Defensive Impact Wins: Re-Evaluating Individual Player Defense in NBA Basketball

By Dylan Stiles

UNH College of Engineering and Physical Sciences

Literature Review

- The Wages of Wins - Berri, Schmidt, Brock - Book that introduced the Wins Produced and Win Score stats off of which this model is loosely based. In a chapter of this book, Berri produces the Win Score metric by regressing points, rebounds, assists, and other box score statistics against wins. Then, these slopes were rounded to either 1 or 0.5 and added to player stats.
- Characterizing the Spatial Structure of Defensive Skill in Professional Basketball - Franks et al – The authors modeled defense as a hidden Markov model. The position of the defender is taken as relative to the hoop and the offensive player. This model has transitive properties to allow it to include switches. Among other checks, this model shows that defenders get closer to their man when he has the ball.
- Counterpoints: Advanced Defensive Metrics for NBA Basketball – Franks et al – At the 2015 MIT Sloan Sports Analytics Conference, the authors of the previous work showed how they had used their model for defense to create Counterpoints, assigning credit and blame to every defensive possession of the 2013-14 season.

Data And Methods

- Collect team defensive playtype data for the 2022-23 season
- Fit binomial GLMs with stop, shooting foul, and turnover rates.
- Disallow obviously-biased models (example: models that negatively associate forced TOVs and wins)
- Find relative stop, foul, and turnover rates for players
- Sum the slopes from the binomial models multiplied by relative player stats (difference from league average)
- Multiply by proportion of minutes played
- The goal is to create a metric that has real units (points or wins) that removes some of the team-bias I felt was present in existing defense metrics
- By centering, we change the interpretation to “defensive wins added above average”

$$rDIW_{v1} = \sum significant, allowed\ GLM\ slopes * (player\ rate - league\ average\ rate)$$

$$DWA_1 = rDIW_{v1} - mean(rDIW_{v1})$$

$$rDIW_{v2} = \sum allowed\ GLM\ slopes * (player\ rate - league\ average\ rate)$$

$$DWA_2 = rDIW_{v2} - mean(rDIW_{v2})$$

	finalplayersheet.PLAYER	finalplayersheet.TEAM	finalplayersheet.defensive_wins	finalplayersheet.defensive_wins_2
66	Draymond Green	GSW	2.882934210	3.022983152
196	Shai Gilgeous-Alexander	OKC	2.546663304	2.474331497
215	Tyler Herro	MIA	2.500191539	2.552755609
29	CJ McCollum	NOP	2.473416757	2.694057790
144	Kristaps Porzingis	WAS	2.320893854	2.330337101
110	Jevon Carter	MIL	2.247118597	2.042611624
222	Zach LaVine	CHI	2.149452962	2.206657527
41	D'Angelo Russell	MIN	2.132556339	2.388927992
106	Jayson Tatum	BOS	2.089155444	2.274814691
15	Bam Adebayo	MIA	2.027466069	2.068034387

University of New Hampshire

Analysis

- Missing Data issues: nba.com data does not include individual player defensive numbers for putback or transition plays. Additionally, all plays listed as “offscreen” were removed for incorrect models. This issue could possibly have been avoided collecting data on multiple seasons
- Some good defenders on bad defensive teams were recognized – Kristaps Porzingis worth about 3 wins on a terrible defensive Wizards team.
- Some rankings pass the “smell test,” some do not.
    - Draymond Green listed as the best defender, but Tyler Herro is listed as the third best.
- Seems to not be scalable to teams the way MLB’s WAR is

Some Interpretations

- Draymond Green’s defense was worth about three wins in 2022-23.
- The Miami Heat’s defense was worth about 5.5 wins in 2022-23.
- Player ratings seem more correct than team ratings here.
    - Teams might have a mix of good and bad defenders, but bad defenders will spend less time impacting the game. This model probably overemphasizes their effects even after adjusting for minutes played.
    - The Spurs very bad defense was only worth about -2 wins. The Spurs lost 60 games in 2022-23.