Star Preference in the NBA: A test of bias in the regular season

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Abstract

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NBA refereeing has a large impact on the outcomes of many games, so much so that many NBA players view it as one of the biggest problems facing the sport. The 2007 NBA betting scandal involving former referee Tim Donaghy exposed many issues regarding NBA officiating impartiality.

In previous years, NBA refereeing has been accused of various biases, a charge the league fervently denies. Nevertheless, I find evidence in the data that there does exist a robust "star bias" in the process of awarding fouls in the NBA. This bias also strengthens in the latter portion of closely contested games.

> "You can't get too close to Michael [Jordan] or it's a foul"
>
> *Magic Johnson, 1992*

1 Background

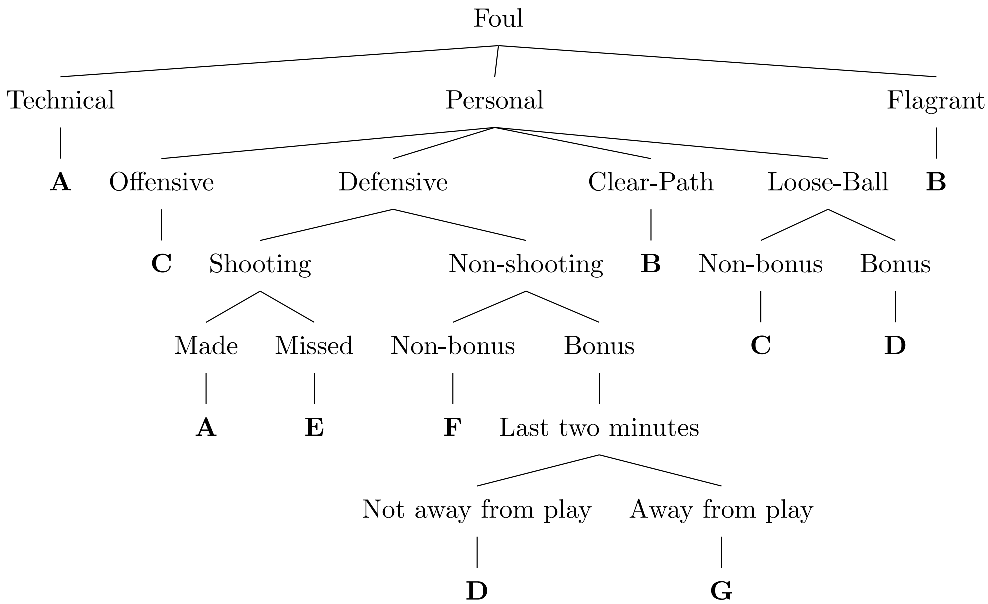
1.1 Introduction

The NBA has always been a business driven by the presence of its biggest individual stars. There are many reasons for this, whether it be because of the relatively small rosters put forth in basketball, or the increased focus on player personalities, or players themselves being more enmeshed in American popular culture. Nevertheless, the deference the league shows towards its most important (and revenue-generating) players is certainly very strong.

This deference shown off-court naturally raises another question: star bias on the court. Many fans of the NBA have often alleged that star players receive preferential treatment on the court from referees and officials in game-time situations. The analysis of this favoritism will be the primary focus of my paper.

NBA referees primarily affect the course of games by awarding (or neglecting to award) fouls and violations. Violations are instances when a player mishandles the ball or makes an illegal move. They are usually punished with a change of possession of the ball. Fouls typically involve illegal contact, and in most cases are punished with either a loss of possession or free throws (see Figure 1). In the case where a player commits six or more fouls, they are suspended for the rest of the game (ie. "Fouled out").

In reality, the decision to award and reject fouls is often times highly subjective. In many instances determining what constitutes as illegal contact is difficult. Referees are forced to make split-second decisions that may in close situations impact the course of the game. Many players are often very vocal about fouls awarded during game-time. This is not helped by the fact that many players



A = Single Free Throw; **B** = Two Free Throws & Possession; **C** = Loss of Possession; **D** = Two Free Throws; **E** = Three Free Throws for a three-point attempt, otherwise Two Free Throws; **F** = Inbound pass; **G** = Single Free Throw & Possession

Note: The Bonus indicates a period of time which occurs if a team has committed greater than or equal to five fouls in a quarter.

Figure 1: NBA Fouls and their penalties. Many times, especially in late-game scenarios, they can mean the difference between a win or a loss.

Type of Violation	Correct Calls	Incorrect Calls	Incorrect Non-calls	Accuracy (%)
Foul: Personal Take	313	0	1	99.7
Turnover: 24 Second Violation	170	0	5	97.1
Violation: Defensive Goaltending	31	0	3	91.2
Foul: Technical	40	0	4	90.9
Foul: Personal	3136	69	339	88.5
Violation: Kicked Ball	41	4	4	83.7
Violation: Delay of Game	25	0	5	83.3
Turnover: Offensive Goaltending	16	0	4	80
Turnover: Stepped out of Bounds	46	1	11	79.3
Foul: Shooting	1684	103	382	77.6
Turnover: Backcourt Turnover	17	3	3	73.9
Foul: Loose Ball	320	16	268	53
Foul: Away from Play	17	1	20	44.7
Turnover: 5 Second Inbound	16	3	27	34.8
Foul: Offensive	189	14	349	34.2
Violation: Lane	10	0	27	27
Turnover: Traveling	64	9	237	20.6
Turnover: 3 Second Violation	3	1	70	4.1
Foul: Defense 3 Second	1	0	140	0.7

Figure 2: Correctly and incorrectly awarded calls in the last two minutes of closely contested in the 2017-2018 season.[3]

have made drawing fouls from other players a dedicated part of their strategy. This means that the decision to award and not to award fouls has the potential to be subject to bias.

Indeed, in an analysis of the calls made and not made in the last two minutes in closely contested games (those where the point margin is within less than five points) shows just how inaccurate officiating can occasionally be. As shown in Figure 2, this relatively low accuracy rating has the potential to seriously impact the outcomes of games.

Statistic	**Value**
Fouls recorded in sample	51,000
Free throws recorded in sample	57,469
Free throws made in sample	43,489
Free throw per foul	1.127
Free throw percentage	75.67%

Table 1: NBA foul statistics during regular season, 2008/09 to 2015/16.

1.1.1 A note on terminology

An NBA player is said to **foul** another player or **commit** a foul if they are the offending paper. An NBA player is said to **draw** a foul or be **awarded** a foul if they are not the offending paper. The player that draws a foul is the player benefits from the call. In almost all cases most players strive to avoiding fouling other players, but fouls are generally considered a normal part of game play in the league.

1.2 Existing Literature

Wolfers and Price (2007) [8] were some of the first to look into the area of referee discrimination in the NBA, specifically regarding the impact of racial bias. Their results demonstrated that there was a significant in-group preference on the part of officials - that "more personal fouls are called against players when they are officiated by an opposite-race refereeing crew than when officiated by an own-race crew".

In addition to racial biases, other biases were shown to exist in the NBA that either implicitly or explicitly enhanced the profitability of the league. Price, Remer and Stone (2009) demonstrated that referees favor home teams, teams losing during games, and teams losing in playoff series [5].

There are two papers that examined star bias (favoritism of popular/good players) in the NBA. Caudill, Mixon and Wallace (2014) used data during the 2011 NBA Playoffs series to conclude that star players are awarded a greater amount of free throw attempts during the fourth quarter of NBA Playoff games. In particular, they found that there was an increase in the number of free throw attempts awarded compared to the early-game period, compared to the increase the amount of field goal attempts. This would signify that star players are indeed getting a boost in the number of free throw attempts relative to their production, relative to their non-star peers. Specifically, the paper estimates that "NBA All Stars are awarded with an additional 0.32 free attempts per minute during the fourth quarter of NBA Playoff games". [7]

However, their results are opposed by Deutscher (2015). In March 2015, the NBA released data regarding *ex post* league evaluation of officials' calls made in the last two minutes of closely contested games. Using regression analysis on the sample set and controlling for several other known biases, Deutscher (2015) demonstrated that there was no bias for star players on a team. Evidently, there is little to no agreement on the existence of star bias in the NBA. [1]

1.3 Gaps in the Literature

So far, both papers are divided on the existence of a "star bias". This could be as the result of several factors that may affect the final result.

The use of the "last two minutes" data set in Deutscher (2015) could potentially introduce bias into the analysis. This data set is a retrospective evaluation of foul calls in the last two minutes of games with a score margin of less than five points. Firstly, there is always the possibility that the release of such a data set could lead towards modified behavior in the last two minutes. For example, Deutscher (2015) mentions the example of Pope, Price and Wolfers (2014), which found an example of racial discrimination that disappeared after close media scrutiny. [1] [2] Secondly, the fact that the last two minutes dataset is constructed *ex post* exposes the data to anchoring bias - it is unlikely that the data is truly objective.

The paper by Caudill, Mixon and Wallace (2014) primarily focuses on results in the last quarter of NBA playoff games. One potential explanation for the positive results in the paper could be structural effects in basketball games that lead towards star players drawing fouls during high-stakes games. The first possible cause is the *increased scrutiny effect.* During close high-stakes games teams and coaches will be under more intense scrutiny to call out fouls. This could mean that referees are under more pressure to make the certain calls in a certain way. This would not be the case in games where the outcome is clear ("blowouts"). A second possible explanation involves a possible need for more pauses on the part of coaches. Since teams have a limited amount of time-outs, players may wish to extend game play, especially if they need time to regroup and coordinate an offence. Often times, the only way to do so will be to play in a manner that draw more fouls. These two mechanisms could skew the results by introducing a selection bias. Since star players are more likely to play in close games, and since increased referee scrutiny is also more likely to occur in close games, this could skew the results in the direction that they did. [7]

One limitation for both papers is that they look search for bias in the latter part of games, or look only into very crucial games. For the reasons explored above, studying only these parts of the games or using specific data sets could lead to a result that is vulnerable to bias. This paper will examine bias over the whole course of a paper. Secondly, the limited scope of these studies means that the power of any tests able to be conducted is limited. This paper will attempt to fill these gaps on the literature by conducting a comprehensive analysis using a complete data set from multiple years that aims to allay some of the concerns with the prior studies.

2 Hypotheses

This paper asks tackles two main questions: is there a star bias in the NBA, and if so does this level of bias change nearer to the end (or during) closely contested games. There are three hypotheses related to this question that we will examine in turn.

2.1 H1: Existence of Star Bias

H1: In the course of regular gameplay, NBA star players are more likely to draw fouls

There are several explanations as to why results may show that NBA star players may be more likely to draw fouls. One explanation is bias. The following examples are possible mechanisms for how such bias may manifest itself.

- **Authority bias:** Star players are could be more likely to have to confidence to argue about and contest closely decided fouls. Referees could grant more calls that favor star players, either in order to avoid confrontation with said star player, or as part of a genuine unconscious bias in favor of a star player's viewpoint.
- **Halo effect:** Referees could believe that a star's superior basketball ability leads to a belief in a star's infallibility in regards to different aspects of his game.
- **Familiarity effect:** Referees could be more familiar with star players given their increased tenure on the court. This could mean that they would be more inclined to make decisions in favor of those who they are familiar with.
- **Selective Perception:** Referees could focus more upon watching the activities of a star, as opposed to the activities of a non-star, causing them to focus more on when a star *draws* a foul.
- **Negative Selective Perception:** Referees could focus more upon watching the activities of non-stars, causing them to focus more on when a non-star *commits* a foul.
- **Crowd Pressure:** Referees feel pressure from the crowd, coaches, peers and other game participants to treat a star leniently, in order to make the game more exciting or to please a crowd.

Although the examination of each of these theories is out of the scope of this paper, the above list shows that there is a significant potential for bias in the refereeing process.

There are other potential unobserved variables that may contribute to the bias that we control for. One possible takeaway could be that more skilled players are better at creating contact/drawing fouls. I try to account for this using ratings of offensive efficiency. That means that increased fouling as a result of increased regular offensive output should be limited.

Another possibility is that stars are able to play the game to their advantage, more so than non-stars. This means that they are more likely to know how to draw fouls compared to non-stars while this argument makes a certain degree of sense for stars like James Harden (who has made drawing fouls a specific portion of his strategy), it is highly unlikely that the increase in skill in drawing fouls should increase at a rate faster than that of non-stars. A linear increase in other metrics, such as player efficiency rating and points scored, should not lead to a quadratic[1] increase in other metrics. We conduct a similar analysis to what is done in Wallace et al. to counteract this possibility. [7]

[1] Various non-linear relationships have also been tested in the model.

2.2 H2 and H3: Impact of late, close games

H2: Any bias in favor of star players would diminish during the later portions of a closely contested game

H3: Any bias in favor of star players would increase during the later portions of a closely contested game

It is unclear initially how the accuracy and objectivity of a game is influenced by the time remaining and point differential of a game. One theory about the influence of late, close games is the **referee focus hypothesis** - since referees know that their actions will be judged with more scrutiny in these game situations, they will be more likely to act in a fully objective manner by paying attention in a game. This would definitely be more true in the case that the selection perception theory (explained above) is valid, and would support hypothesis H2.

Bias in the opposite direction (a sort of **negative referee focus hypothesis**) is also possible - referee focus may decrease as time goes on during the day, and they may become less accurate as time goes on. If this were the case, this would be a potential driver of H3.

As mentioned previously in section 1.3, the fact that closely contested late-game play has more stars could potentially affect the results one way or the other. Since closely contested late-game play could result in more fouls being committed due to increased scrutiny, and an increased desire to pause the game on the part of both referees and members of a team, there is a potential that this could also be a driver of H3. Furthermore, the selection bias involving players that play in the last two minutes plays a part in these results - players that play in the last two minutes in close games are almost always the "cream of the crop" - thus they are more likely to be star players and have star status. Although we attempt to control for this by adjusting for minutes played during a quarter and offensive output, there is always the potential that any other potential unobserved variable biases are missed by the controls.

Although examining H1 is the main thrust of the paper, any insight into H2 and H3 would be especially helpful as well. This is because both prior papers in this subject [1] [7] have primarily concerned themselves with the last couple minutes of close games, allowing for a more accurate comparison of results. This comparison of results is especially important for the last two minutes of games withing five points, as that is the only time period in which the NBA themselves has released data on the validity of foul calls.

3 Data

3.1 Data Sources and Selection

Our primary data source involves play-by-play data from the 2008-09 seasons to the 2015-2016 seasons. This data source was acquired from Eight Thirty-Four, a basketball analytics website. [6] Furthermore, additional data on player production and box scores was acquired from Basketball-reference.com,[2] along with data for NBA all-star appearances.[3]

Year	All-Stars	Non-All-Stars
2009	28	335
2010	28	338
2011	25	360
2012	24	341
2013	25	341
2014	25	340
2015	28	387
2016	26	294

Table 2: Total Sample Size, by Year (Players must play more than 400 minutes a season)

The primary difference between "star" and "non-star" player year-by-year is whether or not a player is considered an all-star: the same differentiating factor used in Caudill, Mixon and Wallace (2014). There are several reasons for this. Firstly, all-star selection is decided upon by a joint vote of fans and the media, meaning that all-star selection is more based upon "star status", rather than "star skill". Since "star status" is the most likely factor to drive bias, this is an appropriate measure. Thus, we analyze the performance of every player by season. Since all stars are determined at the annual level, annual-level regular scores are needed.

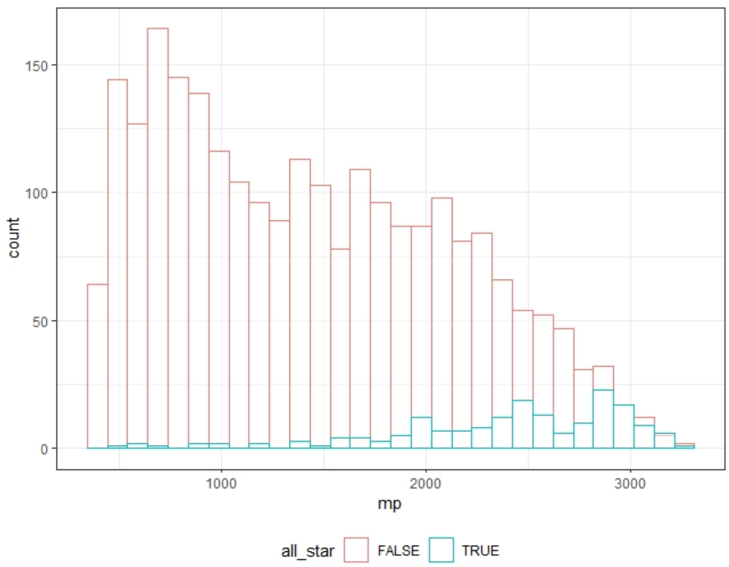


Figure 3: Difference in minutes per year for All-Star and Non-All-Star players (2008-16, all player-season pairs)

[2] I am grateful to Justin Grosz on data.world as well as Justinas Cirtautas and Omri Goldstein on Kaggle.com for their data scraping efforts.

[3] I am grateful to Gabe Salzer on data.world for his data scraping efforts.

Furthermore, to reduce bias from the large amount of players with little to no playing time and little to no fouls action, we will analyze only players who have played over 400 minutes (or an average of slightly less than five minutes a game, assuming a 82-game regular season[4]). The resulting distribution of "minutes played" looks like the above. Note that for smaller periods of time, this difference is "pro-rated" - if we are looking at fouls drawn in the last quarter of an NBA game, we only consider the quarterly amount - ie. players which have played over 100 minutes in the last quarter of a year.

3.2 Variable Selection

The following variables will be included in the model to control for factors affecting a player's fouling rate:

Code	**Definition**
fouls_drawn*	The total amount of fouls drawn by a player over a regular season.
fouls_drawn_l2m*	The total amount of fouls drawn by a player over a regular season, in the last two minutes of a closely contested game (with the point difference less than 5).
fouls_drawn_lq*	The total amount of fouls drawn by a player over a regular season, in the last quarter of a closely contested game (with the point difference less than 10).
fouls_committed*	The total amount of fouls committed by a player over a regular season, in the last two minutes of a closely contested game. Used to control for player aggression.
mp	The total amount of minutes played by a player over a regular season. All players with $mp < 400$ are removed to maintain a non-skewed sample. Used to control for total player workload.
per	Player Efficiency Rating. Used to control for players that involve a more/less efficient playstyle, players that purposefully draw fouls, as well as "basketball IQ".
tm_usg	The team usage rate, or an estimate of the percentage of team plays used by a player while he was on the floor. Used to control for offensive workload.
ts	The true shooting percentage. Used to control for shooters as opposed to players who prefer physicality.
ws	Win Shares. Used to control for player workload and "basketball IQ".
ovorp	Offensive Value Over Replacement Player. Used to control for player offensive workload.
o_bpm	Offensive Box Plus/Minus. Used to control for player offensive workload.
orb*/drb*/reb*	Offensive/Defensive/Total rebounding. Used to control for player rebounding workload.
stl*	Steals. Used to control for player steals.
blk*	Blocks. Used to control for player blocks.
ft_pc	Free Throw Percentage. Used to control for Hack-a-Shaq techniques (where a player would intentionally foul weaker players with a lower free throw percentage to force a change of possession).
yrs_experience	Total Years of Experience at the beginning of the season. Used to control for "basketball IQ".
bbref_pos	Position played by player. Used as a fixed-effect variable to control for position-specific effects. Note that a "1" indicates a Point Guard, "2" indicates a Shooting Guard, "3" indicates a Small Forward, "4" indicates a Power Forward and "5" indicates a Center.
g	Total games played during a regular season.

[4]The NBA season has been 82 games long, with the exception of the 2011 NBA lockout, which lasted for over eight months and forced the 2011–12 season to be shortened to 66 regular season games.

Code	Definition
all_star	An indicator variable showing if a basketball player was selected to be an All Star during the said season.

** Divided by mp in regression (1). Divided by the number of minutes played in the last 2 minutes of close games in regression (2). Divided by the number of minutes played in the last quarter of close games in regression (3). For the regressions in section 4.1*

Table 3: Description of Variables

3.3 Player Summary Statistics

	All-Star	Non-All-Stars
Average mp/game	34.68	19.33
Average fouls drawn/year	278.32	82.13
Average fouls committed/year	149.19	91.27
Average games played	59.57	41.67
Average fouls drawn/game	11.17	3.63
Average "clutch fouls"[a]/eligible game	0.57	0.24

[a] Fouls drawn in the last two minutes of closely contested NBA games

Table 4: Summary Statistics of All-Star and Non-All-Star NBA players within the entire sample

This preliminary table shows support to H1 and H2. All-star players as a group draw more fouls relative to the amount that they commit. However, this is not necessarily the whole story - more advanced statistics are needed to determine how much of this trend can be attributable to other variables.

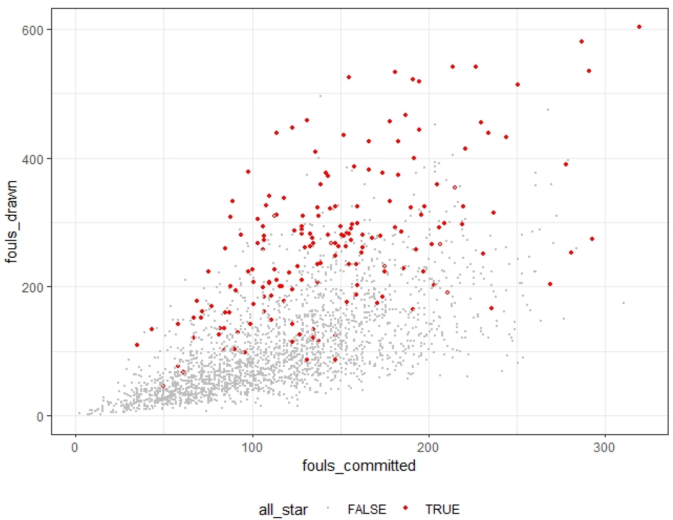


Figure 4: Difference in fouls committed and fouls awarded for All-Star and Non-All-Star players (2008-16, all player-season pairs)

The trend in the prior exhibit can be visualized here. The trend for most regular players appears linear, but all-star players seem to draw fouls at a rate unmatched by non-all-star players. Although "fouls committed" obviously does not show the complete picture, it does demonstrate some insights into the relationship between player physicality, all-star status and fouls drawn.

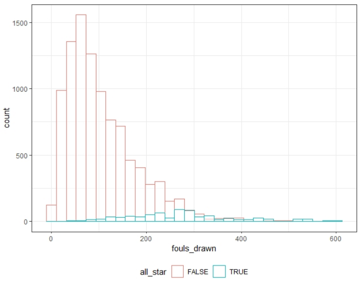


Figure 5: Histogram of fouls_drawn/mp

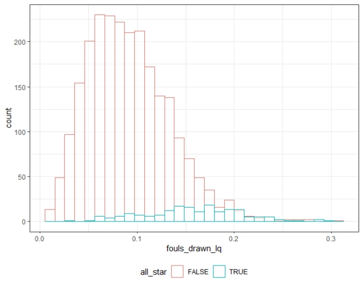


Figure 6: Last quarter of games within ten points

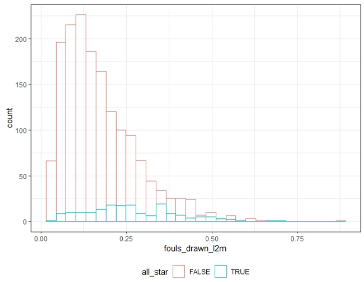


Figure 7: Last two minutes of games within five points

The distribution of values for fouls drawn per minute is visualized in the previous plots. As with before, star players draw significantly more fouls over the course of play. However, other factors do need to be considered. This effect appears to be weaker for closer and later games - indicating support for H2.

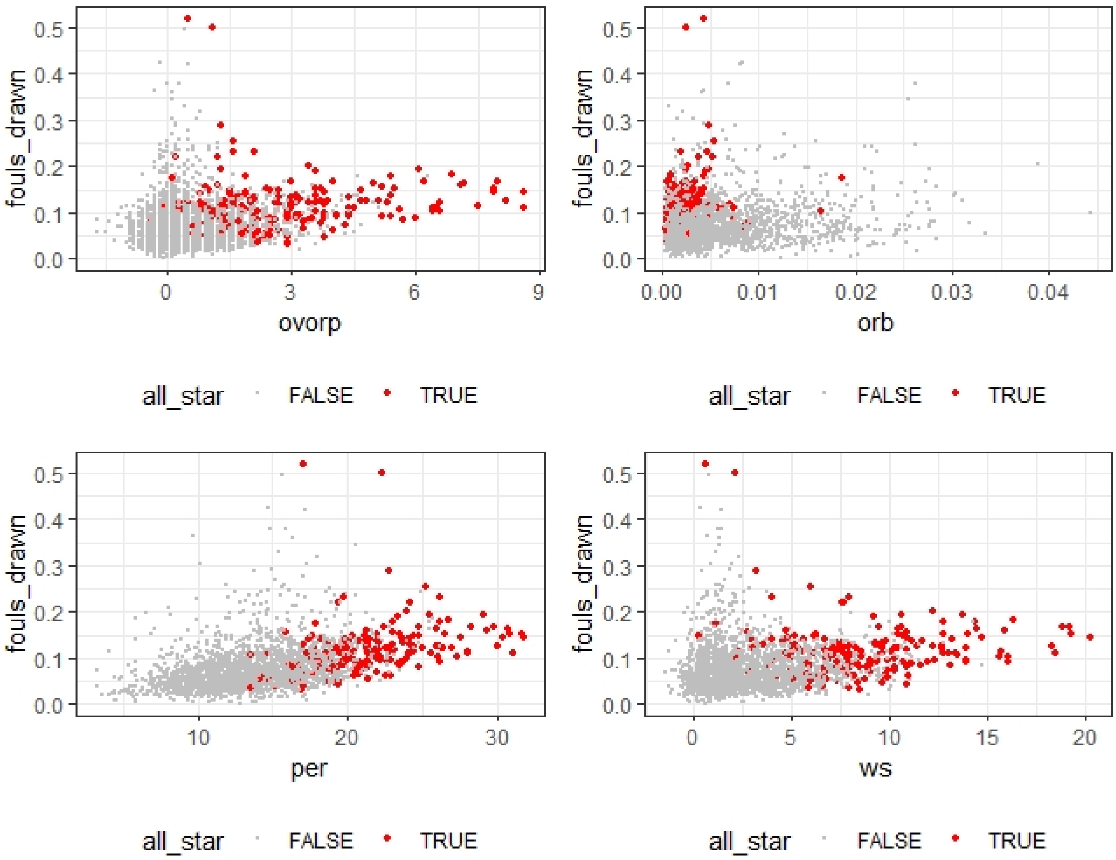


Figure 8: Plots of "Fouls Drawn Per Minute" with various other measures of offensive ability

The above plots demonstrate the relationship between various control variables and fouls drawn per minute. As mentioned before, the relationship between these metrics is largely linear, meaning that a linear increase in most values should, *ceteris paribus*, lead to a linear increase in fouls_drawn. Any excess increase in these offensive ratings could be as a result of bias.

4 Results

4.1 Fixed effect of star status

I tested H1 using a fixed effect regression on star status on the quantity of fouls awarded per minute for every player-season. To tackle any potential unobserved concurrent factors, I adjust for the variables listed in Table 2. I perform the same regression over only games within five points in the last two minutes as well as games within ten points in the last quarter.

The regression specification of (1) is as follows:

$$f_{p,yr}/mp = \alpha \mathbf{1}(\text{All-Star}) + \sum \beta_i x_i + \gamma_p + \delta_{yr} + \varepsilon + C$$

Where $f_{p,yr}/mp$ is the value of fouls_drawn (the total amount of fouls drawn by a player over a regular season) divided the total number of minutes played, x_i are the values of the remaining covariates, β_i are the coefficients of the covariates, γ_p is the the fixed effect of a position, δ_{yr} is the fixed effect of a season, ε is the error term and C is the constant.

The regression specification of (2) is as follows:

$$g_{p,yr}/mp_{l2m} = \alpha \mathbf{1}(\text{All-Star}) + \sum \beta_i x_{il2m} + \gamma_p + \delta_{yr} + \varepsilon + C$$

Where $g_{p,yr}/mp_{l2m}$ is the value of fouls_drawn (the total amount of fouls drawn by a player only in games within five points in the last two minutes) divided the total number of minutes played in the last two minutes of games within five points of each other, x_{i_l2m} are the values of the remaining covariates (appropriately adjusted if needed), β_i are the coefficients of the covariates, γ_p is the the fixed effect of a position, δ_{yr} is the fixed effect of a season, ε is the error term and C is the constant.

The same would be true for (3), but looking at games within ten points in the last quarter.

A positive value of α would demonstrate support of H1, as it would signal that the impact of being a star provides a serious boost to the total amount of fouls awarded. Furthermore, if the coefficient of all-star increases over time, this would show support for H3, while the opposite would be true for H1.

	Dependent variable:		
	fouls_drawn	fouls_drawn_l2m	fouls_drawn_lq
	(1)	(2)	(3)
all_star	0.013***	0.018	0.016***
	(0.003)	(0.015)	(0.003)
ovorp	0.005***	0.043***	0.015***
	(0.002)	(0.014)	(0.002)
per	0.010***	0.012***	0.009***
	(0.0003)	(0.002)	(0.0004)
Observations	2,590	457	2,138
R^2	0.623	0.426	0.458
Adj. R^2	0.619	0.393	0.452
Std. Error	0.030 (df = 2563)	0.091 (df = 431)	0.034 (df = 2112)
F Statistic	163.042*** (df = 26; 2563)	12.802*** (df = 25; 431)	71.397*** (df = 25; 2112)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5: Regression Results (Important Variables Only)

The results on the table shows strong and robust support for H1. Furthermore, the fact that offensive value above replacement (indicating more aggressive play) as well as the player efficiency rating (indicating an increased strategy of drawing fouls) has positive coefficients is in line with expectations. In the interest of space, other variables are not shown, but most measures seem to be in line with expectations.

However, the results of (2) and (3) demonstrate results only mildly in favor of H3. Although the coefficient of *all_star* increases, the significance decreases, meaning that there is some uncertainty in the results.

4.2 Varied Cutoff Sensitivity

We can perform the same regressions above but vary the number of minutes counted for fouls and other stats, as well as the maximum score differential cutoff to determine which games to include in the sample. For each combination, we can calculate the coefficient, p-value and standard error of *all_star*. Regression specification and control variables are all kept constant from above.

Point Diff. Under...	**All Game**	**Final Quarter**	**Last 5 mins**	**Last 2 mins**
5	NA	0.0144***	0.0218***	0.0177
10	NA	0.0161***	0.0177***	0.0191*
No Limit	0.013***	0.0161***	0.0190***	0.0317***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6: Sensitivity table of All-Star coefficient with regards to minute cutoff and score differential cutoff

The results here show that the results in H1 are very highly robust for all different parts of the game - the coefficient is significant or highly significant in all instances. Furthermore, the results show that generally, coefficient of the all-star dummy increases, meaning that there is some mild evidence in favor of H3. However, the results here do become less significant as we get closer to the end of the game.

4.3 Fixed Effects Regression - Fouls in Different Quarters

We can conduct another fixed effects regression to test H2 and H3. As with before, I adjust for any potential unobserved factors using variables listed in Table 2.

$$h_{p,yr,qtr}/mp_{qtr} = \alpha\mathbf{1}(\text{All-Star}) + \rho_{qtr}\mathbf{1}(\text{All-Star})Q_{qtr} + \eta_{qtr}Q_{qtr} + \sum \beta_i x_i + \gamma_p + \delta_{yr} + \varepsilon + C$$

Where $h_{p,yr,qtr}/mp_{qtr}$ is the value of fouls_drawn in a quarter (the total amount of fouls drawn by a player over a regular season in a given quarter of a game) divided the total number of minutes played in that quarter. As with before, x_i are the values of the remaining covariates, β_i are the coefficients of the covariates, γ_p is the the fixed effect of a position, δ_{yr} is the fixed effect of a season, ε is the error term and C is the constant. η_{qtr} is a coefficient that controls for the quarter-by-quarter fouling levels of a player (the difference between a certain quarter and the first quarter), and ρ_{qtr} is a coefficient that measures the change in star bias over a quarter (the difference between a certain quarter and the first quarter). There is no coefficient for ρ_1 and η_1.

As with before, positive values for α would signify support for H1. Furthermore, positive values for ρ_4 signify that star bias increases in the fourth quarter, which would lend support for H3, while the opposite would be true for H2.

	Dependent variable:
	fouls drawn per minute
all_star	0.0069***
	(0.0025)
2nd Quarter	0.018***
	(0.001)
3rd Quarter	0.013***
	(0.001)
4th Quarter	0.027***
	(0.001)
all_star × 2nd Quarter	0.005
	(0.003)
all_star × 3rd Quarter	0.010***
	(0.003)
all_star × 4th Quarter	0.016***
	(0.003)
Constant	0.092***
	(0.035)
Observations	8,062
R^2	0.518
Adjusted R^2	0.516
Residual Std. Error	0.029 (df = 8030)
F Statistic	278.437*** (df = 31; 8030)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 7: Regression Results (Important Variables Only)

Although more fouls are committed later in the game, the number of fouls drawn by all-stars increases at a rate that is higher than the "normal" increase of fouls, all else being equal. The positive coefficient results for the 3rd and 4th quarter show strong support for H3. Furthermore, the positive value of α serve as another confirmation of H1. All other coefficients are also in line with expectations.

5 Conclusion

5.1 Observations

The data shows support for H1: there is a bias towards All-Star players when calling fouls. Being an all-star raises the number of fouls one draws per minute by 0.013, or around an average of 0.45 fouls per game per all-star. This is after accounting for all other effects, including measures of offensive efficiency, player workload and physicality of play. As the result is highly significant and fairly robust across all tests conducted, this is good evidence for H1.

The verdict on H2 and H3 is less clear. However, the evidence does seem to be in favor of H3 being true. The results of the regressions in sections 4.1 and 4.2 demonstrate that although it does seem like the all-star coefficient does increase as we approach later portions of the game, these coefficients do become less significant as time goes on. However, since the results in 4.3 are strongly in favor of H3, it is most probably true that bias in favor of star players in the later part of a game increases.

The estimated benefit to star players in the last quarter of games is very roughly the same as estimates found in Caudill, Mixon and Wallace (2014). According to the regressions in section 4.2, the final quarter of a game typically leads towards an additional 0.0161 fouls per minute for star players. According to section 4.3, this value is an additional 0.0228 fouls per minute for star players. Adjusted to excess free throws per minute using the assumptions in Table 1[5], we have an excess of 0.0182 to 0.0260 excess free throw attempts per minute, which is slightly lower but still within the approximate range of the estimates of 0.32 additional free throw attempts per minute per star player during the last quarter (especially since the latter value looks at playoff games only).

5.2 Discussion

One surprising thing about the results shown is that they seem to agree with the results of both Deutscher (2015) and Wallace et al. (2014). This is because the first paper demonstrates bias in the last quarter of playoff games, while the latter is unable to find bias in the last two minutes. The results in 4.1 and 4.2 are also able to find bias in the last quarter, but unable to do so in the last two minutes. Although these results are probably due to the decreased sample size of players who play in the last two minutes of closely contested games, these results still do raise questions about what is it about game play between these two parts of the game that are so different such that star bias comes into existence.

Furthermore, the results in this paper demonstrates the limitations of relying purely on NBA-generated reports on officiating. In 2007, Wolfers (2007) demonstrated the existence of racial bias in spite of evidence to the contrary from the NBA's own sources. Similarly, this paper demonstrates that, when looking at the whole picture, NBA referees still do have a certain level of bias towards star players, despite results from the last two minutes report that may indicate the contrary.[1]

The increased level of bias in the later parts of NBA games is particularly concerning, as this would imply that games that would suffer the most from unfair officiating would also have a worse problem with this issue. Nevertheless, bias can still be overcome, as mentioned in Wolfers et al. (2014), through increased awareness, training and other mechanisms[2].

Professional and unbiased referees are a critical part of the integrity of any major sports league, but particularly in the NBA due to their potential to alter the result of many major games. However, often times referee biases may indeed be commercially viable, like the preferences towards home teams and underdogs documented in Price et al. (2014). Given by the importance of star players to the league, it is quite probable that there would be significant push back against any potential countermeasures. Ultimately, the protection of and bias towards star players may simply be an effort by the league to maintain consumer demand and protect their main asset - their stars.

[5] 1.127 Free Throw Attempts per Foul

6 Appendix

Plots created using Stargazer.[4]

6.1 Full regression results, using fouls drawn per relevant minute

Table 8: Part 1 of Full Regression Results

	Dependent variable:		
	fouls_drawn	fouls_drawn_l2m	fouls_drawn_lq
	(1)	(2)	(3)
all_star	0.013***	0.018	0.016***
	(0.003)	(0.015)	(0.003)
as.factor(year)2010	−0.003	0.030	0.002
	(0.002)	(0.019)	(0.003)
as.factor(year)2011	−0.001	0.043**	0.003
	(0.002)	(0.018)	(0.003)
as.factor(year)2012	−0.021*	0.068	−0.032**
	(0.011)	(0.083)	(0.014)
as.factor(year)2013	0.0002	0.007	−0.003
	(0.002)	(0.016)	(0.003)
as.factor(year)2014	0.001	0.010	−0.001
	(0.002)	(0.016)	(0.003)
as.factor(year)2015	0.002	0.014	0.0002
	(0.002)	(0.016)	(0.003)
as.factor(bbref_pos)2	−0.0002	−0.052***	−0.007***
	(0.002)	(0.016)	(0.003)
as.factor(bbref_pos)3	−0.003	−0.097***	−0.011***
	(0.002)	(0.016)	(0.003)
as.factor(bbref_pos)4	−0.023***	−0.132***	−0.018***
	(0.003)	(0.018)	(0.003)
as.factor(bbref_pos)5	−0.025***	−0.138***	−0.016***
	(0.003)	(0.022)	(0.004)
Observations	2,590	457	2,138
R^2	0.623	0.426	0.458
Adjusted R^2	0.619	0.393	0.452
Residual Std. Error	0.030 (df = 2563)	0.091 (df = 431)	0.034 (df = 2112)
F Statistic	163.042*** (df = 26; 2563)	12.802*** (df = 25; 431)	71.397*** (df = 25; 2112)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 9: Part 2 of Full Regression Results

	Dependent variable:		
	fouls_drawn	fouls_drawn_l2m	fouls_drawn_lq
	(1)	(2)	(3)
mp	-0.00001	0.0001	0.00000
	(0.00002)	(0.0001)	(0.00002)
tm_usg	-0.00000^{*}	0.00000	-0.00000^{*}
	(0.00000)	(0.00000)	(0.00000)
ts	-0.053^{***}	-0.073	0.026
	(0.020)	(0.171)	(0.026)
ws	-0.003^{***}	-0.005	-0.003^{***}
	(0.001)	(0.004)	(0.001)
ovorp	0.005^{***}	0.043^{***}	0.015^{***}
	(0.002)	(0.014)	(0.002)
o_bpm	-0.006^{***}	-0.022^{**}	-0.011^{***}
	(0.001)	(0.009)	(0.001)
per	0.010^{***}	0.012^{***}	0.009^{***}
	(0.0003)	(0.002)	(0.0004)
ft_pc	0.008	0.189^{***}	0.002
	(0.007)	(0.057)	(0.008)
yrs_experience	0.001^{***}	-0.0005	-0.0002
	(0.0002)	(0.001)	(0.0002)
Constant	0.042	-0.700	0.057
	(0.063)	(0.503)	(0.079)
Observations	2,590	457	2,138
R^2	0.623	0.426	0.458
Adjusted R^2	0.619	0.393	0.452
Residual Std. Error	0.030 (df = 2563)	0.091 (df = 431)	0.034 (df = 2112)
F Statistic	163.042^{***} (df = 26; 2563)	12.802^{***} (df = 25; 431)	71.397^{***} (df = 25; 2112)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 10: Part 3 of Full Regression Results

	Dependent variable:		
	fouls_drawn	fouls_drawn_l2m	fouls_drawn_lq
	(1)	(2)	(3)
fouls_committed	0.736***		
	(0.017)		
fouls_committed_l2m		−0.052	
		(0.057)	
fouls_committed_lq			0.183***
			(0.023)
orb	−0.220		
	(0.247)		
drb	0.013		
	(0.157)		
stl	−3.715***		
	(0.962)		
blk	−4.694***		
	(0.503)		
reb_l2m		0.177***	
		(0.046)	
stl_l2m		0.192	
		(0.133)	
blk_l2m		0.010	
		(0.140)	
reb_lq			0.035**
			(0.017)
stl_lq			0.068
			(0.054)
blk_lq			−0.227***
			(0.047)
Observations	2,590	457	2,138
R^2	0.623	0.426	0.458
Adjusted R^2	0.619	0.393	0.452
Residual Std. Error	0.030 (df = 2563)	0.091 (df = 431)	0.034 (df = 2112)
F Statistic	163.042*** (df = 26; 2563)	12.802*** (df = 25; 431)	71.397*** (df = 25; 2112)
Note:			*p<0.1; **p<0.05; ***p<0.01

6.2 Full regression results, using fouls drawn per game

Table 11: Part 1 of Full Regression Results

	Dependent variable:	
	fouls_drawn/g	fouls_drawn_l2m/CLOSE_GAME_COUNT
	(1)	(2)
all_star	0.706***	0.045***
	(0.105)	(0.016)
as.factor(year)2010	−0.039	0.001
	(0.084)	(0.015)
as.factor(year)2011	0.030	0.025*
	(0.081)	(0.014)
as.factor(year)2012	−1.373***	−0.085
	(0.406)	(0.070)
as.factor(year)2013	−0.318***	−0.040***
	(0.083)	(0.014)
as.factor(year)2014	−0.229***	−0.032**
	(0.083)	(0.014)
as.factor(year)2015	−0.196**	−0.029**
	(0.081)	(0.014)
fouls_committed	0.018***	0.0002**
	(0.001)	(0.0001)
mp	−0.001**	−0.0001
	(0.001)	(0.0001)
tm_usg	−0.00002***	−0.00000
	(0.00001)	(0.00000)
ts	−5.931***	−0.868***
	(0.726)	(0.139)
ws	−0.067***	−0.011***
	(0.023)	(0.004)
ovorp	0.074	0.070***
	(0.062)	(0.011)
o_bpm	−0.069**	−0.016**
	(0.034)	(0.006)
Observations	2,590	1,981
R^2	0.552	0.510
Adjusted R^2	0.548	0.503
Residual Std. Error	1.081 (df = 2563)	0.163 (df = 1954)
F Statistic	121.571*** (df = 26; 2563)	78.201*** (df = 26; 1954)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 12: Part 2 of Full Regression Results

	Dependent variable:	
	fouls_drawn/g	fouls_drawn_l2m/CLOSE_GAME_COUNT
	(1)	(2)
orb	-0.078^{***}	-0.011^{***}
	(0.011)	(0.002)
drb	-0.018^{**}	0.0002
	(0.007)	(0.001)
stl	-0.333^{***}	-0.022^{***}
	(0.042)	(0.007)
blk	-0.195^{***}	-0.009^{**}
	(0.023)	(0.004)
per	0.348^{***}	0.033^{***}
	(0.013)	(0.002)
ft_pc	-0.783^{***}	0.103^{**}
	(0.247)	(0.049)
yrs_experience	0.025^{***}	0.003^{***}
	(0.006)	(0.001)
as.factor(bbref_pos)2	0.080	-0.019^{*}
	(0.069)	(0.011)
as.factor(bbref_pos)3	0.289^{***}	-0.038^{***}
	(0.080)	(0.014)
as.factor(bbref_pos)4	-0.273^{**}	-0.084^{***}
	(0.108)	(0.019)
as.factor(bbref_pos)5	-0.141	-0.062^{**}
	(0.137)	(0.024)
mp:tm_usg	0.000	0.000
	(0.000)	(0.000)
Constant	8.464^{***}	0.665^{*}
	(2.229)	(0.400)
Observations	2,590	1,981
R^2	0.552	0.510
Adjusted R^2	0.548	0.503
Residual Std. Error	1.081 (df = 2563)	0.163 (df = 1954)
F Statistic	121.571^{***} (df = 26; 2563)	78.201^{***} (df = 26; 1954)
Note:		*p<0.1; **p<0.05; ***p<0.01

References

[1] C. Deutscher. No referee bias in the nba: New evidence with leagues' assessment data. *Sports Law Analytics*, 1(2):91–96, 2015.

[2] J. P. . J. W. Devin G. Pope. Awareness reduces racial bias. Technical report, National Bureau of Economic Research, 2014.

[3] R. Goldenberg. Last two minute report for the nba. *The Pudding*, 2018.

[4] M. Hlavac. *stargazer: Well-Formatted Regression and Summary Statistics Tables*. Central European Labour Studies Institute (CELSI), Bratislava, Slovakia, 2018. URL `https://CRAN.R-project.org/package=stargazer`. R package version 5.2.2.

[5] M. R. . D. F. S. Joseph Price. Sub-perfect game: Profitable biases of nba referees. *Journal of Economics and Management Strategy*, 21(1):271–300, 2014.

[6] U. S. Saini. Eight thirty four nba play-by-play data, 2018.

[7] F. M. . S. W. Steven B Caudill. Life on the red carpet: Star players and referee bias in the national basketball association. *International Journal of the Economics of Business*, 21(2): 245–253, 2014. doi: http://dx.doi.org10.1080/13571516.2014.903110.

[8] J. P. . J. Wolfers. Racial discrimination among nba referees. *The Quarterly Journal of Economics*, 125(4):1859–1887, 2010. doi: http://dx.doi.org/10.3386/w13206.