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Article

Evaluating the Utility of Hierarchical Multiple Regression and Quantile Regression in Determining Critical Factors for Success in Elite Men's Basketball

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Abstract: This research investigates the effectiveness of stratified multiple regression (MLR) and quantile regression (QR) in identifying the key performance indicators (KPIs) that impact the outcomes of elite men's basketball games. Using performance data from the Paris 2024 Olympic Games, the study compares MLR and QR across various quartiles to explore both general trends and specific variations within different distributions. Important predictors such as inside-out scoring, centre-back scoring, three-point shooting, free-throw percentage, and pace of play were found to be significant in both models. However, QR uncovered additional insights not captured by MLR, including the relevance of Q50 Offensive Rebounds and Q75 Assists and Caps. QR also demonstrated a higher sensitivity in revealing the intricate, context-dependent relationships between KPIs and game outcomes, offering a more detailed understanding of how these factors fluctuate across different levels of competition. While MLR provided stable results, it was less effective at capturing this variation. This study underscores the importance of quantitative analysis in sports research, shedding light on subtle performance dynamics and offering valuable insights for optimizing team strategies, tactical choices, and training plans. By incorporating advanced statistical techniques, the research contributes to a deeper understanding of basketball performance and establishes a robust framework for future studies in sports analytics.

Keywords: performance analysis; basketball; quantile regression (QR); multiple linear regression (MLR); key performance indicators (KPIs); Olympic Games

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1. Introduction

In recent years, the use of advanced statistical models has gained popularity in the analysis of sports performance [1,2]. Traditional linear regression models have long been used in elite basketball to identify key performance indicators (KPIs) that are closely linked to game outcomes and team success [3-5]. However, these conventional models have certain limitations, particularly when it comes to capturing the complex interactions between multiple variables in real-world sports [6]. Hierarchical regression and quantile regression offer more effective alternatives by addressing the shortcomings of linear models in sports performance analysis. Hierarchical regression enables the analysis of variables at various levels, such as player, team, and league, providing a more structured approach to understanding performance factors [6,7]. Meanwhile, quantile regression allows for a broader examination of the dependent variable's distribution, offering a more comprehensive view of how variable relationships differ across the performance spectrum, particularly at the extremes [8,9].

Recent studies have highlighted the utility of these techniques in basketball analytics. Zhang et al. [10] applied quantile regression to analyze statistics from the 2019 FIBA Basketball World Cup and their influence on tournament outcomes. Yi et al. employed quantile regression to investigate the relationship between technical metrics and team success in the Women's Chinese Basketball Association (WCBA), revealing that shooting metrics significantly impacted the performance of top teams, while ball-handling and defensive stats were more critical for lower-ranked teams [8]. Building on these findings, this study seeks to systematically compare the effectiveness of stratified and quantile regression in identifying the key factors that contribute to success in men's basketball. By focusing on the performance data of elite basketball players, this research aims to offer fresh insights into the dynamics that shape success in elite-level basketball and enhance methodological knowledge on applying statistical modeling techniques in sports analysis.

The primary goal of this study was to evaluate the sensitivity of hierarchical multiple regression and quantile regression in identifying the technical and tactical elements that influence the outcomes of high-level men's basketball games. Specifically, the study aimed to:

Examine the relationship between KPIs and game results by analyzing Olympic men's basketball data, stratifying the sample into three quartiles based on winning percentage, and constructing separate regression models for each quartile.

Conduct quantile regression to assess the influence of KPIs on match outcomes at the 25th, 50th, and 75th percentiles of the winning percentage distribution.

Compare both methods to identify which KPIs are significant predictors of winning and assess the stability of these predictors across different quartiles.

Evaluate the relative sensitivity and effectiveness of stratified regression versus quantile regression in modeling the complex performance relationships of elite basketball players.

From a theoretical standpoint, this research will contribute to the field of sports analytics by offering a comprehensive comparison of two advanced statistical methods capable of handling the complexities inherent in sports performance data [1,6]. By applying these methods to the unique context of Olympic basketball, the study will shed new light on the technical and tactical differences that define successful teams at the highest level of international competition.

The findings of this study will be highly relevant to basketball coaches, analysts, and sports scientists. By identifying the key performance indicators of winning teams at various competition levels, the results can inform decisions related to training priorities, player recruitment, and game strategies [11,12]. Understanding how these relationships vary across the performance spectrum may lead to more targeted performance analysis and intervention strategies [13]. Additionally, this study will offer methodological insights on best practices for modeling sports performance data to maximize predictive accuracy and interpretability [14]. In doing so, it will contribute to the ongoing efforts to translate complex analytical insights into actionable interventions that can enhance both individual and team performance.

1.1. Samples and Variables

The data utilized in this study is divided into basic and advanced metrics. Basic data was sourced from the official Paris 2024 Olympic website, while advanced data was retrieved from FIBA's official site. The sample consists of performance data from 12 teams participating in 26 games.

In line with previous studies, the game outcomes (N = 52) for the 12 teams in the Paris Olympics were selected as the dependent variable, which follows a normal distribution. The independent variables in this study are divided into two main categories: basic variables and contextual variables. The basic variables include several key basketball performance metrics: Paint Score, which refers to the number of points scored by a player or team in the paint area; Mid-Range Score, representing the points scored outside the paint but inside the three-point line; Three-Point Score, which refers to the points scored through three-point field goals; and Free Throws, indicating the points scored through free throws.

In terms of rebounds, Defensive Rebounds refers to the number of rebounds collected by a player or team on defense, while Offensive Rebounds refers to the rebounds collected on offense. Assists occurs when a player completes a pass to a teammate that leads to a field goal; Steals are when a defensive player takes the ball away from an offensive player; Blocks occur when a defensive player prevents an offensive player's shot from scoring; Turnovers are when a player or team loses possession of the ball to the defense; and Foul refers to any infringement penalized as foul play by a referee.

The contextual variables include Quality of Opponent, which distinguishes between strong and weak teams, and Pace, which refers to the speed of play and differentiates between fast-paced and slow-paced teams. These variables have been identified in previous studies as key factors influencing game outcomes, and therefore, they were incorporated into the analysis to account for the impact of external factors on game performance. Basic variables Basic statistical indicators were standardized per possession, following established methods from previous research. The formula for calculating the number of possessions was:

$$possessions = field\ goals\ attempted - offensive\ rebounds + turnovers + 0.44 \times free\ throws\ attempted\ [15]$$

Contextual variables include opponent strength and game pace, which prior studies have identified as key factors influencing game outcomes [16,17]. Therefore, these two variables were incorporated as contextual factors in this research [18].

1.2. Statistical Analysis

Opponent strength was classified using K-means clustering based on the final winning percentages of the 12 teams. Teams were categorized into strong teams (winning percentage = 75.00 ± 14.43%) and weak teams (winning percentage = 20.24 ± 14.31%) [19]. Game pace was defined by the number of team possessions and divided into fast-paced (possessions = 86.67 ± 3.50) and slow-paced (possessions = 59.93 ± 3.95) categories [16].

Previous studies have demonstrated that, regardless of sample size, Quantile Regression (QR) offers several advantages over Multiple Linear Regression (MLR), including: (1) providing more detailed insights, (2) being less sensitive to outliers (which results in more stable regression coefficients), and (3) offering a better description of estimation results across different quantiles [10].

To enhance previous research methodologies, we restructured the normalized data by grouping it based on quantiles of the dependent variable (game score). The dataset was divided into three groups, and Multiple Linear Regression (MLR) was conducted for each game, generating distinct regression equations. This approach enabled a direct comparison between MLR and Quantile Regression (QR) at corresponding quantile points.

Following established research frameworks and considering the sample size, three quantiles — Q25, Q50, and Q75 — were selected for analysis. Each quantile reflects the varying impact of KPIs on game outcomes: Q25 represents the lower end of the distribution, Q50 corresponds to the median, and Q75 captures the upper extreme. All statistical computations were carried out using R software (R Project version 4.4.1), with the significance threshold (Alpha) set at 0.05.

2. Results

The parameter estimates from both Multiple Linear Regression (MLR) and Quantile Regression (QR) across three quantile levels (Q25, Q50, Q75) are detailed in Table 1. A comparative summary of key indicators derived from these two regression models is illustrated in Table 2.

Table 1. Parameter estimation of final score difference quantiles by multiple linear regression (MLR) and quantile regression (QR).

Variables			**Paint Score**		Mid-Range Score	
Q25	(PTS = 77.25)	MLR	1.034*	-0.158	1.216*	-0.254
		QR	0.794**	-0.014	0.776**	-0.017
Q50	(PTS = 85.00)	MLR	0.833**	-0.061	0.806**	-0.046
		QR	0.790**	-0.009	0.775**	-0.009
Q75	(PTS = 93.00)	MLR	0.828*	-0.039	0.862*	-0.093
		QR	0.763**	-0.014	0.776**	-0.017
Variables			Three-Point Score		Free Throws	
Q25	(PTS = 77.25)	MLR	0.973*	-0.126	0.898*	-0.091
		QR	0.775**	-0.013	0.785**	-0.018
Q50	(PTS = 85.00)	MLR	0.831**	-0.06	0.841**	-0.066
		QR	0.773**	-0.008	0.778**	-0.01
Q75	(PTS = 93.00)	MLR	0.726	-0.149	0.587	-0.354
		QR	0.748**	-0.014	0.755**	-0.018
Variables			Offensive Rebounds		Defensive Rebounds	
Q25	(PTS = 77.25)	MLR	-0.225	-0.137	-0.334	-0.208
		QR	-0.013	-0.026	-0.01	-0.025
Q50	(PTS = 85.00)	MLR	-0.007	-0.048	-0.057	-0.036
		QR	0.031*	-0.015	-0.001	-0.014
Q75	(PTS = 93.00)	MLR	-0.003	-0.072	0.248	-0.164
		QR	-0.009	-0.026	-0.009	-0.025
Variables			Assists		Steals	
Q25	(PTS = 77.25)	MLR	0.406	-0.21	-0.234	-0.131
		QR	0.006	-0.027	-0.012	-0.033
Q50	(PTS = 85.00)	MLR	-0.049	-0.043	-0.065	-0.054
		QR	0.016	-0.019	-0.015	-0.019
Q75	(PTS = 93.00)	MLR	0.117	-0.2	0.339	-0.157
		QR	0.059*	-0.029	0.006	-0.033
Variables			Blocks		Turnovers	
Q25	(PTS = 77.25)	MLR	0.194	-0.114	0.286	-0.139
		QR	0.100*	-0.044	0	-0.03
Q50	(PTS = 85.00)	MLR	0.045	-0.102	0.005	-0.052
		QR	0.058*	-0.025	-0.003	-0.017
Q75	(PTS = 93.00)	MLR	0.497	-0.616	-0.267	-0.193
		QR	0.059	-0.045	0.02	-0.03
Variables			Foul		Constant	
Q25	(PTS = 77.25)	MLR	-0.039	-0.066	-139.429*	-30.54
		QR	0.044	-0.031	-90.833**	-2.928
Q50	(PTS = 85.00)	MLR	0.031	-0.047	-94.209**	-13.725
		QR	0.041*	-0.018	-89.923**	-1.681
Q75	(PTS = 93.00)	MLR	0.335	-0.285	-124.361	-13.879
		QR	-0.012	-0.031	-82.483**	-2.972
Variables			Quality of Opponent		Pace	
Q25	(PTS = 77.25)	MLR	4.62	-2.26	1.488*	-0.235
		QR	-0.212	-0.433	1.144**	-0.023
Q50	(PTS = 85.00)	MLR	-0.391	-0.653	1.170**	-0.101
		QR	-0.127	-0.249	1.128**	-0.013

Q75	(PTS = 93.00)	MLR	3.32	-4.335	1.322*	-0.05
		QR	-0.396	-0.439	1.074**	-0.023

Note: standard errors are shown within parentheses; * $p < 0.05$ and ** $p < 0.01$; PTS: Points.

Table 2. Comparison of KPIs based on multiple linear regression and quantile regression. The shaded part represents a significant difference, and the blank part represents a non-significant difference.

Basic Variables	**MLR**	**QR**
Paint Score	25	25
	50	50
	75	75
Mid-Range Score	25	25
	50	50
	75	75
Three-Point Score	5	5
	50	50
	75	75
Three Throws	25	25
	50	50
	75	75
Offensive Rebounds	25	25
	50	50
	75	75
Defensive Rebounds	25	25
	50	50
	75	75
Assists	25	25
	50	50
	75	75
Steals	5	5
	50	50
	75	75
Blocks	25	25
	50	50
	75	75
Turnovers	25	25
	50	50
	75	75
Fouls	25	25
	50	50
	75	75
Contextual variables	MLR	QR
Quality of Opponent	25	25
	50	50
	75	75
Pace	25	25
	50	50
	75	75

2.1. Basic Variables

For basic performance metrics, MLR analysis identified significant positive associations between Paint Score and game outcomes across all three quantiles: Q25 (RC = 1.034), Q50 (RC = 0.833), and Q75 (RC = 0.828). QR analysis mirrored this trend, demonstrating significant positive effects at Q25 (RC = 0.794), Q50 (RC = 0.790), and Q75 (RC = 0.763).

Regarding Mid-Range Score, MLR results indicated strong positive correlations at Q25 (RC = 1.216), Q50 (RC = 0.806), and Q75 (RC = 0.862), while QR analysis revealed comparable significance at Q25 (RC = 0.776), Q50 (RC = 0.775), and Q75 (RC = 0.776).

For Three-Point Score, MLR analysis found significant positive correlations at Q25 (RC = 0.973) and Q50 (RC = 0.831), whereas QR analysis exhibited significance across all quantiles: Q25 (RC = 0.775), Q50 (RC = 0.773), and Q75 (RC = 0.748).

Free Throws were significantly correlated with game performance in MLR at Q25 (RC = 0.898) and Q50 (RC = 0.841), while QR analysis detected positive correlations at all quantile levels: Q25 (RC = 0.785), Q50 (RC = 0.778), and Q75 (RC = 0.755).

For Offensive Rebounds, MLR did not identify significant correlations, whereas QR detected a significant positive association at Q50 (RC = 0.031). Defensive Rebounds showed no statistical significance in either model.

In the case of Assists, MLR did not report any notable correlations, but QR analysis identified a significant positive relationship at Q75 (RC = 0.059). Similarly, Blocks exhibited no significant effect in MLR, whereas QR analysis found positive correlations at Q25 (RC = 0.100) and Q50 (RC = 0.058).

For Fouls, MLR analysis did not detect any significant correlation, whereas QR analysis identified a notable positive association at Q50 (RC = 0.041). Both Steals and Turnovers exhibited no significant relationships across all quantiles in either regression model.

2.2. Contextual Variables

With respect to contextual factors, MLR analysis demonstrated a strong positive correlation between Pace and game outcomes across all three quantiles: Q25 (RC = 1.488), Q50 (RC = 1.170), and Q75 (RC = 1.322). QR analysis yielded similar findings, revealing significant associations at Q25 (RC = 1.144), Q50 (RC = 1.128), and Q75 (RC = 1.074). Conversely, Quality of Opponent did not show any statistically significant effects in either regression approach.

3. Discussion

This study systematically analyzed performance data from 12 teams across 26 matches (N = 52 games) in the 2024 Paris Olympic Games. The findings confirm that traditional statistics (e.g., paint score, mid-range score) positively influence game outcomes. Additionally, game pace significantly impacted results, emphasizing its role in high-level international basketball. By employing hierarchical multiple regression (MLR) and quantile regression (QR), we identified key performance indicators (KPIs) at different competitive levels through three quantiles:

Q25 (Lower Quartile): Teams performing below the median, often struggling or facing stronger opponents.

Q50 (Median): Represents typical game performance, serving as a baseline for evaluation.

Q75 (Upper Quartile): High-performing teams exhibiting peak execution and tactical superiority.

This stratification provides deeper insights into performance dynamics across different competition levels. Notably, QR analysis proved more sensitive than MLR in capturing the impact of KPIs on Olympic game outcomes under this grouping strategy.

3.1. Scoring Metrics and Game Outcomes

Previous research has established that scoring within the three-point line (paint, mid-range) differentiates winning and losing teams and remains crucial in Olympic basketball. However, results for three-point and free throw scoring varied between MLR and QR at the 75th percentile. Specifically, QR identified three-point field goals and free throws as key indicators of success, while MLR found no significant relationship.

This discrepancy contrasts with prior studies, which suggest three-point shooting is more decisive in critical phases of the season (e.g., playoffs), where coaches select specialists for long-range shooting [20,21]. Over the years, three-point attempt rates have increased in both professional and international competitions [22,23]. Since higher three-point volume can yield more points per possession, it aligns with QR's findings that emphasize its impact on game outcomes [24,25].

Similarly, free throw scoring followed the same trend: at Q75, QR detected a positive effect, while MLR did not [26]. Previous studies have suggested that free throws become more influential in close games, where every point is crucial, whereas in one-sided matches, their importance diminishes [20,21]. High-scoring teams tend to advance to the knockout stage [27,28], often defeating weaker opponents early on, leading to less intense games [29]. By categorizing teams by scoring levels, MLR captured only partial tournament data at Q75, whereas QR analyzed the entire dataset, explaining their differing conclusions [30].

3.2. Offensive Rebounding, Assists, and Defensive Contributions

For offensive rebounds, QR revealed a significant effect at Q50, suggesting it benefits teams with average scoring levels [31]. Previous studies have presented mixed results: some identify offensive rebounding as a game-deciding factor, while others find its impact varies across different contexts [32,33]. The current findings indicate that higher-scoring teams convert more efficiently, reducing their need for offensive rebounds. Conversely, low-scoring teams struggle to contest rebounds due to lower shooting efficiency, reinforcing the moderate effectiveness of offensive rebounding at Q50.

Assists positively influenced outcomes only at Q75, implying they play a crucial role for high-scoring teams. In Olympic basketball, elite teams create better scoring opportunities through ball movement, making assists a key factor in victory. Conversely, lower-scoring teams rely more on individual efforts, limiting assists' overall impact.

Interestingly, shot-blocking (blocks) significantly affected game outcomes at Q25 and Q50 in QR analysis, differing from previous NBA studies, which linked it primarily to stronger teams [10]. This suggests that low and mid-tier teams benefit more from interior defense, as it disrupts opponent scoring efficiency.

For fouls, QR showed a positive association at Q50, contradicting earlier findings from the 2019 FIBA Championship, where fouls negatively impacted outcomes [10]. This shift may reflect modern basketball's faster pace, where strategic fouling disrupts opponent rhythm and increases defensive pressure, making it an effective winning strategy.

3.3. Contextual Factors: The Role of Pace and Opponent Strength

No clear correlation was found between opponent strength and game outcomes, aligning with mixed findings in prior research [10]. However, game pace emerged as a significant factor, supporting its importance in Olympic basketball. Faster-paced strategies, such as fast breaks, transition offenses, and early shot attempts, have been shown to enhance scoring efficiency compared to structured half-court plays [15,16].

- Implications and Future Directions

While MLR identifies universal success predictors (e.g., scoring efficiency), QR provides a nuanced view, revealing how performance metrics vary across competition levels. This distinction can inform coaching strategies:

Moderate-performing teams may benefit from shifting focus from offensive rebounding to improving passing and defensive positioning.

High-scoring teams should maximize assists and transition play to sustain offensive dominance.

- Future research could explore:
  1) Comparative analysis across different competitive environments (e.g., domestic leagues vs. international tournaments).
  2) Temporal trends in performance dynamics over multiple seasons or phases of a tournament.
  3) Interdependencies between KPIs, uncovering how various factors interact to shape game outcomes.

This study contributes to the theoretical and practical understanding of basketball analytics, demonstrating how MLR and QR offer complementary insights. By integrating both methods, teams and analysts can develop more targeted strategies to optimize performance at different competition levels.

This study demonstrated the effectiveness of stratified multiple linear regression (MLR) and quantile regression (QR) in identifying key performance indicators (KPIs) that determine success in elite men's basketball. Both methods highlighted the significance of key predictors, including tie scores, mid-range scores, three-point scores, free throws, and game pace. However, QR exhibited superior sensitivity by capturing distribution-specific nuances, such as the impact of offensive rebounds at the 50th percentile (Q50) and the influence of assists and blocks at the 75th percentile (Q75) — insights that MLR did not reveal.

4. Conclusion

The results underscore the robustness of MLR in providing a stable, overall assessment of performance, while also highlighting QR's strength in identifying contextual variations across different competitive levels. By integrating these two approaches, this study offers a deeper understanding of the complex relationships that drive basketball success and provides actionable insights for tailoring strategies to different levels of competition.

These findings emphasize the critical role of advanced statistical techniques in sports analytics, offering practical applications for optimizing training programs, refining tactical frameworks, and enhancing player development in elite basketball. Future research could further explore the interplay of performance metrics across different competition settings and phases, providing even greater insights into the determinants of success in professional basketball.

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