“May the best team win?” Team Bias by NBA referees*

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Abstract: The National Basketball League (NBA) offers an intriguing place for economist to assess discrimination. This paper examines the existence of a “team” bias using evidence of NBA referees’ partial decisions in giving calls towards teams with different valuations. I use simple regression models to prove such a “team bias” towards teams with higher valuation and star players, and we measure the impact of “wrong calls” (to total calls) to game statistics.

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1. Introduction

Referees in sport competitions are supposed to be neutral with their duty to ensure rules are adhered by putting on fair judgment. Yet under time constraints and ambiguous circumstances, mistakes are often inevitable. A bias is defined when referees make wrong decision often based on personal beliefs. Referees would hardly make correct decisions due to various bias (Buraimo et al., 2009). One example would be the "racial bias"; A research conducted by Price and Wolfers (2010) discovered that more personal "fouls" are given towards players when they are officiated by an opposite-race referees. Another example would be the "home bias", which home teams would have a higher chance to win in their own city.

In this paper, we examine the existence of "team bias" which we find evidence of referees favoring teams with higher franchise valuation and teams with more "star player(s)". As referees are employed by the NBA league, it is potentially possible for referees to intervene match results to let "wealthier" teams win or advance. One notorious example in would be the Western Conference finals in 2002[1]. We collected data from the "NBA Officiating Last Two Minute Reports (detailed reports)" and make

[1] Numerous questionable calls went against the Sacramento Kings and caused the Los Angeles Lakers' wining in 2002 western final. Los Angeles Lakers was more developed than Sacramento Kings in either the team-city's economic condition (income), and the team itself, which sport media argued that the NBA league intended to let the King lose.

quick access to comments of each calls for the rightfulness of referees' judgment. We sampled total 72885 call records (and the comments of each call) from 2016 to 2023. To determine whether do referees make wrong decisions, we extracted a list of 5 "wrong classifiers" from the full comments of the report. We consider a call to be wrong if it contains any "wrong classifiers". We then search for additional information from https://www.basketball-reference.com/. and Forbes for additional information such as the commercial Valuation of each team and how many "star players" each team have. The regression model is used to, first prove referees discriminative calls and examine the impact of such calls to team's winning scores. We identify the following summary:

TABLE 1— SUMMARY STATISTICS

	Count	Mean	SD	Max	Min	Median
Team Factors						
Valuation	240	2056.33	1168.63	7000.00	650.00	1712.50
Attendance	240	15871.98	5366.59	21820.00	0.00	17452.00
Age	240	26.28	1.69	30.60	22.10	26.15
Lastwins	240	39.66	11.21	67.00	15.00	41.50
Referees (from NBA Officiating Last Two Minute Reports)						
Total_call	240	294.22	81.19	529.00	124.00	293.00
Disadvantage	240	47.25	28.62	153.00	10.00	37.50
Wrong_Ratio	240	15.63%	6.66%	31.54%	5.41%	14.46%
Game Factors (from https://www.basketball-reference.com/.)						
Offensive Rating	240	110.48	3.9465	119.4	98.8	110.75
Defense Rating	240	110.49	3.5943	120	99	110.65
True Shooting %	240	0.5616	0.0200	0.61	0.5091	0.5625

Before introducing the details, it is essential to first introduce the concept of "wrong" calls in basketball competition: A call is given by referees in NBA to players who violates the game rules. Wrong calls (or bad calls) are referred to calls which wrong mistakenly given to players. Noted calls also implies chances of free throws and transition of ball possession, in other words, referees could influence match results by giving "bad calls' to team for score advantages.

FIGURE 1. PERCENTAGE OF WRONG CALLS IN REGULAR SEASON(S)

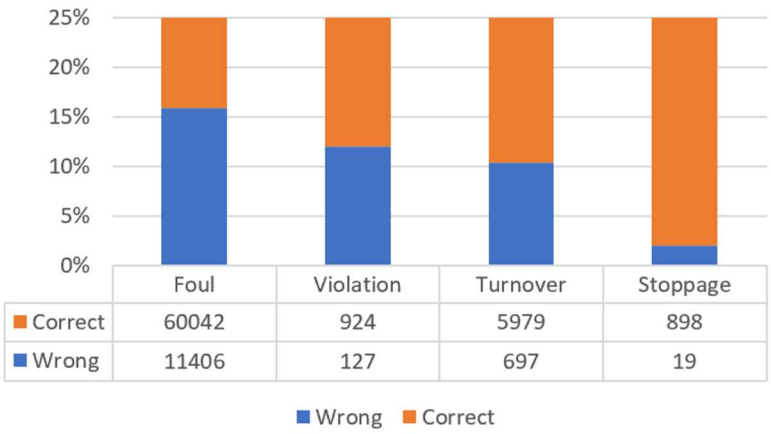

Table 1 presents the descriptive statistics on teams and referees' decisions. By extracted and compare the "wrong classifiers", we found surprising results that referees often give wrong calls. Recall the previous table that we had computed the wrong ratio is around 15.63% on average, even it is inevitable for referees in make immediate decisions, the sharing of wrong calls to total is by somehow too "high", This derives us to further investigate the reason behind. Furthermore, given such bias occurred and theoretically, players could sense such bias, as if referees' give partial call against one

team consistently (not randomly), the favoring teams would have better statistics in offensive side the defensive side (Gong, 2022). The category for "Offensive Rating[2]", "Defense Rating[3]" and "True Shooting %[4]" are used to measure the teams' ability to win games. These data are generated by computing the team's ability. The higher the score recorded, the better the team is doing on offense, defense and shooting respectively. We wish to investigate the impact of referees' bias on game factors.

2. Regression on referees' decision

Table 2 presents the regression results on three variables. "FValuation" indicates the financial assets of the team, and "MVP" & "AllNBA" indicates whether do the team has a star player. "Age", "Lastwins" & "Attendance" are control variables. The column illustrates different regression result on different observation. A call is given to compensate the team's player(s) who was adversely affected by other players, and wrong calls is the wrong compensation which the team's player(s) was actually not affected by the opposing player. Column (1) is the regression result on total calls in season, we do find clear evidence that teams' franchise valuation is positively related to the number of call. Column (2) is the result on wrong calls. It shows a statistically

[2] Offensive Rating = 100 * (Individual Points Produced / Total Possessions)

[3] DRtg = Team_Defensive_Rating + 0.2 * (100 * D_Pts_per_ScPoss * (1 - Stop%) - Team_Defensive_Rating). Team_Defensive_Rating = 100 * (Opponent_PTS / Team_Possessions). Stop% is the rate at which a player forces a defensive stop as a percentage of individual possessions faced.

[4] true shooting percentage is an APBRmetrics (Association for Professional Basketball Research Metrics) statistic that measures a player's efficiency at shooting the ball

significant impact of the All-NBA team player(s) on the number of wrong calls. Column (3) is the result on the ratio of wrong calls to total calls, which shows a statistically significant impact of the franchise valuation where estimates 1000 increase in it will bring more accurate judgment by referees, with the -1.4% effect on the wrong ratio.

TABLE 2—Regression results on referees' calls

Regressor	Total Calls	Wrong Calls	Wrong Ratio
	(1)	(2)	(3)
Intercept	301.6659***	57.9921**	13.7693%*
	(96.8647)	(33.4987)	(7.6592%)
FValuation	0.0171***	-0.0022	-0.0014%***
	(0.0046)	(0.0016)	(0.0004%)
MVP	-32.5805	-1.6728	0.6337%
	(15.5191)	(5.3670)	(1.2271%)
AllNBA	41.0894***	11.3745***	1.3947%
	(11.6473)	(4.0280)	(0.9210%)
Attendence	0.0040***	0.0020***	0.0004%***
	(0.0009)	(0.0003)	(0.0001%)
Age	0.4343	1.1227	0.4705%*
	(3.6416)	(1.2594)	(0.2879%)
Lastwins	-0.0442	-0.2284	-0.0482%
	(0.4789)	(0.1656)	(0.0379%)
n	239	239	239
R-square	0.158226895	0.189823759	0.217666152

***, **, and * Differences statistically significant at 1%, 5%, and 10%, respectively.

$Lastwins$ = *Wins in last seasons*

Attendance = Seat Tickets sold per game

Age = The Team's average age

$FValuation$ = *Franchise valuation of the team (million)*

MVP = *Whether the team have a starting MVP or FMVP (Binary)*

$AllNBA$ = *Whether do the team have an players has All-NBA team player (Binary)*

One interesting phenomenon in the regression is that the control variable "Attendance"

are statistically highly significant in all the three columns. An increase number of visitors watching live games on court implies increasing chances in wrong calls. A possible explanation of that would be the home bias (Boudreaux et al., 2015), the fans of the home team could distract referees from the court through noises (Bilalić et al., 2021). The higher the attendance in the court with home fans would imply a strong noise and its signaling effect to referees' on call decision. Another interesting observation is that compare to the estimator "MVP", "AllNBA" illustrates a much significant estimation in all three column

2. Regression on team performance

Table 2 presents the regression results on the offensive rating (ORtg) and the defensive rating (DRtg). True shooting percentage (TS%) computes a teams' shooting accuracy and is a control variable[5]. Column (I) and (II) illustrates the regression using total number of calls. Even the result are significant in offensive side, column I, the effect is not impactful as 100 additional calls contributes only 0.4 to "Ortg". Column (III) and (IV) illustrates the regression using total number of wrong calls. Same situation happened to column (IV) as 10 additional wrong calls would only estimate -0.3 decrease in the defensive rating "DRtg". However consider the input estimator of calls

[5] Although some researcher would argue the relation between defense and shooting are weak, because the accuracy of free throws are also involved into the equation of shooting %, plus more accurate you shoot in offensive side implies lesser transition (Csapo & Raab, 2015), we would consider it as a valid estimate.

sampled only the last sector of the games, it is reasonable for a weak impact. Column (V) and (VI) illustrates the regression using total number of wrong calls. The regression result illustrates the estimated impact of wrong ratio are negatively related to both the offensive and defensive side. With a 10% rate of wrong calls, it will approximately reduce the "ORtg" and "DRtg" by 0.386 and 1.89. The impact on wrong-calls ratio have a greater impact on defensive side majority because defensive demand higher chance of skin-touching and body movement, due to rebounds and screening (Sun et al., 2023).

TABLE 3—Regression results on team performance in offensive & defensive side

	Total Calls		Wrong Calls		Wrong Ratio	
	ORtg	DRtg	DRtg	DRtg	Ortg	DRtg
	(I)	(II)	(III)	(IV)	(V)	(VI)
Interception	13.71***	92.48***	93.56***	93.56***	13.40***	101.70***
	(3.19)	(6.60)	(6.24)	(6.24)	(3.25)	(6.26)
Totalcalls	0.0046***	0.001				
	(0.0015)	(0.00)				
Wrongcalls			-0.03	-0.03***		
			(0.01)	(0.01)		
WrongRatio					-3.86**	-18.94***
					(1.71)	(3.29)
TS%	169.91***	31.35***	176.40***	32.72***	173.91***	20.92*
	(5.90)	(12.21)	(5.63)	(11.07)	(5.68)	(10.92)

***, **, and * Differences statistically significant at 1%, 5%, and 10%, respectively.

Totalcalls = total number of calls recorded in the last 5 minutes of game, by season

Wrongcalls = total number of calls recorded in the last 5 minutes of game, by season

WrongRatio = ratio of wrong calls to total recorded in the last 5 minutes of game, by season

TS% = True shooting percentage, recorded by season

4. **Conclusion**

We find evidence that referees do intend to favor team with higher valuation and teams with star player (All-NBA team). There is one main caveat to our results. The external validity may not be representative. As we only compute the calls from the last 5 minutes It is possible that the referees could make biased judgment on the earlier period. Which by game theory, if players were noticed that they are disadvantaged due to penalties in the prevailing section, they may have a higher willingness to play negatively in the layer section. Moreover, players make decisions on motivation base on the chance of wining and the possibility of injuries (Lewis, 2018), increasing game load would lead to injuries and so the future income of players and future wins of the teams. Star players especially, with a higher income and better future perspective, the cost of playing continue would increase. Given referees' decision making in the early stages could cause players benching, the estimated impact of our research would be invalid for comprehensive games.

The team bias in NBA competition reveals the unfair situation for team to obtain better match results. There is indeed hope to reduce such bias by promoting the interaction between technology in tracking Controversial cases or increasing the openness on referees' background.

5. **References**

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