Economics & Business Management
ISSN Print: 3079-5214
ISSN Online: 3079-5222
https://doi.org/10.63313/EBM.9041

Moneyball in Competitive team performance in basketball

Jiefang Zhu. Aijun Li and Yanting Ji
The School of Science, Zhejiang University of Science and Technology, Hangzhou 310023, China

How to cite this paper: Zhu, J. F., Li, A. J., & Ji, Y. T. (2025). Moneyball in Competitive team performance in basketball. Economics & Business Management, 1(2), 69–80. ISSN Print: 3079-5214; ISSN Online: 3079-5222.
https://doi.org/10.63313/EBM.9041
Published: 2025-04-29

Abstract

The In the realm of professional sports, the "Moneyball" theory reveals market inefficiencies where player value is systematically undervalued. This theory provides novel insights for sports clubs to utilize data analytics in reducing the cost of winning and enhancing team performance. Addressing the challenge of player efficiency evaluation in the NBA, this study constructs a value scoring model inspired by the Moneyball concept. Specifically, player performance sta-tistics are analyzed using principal component analysis to extract comprehen-sive efficiency indicators, while residual regression quantifies the deviation be-tween players' actual performance and their intrinsic efficiency levels. Results demonstrate that the proposed model effectively evaluates players' competitive capabilities, identifying both undervalued and overvalued individuals. Under-valued players exhibit significantly higher on-court contributions relative to salary expectations, characterized by well-rounded technical proficiency and holistic efficiency. Conversely, overvalued players underperform their salary benchmarks, often relying excessively on isolated statistical metrics while demonstrating subpar overall efficiency.

Keywords

Moneyball; NBA; Cluster Analysis; Regression Analysis

1. Introduction

Basketball, as a key carrier of modern sports civilization, has evolved over more than a century into a global cultural phenomenon. Its origins can be traced back to the late 19th century, when Dr. James Naismith, in response to the societal need for indoor team sports during the latter stages of the Industrial Revolution, creatively combined elements of existing sports such as rugby and hockey to design a new projection-based competitive game characterized by low entry barriers and high inclusiveness. The sport completed its transformation into a competitive discipline at the 1936 Berlin Olympics, marking the beginning of its global dissemination.

In the contemporary era, basketball has developed a multidimensional growth system. In terms of athletic competition, professional leagues such as the NBA in North America, various European leagues have fundamentally reshaped regional sports ecosystems through industrialization and commercialization. Culturally, international tournaments such as the FIBA World Cup have become key platforms for cross-regional cultural exchange. Socially, the perseverance and determination displayed by athletes on the court continue to generate positive motivational effects. This multi-dimensional, value-coexistent model has enabled basketball to transcend the boundaries of sport, evolving into a significant force in advancing human spiritual and cultural development.

2. Literature review

The decision-making process in professional sports trading markets has been widely validated by numerous scholars. This area has been extensively studied in academic literature. One notable case, commonly referred to as "Moneyball," emerged from the baseball career of team manager Billy Beane and was documented by Michael Lewis. In his book, Lewis hypothesized that certain players were undervalued, leading to salary levels that did not accurately reflect their true worth[1].Many empirical studies in Major League Baseball (MLB) have since tested Lewis's hypothesis. Hakes and Sauer employed basic econometric tools to examine the core of Lewis's argument and confirmed his claims[2]. Furthermore, they discovered that during this period, player salaries in baseball did not accurately reflect hitters' contributions to winning games [3].Caporale and Collier also conducted an empirical study on MLB and found that in several seasons prior to 2003, certain performance indicators—such as on-base percentage, batting average, and home runs—exhibited a significant "Moneyball effect"[4]. Duquette, Cebula, and Mixon verified the importance of specific performance metrics, such as on-base percentage, within the Moneyball framework. Their findings provided a comparative assessment of the relative impact of various factors on team success in MLB[5]. However, this effect was mainly observed in seasons preceding the popularization of the Moneyball theory, suggesting that the baseball trading market may have since adjusted salary structures accordingly.Conversely, Berri, Holmes, and Simmons found that there was little change in the market valuation of hitters before and after the emergence of the Moneyball theory. Their study, which used data from 1997 to 2012, supported this conclusion[6].Inefficiencies in trading markets have also been explored in other team sports. Gerrard discussed the difficulties of applying the Moneyball approach to complex, simultaneous-opposition team sports. He evaluated the technical, conceptual, and cultural barriers that limit the application of the Moneyball method to such sports[7]. This supports the notion that identifying an individual player's contribution to team success is a more challenging task in complex team environments.Berri, Brook, and Schmidt found that in the NBA, teams tend to overvalue scoring metrics in player salaries and All-Rookie Team selections, while undervaluing other technical indicators such as defensive efficiency and assist contribution[8]. Staw and Hoang showed that even after controlling for variables such as playing time, injuries, and position, players drafted with more picks ahead of them had significantly reduced playing time, thus shortening their NBA careers[9].Stewart and others analyzed the Australian Football League and proposed a player ranking model to determine whether players were overvalued or undervalued[10]. In the context of the National Football League (NFL), Massey and Thaler discovered that high draft picks were often overvalued[11]. Berri,Schmidt, and Brook provided further evidence that player evaluations are largely based on visually observable actions during games[12].

In the field of soccer, the Moneyball approach has also seen significant results. Wicker and others studied individual effort levels among Bundesliga players—measured by distance covered and high-intensity sprints—and demonstrated that such effort-based performances had no significant correlation with market value, indicating an undervaluation of these traits[13]. Furthermore, Weimar and Wicker showed that both total running distance and high-intensity sprinting significantly increased the probability of a team winning the championship. Their study concluded that effort-related performance traits are underestimated in the soccer transfer market[14].Bryson,Frick,and Simmons, on the other hand, examined how wages are determined in the European soccer market. They found that ambidextrous players—those equally skilled with both feet—earned significantly higher salaries, even though their presence did not noticeably improve team win rates. This led to the conclusion that such players were overvalued in the market[15].

This paper contributes to the Moneyball-related literature by examining the relative impact of basketball players'offensive and defensive behaviors on both team win probabilities and player market value.

3. Empirical Analysis of Player-Level Athletic Performance

3.1. Player Valuation Rating System

In the context of modern professional basketball—particularly under the rapid commercialization of the NBA—players are no longer regarded solely as tactical executors on the court, but as critical variables influencing team competitiveness, market value, and operational decision-making. With the advancement of advanced statistical metrics, the development of a multidimensional, structured, and operational player valuation system not only facilitates a comprehensive assessment of players' offensive and defensive performance and overall efficiency, but also provides theoretical support and data-driven evidence for decisions related to talent acquisition, contract negotiations, and rotation strategies.

At this stage of the study, we propose to construct an integrated scoring model based on existing advanced metrics, incorporating multiple dimensions such as offensive efficiency, defensive capability, team collaboration, and per-minute productivity. We further explore its practical applications in salary forecasting, cost-performance evaluation, and tactical role optimization.

The average career length of an NBA player is approximately 4.5 years, with a median of about 4 years. This implies that the majority of players have professional careers spanning 4 to 6 seasons. Selecting a continuous six-season period effectively captures the main stages of a typical NBA player's career. Additionally, from 2018 to 2024, the style of play in the NBA has undergone significant changes, making this six-season dataset representative of the league's current trend toward "modern basketball."

Therefore, this study focuses on all NBA players who logged more than 500 minutes of playing time during the 2018–2019 to 2023–2024 seasons. Based on data provided by the NBA statistics site Basketball-Reference, this research incorporates a range of advanced performance metrics, including Player Efficiency Rating (PER), True Shooting Percentage (TS%), Three-Point Attempt Rate (3PAr), Free Throw Rate (FTr), Offensive Rebound Percentage (ORB%), Defensive Rebound Percentage (DRB%), Total Rebound Percentage (TRB%), Assist Percentage (AST%), Steal Percentage (STL%), Block Percentage (BLK%), Turnover Percentage (TOV%), Usage Rate (USG%), Offensive Win Shares (OWS), Defensive Win Shares (DWS), Win Shares (WS), Win Shares per 48 Minutes (WS/48), Offensive Box Plus/Minus (OBPM), Defensive Box Plus/Minus (DBPM), Box Plus/Minus (BPM), and Value Over Replacement Player (VORP).

In the evaluation of NBA player performance, the numerous advanced metrics mentioned above span a wide range of dimensions. While each indicator holds specific meaning, significant correlations often exist among them, leading to potential information redundancy and interpretational complexity. Therefore, Principal Component Analysis (PCA) is first conducted to reduce the dimensionality of these high-dimensional performance features. This approach helps minimize variable redundancy and eliminates overlapping information, while enabling player performance to be visualized in a two-dimensional space for the purposes of style recognition and clustering classification. The results of the PCA are presented in Table 1 and Figure 1.

Table 1. Principal Component Analysis Variance Decomposition Table.

Principal Component	analysis result		
	Eigenvalue	Explain the proportion of variance	Cumulative explained variance
PC1	9.055537532984	0.45208455726593	0.45208455726593
PC2	3.630939205532	0.181269365536130	0.63335392280206

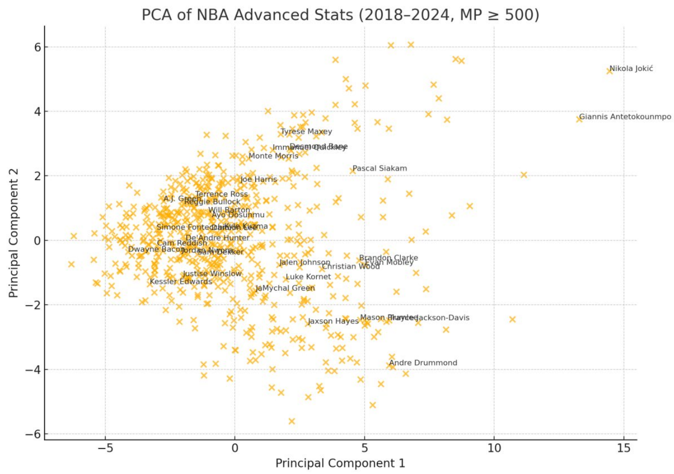

Figure 1. Principal Component Analysis Dimensionality Reduction Diagram.

PC1 can be interpreted as the player's overall "comprehensive impact and efficiency performance," while PC2 primarily reflects the type of role the player assumes on the court.In response to the increasingly rich array of advanced statistical data available for NBA players, and based on the above analysis, we propose a new comprehensive scoring system—Player Value Score (PVS). This score is derived through dimensionality reduction of multiple key advanced metrics (such as Player Efficiency Rating, True Shooting Percentage, Win Shares, and Box Plus/Minus), and combines them using weighted integration based on principal components. The resulting metric offers a unified measure of both player efficiency and role involvement.In practical applications, PVS can serve not only as a ranking basis for overall player performance, but can also be integrated with variables such as salary, playing time, and tactical importance within the team to further evaluate whether a player is "worth the cost" or exhibits "value surplus." Additionally, PVS provides a quantitative reference for team management in areas such as roster optimization, contract negotiations, and draft decisions. It also offers data-driven insights for players seeking to plan and refine their career development trajectories.As a valuable supplement to existing player evaluation models in the era of data-driven basketball, PVS represents a meaningful step forward. The specific definition is provided in the following formula.Among them, the values of α and β are defined based on the proportion of explanatory variance. $\alpha = 0.714$, $\beta = 0.286$.

$$PC1(i) = \frac{PC1_i - \min(PC1)}{\max(PC1) - \min(PC1)} \tag{1}$$

$$PC2(i) = \frac{PC2_i - \min(PC2)}{\max(PC2) - \min(PC2)} \tag{2}$$

$$PVS_i = \alpha \cdot PC1(i) + \beta \cdot PC2(i) \tag{3}$$

3.2. Player evaluation framework

To gain a deeper understanding of the skill composition and playing style of guards (PG/SG), this section selects 10 key advanced metrics (AST%, 3PAr, TS%, TOV%, USG%, FTr, ORB%, DRB%, TRB%, and BLK%) for principal component analysis, and integrates the results with the Player Value Score (PVS) for a comprehensive evaluation.

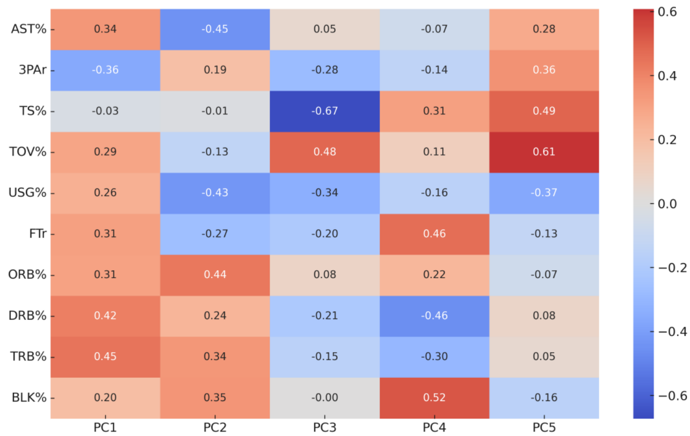

Figure 2. Heatmap of Principal Component Loadings for Guard Players.

Figure 2 illustrates the extraction of multiple principal components to interpret guard players, with each principal component representing a latent “style dimension.” Below is a detailed interpretation of the structural characteristics of each principal component, along with their potential tactical implications and player style classifications.

PC1 is primarily driven by positive loadings on TRB%, DRB%, AST%, FTr, ORB%, and TOV%, indicating a distinct “all-around guard” profile. Players scoring highly on this dimension typically exhibit strong playmaking ability, aggressive rebounding, and sustained influence through drawing fouls. These guards not only dominate ball-handling responsibilities but also contribute on both ends of the floor, demonstrating versatility beyond the traditional guard role. Typical representatives include Josh Giddey and Lonzo Ball, who showcase value through organization, defense, and non-shooting production, thus scoring prominently on this component.

PC2 is positively influenced by ORB%, BLK%, and 3PAr, while TS%, AST%, and USG% load strongly in the negative direction. This suggests a group of physically gifted utility guards, more inclined toward defensive roles on the perimeter with some rim protection and rebounding capacity, but less involved in playmaking or efficient scoring. High PC2 scores often point to wing-type defensive specialists such as Matisse Thybulle and Delon Wright, who generate value through non-traditional guard metrics while maintaining low usage rates.

PC3 captures the trade-off between efficiency and ball control, with TS% and TOV% forming the principal opposing indicators. USG% and 3PAr also exert notable influence. Players with high scores on this component may possess high shooting efficiency but also high turnover rates—or vice versa. This dimension identifies "volatile-efficiency guards," characterized by inconsistent offensive output and minimal organizational duties. Players like Jordan Poole and Bones Hyland are likely to score significantly on this component, reflecting a high-risk, high-reward offensive style.

PC4 is positively driven by BLK% and FTr, and negatively by DRB% and TRB%, indicating traits of aggressive defenders and weak-side finishers. Players scoring highly here tend to actively contest shots and initiate contact, yet do not dominate the glass—possibly representing weak-side help defenders or rim-rotating guards. This style plays a key tactical role in specific systems, with impact not entirely captured by conventional offensive stats. Representative players include Derrick White and Alex Caruso.

PC5 presents multiple opposing indicators, with TOV% and TS% loading positively, while USG%, BLK%, and 3PAr load negatively. This component reflects guards with high on-ball aggressiveness—potentially producing efficiently but with turnovers, and less reliant on perimeter shooting or rim protection. It represents the "classical mid-range dominant, on-ball scoring guard" archetype. DeMar DeRozan partially embodies this style, as reflected in this component.

In summary, guard players exhibit multifaceted stylistic differences across various offensive and defensive dimensions. This structural modeling aids in identifying functional, defensive, and high-output guard types, and also lays a comprehensive data foundation for further analysis such as market value evaluation.

In combination with the PVS (Player Value Score), this section also establishes an evaluative framework for guards by constructing a regression model between PVS and the five principal components. The results are presented in Table 2.

Table 2. Regression Model for Predicting PVS of Guard Players.

Variable	Coefficient	Std.Error	t-Statistic	P-value (P>|t|)	95% Confidence Interval
Intercept	0.5505	0.0003	2005.7400	0.0	[0.5500, 0.5511]
PC1	-0.0009	0.0002	-5.6900	0.0	[-0.0012, -0.0006]
PC2	-0.0004	0.0002	-1.9800	0.0478	[-0.0008, -0.0000]
PC3	-0.0313	0.0002	-133.2900	0.0	[-0.0318, -0.0309]
PC4	0.0152	0.0003	54.6300	0.0	[0.0147, 0.0158]
PC5	0.0232	0.0003	74.3500	0.0	[0.0226, 0.0238]

The regression analysis examines the coefficients of the model, revealing that PC3 has the most significant negative coefficient. This principal component is positively driven by TOV% and negatively by TS%, representing a negative player style characterized by low efficiency and high turnovers. The large and statistically significant regression coefficient indicates that stable efficiency and controlled pace remain the core value drivers in the PVS model, reflecting a strong preference for consistent output.

PC5 has a regression coefficient of 0.0232, the highest positive influence among all principal components. This component is positively associated with TS% and TOV%, and negatively correlated with 3PAr and BLK%, representing a scoring style that is highly efficient but not reliant on three-point shooting or rim protection. This result suggests that players who can maintain scoring efficiency without relying on threes or free throws are highly valued in the PVS framework. Typical examples include Jalen Brunson and DeMar DeRozan, who excel as mid-range scorers outside the typical three-point-dominant mold.

PC4 also shows a significantly positive coefficient, indicating that the PVS model recognizes players who can generate blocks on defense and draw fouls on offense through aggressive play. These players are often not easily identified through traditional statistics, but their real-game impact—via tempo control, defensive rotations, and foul-drawing drives—is structurally acknowledged in the model. Representative players include Alex Caruso and Josh Okogie, reflecting a high-impact, low-volume value profile for guards.

In contrast, PC1 has a coefficient of -0.0009, suggesting a neutral or slightly negative attitude in the PVS model toward all-around, high-usage players. This component combines positive contributions from AST%, FTr, TRB%, and TOV%, indicating that although such players are active in playmaking and defense, their high turnover rates may negate those advantages, reflecting the model's cautious stance toward high-cost ball-dominant roles.

PC2 has a coefficient of -0.0004, which, while negative, is only marginally significant. This component is driven by ORB%, BLK%, and DRB%, representing hustle-oriented defensive guards. Players with high scores in this dimension typically contribute little offensively but are active defensively. The regression results imply that relying solely on defensive stats is insufficient to earn high weighting in the PVS model, revealing a modern preference for well-rounded players over those with single-dimensional profiles.

In summary, this regression model, while maintaining high explanatory power, further confirms the key preferences of modern data-driven scoring systems in evaluating player value: efficient scoring, ball control stability, and multidimensional contributions are more highly valued than pure playmaking volume or blue-collar defense. In evaluating guards, the model differentially weights low-turnover efficiency, foul-drawing ability, and disruptive defense from weak-side actions or off-ball movement, offering a clear framework for tactical role identification and the selection of high-potential players.

In conjunction with the PVS values, to explore potential "Moneyball effects" within the NBA, we aim to identify players who may be undervalued or overvalued within the PVS scoring system. Using the residual analysis shown in Figure 3, we rank players by residuals to pinpoint those who appear to be either undervalued or overvalued based on their model-predicted versus actual PVS scores.

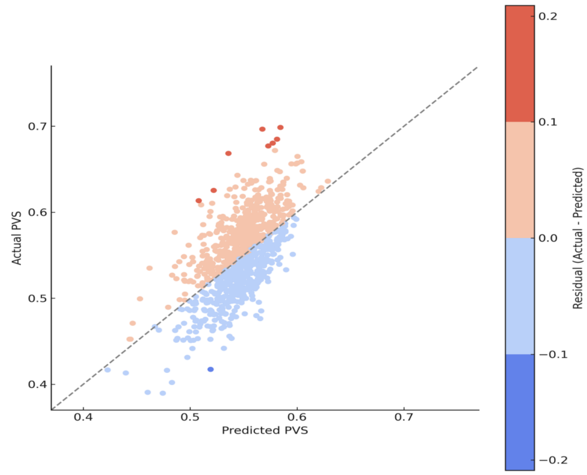

Figure 3. Residual Analysis Chart of Guard Players' PVS.

Table 3. Examples of Overvalued and Undervalued Guard Players.

Player	PVS(Actual)	PVS(Predicted)	Residual (Actual - Predicted)	Season
Jimmy Butler	0.73	0.42	+0.31	2018/2019
Langston Galloway	0.35	0.06	+0.29	2020/2021
James Harden	0.78	0.50	+0.29	2019/2020
James Bouknight	0.15	0.42	-0.27	2020/2021
Scoot Henderson	0.18	0.42	-0.23	2022/2023

In the regression residual analysis, Jimmy Butler stands out as one of the most clearly undervalued players. Although his style-related metrics—such as usage rate and three-point attempt frequency—do not show extreme advantages in the principal component model, his actual impact on both ends of the court far exceeds the model's expectations. His scoring relies more on mid-range shots, low-post isolation, and foul drawing—non-"template" offensive methods that are not fully captured by the principal component system. Additionally, his defensive pressure, versatility in matchups, and elevated postseason performance further contribute to a level of impact that is systematically underestimated by the model. His residual exceeds +0.3, indicating that his real value is significantly higher than the theoretical score predicted by his style features.

Langston Galloway represents a type of understated yet efficient role-playing guard. His characteristics in the principal components are unremarkable—he lacks strong ball-handling ability, has moderate reliance on three-point shooting, and limited foul-drawing ability—leading the model to classify him as a “neutral” player. However, thanks to his stable three-point shooting accuracy, low turnover rate, and strong tactical adaptability, he delivers highly efficient output within limited playing time. Galloway's actual PVS significantly exceeds the model's prediction, with a residual of +0.29, showing that although he does not possess the traits of a "primary ball-handler" or an obvious tactical role, his "invisible contributions" are substantially undervalued by the system. This reflects a limitation in the model's ability to detect low-usage, high-efficiency players.

James Harden serves as a more prominent case. While he exhibits typical high-usage characteristics and solid efficiency in the principal components, the model still falls short in fully capturing his holistic impact on game tempo, spatial gravity, passing creativity, and offensive orchestration. His actual PVS far exceeds the predicted value, with a residual of +0.29. This suggests that even though the principal component system includes key variables (e.g., usage rate, turnover rate, true shooting percentage), it still underrepresents players with "transcendent skill sets." Harden's case demonstrates that accurately evaluating such all-around guards requires incorporating more non-tactical data dimensions.

On the other hand, James Bouknight is identified as one of the most overvalued players in the regression residual analysis. In the principal component structure, he shows high usage and shot frequency, which, from the model's perspective, suggests a certain degree of tactical value. However, in actual games, Bouknight's true shooting percentage is low, his shot selection is inconsistent, and his turnover control is poor—resulting in much lower overall efficiency than expected for a player with his theoretical offensive role. His scoring style relies on aggressive drives and contested mid-range shots, but without efficient conversion, such traits fail to generate positive value. Thus, he displays a typical case of "unfulfilled potential," with a large negative residual.

Scoot Henderson exhibits a similar pattern of overvaluation. As a highly touted recent lottery pick, his data profile shows high usage, possession control, and a tendency to draw fouls—reflected in strong PC1 and PC3 values—leading the model to classify him as a "primary ball-handling offensive guard." However, his actual game performance has yet to live up to this theoretical profile. His shot selection is often rushed, his true shooting percentage is low, and his turnover rate is high, all of which severely undermine his offensive efficiency. Although he shows glimpses of court vision and athleticism, he has not yet established an efficient and consistent output pattern. While the model assigns him a relatively high theoretical score, his current in-game performance falls well short of that assessment, resulting in a negative residual. This highlights how models may overestimate young players based on their potential roles and tactical projections, without fully accounting for technical maturity and real-game adaptation.

4. Conclusion

The core of the Moneyball theory lies in optimizing resource allocation through data analysis and statistical methods, thereby challenging traditional experience-based judgments. Drawing on this theoretical foundation, and in light of modern basketball's emphasis on efficiency and positional versatility, this study develops a new rating mechanism to evaluate players' performance across multiple dimensions. This approach serves to assess the balance of value systems in both team development and individual player progression. The main conclusions are as follows:

This study employs Principal Component Analysis (PCA) to effectively extract the key dimensions of player performance. It reduces the dimensionality of numerous correlated indicators in raw statistics into a few independent principal component factors, encompassing scoring efficiency, playmaking, defensive contributions, and other core aspects. The dimensionality reduction eliminates information redundancy, allowing for a clearer and more streamlined evaluation of player efficiency, and provides the foundation for constructing a comprehensive assessment model.

Based on the PCA results, a Player Value Score (PVS) is developed as a composite efficiency metric. This score compresses and integrates multiple key performance indicators—such as Player Efficiency Rating, True Shooting Percentage, Win Shares, and Box Plus/Minus—into a single weighted score that reflects a player's overall efficiency and contribution. PVS objectively quantifies a player's comprehensive impact on the game, and its rankings align closely with the actual performance of star players. Moreover, PVS offers a quantitative path for role players, whose traditional statistics may be modest, to demonstrate their value, enabling a more well-rounded evaluation of players with differing roles and styles.

A regression model between PVS and the principal components is constructed to analyze the directional influence and weight of various performance factors on a player's overall value. The results show that players who exhibit efficient scoring, consistent performance, and multidimensional contributions tend to receive higher PVS ratings. In contrast, players who excel in a single area but show inefficiencies elsewhere receive relatively lower scores. This finding reveals the preference of modern data evaluation systems: balanced, high-efficiency performance across multiple areas is more favored than pure accumulation of scoring stats or defensive metrics.

By applying a PVS residual model, this study further explores the presence of undervalued and overvalued players in the NBA. Some players exhibit significantly higher actual PVS than the predicted value, resulting in positive residuals. These players often have modest traditional statistics but deliver exceptional per-minute production or excel in tactical execution and intangible contributions, suggesting that they are undervalued under conventional evaluation systems. Conversely, other players show negative residuals, where actual PVS is lower than predicted. These players may have flashy statistical profiles but suffer from inefficiencies such as low shooting percentages or high turnover rates, indicating overvaluation by traditional standards.

These empirical findings strongly support the applicability of Moneyball principles in the NBA, offering a scientific foundation for teams to identify high-value, cost-effective talent in a data-driven era.

Acknowledgements

Special thanks to Basketball-Reference for providing free access to the data used in this study, and to Professors Aijun Li and Yanting Ji for their valuable guidance and support in topic selection and article structure.

References

[1] Lewis, M. 2003. Moneyball: The Art of Winning an Unfair Game. [M]New York: Norton.

[2] Hakes, J. K., and R. D. Sauer. 2006. "An Economic Evaluation of the Moneyball Hypothesis." [J]Journal of Economic Perspectives 20 (3): 173–186.

[3] Hakes, J. K., and R. D. Sauer. 2007. "The Moneyball Anomaly and Payroll Ef-ficiency: A Further Investigation." [J]International Journal of Sport Finance 2 (4): 177.

[4] Caporale, T., and T. C. Collier. 2013. "Scouts Versus Stats: The Impact of Moneyball on the Major League Baseball Draft." [J]Applied Economics 45 (15): 1983–1990.

[5] Duquette, C. M., R. J. Cebula, and F. G. Mixon Jr. 2019."Major League Baseball's Moneyball at Age 15: A ReAppraisal."[J]Applied Economics 51 (52): 5694–5700.

[6] Berri, D. J., Holmes, P. M., & Simmons, R. (2014). Moneyball and the baseball players' labor market. Paper presented at the 89th Annual WEAI Conference in Denver, CO. Biermann, C. (2014). Niemals mehr als 25 Leute! 11 Freunde, August, 44-46.

[7] Gerrard, B. 2007. "Is the Moneyball Approach Transferable to Complex Inva-sion Team Sports?"[J]International Journal of Sport Finance 2 (4): 214.

[8] Berri, D. J., S. L. Brook, and M. B. Schmidt. 2007. "Does One Simply Need to Score to Score?" [J]International Journal of Sport Finance 2 (4): 190–205.

[9] Staw, B. M., and H. Hoang. 1995. "Sunk Costs in the NBA: Why Draft Order Affects Playing Time and Survival in Professional Basketball."[J]Administrative Science Quarterly 40 (3): 474–494.

[10] Stewart, M. F., Mitchell, H., & Stavros, C. (2007). Moneyball applied: Econo-metrics and the identification and recruitment of elite Australian footballers. [J]International Journal of Sport Finance, 2, 231-248.

[11] Massey, C., and R. H. Thaler. 2013. "The Loser's Curse: Decision Making and Market Efficiency in the National Football League Draft."[J]Management Science 59 (7): 1479–1495.

[12] Berri, D., M. Schmidt, and S. Brook. 2006. The Wages of Wins: Taking Meas-ure of the Many Myths in Modern Sport. Stanford: Stanford University Press.

[13] Wicker, P., J. Prinz, D. Weimar, C. Deutscher, and T. Upmann. 2013. "No Pain, No Gain? Effort and Productivity in Professional Football."[J]International Journal of Sport Finance 8 (2): 124.

[14] Weimar, D., and Wicker, P. 2017. "Moneyball revisited: Effort and team performance in professional soccer."[J]Journal of Sports Economics 18(2): 140-161.

[15] Bryson, A., B. Frick, and R. Simmons. 2013. "The Returns to Scarce Talent: Footedness and Player Remuneration in European Football."[J]Journal of Sports Economics 14 (6): 606–628.