Investigating Coach Effect Based on Recent Team Performance and Player Salary in the NBA

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Introduction

- There are many factors that affect an NBA team's performance such as players, **coaches**, **previous performance**, and **salary**.
- In professional sports, coaches are often credited or blamed for the success or failure of their teams, and they are compensated as if they are one of the most important features of a franchise (Berry & Fowler, 2019).
- In general, coaches have **not** been the subject of the rigorous empirical analyses unlike players. This results in less knowledge about coaches who train and direct players on the field. (Berry & Fowler, 2019).
- It has been shown that effective statistics for evaluation of team performance include **win percentage**, **offensive rating** (Mikołajec et al, 2013), and **defensive rating** is another measure which has gained relatively less attention.
- As there is a lack of research examining coaches' effect on team performance, we applied linear mixed-effects model to identify effective coaches and quantify their impact on team performance after adjusting recent team performance prior to the coach and players' salaries.

Methods

- Data was collected for 1997 - 2025 NBA seasons for team performance and coaches (basketballreference.com) and for team salary (Kaggle.com).
- We wrangled data such that each observation included the coach, team, their coaching duration, average performance metrics, and average salary of players in the team.
- Additionally, each observation included the previous coach of the same team and their average performance metrics.
- We used linear mixed-effects models to quantify the random effects coaches have on different outcomes: **win percentage**, **offensive rating**, **and defensive rating**.
- We let Y_{ij} be an outcome variable of the j-th team for the i-th coach in the data, X_{ij} be the adjusted team average salary of players during the coach's tenure, Z_{ij} be the team's outcome of the season prior to the coach, $\boldsymbol{\alpha}_i$ be the random effect which captures the i-th coach effect given X and Z, and $\boldsymbol{\varepsilon}_i$ be the unexplained random error.
- The models are structured as follows:

$$Y_{ij} = \beta_0 + \beta_1 X_{ij} + \beta_2 Z_{ij} + \boldsymbol{\alpha}_i + \epsilon_i$$

Results

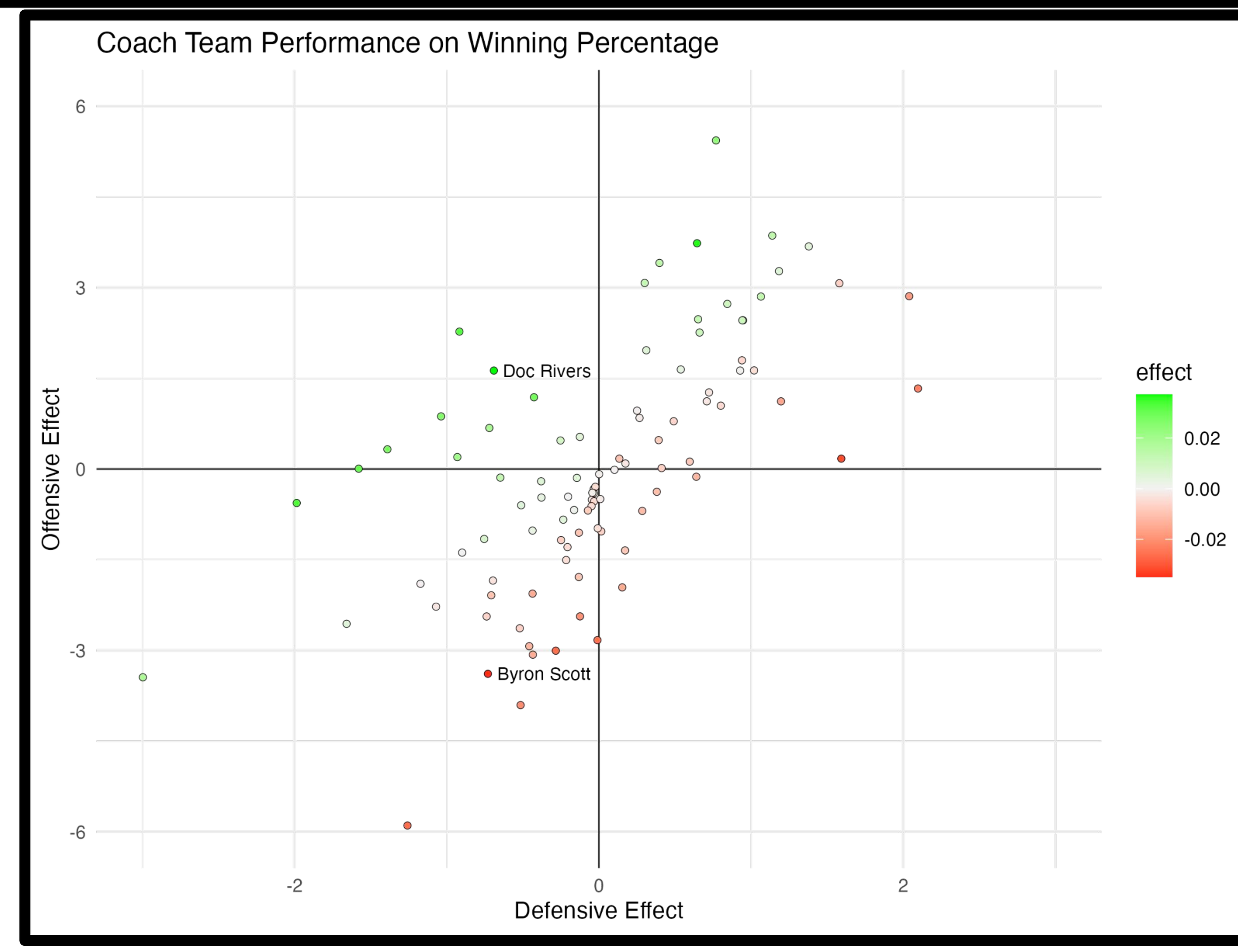

Figure 1: Defensive and Offensive effects and how they relate to winning effect

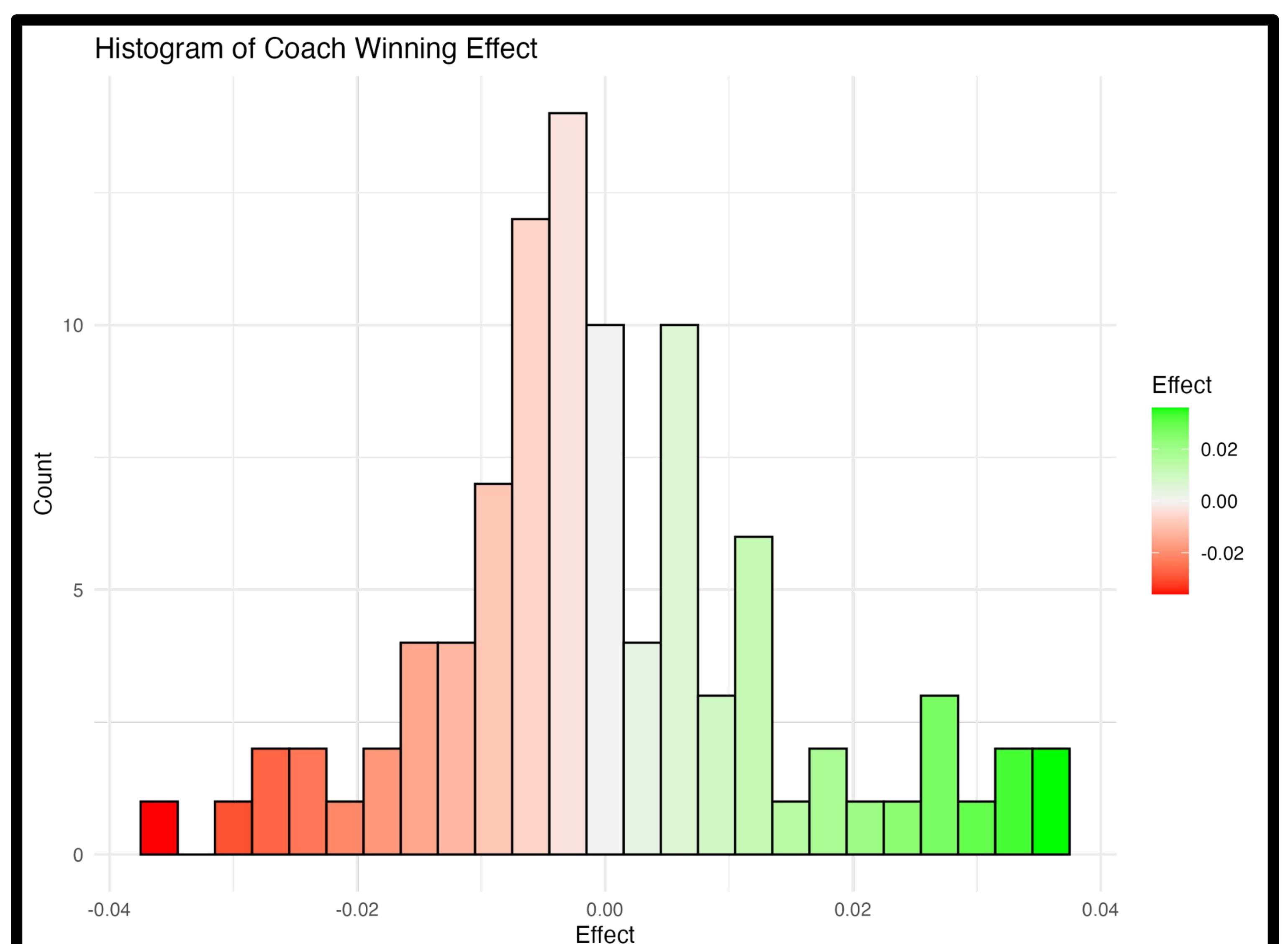

Figure 2: Distribution of winning effects for all coaches

Coach	Win Effect	Offensive Effect	Defensive Effect
Doc Rivers	0.037	2.233	-0.889
Steve Kerr	0.036	3.937	0.407
Rick Adelman	0.033	0.066	-2.120
Quin Snyder	0.032	2.032	-1.008
Tom Thibodeau	0.030	-0.296	-2.078

Table 1: Coaches with highest winning effect and their respective offensive and defensive effects (estimated by the random effect of the mixed-effects model)

Discussion

- Our study examined the coaching effect on defensive rating, offensive rating, and win percentage in the NBA from 1997 to 2025 while accounting for team salary and team's performance prior to the coach.
- The mixed-effect models including coach, salary, and previous performance were not statistically significant. (R^2 = 0.0015, 0.0039, 0.0019 for outcomes win percent, offensive rating, and defensive rating respectively).
- The estimated effect for the strongest coach, Doc Rivers, was small. On average, he increased his teams win percentage by 3.7%, score 2.23 more points per game, and prevented 0.89 points per game.
- Doc Rivers' overall win percentage (59.2%) ranks 16th, but he ranks 1st after accounting for players' salary and the team's performance prior to his coaching. On the other hand, the winningest coach, Joe Mazzulla (73.9%), ranks 9th (+2.25%) under the mixed-effect model.
- We found that ~59% of coaches have a negative effect on win percentage (Figure 2), and We found that winning effect has a higher correlation with offensive effect (ϱ = 0.53) than defensive effect (ϱ = -0.29).

Limitations/Future Direction:

- Our study incorporated only three metrics for quantifying team performance. It would be reasonable to examine coach effect with more sophisticated metrics, like **pace,** and **offensive** and **defensive four factors,** which have been shown to strongly relate to winning (Baghal, 2012).
- Our models did not well explain the variability of the three outcomes. In the future, we should consider more factors that might contribute to team performance and coaching.

Conclusion:

- We recommend accounting for known factors (fixed-effect) for evaluating coaches, but need to further study the factors which can well explain the outcome variable of interest. We have found that offensive coaches are more effective than defensive coaches.

References

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