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Positional salaries and performance: A linear regression analysis of investment efficiency in the NBA

Jingbo Ma

Department of mathematics, university of Southampton, Southampton, United Kingdom

jm6n21@soton.ac.uk

Abstract. In many previous dissertation studies, the relationship between NBA player performance and team wins and losses has been demonstrated. At the same time, many papers discussed the relationship between players' performance at different NBL positions, game wins and losses, and their salaries. This will help team managers visualize the players that will better enhance their team based on their salary level through data. There needs to be more literature on this specific task in the NBA. While the prominence of star players often drives a significant portion of a team's payroll, the distribution of salaries across various positions can play a critical role in a team's overall performance. This study delves into the intricate relationship between positional spending and associated on-field metrics. This paper utilized a linear regression model to investigate the correlation between a team's investment in individual positions and the resultant win shares. Preliminary findings suggest that while star players undeniably uplift a team's performance and revenue through various streams, a balanced allocation strategy catering to all positions may yield optimal results. This research aims to offer teams a data-driven perspective to optimize their investment and achieve maximum returns under the constraints of the salary cap, fostering a competitive edge in the league.

Keywords: NBA Analytics, Salary Cap Efficiency, Positional Performance Evaluation.

1. Introduction

The focus on analytics has increased within all major sports leagues in the United States since the early 2000s [1]. The NBA was also among the first sports leagues to use various analytics.

While basketball enthusiasts often see the sport as a battle of talent and strategy on the court, team managers and franchise owners perceive it through a dual lens of athletic competition and financial prudence. Every season, teams face the intricate challenge of optimizing their roster to secure a delicate balance between player salaries and on-court performance.

Historically, the limelight often falls on marquee players who command staggering salaries, sometimes dwarfing the combined wages of their teammates [2]. However, these superstars, although invaluable, form just one piece of a multifaceted puzzle. The collective contributions of players occupying specific positions, often overshadowed by their high-flying teammates, play a pivotal role in a team's overall success. Understanding their value becomes paramount because these players might not command the same astronomical salaries as star players. How to optimize an National Football League (NFL) team's salary structure to improve individual player performance and, therefore, overall

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team performance, which in turn improves the team's overall performance. Mondello and Maxcy found that performance bonuses accompanied increases in player salaries [3]. In a largely uniform salary structure (small player pay gap, small player pay gap), giving players a salary increase with performance incentive bonuses will increase player performance on the field. Meanwhile, Jane, San, and Ou found that a uniform salary structure favors team performance in the Taiwanese professional baseball league [4]. The paper will attempt to optimize NBA teams based on how the NFL optimizes its please-to-pair lineups.

The economic factor must be addressed in the highly competitive world of professional sports. For a franchise to remain profitable, it must ensure that its investment in players brings a substantial return, not only in terms of wins but also in terms of financial metrics. Ticket revenues, local televising contracts, and distributed national televising contracts constitute a significant source of revenue for these franchises [5]. Even without a superstar, a better-performing team attracts more viewers on the field and television. Thus, profitability is intrinsically linked to team performance and, by extension, to the efficiency of player salary expenditures.

This paper aims to delve into the often-overlooked issue of player salaries based on a player's specific position. The research will use linear regression to examine the correlation between spending at different player positions and team winning percentage. Berry, Schmidt, and Brooks provide a more in-depth study of the "superstar" effect [6]. Instead, this paper hopes to gain more applicable insights by focusing on teams that do not have a significant star effect rather than being swayed by the outlier performance that superstar players often bring to the table [7]. In subsequent sections, the paper details the research methodology and discusses potential implications for team managers and franchise owners looking to optimize their investments in player talent.

2. Data and Methodology

This paper requires data on NBA player position, NBA player salary, and NFL player performance in the 2022-2023 season. It will be beneficial to analyze the upcoming 2023-2024 season. The data on NBA player earnings in each position is from spotrac.com [8]. Each team's spending on different positions will be able to visualize the position's teams value, and subsequent analysis will allow teams to adjust the roster structure and optimize the roster based on their payroll situation.

2.1. Spending

The spending statistics in this article only account for what the team spends over a full season at that position, not taking into account money received from trades made during the season and major team changes due to off-the-field factors such as a team changing ownership.

2.2. Team

This paper team is all 30 reams in NBA [9]. In the next part, the paper will use abbreviations instead of team names, such as Atlanta Hawks -ATL.

2.3. Win Share

This paper will use win share to describe the performance of NBA players. Win share is a player statistic designed to give credit for a team's success to individuals within the team [10]. See below for details, but it's important to note that it's calculated using player, team, and league-wide statistics and that a team's total player win share will roughly equal the total number of wins that team has this season. Kareem Abdul-Jabbar's 25.4 win shares per game in 1971-72 is the all-time single-season record, and his 273.4 career win shares per game is the all-time career record. Abdul-Jabbar has played long enough to set many such career records. The first person in history to share a victory every 48 minutes is Michael Jordan (this is with Jordan G.O.A.T. The general view of status is consistent).

The premium part of a player's commercial value will not be considered in this article, as the impact of a superstar on the city's revenue may be a more important aspect for the team's management to consider; in this article, will only analyze it in terms of the price and the player's ability. The author

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selected data for a total of 500 players playing for 30 teams; this data includes players who were duplicated after a mid-season transfer, because even if the transfer took place, the player performed differently for different teams and had a different price, and can be treated as a brand new player [8]. Figure 1 deals with win-share data. In Excel use position to filter for players in each position. Then filter by the team they play for, filter all the players at that position for each team, and add their WS to get the total value of ws for that team at that position. Table 1 is the sum of 30 teams all positions win share data.

Table 1. Ws in C, PF, PG, SF, SG.

Team	Ws (C)	Sppending (C)	Ws (PF)	Spending (PF)	Ws (PG)
ATL	14.9	31.31	4.2	1.12	1
BOS	12.2	23.98	0.1	69.74	5.8
BRK	9.1	13.85	8.7	21.06	6.7
CHI	3	21.88	2.4	0	5.3
CHO	6.8	8.91	0	21.73	2.6
CLE	10.3	24.61	10.6	24.51	9.1
DAL	0.6	20.82	3.9	28.16	10.2
DEN	16.6	49.63	11.8	28.81	6.1
DET	6.6	21.72	4.5	12.5	1.2
GSW	8.7	7.5	9.4	31.47	11
HOU	3.4	13.56	2.6	22.45	1.7
IND	3.1	30.08	1.2	20.6	10.7
LAC	3.3	15.93	7.5	14.11	1.1
LAL	16.1	45.47	6.8	72.56	0
MEN	10	16.72	10.1	49.08	12.1
MIA	8.2	40.77	14.9	0	3.4
MIL	8.7	29.04	9.9	57.35	11.7
MIN	9.6	89.97	5.1	13.12	3.8
NOP	8	17.45	4.2	46.18	5.5
NYK	4.6	27.97	0	30.29	9.4
OKC	2.6	12.39	5.4	32.67	12
ORL	7.7	23.12	5	34.27	7.4
PHI	14.7	59.37	2.6	51.4	8.4
PHO	10.9	36.83	6.5	3.14	8
POR	7.1	18.89	4.1	31.55	9.6
SAC	1.1	4.04	11.5	66.03	9
SAS	7	31.37	3.3	5.32	4.2
TOR	7.2	21.22	5.9	70.03	1.3
UTA	13.2	6.75	8.6	62.43	4.9
WAS	7.4	15.9	3	36.09	6.6

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Table 1. (continued).

	Spending (G)	Ws (SF)	Spending (SF)	Ws (SG)	Spending (SG)
ATL	69.18	8.5	31.28	7.6	22.72
BOS	46.91	8.4	37.04	0.1	2.02
BRK	60.27	5.3	56.88	4.2	7.23
CHI	47.3	9.9	45.7	10	52.87
CHO	38.59	6.3	59.66	-0.3	6.29
CLE	41.95	7.5	0	13.7	79.53
DAL	80.1	5.3	4.04	11.2	28.38
DEN	40.54	8.6	36.94	6.4	23.1
DET	32.7	4.2	21.84	3.3	48.93
GSW	93.45	2.5	24.33	8	50.49
HOU	67.5	5	33.47	3.6	13.71
IND	16.64	7.2	11.17	3.6	48.2
LAC	7.98	12.3	76.4	6.6	79.72
LAL	33.3	2.9	3.28	2.4	15.97
MEN	58.06	5.1	4.81	8	23.49
MIA	29.68	3.7	78.02	4.1	29.89
MIL	36.86	9	35.6	5.9	26
MIN	28.7	4.7	3.52	5.4	29.64
NOP	13.34	13.6	51.14	4.3	40.11
NYK	36.39	2.9	1.12	7.1	73.07
OKC	49.59	3.2	11.16	3.8	35.15
ORL	26.36	1.4	18.51	3.5	34.54
PHI	8.59	8.2	6.33	12.7	51.03
PHO	1.93	4.9	53.94	11.4	91.3
POR	55.41	3.8	7.97	0.3	44.85
SAC	37.66	4.7	12.39	9.2	27.64
SAS	22	3.3	53.96	0.4	12.58
TOR	18.3	9.8	29.46	0.2	25.13
UTA	19.91	-0.4	9.61	5.6	40.42
WAS	22	6.1	18.94	3.7	46.1

2.4. Linear Regression Analysis

To discern the relationship between a team's spending on a specific position and the associated win shares, a simple linear regression model was employed. The independent variable was the spending (SPENDING), and the dependent variable was the win shares for each position (WS. PF, WS. PG, WS. C, WS. SF, and WS. SG).

For each player position, a separate linear regression model was constructed:

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$$WSposition = \beta 0 + \beta 1 \times SPENDING + \epsilon. \quad (1)$$

Where:

WS position: Represents the Win Shares for a given position, which serves as the dependent variable. It quantifies the player's contribution to the team's wins.

$\beta 0$: Denotes the y-intercept, which is the expected value of the dependent variable when the spending is zero. This provides insight into the baseline performance when no spending is directed toward that specific player position.

$\beta 1$: Refers to the slope of the regression line, representing the change in the dependent variable (Win Shares) for a unit change in spending. This coefficient offers insight into the return on investment; for example, how many additional wins are generated for each unit increase in spending.

ϵ: The error term capturing the residual difference between the observed values and the values predicted by the model. It encompasses the variability not explained by the spending.

Statistical Analysis

Upon fitting the regression models, key statistical parameters were extracted for further interpretation:

1. P-value for Slope ($\beta 1$): This parameter was used to assess the statistical significance of the relationship between spending and win shares for each player position. A smaller p-value (typically less than 0.05) would indicate that the relationship is statistically significant.

2. Coefficient of Determination (R^2): This metric quantifies the proportion of the variance in the dependent variable that's predictable from the independent variable. A higher $R2$ value suggests that the model explains a significant proportion of the variability in the win shares.

Then the author used R code to finish the linear regression analysis:

If do it five times it can get the Figure 1.

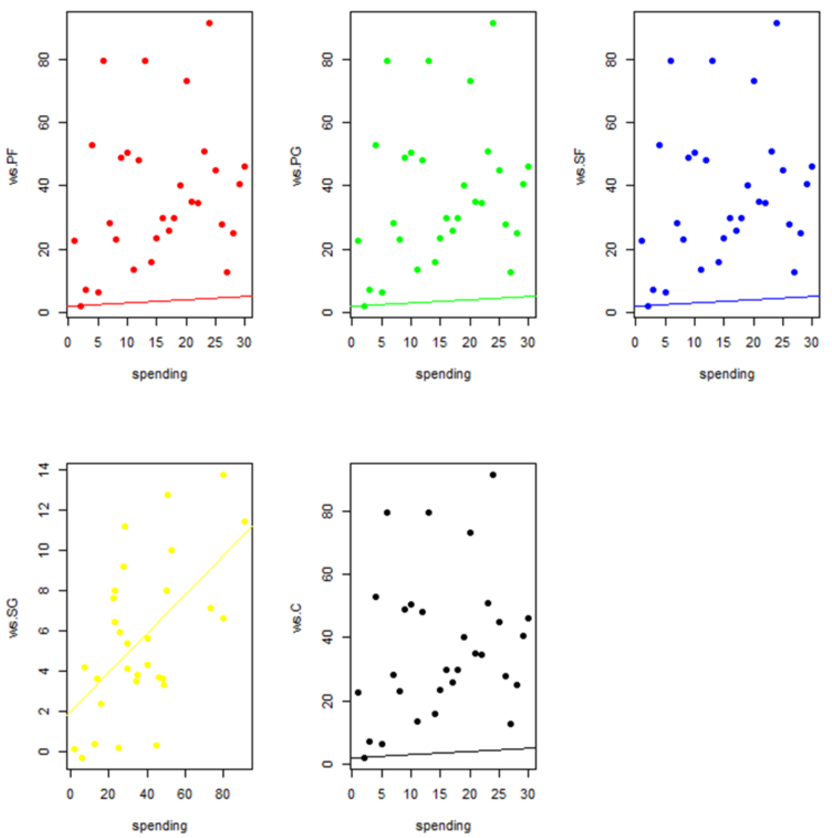

Figure 1. WinShare and spending linear analysis.

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3. Result and conclusion

3.1. Result

Figure 1 gets the five graphs, and gets the p-value and R^2:

This data means:

PF: Multiple R-squared: This value indicates that only about 0.54% of the variability in Win Shares for the Power Forward position can be explained by the team's spending on that position. This is a very low percentage and indicates a weak relationship between spending and performance for this position.

Adjusted R-squared: After adjusting for the number of predictors in the model, the R-squared stands at approximately -3.012%. This negative value can occur when the predictor isn't helping the model, suggesting that spending isn't a significant predictor for win shares in this position.

F-statistic and p-value: The F-statistic is 0.1521, with an associated p-value of 0.6995. Since the p-value is greater than 0.05, this means that the relationship between spending and win shares for the Power Forward position isn't statistically significant in our dataset.

PG: Multiple R-squared: Approximately 5.588% of the variance in Win Shares for the Point Guard position can be accounted for by team spending. This suggests a relatively weak correlation between spending and on-court performance for this position.

Adjusted R-squared: This is slightly adjusted to 2.217%, but still conveys a similar message.

F-statistic and p-value: The F-statistic is 1.657, and the p-value stands at 0.2085. With a p-value above 0.05, the relationship between spending and win shares isn't statistically significant for the Point Guard position.

SF: Multiple R-squared: The variability in Win Shares explained by spending for the Small Forward position is around 14.98%, indicating a more significant correlation than some other positions but still moderate.

Adjusted R-squared: Slightly adjusted down to 11.94%.

F-statistic and p-value: With an F-statistic of 4.933 and a p-value of 0.03461, there's a statistically significant relationship between spending and win shares for the Small Forward position, as the p-value is less than 0.05.

SG: Multiple R-squared: A significant 32.85% of the variance in Win Shares for the Shooting Guard position can be attributed to team spending, highlighting a stronger relationship for this position compared to others.

Adjusted R-squared: This remains relatively high at 30.45%.

F-statistic and p-value: With an F-statistic of 13.7 and a p-value of 0.0009313, the relationship between the team's spending on the Shooting Guard position and the Win Shares for that position is statistically significant

C: Multiple R-squared: This statistic indicates that approximately 20.57% of the variability in Win Shares for the Center position can be explained by the team's spending on that position. Although it's not a very high value, it's a significant percentage and indicates a moderate relationship.

Adjusted R-squared: Adjusted for the number of predictors in the model, the R-squared is approximately 17.73%. This is slightly lower than the Multiple R-squared, but this is expected as the adjusted value accounts for the number of variables in the model.

F-statistic and p-value: The F-statistic is 7.25, and the associated p-value is 0.01183. Since the p-value is less than 0.05, it suggests that the model fits the data better than the intercept-only model, meaning there's a statistically significant relationship between the team's spending on the Center position and the Win Shares for that position.

3.2. Conclusion

The analysis of the relationship between team spending and win shares across different positions within basketball teams yields several insights:

3.2.1. Shooting Guard (SG): This position stands out, with a significant portion (about 32.85%) of the variability in win shares being explained by spending. Financial investment in this role is shown to correlate more directly with performance. This suggests that teams might gain more in terms of on-court performance by allocating resources wisely to this position.

3.2.2. Small Forward (SF) and Center (C): For these positions, spending has a statistically significant relationship with win shares, albeit less pronounced than Shooting Guards. Nevertheless, there is evidence that investing in quality players in these roles could yield better on-court results.

3.2.3. Point Guard (PG) and Power Forward (PF): For these positions, the relationship between spending and win shares is weaker and not statistically significant. This may suggest that other factors, such as player fit, coaching, or training regimens, might be more influential in determining win shares for players in these roles.

4. Conclusion

This research delves into the intriguing interplay between a team's financial investment in players and the resultant performance on the basketball court, specifically within the NBA. While most NBA franchises have shifted their attention towards star-driven salaries and performances, this study underscores the significance of analyzing the return on investment (ROI) from individual player positions. The study used linear regression models to determine the correlation between a team's spending on specific player positions and the resultant win shares. Initial findings suggest that while star players undeniably boost a team's revenue streams and on-court performance, a balanced financial approach to filling other positional slots can offer teams a competitive edge. The NBA's evolution into a star-centric league is well documented. Our linear regression models reveal nuanced insights. Firstly, a measurable relationship exists between the money invested in specific player positions and the resulting win shares. This suggests that, while marquee players have their undeniable advantages, there is merit in evenly distributing a team's salary cap across positions. When sculpting a roster, team managers should consider a dual strategy. On one hand, they can invest in a star player who can singularly elevate the team's performance and market value.

On the other hand, judicious investments in other positions, based on analytic insights, can ensure balanced team performance. Such an approach augments the chances of winning games and offers financial prudence. After all, a team overly reliant on a star player might find itself in a precarious position should that player get injured or underperform. In conclusion, while the allure of star players is undeniable, NBA teams would balance their checkbooks with a more positionally rounded approach, ensuring success both on the court and in the financial ledger.

References

[1] Michael J, Jeffrey F, Ohlmann F 2012 General Sports Appl. Inter. 42 2 105-108
[2] Hausman J A, Leonard G K 1997 J. of Labor Econo. 15 4 586-624
[3] Mondello M, Maxcy J 2009 Management Decision 47 1 110-123
[4] Jane W J, San G, Ou Y P 2009 International Journal of Sport Finance 4 2 136-150
[5] Mulholland J, Jensen S T 2019 International Journal of Forecasting 35 2 767–775
[6] Berri David J, Martin Schmidt B, Stacey Brook L 2004 Journal of Sports Economics 5 1 33-50
[7] Thesis H, Li H, Card D 2011 True Value in the NBA: An Analysis of On-Court Performance and Its Effects on Revenues
[8] Spotrac 2023/9/30 2023/10/5 NBA Positional Payrolls https://www.spotrac.com/nba/positional/breakdown/
[9] NBA 2019 NBA Teams NBA com
[10] Basketball R 2022/2/3 2023/10/5 NBA Player Stats: Advanced. https://www.basketball-reference.com/leagues/NBA_2023_advanced.html#advanced_stats::ws