Factors Determining NBA Salaries

Info Crunchers

Background

In an article published by Dario AS, a sports newspaper company, it was revealed that during the 2022-2023 NBA season, "the lowest-paid player in the league is held by Ishmail Wainright of the Phoenix Suns, who earns a total of \$633,891" while "the highest-paid player in the league, Steph Curry earns \$48,070,014 a year" (Rudder, 2023). What causes this considerable discrepancy between NBA players and their respective salaries? Fortunately, many possible predictors within the NBA can be analyzed to determine whether correlations exist between an NBA player's salary and their statistics. In this report, the three main research question being explored to answer these ongoing disparities are:

- Does a player with a higher true shooting percentage have a higher salary on average?
- Does a player that plays more games per season have a higher salary on average?
- Do older players have a high salary than younger players on average?

Firstly, in a past study, it was discovered that "a higher field goal attempt rate represents the players' offensive importance in the team, [and thus] these players with high field goals will usually be paid more" (Yin, 2022). This proposes a potential relationship between salary and a player's true shooting percentage since that statistic is heavily dependent on field goals. Therefore, it is hypothesized that if the true shooting percentage increases, then player's salary will increase accordingly.

Moreover, in a study published by The Sports Journal, it was brought into attention that many believe that being in the league for a long period of time, indicating more firsthand experiences in play and thus possessing increasingly vital skills, justifies the demands for a higher salary (Sigler, 2018); these firsthand experiences are accumulated through a player participating in more games played per season. This sparks the question whether playing more games per season, developing crucial hands-on skills for their profession, correlates to a higher salary.

Lastly, in a study published by the Atlanta Press, it was uncovered that some evidence points to the conclusion that "for every 1 year increase in the NBA player's age, the player's salary will increase by \$0.414 million" (Zhao, 2022). This suggests that NBA players who are older tend to make more money than NBA players who are younger. In order to examine this, this report will continue onto analyzing the trend between explanatory predictors, such as age, with the response variable of player salaries.

Data Description

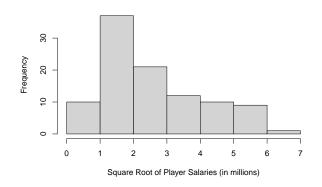
In this report, the data collected consists of NBA players in the 2022-2023 NBA season gathered to reveal possible indicators of NBA annual salaries. The data combines three different datasets from Basketball Reference, for the majority of the advanced statistics; Hoopshype, for NBA player salaries; and the official NBA website, for previously attended colleges of each player. These datasets were utilized because they include valuable statistics such as a player's position, their NBA team, individual shooting percentages, etc., which are all variables that can contribute to NBA salaries. In the original data, the dataset featured over 400 observations, accounting for all NBA players in the 2022-23 season. In this study, a simple random sample of 100 players is extracted from the original observations.

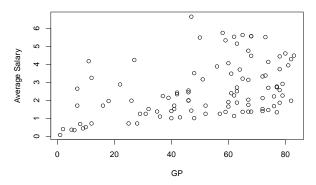
In addition, manipulations made to the dataset include removing repeated predicators throughout the three data sources. Secondly, explanatory variables that measure uninterested values to the research and/or suggest clear multicollinearity were also removed. Thirdly, this report deemed it necessary to transform the response variable from the normal Salary in millions into the square root of those values to better account for the relationships between the response and the predictors. The only potential issue in the finalized dataset is that the sampling method could not be completely representative of the population. Specifically, a few players without complete statistics were removed from the sample consideration. This report also sought to remove any duplicate players that transferred teams from consideration to avoid any confusion within the sample population, however, the examined statistics for a duplicate observation were not necessarily the same. The final concern involves the method of sampling; a different sampling method may have been more representative of the population of NBA players by accounting for more of the variability within the players. Lastly, the sources of the data are all reputable sports news websites, so they are reasonably trustworthy sources.

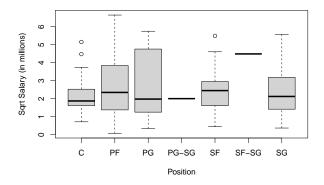
Exploratory Data Analysis

[,1] Age 0.315 TS% 0.304









Conclusion

In the above graphics, the first summary is the histogram for the response variable, player salary in millions. The original graphical representation of a player's annual salary appears to be unimodal and continuous but extremely skewed to the right. In order to make the response variable more suitable for regression analysis, the variable in consideration was transformed by taking the square root of the annual salary results to "pull in" extreme values. Although a right skew is still visibly present, this modification allowed the histogram to appear slightly more symmetric with values more evenly represented in the x-direction.

For the relationships with the explanatory variables, the scatterplot features games played on the x-axis versus the square root of the salary in millions. While there does seem to be a

slightly positive linear relationship between the two variables, the observations are displaying a "fanning out" trend as x increases; this indicates that the relationship between the two is not necessarily strong. Similarly, in the numerical summaries of the correlation table, the correlations for the variables of interest, age and true shooting percentage, are 0.315 and 0.304 respectively. These values suggest weak positive relationships with salaries. In terms of the age variable, there is likely not enough data sampled on different ages to fully understand whether a linear relationship exists with salaries. A majority of the current players range from late 20s to early 30s, and since it is a simple random sample of 100 observations, the few older players may not have been fully accounted for when compared to the potential results if a cluster sampling method was preformed. For the true shooting percentage, the weak relationship with salaries may encourage further evaluations of a different variable, but the correlations are not determined to be insignificant until the model-building step where its relationships with multiple variables are considered, so they are still kept.

Lastly, among the graphics, there is a box plot between the qualitative variable, player positions, and their squared root salary. Although the few players with multiple positions, PG-SG and SF-SG, have a lack of data available, the results from the other individual playing positions are noteworthy. The salaries for the center, small forward, and shooting guard exhibit a pretty similar distribution for salaries with 50% of the players earning around two million to six million yearly. Two outliers exist in the center position earning around 20 and 25 million each, and one outlier exists in the small forward position earning slightly above 25 million dollars annually. In addition, while the median salary for all positions is around four million, the point guard position is notable for its large disparity within the upper quartile. This variation in position salaries stipulates a potential importance that can be further analyzed in the multiple regression model.

Ultimately, since the explanatory variables of interest are not extremely strong compared to the other variables available, to continue, the report should consider including some stronger predictors, such as games started (r=0.621), win share (r=0.659), and value over replacement player (r=0.659), to ensure a more meaningful statistic summary from the regression.

Appendix A: Data Dictionary

Variable Name	Abbreviated Name	Description
Player	Player	Individual players in the NBA 2022-23 season
Salary	sqrtSalary	Square root of the player's
	5qi usalar y	salary in millions of U.S.
		dollars
College	College	U.S. university the player
		last attended
Position	Position	Player's NBA team position
		C=center, PF=power
		forward, PG=point guard,
		SG=shooting gaurd,
		SF=small forward
Team	Team	Player's NBA team
Age	Age	Player's age as of February
		1st of the 2022-23 season
Games Played	GP	Number of games the player
		played in
Games Started	GS	Number of games which the
		player started in
Minutes Played	MP	Number of total minutes the
		player played
Minutes Per Game	MPG	Average minutes per game
		played
Player Efficiency Rating	PER	Measure of per-minute
		production standardized
		such that the league average
		is 1
True Shooting Percentage	$\mathrm{TS}\%$	Measure of shooting
		efficiency accounting 2-point
		field goals, 3-point field
		goals, and free throws.

Variable Name	Abbreviated Name	Description
Free Throw Percentage	FT%	Percent of free throws made
		to attempted
3 Pointer Percentage	3P%	Percent of field goal
		attempts from 3-point range
Usage Rate Percentage	$\mathrm{UR}\%$	Estimate of percentage of
		team plays used by a player
		while they were on the floor
Offensive Win Share	OWS	Estimate of the number of
		wins contributed by a player
		on offense
Defensive Win Share	DWS	Estimate of the number of
		wins contributed by a player
		on defense
Win Share	WS	Estimate of the number of
		wins contributed by a player
Value Over Replacement	VORP	Box score estimate of the
Player		points per 100 TEAM
		possessions that a player
		contributed above a
		replacement-level (-2.0)
		player, translated to an
		average team and prorated
		to an 82-game season
Field Goal Made	FGM	Number of average field
		goals made per game
Field Goal Attempted	FGA	Number of average field
		goals attempted per game

Appendix B: Data Rows

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Player sqrtSalary
                                     College Position Team Age GP GS
                                                                       MP MPG
  Cameron Johnson
                    2.426499 North Carolina
                                                      TOT
                                                            26 42 41 1199 28.5
                                                  PF
  Pat Connaughton
                    2.393406
                                 Notre Dame
                                                   SF
                                                      MIL
                                                            30 61 33 1443 23.7
3
       Kevin Love
                    5.527836
                                       UCLA
                                                  PF
                                                      TOT
                                                            34 62 20 1240 20.0
4
     Anthony Gill
                                                      WAS
                    1.355024
                                   Virginia
                                                  PF
                                                            30 59 8 624 10.6
                                  Ohio State
5 Keita Bates-Diop
                    1.370664
                                                   PF
                                                      SAS
                                                            27 67 42 1452 21.7
                                                                      248 7.1
        KZ Okpala
                    1.379178
                                    Stanford
                                                   PF
                                                       SAC
                                                            23 35 3
   PER
        TS%
                     3P% UR% OWS DWS WS VORP FGM FGA
1 17.1 0.617 0.842 0.404 20.6 2.1 1.4 3.5 1.4 5.3 11.3
2 10.0 0.531 0.659 0.339 13.8 0.7 1.8 2.5 0.3 2.7
3 13.1 0.548 0.879 0.334 19.2 0.6 2.0 2.6 0.8 2.7
                                                    6.8
4 11.1 0.604 0.731 0.138 12.3 1.0 0.4 1.3 -0.2 1.2
5 14.9 0.609 0.793 0.394 16.7 2.1 0.6 2.7 0.5 3.5
                                                    6.9
6 6.2 0.554 0.875 0.333 8.4 0.1 0.2 0.3 -0.1 0.5
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Appendix C: References

- 1. Your resources go here in APA styling. Hanging indent is not required. Links should be surrounded by <>.
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