias by examining the number of fouls they draw per 48 minutes in relation to their salaries. The finding show that star-player bias does exist in the NBA, players with higher salaries receive preferential treatment by having a greater number of fouls called in their favor, even when controlling for outside relevant factors. The results showed salary was significant in increasing the number of fouls a player draws for each of the quantiles tested and the impact of salary increases at the higher quantiles. While the results are statistically significant the small magnitude of the salary variables shows only a significant change in salary would result in a meaningful impact on the number of fouls drawn for a player. The results of this study match the result of previous literature examining star-player bias by referees in the NBA.

Due to the highly skewed dependent variable a quantile regression was used which differed from the previous literature. Salary was also used a proxy for star-player status in place of all-star or all-NBA team selections more commonly used to determine star-player status. This bias by referees allows higher paid players to exploit the bias by playing more aggressively, confident they will receive a greater number of foul calls. Lower paid players, meanwhile, would be advised to play less aggressively since they are likely to receive less calls in their favor. This can also impact a coach's decision-making and situational strategies in games. Future research could focus on other potential sources of bias by referees which may impact the decision-making of teams and coaches or affect the outcome of games. Research should also examine how a team's decision-making may be affected by the existence of star-player bias and how both high paying players adjust their playing styles to benefit from or lower paid players avoid the negative effects of star-player bias.

Appendix

Appendix A: Data Description

Variable Name	Description	Source
Foul_Drawn_Rate	Number of fouls drawn by a player per 48 minutes played	Basketball-reference.com
Salary	Player	ESPN Salary Database
Age	Player age at start of season	Basketball-reference.com
Center	Player position = Center; 0 = No / 1 = Yes	Basketball-reference.com
GS	Games started	Basketball-reference.com
PTS	Total points scored	Basketball-reference.com
DBPM	Defensive Box Plus / Minus , estimate of the number of points better or worse a team can expect to perform with this specific player on the court (Average is zero)	Basketball-reference.com

FGA	Total field goal attempts	Basketball-reference.com
ThreePA	Total three-point field goal attempts	Basketball-reference.com
TOV	Total turnovers	Basketball-reference.com

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