Benjamin Baker
05/11/2022

Replication of *Subperfect Game: Profitable Biases of NBA Referees*

In the presence of the media, laws, and regulations, firms are met with limitations as to the degree to which they can maximize profits. The way firms respond to these limitations varies, as there is a tradeoff between following the rules and committing illegal or unethical behavior that maximizes profits. This tradeoff in the NBA can be shown in the actions of referees. Allowing referees to exhibit bias when officiating a game can increase profits for the league. However, maximizing profit through referee bias has a tradeoff of sacrificing the integrity of the sport. The paper, Subperfect Game: Profitable Bias of NBA Referees, aims to empirically test three forms of referee bias that could be profit-enhancing for the league. These results can help better understand firms that potentially "bend the rules" to increase profits even though fans and the media closely watch them.

The main obstacle of this analysis is separating the player behavior from referee behavior. Nearly every basketball statistic, particularly turnovers and fouls, is simultaneously affected by player and referee behavior. This makes it difficult to determine whether there is referee bias present. To separate the behaviors, play-by-play data is used because it is a more detailed statistic set than game-level data. Using the play-by-play data allows the authors to utilize the fact that referees have a varying degree of effect on specific turnovers and distinguish turnovers into those with heavy influence and low influence by referees. The turnovers are classified as either discretionary or nondiscretionary turnovers. In the case of discretionary turnovers (DTOs), these are always called by the referees, such as traveling violations or offensive fouls. In the case of nondiscretionary turnovers (NTOs), these are more directly affected by player behavior than referee behavior, such as bad passes or lost balls. Referee behavior is thus more influential on DTOs than it is on NTOs.

The authors use a treatment and control style analysis to determine whether referees are exhibiting biases. They compare how DTOs are affected relative to how NTOs are affected by variables usually associated with bias. Since both turnover types are simultaneously affected by both referee and player behavior, the identification of bias is dependent on the assumption that referees have more influence on DTOs than NTOs, on average. The authors find evidence that referees exhibit biases that favor home teams, teams losing during a game to keep the game close, and teams losing in a playoff series to extend the series. These three biases are all plausibly profit-enhancing for the league. Biased calls in favor of the home team can increase ticket sales for future games. Biased calls in favor of teams losing during a game allow the games to remain competitive and entertaining, possibly leading to increased television coverage. Biased calls in favor of teams losing in a playoff series can extend the series, leading to increased ticket sales and television coverage.

The NBA has been very outspoken about how much their referees are monitored for bias, possibly suggesting that some system has been put into place to detect these biases. The fact that the bias exists indicates the NBA is possibly encouraging or not disincentivizing enough the referee bias because it increases the league’s profits. NBA management may be unaware of their referees' biases. Regardless, this paper provides an empirical strategy that can be used to detect referee biases.

Literature Review.

There have been several instances and studies of referee bias within other sports besides the NBA. Zitzewitz (2006) found that figure skating judges gave higher scores to athletes of the same nationality and participated in strategic vote-trading with other judges on the panel. In both the Chinese and Italian professional soccer leagues, referees were arrested for accepting bribes and fixing matches (Delaney (2006) and Yue (2010)). Sutter and Kocher (2004), Garicano et al. (2005), Dohmen (2008), and Pettersson-Lidbom and Priks (2010) all found evidence of soccer referees exhibiting biases in favor of the home teams. However, these biases were mainly attributed to psychological factors, such as the home crowd influence. Within the NBA, studies showed that referees exhibited racial bias through fouls (Price and Wolfers (2010)) and found evidence that referees favored larger market teams to prolong a playoff series (Zimmer and Kuethe (2009)).

The NBA has also dealt with a major scandal involving its referees. In 2007, Tim Donaghy, an NBA referee, was arrested for using his insider information to illegally bet on games, including some that he was a part of the officiating crew. He also "advised professional gamblers about which teams to pick (bet on), through telephone calls and coded language" (Beck and Schmidt (2007)). After Donaghy was arrested, he claimed that other NBA referees exhibited favorable biases toward star players, home teams, teams losing during the game, and teams losing in a playoff series, with the league encouraging the behavior in some cases. The NBA employed Pedowitz (2008) to review the officiating crews and determine if any of the claims were true. Pedowitz (2008) found no evidence of any of the claims alleged by Donaghy, though no empirical analysis was conducted.

Since no empirical analysis was conducted by Pedowitz (2008), this paper aims to empirically investigate the claims made by Donaghy. The paper will contribute to the economic literature by being one of the first papers investigating home bias by referees in a sport other than soccer. In addition, it will be one of the first papers to empirically investigate two other biases, close and playoff bias, both of which have not been thoroughly investigated within other sports.

Data and Summary Statistics.

The authors used play-by-play data from ESPN.com for all regular-season and playoff games from the 2002-2003 through 2007-2008 seasons. The play-by-play data gives a more detailed look at in-game events than game-level box score data. It is important to have the play-by-play data rather than the box score data for this analysis because the box score data does not go into detail on the types of turnovers/fouls committed and called within the game. While the authors extracted the data from ESPN.com, I was able to find the dataset, along with the replication code, on one of the authors, Daniel Stone's website. This dataset also included the attendance for each game, whether the teams were home or away, what quarter the game was in at each minute, the scoring differential for each team at each minute, whether it was a playoff game or not, and how many games a team had won in a playoff series prior to the current game. There are two observations for each minute, one for each team. Games with missing minutes and the final three minutes of each game are dropped from the sample due to player behavior changing. The results using this dataset will be shown in Tables III and IV.

A complementary analysis is performed with a second dataset to test for referee bias in playoff games. This dataset uses game-level box-score data from ESPN.com from the 1992-1993 through 2007-2008 seasons. This analysis is conducted due to the smaller sample size of playoff games in the previous dataset. The results for this dataset will be shown in Table V.

It's important for this analysis to distinguish between turnovers and fouls that are more subjective and influenced by referee behavior rather than player behavior. The two categories in the turnovers section are DTOs (discretionary turnovers) and NTOs (nondiscretionary turnovers). In the case of DTOs, these are always called by the referees and are highly subjective and inconsistently called throughout the NBA, possibly noting that these calls can be biased. For NTOs, these are not called by referees, or the referee's influence on the call is minimal. For instance, a player can touch the ball out of bounds, forcing the referee to make a turnover call. We will compare how DTOs are affected by variables associated with possible bias relative to how NTOs are affected to test for referee bias. In addition to examining turnovers, the authors look at fouls, which is a more commonly used metric to gauge referee bias. However, it is harder to determine what fouls are more influenced by the referee or player behavior.

Table II provides summary statistics (mean and standard deviation) on different categories of turnovers and fouls. These summary statistics are all the calls made at the team-game-minute level for each turnover/foul type. The data is further separated into calls for the home team versus the away team and when a team is winning or is losing/tied at the current minute. Columns (3) and (6) are performing a T-test that the difference in means is equal to zero. These results show that home and losing/tied teams have statistically fewer DTOs and fouls called against them than away and winning teams. This gives us a preview of the main results.

Benjamin Baker
05/11/2022

Table II. Minute-Level Summary Statistics

	(1)		(2)		(3)	(4)		(5)		(6)
	Away		Home		Diff	Losing/Tied		Winning		Diff
	mean	sd	mean	sd	(Home-Away)	mean	sd	mean	sd	(Losing-Winning)
Discretionary Turnovers										
Travel	0.0241	(0.155)	0.0202	(0.142)	-0.0039***	0.0210	(0.144)	0.0235	(0.153)	-0.0025***
Three Seconds	0.0066	(0.081)	0.0073	(0.085)	-0.0007***	0.0059	(0.077)	0.0082	(0.090)	-0.0022***
Offensive Foul	0.0451	(0.211)	0.0416	(0.203)	-0.0035***	0.0418	(0.203)	0.0452	(0.211)	-0.0034***
Offensive Goal-Tend	0.0012	(0.034)	0.0011	(0.033)	-0.0001	0.0011	(0.034)	0.0011	(0.033)	0.0000
Nondiscretionary Turnovers										
Bad Pass	0.1261	(0.350)	0.1285	(0.353)	0.0024***	0.1242	(0.347)	0.1308	(0.356)	-0.0066***
Lost Ball	0.0635	(0.251)	0.0603	(0.244)	-0.0032***	0.0624	(0.248)	0.0614	(0.247)	-0.0001
Shot Clock	0.0057	(0.075)	0.0052	(0.072)	-0.0005***	0.0052	(0.072)	0.0057	(0.075)	-0.0005***
Nonshooting Fouls										
Personal Foul	0.1556	(0.393)	0.1556	(0.393)	0.0000	0.1476	(0.383)	0.1649	(0.404)	-0.0173***
Loose Ball Foul	0.0283	(0.168)	0.0275	(0.166)	-0.0008***	0.0263	(0.162)	0.0298	(0.173)	-0.0035***
Inbounds Foul	0.0002	(0.016)	0.0002	(0.015)	0.0000	0.0002	(0.014)	0.0003	(0.016)	0.0000
Clearing Foul	0.0007	(0.026)	0.0005	(0.023)	-0.0001***	0.0005	(0.023)	0.0007	(0.026)	-0.0001***
Away From Ball Foul	0.0004	(0.020)	0.0004	(0.020)	0.0000	0.0003	(0.018)	0.0004	(0.021)	-0.0001***
Shooting Fouls										
Nonflagrant Foul	0.2167	(0.443)	0.2058	(0.433)	-0.0109***	0.1981	(0.425)	0.2267	(0.452)	-0.0286***
Flagrant Foul	0.0010	(0.032)	0.0009	(0.029)	-0.0002***	0.0011	(0.033)	0.0008	(0.028)	0.0003***

*Notes: Sample includes all games from 2002-2003 to 2007-2008 seasons with play-by-play data available on ESPN.com; overtime periods and last three minutes from fourth quarters dropped from all games, and games with missing minutes dropped. "Winning" = winning by one or more points at start of quarter; "Losing/Tied" = losing or tied at quarter start. In total there are 632,880 observations: 316,440 minutes, with two observations for each minute (one for each team). *, **, *** denote 10%, 5%, and 1% significance, respectively (for difference; two-tailed tests, unequal variances).*

Methods.

The objective of this paper is to test three hypotheses that investigate NBA referee bias. The authors state these hypotheses as follows:

Hypothesis 1: Referees favor home teams (home bias)

Hypothesis 2: Referees favor teams losing during games to keep games close (close bias)

Hypothesis 3: Referees favor teams losing in the playoff series to extend the series (playoff bias)

The empirical strategy to analyze these hypotheses will be to perform four different regressions using DTOs, NTOs, shooting fouls, and nonshooting fouls as the dependent variables. Since these variables are count variables, the Poisson estimation technique will be the best technique for this analysis. The Poisson regression model is estimated through maximum likelihood. The dependent variable is assumed to take on a Poisson distribution with a log-expectation equal to a linear function of the regressors. This allows for the coefficients to be interpreted as percentage effects. The models' makeup is comprised of dummy variables indicating a home game or playoff game, scoring differential variables at the current minute, attendance variables, and interaction variables for attendance and home, playoff and home, and quarter and matchup (fixed effects). The fixed effects allow the authors to control for variation in team quality and the change in the game's atmosphere. For instance, a large crowd might be loud and influential on referee behavior at the beginning of the game, causing the biases of favoring the home team or losing team to be overestimated throughout the game.

The formal empirical models used to analyze the three hypotheses are as follows:

$$lnT_D = \widetilde{\beta_0^D} + (\beta_1^D\gamma_1^R + \beta_2^D\gamma_1^P)Z + QFE + MFE + \widetilde{u_1},$$

$$lnT_N = \widetilde{\beta_0^N} + (\beta_1^N \gamma_1^R + \beta_2^N \gamma_1^P)Z + QFE + MFE + \widetilde{u_2},$$

Where lnT_D and lnT_N are the log on DTOs and NTOs. *Z* will be a dummy variable for whether it is a home game, playoff game, the score differential, etc. The coefficient on *Z* in the lnT_D equation will be the effect of referee bias plus player behavior of *Z* on DTOs. The coefficient on *Z* in the lnT_N equation will be the effect of referee bias plus player behavior of *Z* on NTOs. The *QFE* and *MFE* represent the quarter and matchup fixed effects. The error terms are denoted as $\widetilde{u_1}$ and $\widetilde{u_2}$, respectively. To test for the presence of referee bias, we will compare the coefficients on *Z* in both equations. For there to be evidence of referee bias, the coefficient on *Z* in the lnT_D equation must be negative, statistically significant, and in absolute magnitude, greater than the coefficient on *Z* in the lnT_N equation. This will follow the assumption that referees have more influence on DTOs than NTOs. The equations for shooting and nonshooting fouls will follow a similar structure, though the coefficient on *Z* needs only to be negative and statistically significant for there to be a presence of referee bias.

Main Replication Results.

The paper's main results that I replicated are Tables III-V. These tables display the results that determine whether referees exhibit biases in favor of home teams (home bias), teams that are losing during the game (close bias), and teams losing in a playoff series (playoff bias). Table III presents the results of the home and close biases using two Poisson regressions for each of the four dependent variables (DTOs, NTOs, shooting fouls, and nonshooting fouls) using team-game-minute level data. In the first column of each dependent variable, the model is estimated with quarter and home interaction variables excluded, while the second column includes the quarter and home interaction variables. Tables IV and V present the results of the playoff bias.

Table IV displays the playoff bias results of two models for each of the four dependent variables using team-game-minute level data, though the makeup of the models is slightly different from Table III. Table V looks at playoff bias through the game-level data in a wider timeframe than Tables III and IV and uses different dependent variables for the Poisson regressions.

I. Home Bias Results

Table III presents results supporting the hypothesis that referees exhibit bias in favor of home teams and losing teams. For the models without the home-quarter fixed effects, the home team is likely to have an 11.5% decrease in DTOs called against them, relative to the away team, while only having a 2.4% decrease in NTOs called against them. Both coefficients are statistically significant at the 1% level. Based on the explanation for testing for referee bias in the *Methods* section, this implies that referee bias does exist for home teams. Home teams see an 8.7% and 2.9% decrease in shooting and nonshooting fouls called against them, respectively. These coefficients are both statistically significant at the 1% level. The home teams in the playoffs see a 9.8% and 3.3% decrease in DTOs and NTOs, respectively, called against them, on average. The DTO coefficient is statistically significant at the 5% level, while the NTO coefficient is not statistically significant. There is a 4.7% and 2.1% decrease in shooting and nonshooting fouls, respectively, called against the home team in the playoffs. The shooting fouls coefficient is statistically significant at the 5% level, while the nonshooting fouls coefficient is not statistically significant. Lastly, the only statistically significant coefficient for the home-attendance term is the coefficient in the nonshooting fouls models. There is a 0.6% decrease in nonshooting fouls called against the home team per 1,000 home fans, on average. This coefficient is statistically significant at the 5% level. These results support the hypothesis that referees favor the home teams by calling statistically less DTOs, shooting and nonshooting fouls against the home teams.

Now, looking at the models that include the home-quarter fixed effects, the variable Home represents the home bias in the fourth quarter. The results show that home teams have an 8.2% decrease in DTOs called against them, on average, while only seeing a 1.2% decrease in NTOs called against them. The DTO coefficient is statistically significant at the 1% level, though the NTO coefficient is not statistically significant. The home team also has a 7.5% and 4.4% decrease in shooting and nonshooting fouls, respectively, called against them, on average. These coefficients are both statistically significant at the 1% level. These results again support the hypothesis that referees favor the home teams by calling statistically less DTOs, shooting and nonshooting fouls against the home teams.

Table III. Home and Close Bias Poisson Regression Results

	Discretionary Turnovers		Nondiscretionary Turnovers		Shooting Fouls		Nonshooting Fouls	
Home	-0.1152***	-0.0824***	-0.0238***	-0.0128	-0.0877***	-0.0759***	-0.0293***	-0.0449***
	(0.0101)	(0.0215)	(0.0061)	(0.0133)	(0.0055)	(0.0111)	(0.0061)	(0.0123)
Attendance	-0.0050	-0.0050	-0.0005	-0.0005	-0.0005	-0.0005	0.0039*	0.0039*
	(0.0034)	(0.0034)	(0.0020)	(0.0020)	(0.0018)	(0.0018)	(0.0021)	(0.0021)
Attendance x Home	-0.0028	-0.0028	0.0026	0.0026	0.0017	0.0017	-0.0063**	-0.0063**
	(0.0044)	(0.0044)	(0.0027)	(0.0027)	(0.0024)	(0.0024)	(0.0027)	(0.0027)
Playoff	0.0823**	0.0822**	-0.0109	-0.0109	0.0316	0.0316	0.1094***	0.1094***
	(0.0347)	(0.0347)	(0.0225)	(0.0225)	(0.0210)	(0.0210)	(0.0197)	(0.0197)
Playoff x Home	-0.0981**	-0.0981**	-0.0335	-0.0336	-0.0478**	-0.0479**	-0.0214	-0.0214
	(0.0382)	(0.0382)	(0.0232)	(0.0232)	(0.0205)	(0.0205)	(0.0214)	(0.0214)
Score Diff < -10	-0.1505***	-0.1498***	0.0075	0.0070	-0.0482***	-0.0489***	-0.0217**	-0.0220**
	(0.0179)	(0.0179)	(0.0104)	(0.0104)	(0.0098)	(0.0098)	(0.0110)	(0.0110)
-10 ≤ Score Diff ≤ -4	-0.0369***	-0.0369***	-0.0015	-0.0017	-0.0278***	-0.0279***	0.0171**	0.0172**
	(0.0138)	(0.0138)	(0.0082)	(0.0082)	(0.0076)	(0.0076)	(0.0085)	(0.0085)
4 ≤ Score Diff ≤ 10	0.1109***	0.1109***	0.0488***	0.0489***	0.1427***	0.1427***	0.1254***	0.1253***
	(0.0133)	(0.0133)	(0.0080)	(0.0080)	(0.0075)	(0.0075)	(0.0086)	(0.0086)
10 < Score Diff	0.1817***	0.1810***	0.1622***	0.1627***	0.2708***	0.2714***	0.1758***	0.1761***
	(0.0169)	(0.0170)	(0.0103)	(0.0104)	(0.0090)	(0.0090)	(0.0105)	(0.0105)
Q1 x Home		-0.0275		0.0045		-0.0029		0.0100
		(0.0281)		(0.0171)		(0.0148)		(0.0167)
Q2 x Home		-0.0469*		-0.0274		-0.0054		0.0259
		(0.0269)		(0.0169)		(0.0145)		(0.0159)
Q3 x Home		-0.0452*		-0.0178		-0.0348**		0.0220
		(0.0268)		(0.0171)		(0.0143)		(0.0163)

*Notes: N = 632,700; unit of observation = game-minute-team. All models include match-up (team-opponent-season) fixed effects, quarter fixed effects and a constant as RHS variables. Attendance is de-meaned and measured in thousands. Score Diff = start of minute own score minus opponent score (dummy variables for difference being less than -10, between -10 and -3, etc.) Q1/Q2/Q3 = dummies for 1st/2nd/3rd quarter; Home = dummy for home game. Robust standard errors clustered by match-up in parentheses. *,**,*** denote 10%, 5%, and 1% significance.*

II. Close Bias Results

For the close bias results of Table III, we will look at the score differential variables. The baseline team score omitted from the regressions is teams that are winning or losing by three or fewer points ($-3 \leq$ score diff ≤ 3). For teams that are losing at the current minute, whether that be by four to ten points or more than ten points, the teams losing see a 3.7% and 15% decrease in DTOs called against them compared to the baseline teams. Both coefficients are statistically significant at the 1% level. Losing teams commit more NTOs than winning teams, however, this coefficient is not statistically significant. Teams losing by four or more points have statistically fewer shooting and nonshooting fouls called against them, on average. If the team is winning by four to ten points or more than ten points relative to the baseline team, they have statistically more DTOs, NTOs, shooting, and nonshooting fouls called against them. Based on these results, teams losing during games are favored by referees by having statistically fewer DTOs, shooting, and nonshooting fouls called against them. This supports the hypothesis that referees favor teams losing during a game to keep games close.

Table IV. Playoff Bias Poisson Regression Results

	Discretionary Turnovers		Nondiscretionary Turnovers		Shooting Fouls		Nonshooting Fouls	
Series Diff	0.034**	-0.073	-0.005	-0.025	0.004	0.015	-0.013*	0.006
	(0.014)	(0.055)	(0.010)	(0.035)	(0.008)	(0.027)	(0.008)	(0.027)
Home	-0.165***	-0.164***	-0.040	-0.040	-0.113***	-0.113***	-0.064***	-0.065***
	(0.039)	(0.039)	(0.026)	(0.026)	(0.020)	(0.020)	(0.020)	(0.020)
Home x Attendance	-0.073***	-0.073***	-0.006	-0.006	0.004	0.004	-0.020*	-0.020*
	(0.022)	(0.022)	(0.015)	(0.015)	(0.011)	(0.011)	(0.011)	(0.011)
Score Diff < -10	-0.075	-0.108	0.064*	0.183***	0.040	-0.016	0.060	-0.018
	(0.063)	(0.107)	(0.039)	(0.066)	(0.035)	(0.054)	(0.039)	(0.062)
-10 ≤ Score Diff ≤ -4	0.002	-0.011	-0.012	-0.017	-0.014	-0.036	0.043	0.021
	(0.051)	(0.052)	(0.032)	(0.032)	(0.030)	(0.030)	(0.032)	(0.032)
4 ≤ Score Diff ≤ 10	0.013	0.004	0.008	0.006	0.119***	0.098***	0.154***	0.133***
	(0.053)	(0.053)	(0.030)	(0.030)	(0.028)	(0.028)	(0.030)	(0.030)
10 < Score Diff	0.116*	0.082	0.103***	0.222***	0.264***	0.207***	0.189***	0.112*
	(0.064)	(0.107)	(0.039)	(0.067)	(0.032)	(0.054)	(0.035)	(0.060)
Series Diff x mins remaining		0.003		0.000		-0.001		-0.000
		(0.003)		(0.002)		(0.001)		(0.002)
Series Diff x |Score Diff| ≤ 10		0.081		-0.020		-0.023		-0.037
		(0.070)		(0.045)		(0.033)		(0.035)
Series Diff x |Score Diff| ≤ 10 x mins remaining		-0.001		0.001		0.001		0.001
		(0.003)		(0.002)		(0.002)		(0.002)
|Score Diff| ≤ 10 x mins remaining		-0.001		0.006**		-0.001		-0.002
		(0.004)		(0.003)		(0.002)		(0.002)

*Notes: N = 42,480 (playoff games only). Series Diff = own games won in series thus far minus opponent's games won in series thus far. Attendance is de-meaned for playoffs and measured in thousands. Match-up (team-opponent-season) regular season means, quarter fixed effects, and a constant included as RHS variables in all models. Score Diff = start of minute own score minus opponent score (dummy variables for difference being less than -10, greater than -11, and less than -3, etc.); Q4 = dummy for 4th quarter; Home= dummy for home game; Mins remaining = regulation minutes remaining in the game. Mins remaining included as stand-alone regressor in models including it in interactions. Robust standard errors clustered by game in parentheses *,**,*** denote 10%, 5%, and 1% significance.*

III. Playoff Bias Results

Table IV presents the results of the playoff bias hypothesis. In this specification, the models drop the quarter and matchup fixed effects and are replaced with matchup control variables. These matchup control variables are equal to the mean of the dependent variable from regular-season games against the same opponent, within the same season. The sample is only of games that happened in the playoffs. The variable of interest in this part of the analysis is called *Series Diff*, which indicates the number of games the team has won in the series prior to the current game, minus the number of games the opposing team has won. The values for the *Series Diff* term range from negative three to three, as the series will end when a team wins four games. This specification for *Series Diff* is noted to be restrictive, as it implies that the bias by referees will be the same when a team is up 1-0 or 3-2.

Looking at the coefficient on the *Series Diff* term, we see that when a team is down in the series (meaning these teams will have a negative value for *Series Diff*), they have a 3.4% decrease in DTOs called against them. In comparison, teams up in the series (meaning these teams will have a positive value for *Series Diff*) have a 3.4% increase in DTOs called against them. This coefficient is statistically significant at the 5% level. There are no other statistically significant coefficients for the *Series Diff* term, except for the nonshooting fouls, which is only statistically significant at the 10% level. For the nonshooting fouls, we see that teams down in a series have statistically more nonshooting fouls called against them, while teams up in a series have statistically less fouls called against them. This is expected as player behavior will change depending on if their respective team is up or down in the series. Players on teams up in a series do not play as reckless and protect their leads, leading to nonshooting fouls to decrease. In addition, the results found within Table III for home and close bias hold for the playoff game samples, though the magnitude of the estimates are lower. Overall, these results indicate that referees favor teams losing in a playoff series to extend the series.

Table V. Playoff Bias, Game-Level Sample: Poisson Regression Results

	Turnovers	Fouls	Blocks	Rebounds	Assists	Field Goals Made
serdiff	0.012**	-0.004	0.011	0.007**	0.010**	-0.001
	(0.005)	(0.003)	(0.009)	(0.003)	(0.004)	(0.002)

*Notes: N = 2,350; unit of observation = game-team; sample includes only playoff games from 1992-2007. Series Diff = own games won in series thus far minus opponent's games won in series thus far. Match-up (team-opponent-season) regular season means, home game dummy and a constant included as RHS variables in all models. Robust standard errors in parentheses. *,**,*** denote 10%, 5%, and 1% significance.*

Table V presents the results of the complementary analysis conducted for referee playoff bias. As mentioned before, Table V uses game-level box-score data and a wider time frame than those used in Tables III and IV. Since the turnover type cannot be distinguished within game-level data, other statistics are needed to be examined as dependent variables to use as a type of control that will substitute for NTOs. Based on the coefficient for the *Series Diff* term in the model with Turnovers as the dependent variable, we see that teams trailing in a series have a larger decrease in turnovers called against them, on average. The magnitude of the turnover effect is greater compared to the other statistics. This indicates that just changes in player behavior do not increase the effects of turnovers. These results again show that referees do favor teams losing in a playoff series, however, it only affects turnovers, but not fouls in this case.

Conclusion.

The paper, *Subperfect Game: Profitable Biases of NBA Referees*, was one of the first empirical investigations into the home biases, close biases, and playoff biases of NBA referees. Based on the results presented within this paper, the evidence suggests that referees do favor home teams, teams losing during games to keep games close, and teams losing in a playoff series to extend the series. Referees, on average, call statistically fewer DTOs, shooting and nonshooting fouls against teams at home, losing in games, and losing in a playoff series. While the effects on the turnover/fouls could be from player behavior, it is doubtful that would be the case since the results are consistent across all three tables.

The NBA continues to be outspoken about the degree to which its referees are monitored. Since these biases persist however, the evidence suggests that the league has at least not created a strong disincentive to discourage referee biases. And while the connection is made between maximizing profits and the three hypotheses investigated, the conclusion on whether the NBA allows referee bias to persist to increase profits remains only speculative. Regardless, future work can be done to see if the referee bias found in this paper has a statistically significant impact on the betting markets, which operate under weak assumptions of market efficiency.

References.

Beck, H., & Schmidt, M. S. (2007). NBA referee pleads guilty to gambling charges. *The New York Times*.

Delaney, S. (2006). Scandal Hits Italian Soccer on Eve of the World Cup. *Washington Post*.

Dohmen, T. J. (2008). The influence of social forces: Evidence from the behavior of football referees. *Economic inquiry*, *46*(3), 411-424.

Garicano, L., Palacios-Huerta, I., & Prendergast, C. (2005). Favoritism under social pressure. *Review of Economics and Statistics*, *87*(2), 208-216.

Pedowitz, L. B. (2008). Report to the board of governors of the National Basketball Association. *Wachtell, Lipton, Rosen & Katz*.

Pettersson-Lidbom, P., & Priks, M. (2010). Behavior under social pressure: Empty Italian stadiums and referee bias. *Economics Letters*, *108*(2), 212-214.

Price, J., Remer, M., & Stone, D. F. (2012). Subperfect game: Profitable biases of NBA referees. Journal of Economics & Management Strategy, 21(1), 271-300.

Price, J., & Wolfers, J. (2010). Racial discrimination among NBA referees. *The Quarterly journal of economics*, *125*(4), 1859-1887.

Sutter, M., & Kocher, M. G. (2004). Favoritism of agents–the case of referees' home bias. *Journal of Economic Psychology*, *25*(4), 461-469.

Yue, T. (2010, March 17). *Match Fixing: 3 Referees Arrested*. Match Fixing: 3 referees arrested. Retrieved March 30, 2022, from https://www.chinadaily.com.cn/china/2010-03/17/content_9599952.htm