Quantifying the True Trade Value of NBA Players: A Data Driven Approach

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Abstract

The fairness of NBA trades has long generated debate, with some attributing the player valuation primarily to on-court performance and statistics, while others argue other factors come into consideration, such as hype, contracts, and backroom politics. This work aims to explore the true drivers or NBA players valuation by analyzing a comprehensive NBA season dataset from the 2022-2023. The dataset includes basic performance metrics (e.g. points, rebounds, assists); advanced statistics (e.g. efficiency ratings), and player salaries. Using regression models, we examined the relationship between performance indicators and salaries as trade value. Results show that approximately 90% of teams' payroll were strongly correlated with the team performance. Yet, at the individual level, many players appeared to be significantly overpaid or underpaid relative to their statistics. These findings suggest that while performance is a critical factor in valuation, other variables such as years of experience, contract timing and team fit play a substantial role. NBA player valuation, therefore, is a multidimensional construct influenced by both performance data and broader organizational strategies.

Introduction

In basketball, there has never been a lot of talk about what really makes an NBA player valuable. Is it as simple as points scored or on-court performance? Or do other factors, like hype, contract timing, or even backroom politics, enter into the equation just as much? This research investigates how NBA players are valued. For this project, We analyzed player statistics and salaries for the 2022–2023 NBA season. We were working with a dataset that included both basic statistics like points, rebounds, and assists, as well as advanced statistics like efficiency ratings. We also had the salary of each player, which allowed for a direct comparison of how much players are being paid versus how well they're actually performing. The goal was to see whether performance is the greatest determinant of a player's value, or whether there is more going on behind the scenes. To do this, we used a type of analysis called regression, which helps demonstrate how directly linked certain things are, like salary and performance here. What we found was that for the majority of squads, there's a close relationship between a squad's performance and what they pay their players. But if you look at the players one by one, many players appear to be compensated in ways that do not align directly, as their statistics would suggest. That tells you that performance definitely comes into it, but it's not the only factor teams take into account. The objective is to determine whether performance indicators acknowledge just how complicated player value really is. It's not simply a matter of numbers, but of timing, popularity, and strategy for the team. This paper also reviews related literature on how teams make these decisions. We can have more balanced and better-informed discussions about trades, salaries, and what players are really worth. When we started on this project, we were attempting to figure out what exactly goes into making an NBA player worth their weight in gold. Is it just how many points they can score? Or is there something else, like timing, popularity, or even back-room politics, behind how much they're paid? To help answer that, we drew upon a series of studies examining similar questions. Others, like the one by Arkow, Jachuck, and Kolar (2023), illustrated that some statistics are exaggerated while others get too little attention when teams assess players. Berri (1999) also highlighted what truly makes a player worth their team, not on paper. Another interesting study by Franks and his co-authors (2014) illustrated that defense is often misunderstood and deserves more recognition. Rust (2014) also addressed which statistics help teams win and how that impacts what players are compensated, similar to what we were trying to find out with the regression analysis. Other researchers place more focus on funds. Lautier (2023) came up with a way to measure if players actually are worth as much money as they receive compensation for, and Papadaki & Tsagris (2020) used machine learning to connect how much players receive in compensation with how effectively they play. Maddock (2018) explored how well player performance can influence even large companies, such as sports brands, and Sigler & Compton (2018) jumped into what statistics are most vital when it comes to pay. There were, of course, some studies that extended to the team or league level. For example, Ma & Ning (2023) found that when star players switch teams, it really does increase or lower a team's value. Huang & Lyu (2023) talked about how the NBA makes money overall and why it's not simply a sports league, it's business with a capital B. Certain research enabled me to understand how to break down all of this. Terner & Franks (2020, 2021) illustrated different ways of modeling the performance of players using data, which helped me with the regression analysis that we did. And a review paper by Wellm and others (2024) listed all the major factors influencing the manner in which players play over the years. Finally, there were also some researchers who spoke about how public perception is not always what the player actually is. Righini (2021) found that people tend to overrate or underrate players. Sigler & Compton (2018) also said that what the fans and teams 'feel' matters might not actually be what *really* matters. Welsh (2023) provided me with the salary data that we utilized for the comparison of the 2022–2023 season. In general, all these studies helped to confirm what We found that performance is crucial, but it's not the whole story. There are other factors, like hype, timing, and team strategy, that also play a big role in how much money a player earns and how much they're worth.

Background

In recent years, the issue of pay disparity has been a topic of interest in various industries, including sport. The National Basketball Association (NBA), one of the most influential sports leagues in the world, provides a compelling context to observe salary patterns and variation among its players. The level of player performance, experience, draft position, and marketability are generally believed to influence salary levels. However, the precise impact of these factors on the salary distribution remains the subject of ongoing debates and investigation. The NBA operates under a salary-cap framework,which sets limits on the total amount teams can spend on player salaries. Under this arrangement, however, drastic differences in the incomes of players still persist. These studies suggest that while performance remains about how much of an influence measurable benchmarks, such as points per game, assists, and player efficiency rating (PER), and variables that are difficult to quantify such as team market size and media coverage have on these incomes. Given improved data access and analytical technology development, one can study the determinants of NBA wages more empirically and systematically than in the past. This research aims to use statistical modeling techniques to identify the primary predictors of wages and assess the extent to which performance indicators and other explanatory variables account for pay differences. Zhang (2024) used linear regression to analyze 2022–2023 NBA data and found that defensive skills and shooting accuracy had a close correlation with how much money the players were paid. From a financial perspective, Tyler Stanek's thesis explored the concept of marginal revenue product (MRP), or the additional money a player brings to a team. His research showed that while star players are generally paid more than their MRP, they do bring considerable value through increased ticket sales, merchandise revenue and brand appeal. This supports the belief that a player's worth isn't merely gauged on the court, but also by broader contribution to the team economics and branding. Advanced statistical techniques have also been employed to improve salary prediction accuracy.Feng et al. (2023) are one such case, using techniques including multiple linear regression, ridge regression, lasso regression, and elastic net regression. They analyzed variables like age, games played, and statistics of performance, and arrived at the conclusion that three-point shooting, defense, and teamwork were traits highly prioritized by teams, traits that are especially prized in the modern NBA. In summary, this research builds upon these insights that NBA player valuations are not such a straightforward thing. While on-court performance continues to matter, other factors like experience, efficiency, and economic impact also become important. Clubs that want to make wise choices in terms of signing players and negotiating contracts have to consider all these different variables. Future studies can perhaps do even better by observing how all these different variables interact with each other to ascertain a player's overall value.

Methods and Models

Data Description

In the project, we used a data set called "NBA Player Salaries: 2022–23 Season" from Kaggle, which is a data set of 467 NBA players, one row per player, with numerical (e.g., points per game, rebounds, salary) and categorical features (e.g., position, team). The Table in the Appendix describes the 50 features of this dataset, while Table 1 presents an analysis of the main ones.

We selected this data set because it contained extensive performance statistics and salaries, so that we could see what actually affects an NBA player's salary. The goal was to determine whether players are paid predominantly based on merit or whether other criteria like popularity, timing of contract renewal, or position on the team also play a significant role. We started by pre-processing the data by removing missing values, interpreting salary strings as numerical values and normalizing formatting. We removed features like player name, team, height, weight, and position since pre-processing steps included that they were not significantly correlated with salary. In order to examine the data, visualizations were generated like histograms (for salary distribution), scatter plots (for salary against performance metrics), and a heatmap (to see which statistics correlate with salary). The heatmap revealed that statistics like points per game and assists correlate with salary, though not nearly as much as one would think. To model, We utilized key performance indicators, assists, rebounds, win shares, PER (Player Efficiency Rating), points per game, and games played, since they best portrayed a player's performance throughout a season. We separated the data into 80% training and 20% testing sets and utilized simple linear regression and ridge regression to determine how well performance can forecast salary.

Preprocessing of data included numerical conversion from salary strings, z-score standardization for normalization of the data, and missing data treatment through removal of incomplete player records.

Outliers were identified through the interquartile range (IQR) method but preserved to retain natural variations in salaries and performances of players, particularly for rookie deals and max contracts.
The results suggested that while performance is a contributing element, it does not entirely explain salary variance. Certain players earn significantly more or less than their statistics would suggest, indicating other elements, such as popularity, contract details, or franchise standing, also influence compensation. Ultimately, the project helped to perpetuate the idea that NBA player value is not entirely driven by statistics but also by business considerations like marketability and contract timing.

Feature	Mean	Standard Deviation	Minimum	Maximum
Salary (USD)	7,136,895	8,945,734	58,493	47,345,760
Points per Game (PPG)	11.3	7.4	0.0	33.1
Assists per Game (APG)	3.1	2.5	0.0	10.2
Rebounds per Game (RPG)	4.2	3.0	0.0	12.3
Player Efficiency Rating (PER)	15.5	4.3	-6.8	45.5
Win Shares (WS)	2.3	3.2	-0.5	15.1
Games Played (GP)	29.8	20.4	1	82

Table 1: Main Feature Analysis

About Basketball

Basketball is a team sport characterized by dynamic play that demands a mix of athleticism, strategy, and teamwork. NBA player performance is measured in relation to a set of statistical indicators that capture multiple dimensions of the sport, such as scoring, passing, rebounding, and overall influence. The statistics not only capture a player's on-court contribution but also influence how they are paid and valued. The features used here in this data set, for example, Points per Game, Player Efficiency Rating, and Win Shares, commonly used in basketball analytics in the analysis of basketball to gauge a player's performance and contribution towards team victories.
NBA basketball performance is quantified with a wide range of advanced and traditional statistics, which serve as key indicators in determining a player's on-court value and trade value. Clubs and analysts routinely use stats like Points per Game, Player Efficiency Rating (PER), and Win Shares to approximate a player's contribution to team success and long-term potential. These statistics also have a significant impact on player contracts and front-office decisions in trades. By incorporating these basketball-specific statistics into the modeling process, this study aims to identify which variables most accurately reflect a player's true market value in the NBA trade market.

Methodology and Modeling Approach

In order to determine how much NBA player salaries really have to do with their performance, we decided to use a data-oriented methodology called regression modeling. The objective was to determine whether the statistics, how many points or assists a player gets, are the main reason why they get paid what they get paid, or whether popularity and the timing of contracts are also driving factors. To do this, the data was retrieved, cleaned, picked the most important statistics, and tried out some simple machine learning models to see how well they could predict salaries.

Choosing the Best statistics

The heat map in Figure 1 shows the bigger picture. It allows you to compare all relevant player statistics to each other to see which has the bigger effect on player valuability. It's a step further from the linear regression model.

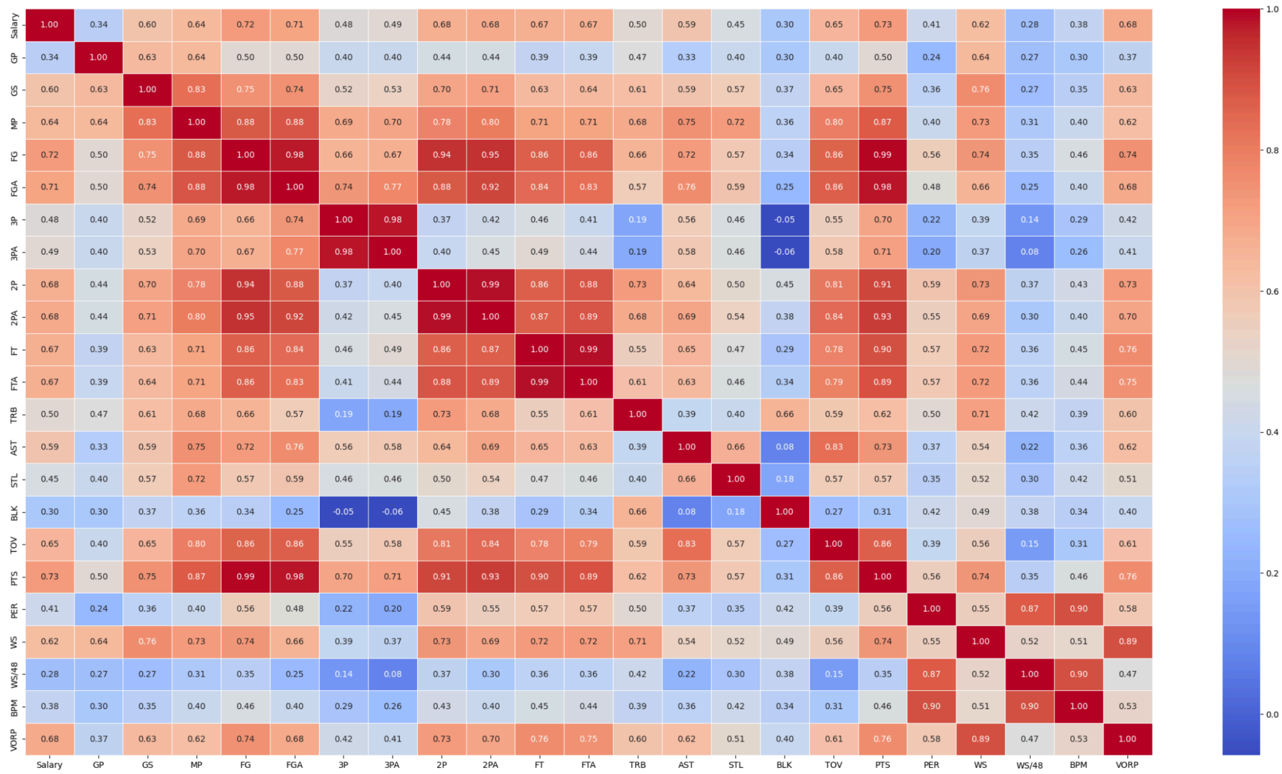

Figure 1: Correlation Matrix Heat Map

To shorten the list, We chose six statistics that seemed to be most significant:
- Points per game (PPG)
- Assists per game (APG)
- Rebounds per game (RPG)
- Player Efficiency Rating (PER)
- Win Shares (WS)
- Games played (GP)

We omitted height, weight, age, and position as they didn't seem to be a relevant factor in predicting salary based on what we saw in the heatmap of Figure 1.

Trends and Correlations

Exploratory analysis was utilized to uncover meaningful trends within the dataset before model building. Player salary was highly correlated with points ($r \approx 0.73$) and more moderately correlated with player efficiency rating (PER) ($r \approx 0.41$), showing that both scoring ability and general efficiency contribute heavily to determining salary. Rebounds per game, assists per game, and win shares/48 also exhibited positive but weaker correlations ($r = 0.59$ to $r = 0.50$ to $r = 0.28$) with salary.

Conversely, age exhibited a weak correlation with salary (r ≈ 0.42), suggesting that performance statistics weigh more in player salaries than experience by itself. Notably, a few high-paid players had poor statistical production, usually because of long-term contracts or marketability factors.
These patterns suggest that while statistical performance hugely influences compensation, other than salary, such as team needs, market size, and contract structure, all influence this as well. Consideration of these dynamics informed the selection of features for the predictive modeling stage.

Machine Learning Models
In order to find out how much these statistics actually affect salary, we applied a number of machine learning models from Python's `scikit-learn` library.
We split the dataset: 80% for training and 20% for testing. That way, we could train the model on one half and then test to see how well it did on the other. We used the "train_test_split" utility to do this. Here are the results We got from each model:

Model	R^2 Score (Test Set)	Adjusted R^2 Score
Linear Regression	0.57	0.56
Ridge Regression	0.62	0.57
Decision Tree Regression	0.50	0.43

Table 2: Model Performance

Ridge regression worked best, i.e., it was best in predicting salary from the statistics. But even the best model only explained about 62% of the variations in salary. This suggests that while statistical performance significantly contributes, they don't tell the entire story.

What We Learned
The research uncovered that while player performance can explain some of the variation in NBA salaries, it doesn't fully account for compensation patterns. Even using very well-optimized models, other influences, e.g., popularity of players, timing of contracts, and team function, also appear to significantly affect salary outcomes. Future research may include aspects such as social media popularity, endorsement contracts, or contract year indicators to more accurately account for these non-performance-related factors. Further, delving into more intricate modeling may be able to enhance the capacity to account for player pay's more subtle underlying factors.

Results

The linear regression model learned to predict NBA player salaries based on six performance metrics, points per game, assists per game, rebounds per game, player efficiency rating (PER), win shares, and games played, recorded an R^2 value of 0.57 on the test set. This suggests that roughly 57% of the variance in player salaries was attributable to statistical performance in isolation. As is evidenced in Figure 1, which plots predicted salary versus actual salary, mid-range earning players lined up with the predictions of the model, while the highest and lowest paid players diverged. This means that for extreme values of salaries, other factors unrelated to performance, popularity, timing of contract, or position on the team, for instance, kick in. In an attempt to quantify valuation, a 'valuability' measure was used, defined as: Valuability = Predicted Salary/Actual Salary.

Player Name	Salary	Predicted Salary	Valuability	VORP	PTS	TRB	PER	USG %	GP	MP	WS
RaiQuan Gray	$5,849	$15,357,243	2625	0.0	16.0	9.0	15.5	21.4	1	35.0	0.1
Jacob Gilyard	$5,849	$2,620,928	448.1	0.0	3.0	4.0	7.3	5.1	1	41.0	0.1
Gabe York	$32,171	$6,776,075	210.6	0.0	8.0	2.0	11.8	16.4	3	18.7	0.1
Justin Minaya	$35,096	$7,139,504	203.4	-0.2	4.3	3.8	4.0	13.4	4	22.3	-0.1
Jeenathan Williams	$52,644	$7,801,243	148.2	0.0	10.6	3.0	15.5	15.2	5	25.4	0.3
Skylar Mays	$116,574	$13,387,810	114.8	0.1	15.3	3.2	19.4	19.3	6	31.5	0.7
Kobi Simmons	$32,795	$2,374,175	72.39	0.0	1.0	0.8	9.0	11.8	5	5.6	0.0
Mac McClung	$160,856	$10,286,351	63.95	0.0	12.5	5.0	19.2	27.5	2	20.5	0.1
Shaquille Harrison	$134,862	$8,576,318	63.59	0.1	8.8	4.4	17.9	17.6	5	24.0	0.3
Lindell Wigginton	$99,438	$5,556,385	55.88	-0.1	7.1	1.0	11.8	25.6	7	12.4	0.1
Jay Huff	$116,986	$5,694,953	48.68	0.1	7.3	3.0	22.3	16.9	7	13.6	0.5
Jay Scrubb	$49,719	$2,405,262	48.38	0.0	6.5	3.0	14.2	15.6	2	15.0	0.1
Jarrell Brantley	$105,522	$4,558,594	43.20	0.1	5.5	1.5	18.5	18.1	4	9.8	0.1
Xavier Sneed	$102,910	$3,951,740	38.40	0.0	4.3	1.3	9.5	12.9	4	12.0	0.1
Louis King	$307,089	$11,493,028	37.43	0.0	20.0	4.0	21.3	23.8	1	29.0	0.1
Frank Jackson	$113,114	$3,149,038	27.84	0.0	0.0	2.0	-6.8	25.1	1	5.0	0.0
Jamaree Bouyea	$116,986	$3,101,032	26.51	0.0	3.0	1.2	6.5	11.8	5	14.2	0.0

Quenton Jackson	$219,630	$5,087,009	23.16	-0.1	6.2	0.9	12.2	17.9	9	15.0	0.2
Deonte Burton	$105,522	$2,189,462	20.75	0.0	0.0	0.0	-12.6	14.3	2	3.0	0.0
Xavier Moon	$116,986	$2,062,273	17.63	0.0	1.8	0.8	7.2	21.8	4	5.0	0.0

Table 3: High Valuability Players

Player Name	Salary	Predicted Salary	Valuability	VORP	PTS	TRB	PER	USG %	GP	MP	WS
DeAndre Jordan	$10,733,758	$2,999,269	0.279	0.0	5.1	5.2	14.7	13.7	39	15.0	1.4
Garrett Temple	$5,155,500	$1,358,818	0.263	0.0	2.0	0.7	10.5	13.4	25	6.5	0.3
Nerlens Noel	$9,391,069	$2,441,641	0.259	-0.1	2.1	2.7	7.9	12.0	17	11.5	0.0
John Wall	$47,345,760	$11,258,785	0.237	0.1	11.4	2.7	13.6	27.0	34	22.2	0.3
Jonathan Isaac	$17,400,000	$4,012,096	0.230	0.2	5.0	4.0	20.3	21.1	11	11.3	0.3
Dwight Powell	$11,080,125	$2,515,853	0.227	0.3	6.7	4.1	15.5	12.6	76	19.2	5.1
Ben Simmons	$35,448,672	$8,005,287	0.225	0.7	6.9	6.3	13.4	14.3	42	26.3	2.2
Khem Birch	$6,667,500	$1,497,281	0.224	-0.1	2.2	1.3	9.4	11.1	20	8.1	0.2
Duncan Robinson	$16,902,000	$3,505,030	0.207	-0.5	6.4	1.6	7.8	17.9	42	16.5	0.5
Kemba Walker	$37,281,261	$7,509,135	0.201	0.1	8.0	1.8	15.0	22.1	9	16.0	0.3
Thanasis Antetokounmpo	$1,878,720	$372,556	0.198	-0.3	1.4	1.2	6.7	13.8	37	5.6	0.1
Tony Bradley	$2,036,318	$310,409	0.152	0.1	1.6	0.9	21.7	19.8	12	2.8	0.2
Richaun Holmes	$11,215,260	$1,610,405	0.143	-0.1	3.1	1.9	12.9	13.7	42	8.3	0.8
Sterling Brown	$3,122,602	$348,918	0.111	0.0	0.0	2.0	7.0	7.0	4	6.0	0.0

Braxton Key	$201,802	$14,205	0.070	0.0	1.3	0.3	18.6	8.9	3	3.0	0.0
Dylan Windler	$4,037,277	$-231,568	-0.057	0.0	1.7	0.0	19.0	17.9	3	3.3	0.0
Malcolm Hill	$508,891	$-59,065	-0.116	0.0	1.0	0.6	15.4	19.7	5	1.8	0.0
Jordan Schakel	$96,514	$-537,307	-5.57	0.0	1.5	0.0	24.3	14.5	2	3.0	0.0
Tyler Dorsey	$201,802	$-1,669,370	-8.27	0.0	3.0	0.7	45.5	28.3	3	2.7	0.1
Stanley Umude	$58,493	$-1,121,097	-19.2	0.0	2.0	0.0	65.6	40.0	1	2.0	0.0

Table 4: Low Valuability Players

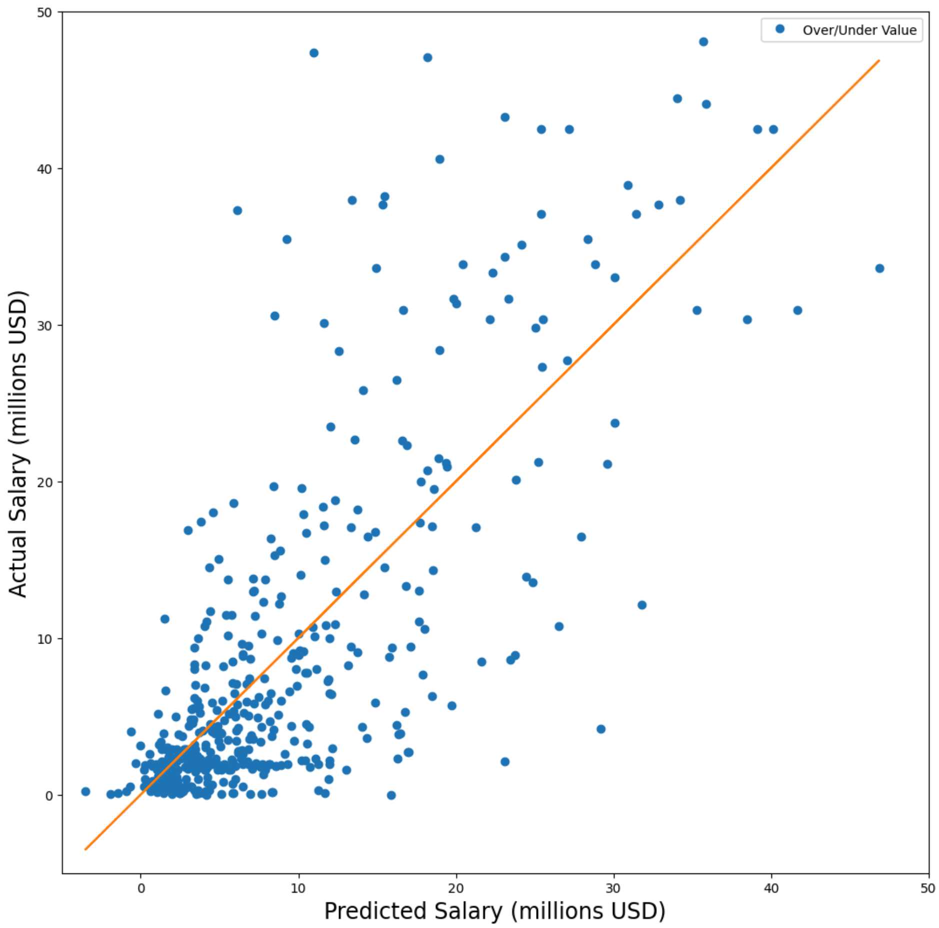

Figure 2: The Valuability "Curve"

Players with a valuability of over 1.0 were undervalued (performing better than they are being paid), while players with a valuability of under 1.0 were overvalued (being paid more than their performance deserves). According to this measure, Table 3 lists the Top 20 most undervalued players and Table 4 the Top 20 most overvalued players of the 2022–2023 season. Figure 2 shows a scatter plot with a regression line depicting these relationships graphically, and the spread of valuability across the league reveals more broad salary-performance inefficiencies. The results highlight that, though measures of performance are significant predictors of salary, they are far from the only determinants of player valuation in the NBA. The points that are below the line show that the salary of the player is below the predicted, meaning he is undervalued while the points above the line show that the salary of the player is above the predicted, meaning he is overvalued.

Discussion

Analyzing Player Performance and Salary

After running the models and examining the data, we found that while a player's performance does influence their salary, it is not the only factor. We applied linear regression and ridge regression models to estimate how well statistics like points, assists, and efficiency could predict a player's salary. Among all the players analyzed from the 2022–2023 NBA season, results showed that performance plays a significant role, but teams also consider many other factors when determining salary. The linear regression model produced an R^2 value of 0.57, meaning about 57% of the variation in salaries could be explained by the six statistics selected. A heat map analysis offered a different perspective by showing how each statistical category related to the others. However, this still left nearly half of the data unexplained, suggesting that salary is influenced by additional factors beyond statistics.

Model Accuracy and Influential Metrics

A scatter plot comparing predicted versus actual salaries showed that predictions were fairly accurate for players with average earnings. However, the models were much less accurate for players earning at the high or low ends of the salary scale. Players like Russell Westbrook and Klay Thompson, for example, are earning significantly more than their current statistics would predict. This implies that factors such as fame, past performance, and player popularity also impact salary. In another chart ranking the importance of statistics, "points per game" and "win shares" were the top two predictors of salary. Those had the biggest influence on how much a player was paid. "PER" and "assists" were also relevant to some extent, while "rebounds" and "games played" appeared to be less influential. Although we expected games played to matter more, it seems teams prioritize the quality of play over quantity.

Limitations, Intangibles, and Future Steps

Although the model offered useful insights, it had notable limitations. One key limitation is that some impactful factors cannot be captured through statistics, such as contributions to team chemistry, jersey sales, or the timing of a player's contract. Some players continue to earn high salaries based on past contracts signed during peak performance years, regardless of current output. Standardized contracts, like rookie deals or veteran minimums, also reduce predictability because they are fixed and don't always reflect current performance. Another major limitation is evaluating defense, basic stats like blocks or steals often fail to reflect a player's full defensive impact. Many elite defenders impact the game by limiting opponents without producing standout numbers, which supports earlier studies showing that intangibles are valuable even if not well-captured by models.These findings align with previous research, such as Zhang and Feng's study. Performance metrics like points and assists are important, but they are not the only contributors to salary. Tyler Stanek's research similarly found that high-profile players often earn more than their stats alone justify, due to their ability to drive revenue through ticket and merchandise sales. Future work could expand on this study by incorporating off-court data, such as an athlete's social media following, endorsement profile, or contract status, to better explain discrepancies between performance-based metrics and actual salary or trade value. For instance, Russell Westbrook earned over $47 million in the 2022–23 season despite a declining on-court role and efficiency. His high salary may be better explained by his massive social media presence, global fan recognition, and off-court marketability, which teams may consider when making personnel decisions. Similarly, Jordan Clarkson and Fred VanVleet, both in contract years during 2022–23, had trade values that likely reflected not just their performance but also their expiring contracts and teams' perceptions of re-signing likelihood or cap flexibility. On the other end of the spectrum, players like Tyrese Haliburton and Desmond Bane were significantly underpaid relative to their on-court contributions due to rookie-scale contracts, which made them highly attractive trade targets despite appearing as low-salary players in the dataset. In contrast, players like Gordon Hayward had high salaries that may not align with recent performance, potentially due to injury history, legacy contracts, or prior All-Star status. Including additional off-court variables—such as contract terms, endorsement deals, player options, and social media metrics—could help future models better account for the true market forces that drive NBA player valuation and trade decisions.This could improve predictive accuracy. Additionally, using more advanced models may help detect subtler patterns. In conclusion, determining the "true value" of an NBA player is highly complex. While statistics matter, they do not provide the full picture. Player popularity, contract timing, and strategic fit all contribute to salary decisions. Ultimately, assessing a player's worth appears to involve both performance and business/image considerations.

Conclusion

This study concludes that it's not as simple as looking at their numbers to establish how much an NBA player is truly worth. Sure, points per game and win shares matter, and they certainly cover a fair share of the reasons why the players are being paid what they are. But by the models, numbers only cover a bit more than half. The other is with respect to things that you can't always measure, like how popular a player is, when they signed their contract, how well they fit into the plan of the team, or even the number of jerseys they sell. Some players are getting paid more on reputation or whatever they've done in the past, and other players are getting paid less even when they're playing better than ever. It shows how business and performance are both considered by NBA teams in their choices.Future modeling efforts may benefit from incorporating such things as social media support or if it's a contract year for the player to check and see if that would help the model. All in all, we discovered that player value in the NBA is half statistics, half business, and half timing, indicating the complexity of decision-making in professional sports.

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Appendix

Feature	Description
Salary	The player's annual salary for the 2022-23 NBA season.
Position	The primary playing position of the player (e.g., Guard, Forward, Center).
Age	The player's age during the 2022-23 NBA season.
Team	The NBA team that the player is associated with during the 2022-23 season.
GP	Games Played: The number of games the player participated in during the season.
GS	Games Started: The number of games the player started in.
MP	Minutes Played: The total number of minutes the player has played across all games.
FG	Field Goals Made: The total number of successful field goals made by the player.
FGA	Field Goals Attempted: The total number of field goals attempted by the player.
FG%	Field Goal Percentage: The ratio of successful field goals (FG) to attempts (FGA), representing shooting accuracy.
3P	Three-Point Field Goals Made: The total number of successful three-point shots made by the player.
3PA	Three-Point Field Goals Attempted: The total number of three-point shots the player has attempted.
3P%	Three-Point Percentage: The ratio of successful three-point shots (3P) to attempts (3PA), indicating shooting accuracy from beyond the arc.
2P	Two-Point Field Goals Made: The total number of successful two-point shots made by the player.
2PA	Two-Point Field Goals Attempted: The total number of two-point shots attempted by the player.
2P%	Two-Point Percentage: The ratio of successful two-point shots (2P) to attempts (2PA), representing shooting accuracy from inside the arc.
eFG%	Effective Field Goal Percentage: A modified version of FG% that accounts for the extra value of a three-point shot (adds 50% weight to 3PM).
FT	Free Throws Made: The total number of successful free throws made by the player.
FTA	Free Throws Attempted: The total number of free throws the player has attempted.

FT%	Free Throw Percentage: The ratio of successful free throws (FT) to attempts (FTA), indicating free throw shooting accuracy.
ORB	Offensive Rebounds: The number of rebounds collected by the player on the offensive end of the court.
DRB	Defensive Rebounds: The number of rebounds collected by the player on the defensive end of the court.
TRB	Total Rebounds: The total number of rebounds (ORB + DRB) collected by the player.
AST	Assists: The total number of assists made by the player.
STL	Steals: The total number of steals made by the player.
BLK	Blocks: The total number of shots the player has blocked.
TOV	Turnovers: The total number of times the player has lost possession of the ball.
PF	Personal Fouls: The total number of personal fouls committed by the player.
PTS	Points: The total number of points scored by the player.
Total Minutes	Total Minutes: The total number of minutes played by the player across all games.
PER	Player Efficiency Rating: A per-minute rating that summarizes a player's statistical accomplishments in a single number.
TS%	True Shooting Percentage: A measure of shooting efficiency that accounts for field goals, three-pointers, and free throws.
3PAr	Three-Point Attempt Rate: The percentage of a player's field goal attempts that are three-pointers.
FTr	Free Throw Rate: The ratio of free throws attempted to field goals attempted, indicating a player's ability to get to the free-throw line.
ORB%	Offensive Rebound Percentage: The percentage of total available offensive rebounds the player grabs while on the court.
DRB%	Defensive Rebound Percentage: The percentage of total available defensive rebounds the player grabs while on the court.
TRB%	Total Rebound Percentage: The percentage of total available rebounds (offensive + defensive) the player grabs while on the court.
AST%	Assist Percentage: The percentage of teammate field goals a player assisted while on the court.

STL%	Steal Percentage: The percentage of opponent possessions that end in a steal by the player.
BLK%	Block Percentage: The percentage of opponent shots a player blocks while on the court.
TOV%	Turnover Percentage: The percentage of a player's possessions that end in a turnover.
USG%	Usage Rate: The percentage of a team's possessions used by the player while on the court, accounting for shots, assists, and turnovers.
OWS	Offensive Win Shares: A measure of a player's contribution to the team's offense, in terms of wins.
DWS	Defensive Win Shares: A measure of a player's contribution to the team's defense, in terms of wins.
WS	Win Shares: A composite statistic that combines a player's offensive and defensive contributions to their team's total wins.
WS/48	Win Shares per 48 minutes: A per-48-minute measure of a player's contribution to wins, adjusted for playing time.
OBPM	Offensive Box Plus-Minus: A box score-based metric that estimates a player's offensive impact per 100 possessions.
DBPM	Defensive Box Plus-Minus: A box score-based metric that estimates a player's defensive impact per 100 possessions.
BPM	Box Plus-Minus: The sum of OBPM and DBPM, providing an estimate of a player's overall impact per 100 possessions.
VORP	Value Over Replacement Player: A box score-based metric that measures a player's overall value relative to a replacement-level player.

Table: Description of Features