NBA Salaries: How Much is that Buzzer Beater Worth?

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Introduction

Professional sports salaries, especially in the NBA, are a topic of continuous public debate because they sit at the intersection of performance, marketability, and organizational strategy. Understanding what truly drives a player's salary is valuable not only to analysts and researchers, but also to teams making contract decisions and fans trying to understand the economics behind the sport. Prior studies suggest that both quantitative performance metrics and qualitative recognition, such as awards or team roles, significantly influence earnings. Motivated by this, our research explores the statistical relationships between player attributes and their salaries.

Our general research question is: What factors best explain variation in NBA player salary?

From this, we developed three specific research questions, each tied to a chosen predictor and one response variable. The response variable in all three questions is NBA player salary.

Quantitative Predictor: Do NBA players who score more points (PTS) earn higher salaries on average?

Quantitative Predictor: Is there a significant relationship between a player's total defensive contributions (steals + blocks, "stocks") and their salary?

Qualitative Predictor: Do players who have won at least one major NBA award (e.g., MVP, All-NBA Team selections) earn higher salaries than those who have not?

Overall, this project is relevant because salary determination is central to team strategy, player valuation, and league-wide competitive balance. By analyzing both quantitative and qualitative predictors, we aim to identify which factors hold the strongest statistical relationship with NBA salary and how these insights compare to findings in the sports economics literature. ## Data Summary

Data Sources

The data in this project were compiled from publicly available and reputable basketball statistics platforms. Performance statistics, biographical information, and award histories were collected from Basketball Reference, a database known for its accuracy, professional documentation, and long-standing use in academic sports analysis. Together, these sources provide a complete picture of each player's performance and compensation.

To prepare the data for analysis, we standardized naming conventions across the two sources and combined the datasets so that each player occupied a single row with salary, performance, and awards information. Awards were originally stored in long strings listing placements, team selections, and voting outcomes, so we simplified these into a three-level qualitative variable representing the general number of accolades received. Age was also simplified into qualitative brackets to match our research questions.

Overall, the combined dataset contains a rich mixture of performance and recognition indicators, allowing us to meaningfully evaluate how both quantitative and qualitative factors relate to NBA salary. While subjective elements such as awards voting and contract timing may influence individual observations, the breadth and reliability of the sources allow us to confidently proceed with statistical analysis. ### Exploratory Data Analysis

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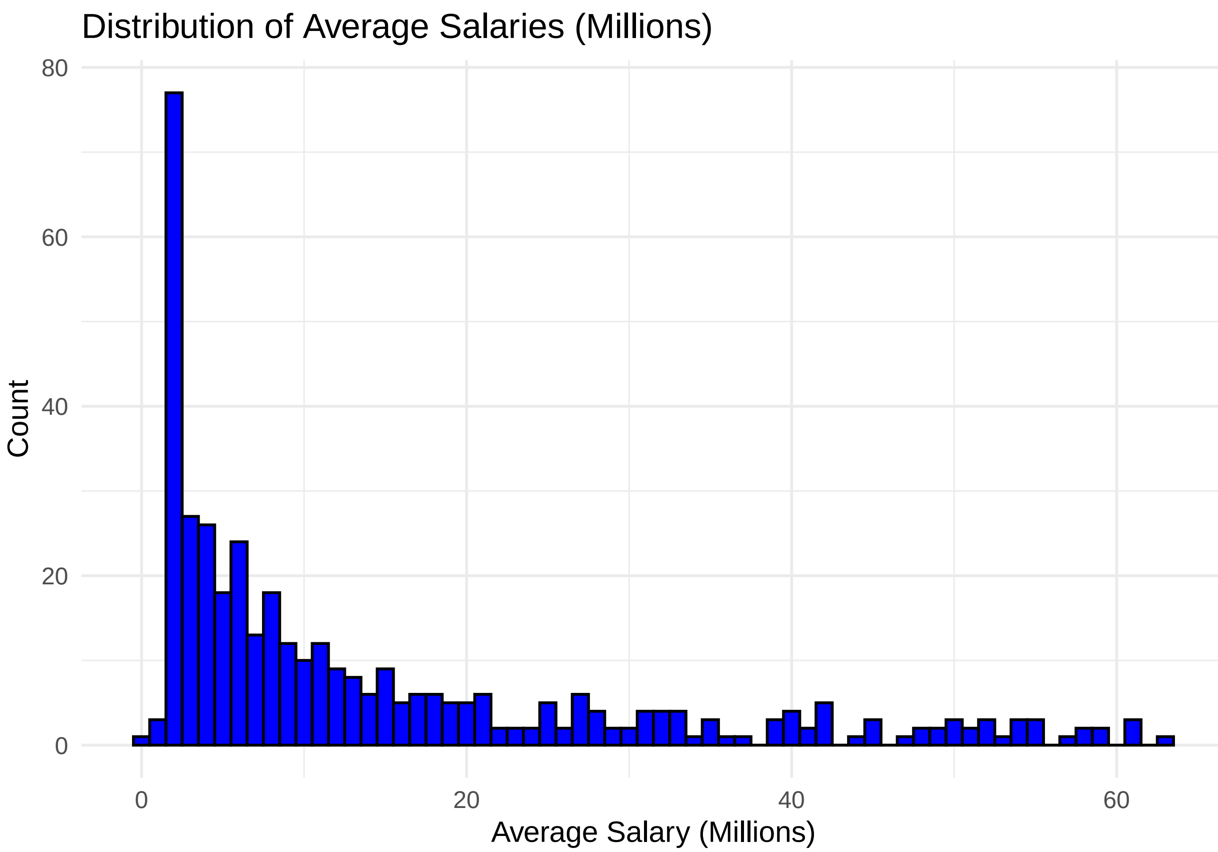


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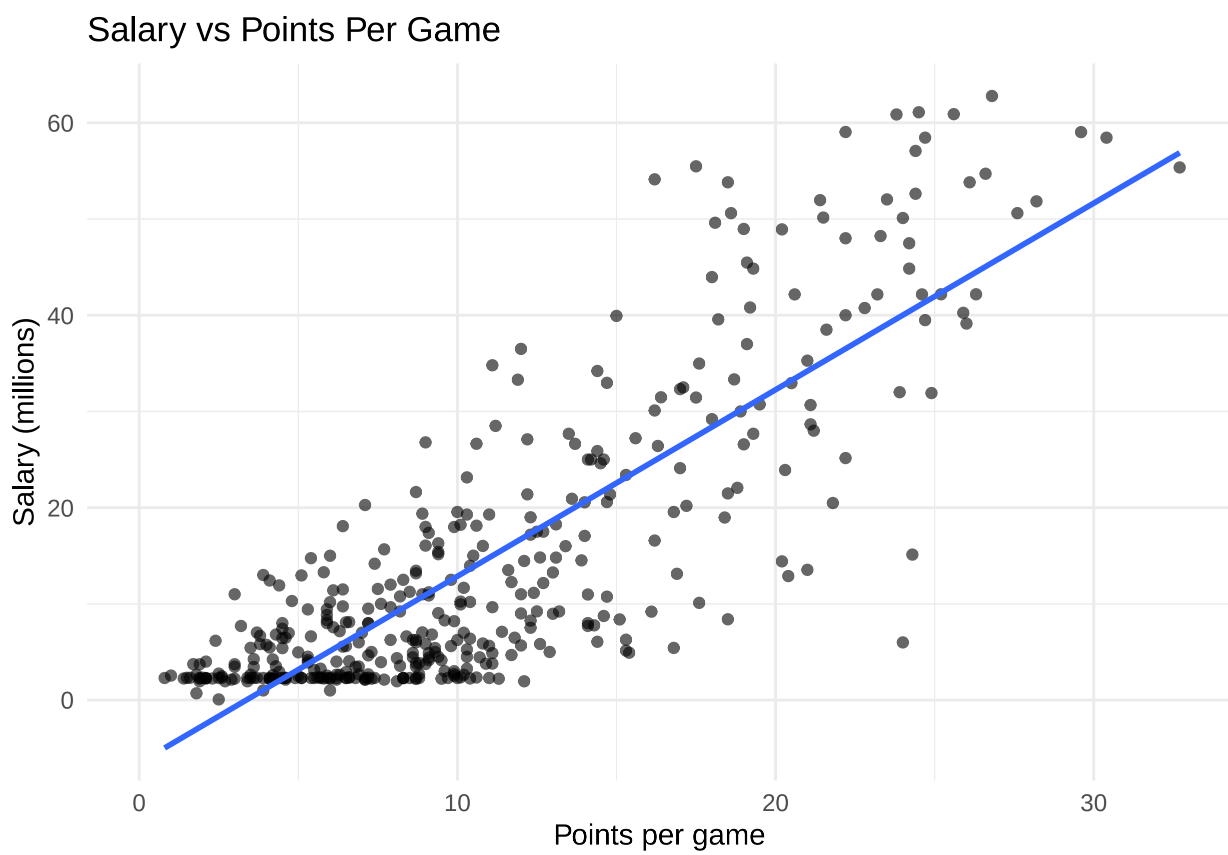


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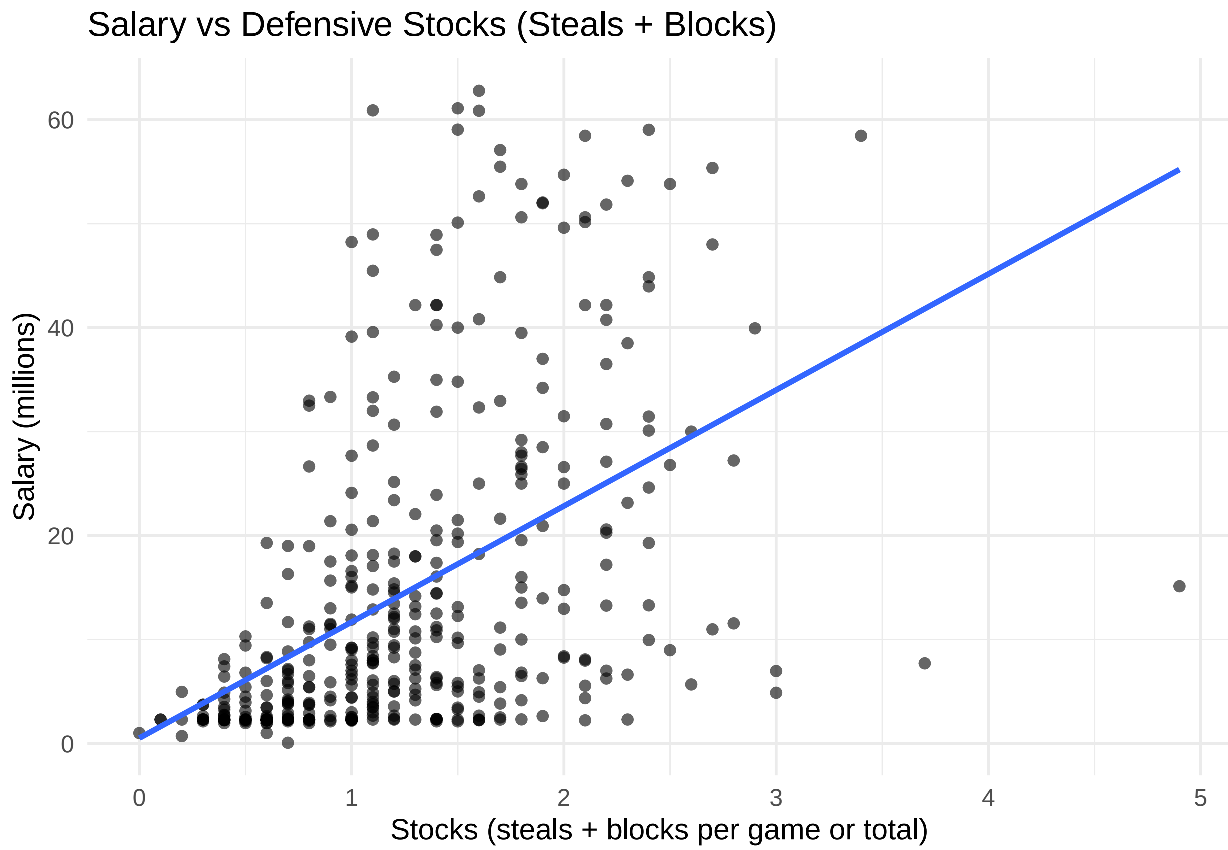


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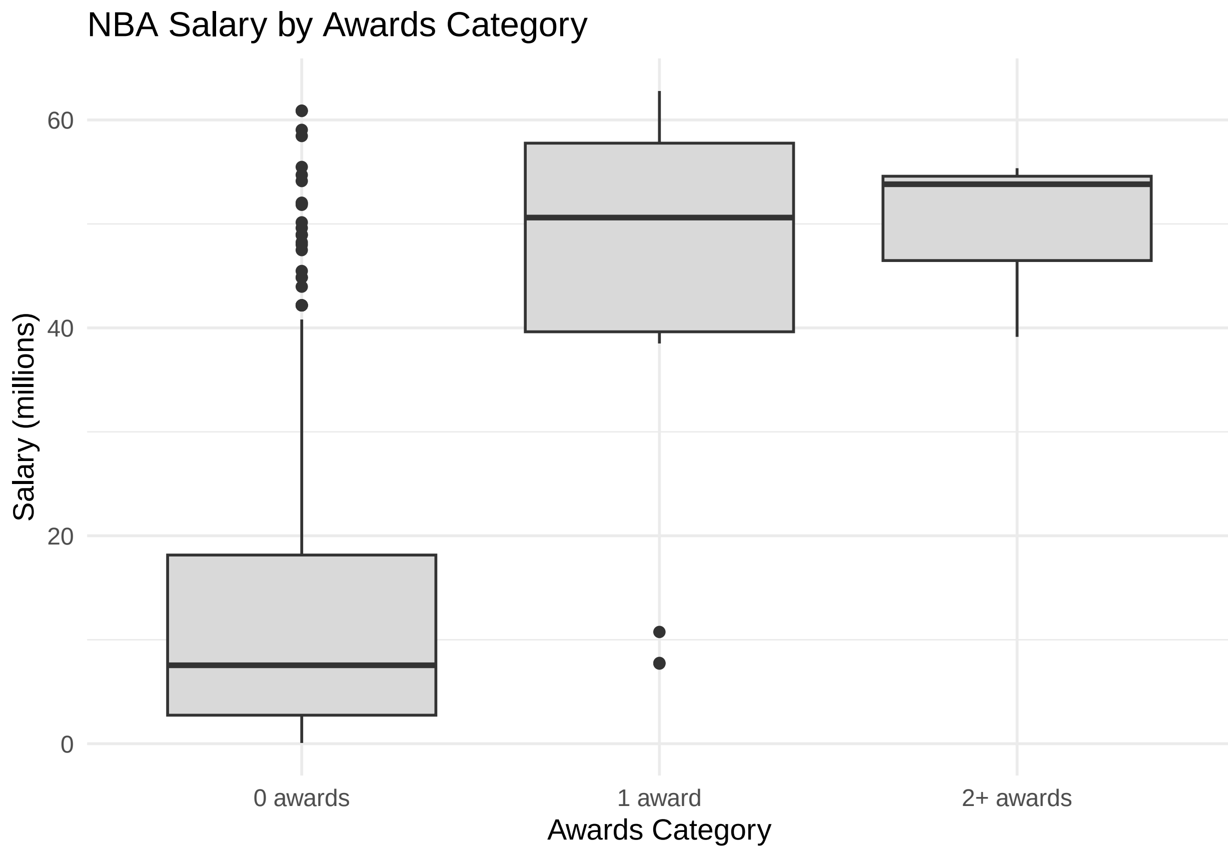

EDA Summary

To understand how performance and recognition relate to NBA player salaries, we began by examining the distribution of our response variable, average salary (in millions of dollars). The histogram shows that salaries are heavily right-skewed, with the majority of players earning under $10 million per year. Numerically, the median salary in our sample is approximately $5.4 million, while the mean salary is higher at $9.0 million, reflecting a small group of extremely high-earning players who pull the average upward. This skewed structure is expected in the NBA, where superstars sign "max contracts" much larger than the salaries of role players. Importantly, salary is a continuous quantitative variable, making it appropriate as a response variable for multiple linear regression. Although the data are skewed, the linear model can still be interpreted meaningfully; however, if model assumptions are violated later, we may consider transformations such as logging salary.

Relationship Between Scoring and Salary A scatterplot of salary versus points per game (PTS) shows a clear positive trend: players who score more tend to earn more. The fitted regression line rises steeply, suggesting scoring is strongly associated with higher pay. Numerically, high scorers (20+ PPG) earn an average of $35–$45 million, while low scorers (under 5 PPG) typically earn below \$5 million. This relationship aligns with economic expectations. Scoring is perhaps the most visible and rewarded skill in basketball, and our EDA indicates it is likely to be a significant predictor in the regression model.

Relationship Between Defensive Stocks and Salary We also explored the connection between salary and defensive activity, measured by “stocks” (steals + blocks). The scatterplot shows a weaker but still positive trend. On average, players who average 2 or more stocks tend to earn \$20–\$40 million, while those with fewer than 1 stock per game cluster near lower salaries. The numerical spread suggests that although defense contributes to player value, it may not influence salaries as strongly as scoring, which is consistent with league-wide patterns where offensive stars typically command the highest contracts.

Salary Differences Based on Awards To evaluate whether league recognition affects earnings, we created a categorical variable Awards with three levels: “0 awards,” “1 award,” and “2+ awards.” The boxplot shows clear separation among these groups. Players with 0 awards have a median salary of about \$8 million, while players with 1 award have a median salary of roughly \$50 million. Those with 2+ awards earn even more on average, with a median close to \$55 million. These numerical patterns strongly suggest that award recognition, representing public and league-wide acknowledgment of excellence, is associated with substantially higher pay.

The broad salary range within each group also highlights the importance of including additional variables, since recognition alone does not explain all variation. Still, the clear upward shift in salary distributions across the award categories implies that awards are likely to be an important qualitative predictor.

Suitability of Variables and Consideration of Multicollinearity Before finalizing our regression model, we assessed potential multicollinearity among predictors. Scoring (PTS) and some other offensive statistics (not included in our model) can be highly correlated, which may inflate standard errors if included simultaneously. However, in our chosen model, stocks and awards do not appear strongly correlated with scoring, meaning multicollinearity should be minimal. Variance Inflation Factor (VIF) checks later in the analysis will confirm this formally.

All selected predictors: PTS, stocks, and Awards, show meaningful variation and substantive relationships with salary. The EDA supports the idea that each variable ties directly to one of our research questions and is suitable for inclusion in a multiple linear regression model.

Methods and Analysis

Results

Conclusions

Appendix A: Data Dictionary

Variable Name	Abbreviated Name	Description
Variable 1	Var1	This is the first variable.
Variable 2	Var2	This is the second variable.

Appendix B: Data Rows

Appendix C: Final Model Output and Plots

Appendix D: References

Background

Data Sources

Additional Help