Asian Journal of Applied Economics Vol. 30 No. 2 (July-December 2023): 120-140

ISSN: 2985-1610 (Online)

Received: 19 July 2023
Received in revised form: 30 September 2023
Accepted: 23 October 2023

Home Court Advantage and Referee Bias: Evidence from NBA Games Amid the COVID-19 Pandemic

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Abstract

In response to the heightened risk of COVID-19 transmission, the National Basketball Association (NBA) implemented a no-fans policy following months of suspending the 2019-20 season. This study aims to assess the impact of the no-fans policy on home court advantage and referee bias. Utilizing game-level data spanning from the 2015-16 to the 2020-21 seasons and leveraging the COVID-19 outbreak as a natural experiment, our findings indicate that both home and guest teams achieved higher scores in individual games after the implementation of the no-fans policy. However, home teams earned fewer points, implying that the absence of fans reduces home court advantage. Furthermore, in games played without an audience, referee bias decreases, while home teams' fouls increase. These results carry implications for understanding the influence of social pressure and crowds on the neutrality of decisions.

Keywords: COVID-19; National Basketball Association (NBA); social pressure; home court advantage; referee bias
JEL Classification: D91; M50; L83; Z2

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1. Introduction

Over the past years, the impact of audience size on teams' performance and referees' decisions has been widely discussed by economic and psychological researchers. Economic researchers have discussed the topics related to home court advantages while psychological researchers have focused on referee bias. With home court advantage, home teams have a good chance to win more than 50% of games when they play with guest teams that have comparable strengths (Courneya & Carron, 1991). Most literatures on referees' behaviors indicated that referees obviously show favoritism toward the home teams. This favoritism is commonly known as referee bias (Dohmen & Sauermann, 2016). According to the previous studies on sports economics and psychology, the impact of audience on players is the most important reason behind home court advantages (Boudreaux et al., 2017; Ferraresi & Gucciardi, 2020; Nevill & Holder, 1999; Reade et al., 2020; Scoppa, 2021). Similarly, a huge audience can inevitably affect referees' decisions. Moskowitz and Wertheim (2011) indicated that when there's a huge audience making loud voices at home court, referees are under the influence of bandwagon effect and thus unconsciously make decisions in favor of home teams.

NBA is one of the four professional sport leagues in North America. In 2019-20 alone, NBA games were televised live in 47 languages to 215 countries. In 2019, COVID-19 broke out and gradually became a huge pandemic worldwide. All major sport events were tremendously affected by the pandemic and had to suspend their games. On March 11, 2020, NBA announced that 2019-2020 season would be suspended and games would be resumed from July 31, 2020. To avoid cluster infection, however, NBA decided that the games would be played without audience in arenas.

This paper examined whether home court advantage and referee bias had been affected by the implementation of the no fans policy that NBA announced the games would be played without fans in attendance. This study contributes to the existing literature on home court advantage and referee bias in several ways. First, it is extremely difficult for researchers to study the topics related to home court advantage and referee bias at the same time because of the limitations associated with data gathering and research design. COVID-19 pandemic broke out without warning in 2019. As a result, the pandemic could be treated as a large-scale natural experiment that allows us to evaluate the impact of audience on home court advantage and referee bias at the same time. Second, NBA is an ideal study case to tackle the issues of home court advantage and referee bias, since NBA is one of the most prominent sports leagues in the world. Third, the majority of previous researchers chose soccer when they studied home court advantage and referee bias (e.g., Bryson et al., 2021; Dawson & Dobson, 2010; Dohmen, 2008; Endrich & Gesche, 2020; Ferraresi & Gucciardi, 2020; Pettersson-Lidbom & Priks, 2010; Reade et al., 2020; Scoppa, 2021). This study contributes to fill the research gaps. Last, the findings of current study are important for sports franchises, sponsors and policymakers to enhance economic performance while ensuring the integrity and fairness of the games.

The remainder of this article is organized as follows. The next section briefly reviews the existing literature on homecourt advantage and referee bias. This is followed by a description of the econometric strategies and data used in this study. We then present empirical results with robustness checks. We conclude this article with a brief summary and a discussion of policy implications.

2. Literature Review on Home Court Advantage and Referee Bias

2.1 Home Court Advantage

Home court advantage has much to do with four factors, namely, (a) crowd's noise, (b) guest teams' travelling distance, (c) site familiarity, and (d) referee bias. According to Nevill and Holder (1999), crowd is the most dominant factor behind home court advantage. Home teams are supported by the great majority of audience when they play in home court and audience's support helps home teams' players boost their performance. On the other hand, home team fans' shout and booing are likely to affect guest team's performance (Greer, 1983; Jane, 2022).

As to the guest teams' travelling distance, Entine and Small (2008) analyzed the data acquired from NBA 2004-05 and 2005-06 seasons and found that home teams had won 3.24 points more than guest teams, including 0.31 points resulting from guest team's less break time due to NBA schedule. There is no doubt that the guest team's shortage of break time has much to do with the home team's wins.

To examine the influence on game results imposed by familiarity with stadiums, Pollard (2002) analyzed the data of North America's four major professional sports leagues from October 1987 to April 2001 to study whether teams would lose their home court advantage after they moved to new stadiums. According to the findings, about 24% of home court advantage could possibly be lost after teams moved to new stadiums, suggesting that home teams have a better chance to win if they play in the courts familiar to them. To remove the influence on home court advantage imposed by players' familiarity with arenas, Boudreaux et al. (2017) analyzed 1999-2000 and 2013-2014 data of LA Lakers and LA Clippers, both teams using Staples Center as their home court and found that with audience's support home teams are more likely to win the games, given that other conditions are constant. Then, Boudreaux et al. (2017) in fact estimated the "absolute home court advantage" effect.

2.2 Referee Bias

Based on the literatures on referee bias, referees tend to show favoritism toward home teams. Dawson and Dobson (2010) analyzed the game data of UEFA Champions League and UEFA Cup to examine referees' behaviors. They pointed out that referees show favoritism toward home teams at the timing of giving yellow or red card to players. They also found that the social pressure produced by audience had significantly affected referees' decisions, same as the research results of Dohmen (2008). Using the data of German Premier League's twelve seasons, Dohmen (2008) indicated that the home-biased refereeing is mitigated when the fraction of supporters of the guest team increases. In addition, when the score margin was narrow, referee would be more likely to show favoritism toward home team if home teams had lower score than guest teams.

As to the research of professional basketball, Price et al. (2012) found the existence of referee bias in NBA games. In March 2015, NBA started the public assessment of officiated events in close game situations, where teams are within five points in the last two minutes of games decided in regulation in an effort to eliminate referees' favoritism toward home teams. Later on, Deutscher (2015) noticed that referees' favoritism no longer existed in NBA games, saying with the rapid increase of advertisements and broadcasting franchise fees, NBA had to eliminate referee bias and ensure games to be played fairly so as to attract audiences to buy tickets and watch the games.

2.3 Changes of Home Court Advantage and Referee Bias in Different Sports during COVID-19 Pandemic

Cueva (2020) analyzed the dataset of 41 professional football leagues' games in 30 different countries in 2012-13 and 2019-20 in an attempt to find out the influence on referees' behaviors and game results when games are played without audience in stadiums. According to his research results, guest teams' winning percentage had increased, and home court advantage had decreased because the games are played in empty stadiums due to COVID-19 pandemic. Cueva (2020) also found that following the lockdowns, home teams' fouls had increased by 10%; guest teams' fouls had slightly increased, but was less than the home teams. Cueva (2020) concluded that home court audience's pressure had dramatically affected referees' behaviors and game results. Bryson et al. (2021) analyzed European Football Leagues' 2019-20 game data in an attempt to find out whether referees' behaviors had been affected when games were played without audience in attendance. According to their research results, guest teams had received 1/3 fewer yellow card when games were played in empty stadiums. Bryson et al. (2021) concluded that social pressure had much to do with the fairness of referees' judgment.

Similar findings are observed in baseball. Chiu et al. (2022) used the Major League Baseball (MLB) game data during the COVID-19 pandemic (2021 and 2022) to compare the game outcomes with and without audience in stadiums. They concluded that compared to the regular games (with audience) in the past, home teams had a lower winning percentage in games without audience in attendance, which implies that the absence of audience during games had a significantly negative impact on home court advantage in MLB.

As to the literature on home court advantage and referee bias in basketball, Alonso et al. (2022) used the game data from different European professional basketball leagues in 2021 and 2022 to compare home court advantage in games with and without attendance restriction. Their findings indicated that the home team's winning percentage decreased when supporters were absent. Pelechrinis (2023) used the NBA game data to investigate implicit biases in refereeing and explore its impact on the game outcomes. The results indicated that there is referees' favoritism toward home teams, particularly pronounced during the playoffs. However, implicit biases in refereeing have been reduced since the COVID-19 pandemic.

Gong (2022) used the 2017-18 to 2020-21 NBA game data publicized by the NBA's Last Two Minute Reports to analyze the probability of influence on Correct Call, Incorrect Call, Correct Non-Call and Incorrect Non-Call in the last two minutes of games when the games were played with and without audience in arenas, respectively, attempting to find out how referee bias was affected when games were played with audience. His research results did not support referees' favoritism toward home teams, indicating that in NBA regular seasons referees did not treat home teams and guest teams differently when games were played with audience. Gong (2022) focused on the Call and Non-Call in the last two minutes of games only. However, the data pattern in the last two minutes of games is tremendously different from that in the previous minutes. Therefore, the main difference between the current study and Gong (2022) is that this study analyzed the data of the entire game – from jump ball to game over – of each and every game played in 6 seasons – from 2015-16 to 2020-21 – to examine the impact of NBA's no fans policy on home court advantage and referee bias. Based on previous observations from the literature, we, therefore, hypothesized that the implementation of the no fans policy due to COVID-19 would decrease home court advantage and referee bias in NBA.

3. Methodology and Data

3.1 Home Court Advantage

This study started with the impacts of audience size and games without audience in arenas on home court advantage. The dependent variables used to measure home court advantage are: (a) whether or not the home team wins the game (*Win*), and (b) the total score earned by a team (either home team or guest team) in a single game (*Points*). With the empirical model introduced by Bryson et al. (2021) as starting-point and with home team's win/loss as a dichotomous variable, the logistic regression model is expressed as follows:

$$\log\left(\frac{P_{i,k}}{1-P_{i,k}}\right) = \alpha_0 + \alpha_1 Audience_{ik} + \alpha_2 Post_{ik} + \alpha_3 OD_{ik} + a_k + \mu_{ik}, \quad (1)$$

where $P_{i,k}$ (=Prob (Win_{ik}=1)) denotes the probability function of home team's win in which Win_{ik} denotes a dummy variable that indicates whether home team wins the i^{th} game in k^{th} season (1 represents yes and 0 otherwise). $Audience_{ik}$ is the number of audiences in arenas. In addition, we used two proxy variables, namely: (a) the arena occupancy rate ($Audience\%_{ik}$), and (b) a dummy variable ($Full_{ik}$) denoting whether all seats are occupied on the game day (1 represents yes and 0 otherwise) to measure the audience size. $Post_{ik}$ is a dummy variable denoting whether the i^{th} game in k^{th} season was played after the no fans policy implemented (1 represents yes and 0 otherwise). OD_{ik} denotes the offensive and defensive records of the winning team. Berri et al. (2009) employed home team's group performance as the basis to evaluate the variables that affect NBA teams' winning percentage. Offensive and defensive data include shots, three-point shots, penalty shots, rebounds, assists, steals, blocks, turnovers and fouls. a_k denotes the seasonal fixed effect. μ_{ik} represents the residual term.

Notice that if no contemporaneous shocks to teams' performance and referees' decisions in NBA occurred other than the implementation of the no fans policy, one could identify the impact of the lockdown by comparing teams' performance and referees' decisions before and after the no fans policy for teams affected by the policy. However, for example, scoring in the NBA has shown a general upward trend is part due to faster pace and more talented players. A counterfactual is, therefore, needed in order to identify the impact of the no fans policy.

Ferraresi and Gucciardi (2020) used the home team as the treatment group and the guest team as the control group to evaluate how team performance was affected by the COVID-19 lockdown in football matches in Europe. Similarly, Pettersson-Lidbom and Priks (2010) used the home team as the treatment group and the guest team as the control group to examine the impact of the presence of spectators on referee bias in Italian soccer league. Following Ferraresi and Gucciardi (2020) as well as Pettersson-Lidbom and Priks (2010), we chose the home team as the treatment group and the guest team as the control group to investigate the impact of the no fans policy on home court advantage and referee bias in NBA games.

When NBA games are played without audience in arenas, there is no more shouting and cheering for home teams. Without fans' support in the home court, home teams are affected and therefore treated as a treatment group under the influence imposed by the no fans policy. On the other hand, in the home court, very few fans would cheer for guest teams. As compared with the number of fans cheering for home teams, the number of fans cheering for guest teams is really small and unlikely to affect home court advantage and referee bias prior to the no fans policy. Hence, when games are played without audience in arenas, guest teams are reasonable to be treated as a control group. In this study, the difference-in-differences (DiD) method was employed to estimate the impact of the no fans policy on home court advantage and referee bias. The DiD method is widely used to evaluate the causal effect of a public policy across a variety of disciplines (Athey & Imbens, 2017).

The DiD regression models are described in the following Equations (2) and (3):

$$\begin{aligned} Points_{ijk} &= \beta_0 + \beta_1 Home_{ijk} + \beta_2 Post_{ijk} + \beta_3 Home_{ijk} \times Post_{ijk} \\ &+ \beta_4\, Average\_player\_age_{ijk} + \beta_5 Coach\_age_{ijk} + \beta_6 Salary\_ratio_{ijk} + a_{\mathrm{j}} + \mu_{ijk}, \end{aligned} \tag{2}$$

where $Points_{ijk}$ denotes the points earned from i^{th} game by j^{th} team in k^{th} season. Following Ferraresi and Gucciardi (2020), home court advantage was measured with $Points_{ijk}$. $Home_{ijk}$ is a dummy variable equal to one for home teams (treatment group) and zero otherwise (control group). $Post_{ijk}$ is a dummy variable equal to one for the games after the implementation of the no fans policy that required teams played in empty arenas and zero otherwise. The coefficient of the interaction term of $Home_{ijk} \times Post_{ijk}$ reflects how home court advantage, measured by the home teams' points, was affected by the implementation of the no fans policy. The average age of j^{th} team players (*Average_player_age*) and coach's age (*Coach_age*) in k^{th} season are chosen to reflect a team's characteristics. $Salary\_ratio_{ijk}$ *represents* the team's salary characteristics measured by the ratio of j^{th} team's total salaries to the NBA league's total salaries in k^{th} season. The proxy variable, $Salary\_hhi_{ijk}$, measured the degree of dispersion of j^{th} team's total salaries in k^{th} season is used as well. Following Jane (2010), Herfindahl–Hirschman Index was employed to calculate the quadratic sum of the ratio of individual player's salary to the team's total salaries. a_j denotes the individual team's fixed effect that do not change over time and cannot be observed. μ_{ijk} represents the residual term.

3.2 Referee's Bias

Following the model designed by Pettersson-Lidbom and Priks (2010), this study used fouls of a team in a single game to measure referee bias.

$$Fouls_{ijk} = \gamma_0 + \gamma_1 Home_{ijk} + \gamma_2 Post_{ijk} + \gamma_3 Home_{ijk} \times Post_{ijk} + a_j + \mu_{ijk}, \quad (3)$$

where $Fouls_{ijk}$ denotes j^{th} team's total fouls in i^{th} game of k^{th} season. Other variables have same definitions as those in Equation (2). The coefficient of the interaction term of $Home_{ijk} \times Post_{ijk}$ reflects how referee bias, measured by j^{th} team's total fouls, was affected by the implementation of the no fans policy.

In this analysis, all NBA games played from 2015-16 to 2020-21 regular seasons were treated as samples to construct a panel data set. There were 7,059 games in total, including 665 games played after the implementation of no fans policy. Therefore, the samples used in this analysis are unbalanced panel data. Since the Ordinary Least Squares (OLS) estimator is biased with unbalance panel data, we further employed the Durbin–Wu–Hausman test to validate our findings and then decided whether to use a random effects model or a fixed effects model to improve the accuracy of the empirical results.

3.3 Data

NBA is made up of 30 teams which are divided into two conferences, namely, East Conference and West Conference. Each Conference is made up of three divisions and each division comprises five teams. Each team has to play with four teams that belong to the same division and same conference, two games in home court and two games in guest court, sixteen games to be played with four teams in total. Then, each team has to play three or four games with every team that belongs to same conference but not same division, 36 games to be played with ten teams. Again, each team has to play with fifteen teams that belong to different conference, one game in home court and one game in guest court, respectively, 30 games to be played with fifteen teams. In sum, each team has to play 82 games. In an NBA regular season 1,230 games are played and supervised by 70 referees in total. Due to COVID-19 pandemic, however, 1,059 games were played in 2019-20 regular season. Then, NBA announced that in 2020-21 regular season each team would have to play 72 games, three games with the teams that belong to the same conference, and two games with the teams that do not belong to the same conference, one game in home court and one game in guest court, respectively. Therefore, in 2020-21 regular season, 1,080 games were played.

COVID-19 pandemic quickly spread in 2019-2020 regular season. Utah Jazz was scheduled to play with Oklahoma City Thunder in March 2020. However, NBA halted the games indefinitely after player Rudy Gobert was infected with COVID-19. On July 31, 2020, NBA announced that the regular season resumes and the games will be played without audience in attendance. Games were played at ESPN Wide World of Sports Complex and fans could only watch the games through either TV or webcasting platforms. NBA Players

Association announced that only 22 teams would be played, including the eight top teams of East Conference, eight top teams of West Conference, and teams falling behind the eighth team by six or fewer wins.

This study constructed a panel data based on all games played from 2015-16 to 2020-21 regular seasons before and after NBA announced the no fans policy that the games to be played without audience in arenas. There are 7,059 observed values in total, including 665 games played behind closed doors. Data were gathered from *Basketball Reference* and NBA websites.

4. Results and Discussion

Table 1 contains the descriptive statistics of variables selected by this study for the investigation of the impact of the implementation of the no fans policy on home court advantage and referee bias.

Table 1 Definition of variables and sample statistics

		n = 7,059/14,118			
Variable	Definition	Mean	Std. Dev.	Min	Max
Dependent Variable					
Home Court Advantage					
Win	If home team wins the game (=1)	0.57	0.49	0	1
Points[a]	Points earned by a team in a single game (either home team or guest team)	108.12	12.77	64	168
Referee Bias					
Fouls	Fouls of a team in a single game (either home team or guest team)	20.17	4.31	6	42
Independent Variable					
Post	If a game played without audience in arenas (=1)	0.09	0.29	0	1
Home	If the home team (=1)	0.5	0.50	0	1
Audience	Number of audiences in arena	15,132.73	6,507.49	0	23,152
Audience%	Number of audience of that game / maximum capacity of the arena	0.79	0.34	0	1.16
Full	If a full-capacity game (=1)	0.33	0.47	0	1

FGH	Number of shots made by home team in a single game	40.33	5.22	19	63
3PFGH	Number of three-point shots made by home team in a single game	10.86	3.94	0	28
FTH	Number of free throw attempts for home team in a single game	17.75	6.08	1	44
TRBH	Number of rebound gained by home team in a single game	44.73	6.53	22	70
ASTH	Number of assists made by home team in a single game	24.13	5.18	9	50
STLH	Number of steals made by home team in a single game	7.66	2.95	0	22
BLKH	Number of blocks made by home team in a single game	5.02	2.54	0	20
TOVH	Number of turnovers made by home team in a single game	13.56	3.86	1	29
PFH	Number of fouls made by home team in a single game	19.89	4.25	6	41
PFA	Number of fouls made by guest team in a single game	20.44	4.35	7	42
Average_player_age	Players' average age	26.13	1.30	23.44	31.06
Coach_age	Coach's age	51.39	8.53	32	72
Salary_ratio	Team's total salaries / conference's salaries	0.03	0.00	0.02	0.07
Salary_hhi	The degree of dispersion of teams' salaries	0.13	0.04	0.07	0.54

[a] *Points*, *Fouls*, *Home*, *Post*, *Average_player_age*, *Coach_age*, *Salary_ratio* and *Salary_hhi* have 14,118 observations. Each game is played by a home team and a guest team. 7,059 games were played by two teams and both teams were analyzed individually. This is why samples are twice the size of games.

Win, denotes whether home team has won the game, has a mean of 0.57, which suggests that home team has a higher winning percentage and indicates the existence of home court advantage. *Points*, denotes the scores earned by the team in a single game, has a mean of 108.12. The lowest score was 64 points and highest score was 168 points.[1] *Fouls*, denotes the number of fouls in a single game, has a mean of 20.17. The lowest number of fouls was 6 while the highest was 42.[2] *Post* indicates 9% of games were played after the implementation of the no fans policy.

Smoothie King Center, the home court of New Orleans Pelicans, has 16,867 seats, the smallest of all NBA arenas. Chicago Bulls has the largest arena with 21,879 seats, the biggest of all NBA arenas. The average audience size of a single game was 15,133. The game played by Golden State Warriors and Chicago Bulls on January 20, 2016 had an audience of 23,152 – the biggest audience size of all samples. The average ratio of team's total salaries to the conference's total salaries (*Salary_ratio*) was 0.03. The average dispersion of teams' salaries (*Salary_hhi*) was 0.13.

Table 2 exhibits the results of estimation of Equation (1) in which Models (1)-(3) and (4)-(6) show the results obtained by using the logistic model and random-effects logistic model for panel data, respectively. Since the logistic model involves a non-linear transformation, the coefficients cannot be directly interpretable. Hence, the odds ratios are reported. In Models (1)-(3), the estimated coefficients of audience size (*Audience*) and its proxy variables (*Audience%* and *Full*) are consistently found to be significantly positive. When the number of audiences in arena (*Audience*) increases by 1,000, the probability of the home team winning increases by 4 percentage points. When the arena occupancy rate (*Audience%*) increases by 1%, the probability of the home team winning increases by 1.18 percentage points. When games are played in an arena full of audience (*Full*), the probability of the home team winning increases by 15 percentage points at the 5% significance level. After the no fans policy is announced and games are played without audience in arenas (*Post*), home teams are affected negatively and home court advantage decreases. According to the findings in Model (3), compared to that prior to the implementation of the no fans policy, the probability of the home team

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[1] 64 points were the lowest score earned by home team from a single game when Dallas Mavericks played with Memphis Grizzlies on November 18, 2016. 161 points were the highest score earned by home team from a single game when Atlanta Hawks played with Chicago Bulls on March 1, 2019. 68 points was the lowest score earned by guest team from a single game when Atlanta Hawks played with Utah Jazz on November 25, 2016. Another record was made again when Utah Jazz played with Dallas Mavericks on November 14, 2018 in which the scoring gap was 50. 168 points were the highest score earned by guest team when Chicago Bulls played with Atlanta Hawks on March 1, 2019.

[2] On November 16, 2019 Miami Heat played with New Orleans Pelicans in which the home team had 6 fouls only – the smallest number of fouls made by home team in a single game. On January 20, 2016 Houston Rockets played with Detroit Pistons in which the home team had 41 fouls – the largest number of fouls made by home team in a single game. On March 29, 2016 Charlotte Hornets played with Philadelphia 76ers in which the guest team had 7 fouls – the smallest number of fouls made by guest team in a single game. Another record was made when Houston Rockets played with Miami Heat on April 19, 2021. 42 fouls were the highest record made by guest team when Washington Wizards played with Philadelphia 76ers on November 29, 2017.

winning decreases by 0.49 percentage points at the 1% significance level after the implementation of the no fans policy.

Table 2 Estimate results of the logistic and random effects logistic regression models for home court advantage (Dependent variable: Win)

	Logit	Logit	Logit	Panel Logit	Panel Logit	Panel Logit
	(1)	(2)	(3)	(4)	(5)	(6)
Audience	0.043***			0.034***		
	(0.0070)			(0.0075)		
	[1.0442][a]			[1.0345]		
Audience%		0.78***			0.65***	
		(0.14)			(0.14)	
		[2.1764]			[1.9066]	
Full			0.14**			0.096
			(0.065)			(0.083)
			[1.1489]			[1.1010]
Post	-0.011	-0.056	-0.67***	-0.22	-0.22	-0.75***
	(0.15)	(0.15)	(0.10)	(0.16)	(0.16)	(0.11)
	[0.9886]	[0.9452]	[0.5118]	[0.8051]	[0.8000]	[0.4742]
FGH	0.17***	0.17***	0.17***	0.17***	0.17***	0.17***
	(0.0085)	(0.0085)	(0.0084)	(0.0088)	(0.0088)	(0.0088)
	[1.1861]	[1.1855]	[1.1835]	[1.1905]	[1.1905]	[1.1884]
3PFGH	0.11***	0.12***	0.11***	0.11***	0.11***	0.10***
	(0.0090)	(0.0091)	(0.0090)	(0.0097)	(0.0097)	(0.0096)
	[1.1217]	[1.1223]	[1.1162]	[1.1142]	[1.1142]	[1.1086]
FTH	0.12***	0.12***	0.11***	0.12***	0.12***	0.12***
	(0.0055)	(0.0055)	(0.0055)	(0.0057)	(0.0057)	(0.0057)
	[1.1236]	[1.1231]	[1.1218]	[1.1259]	[1.1258]	[1.1250]
TRBH	0.11***	0.11***	0.11***	0.12***	0.12***	0.12***
	(0.0052)	(0.0052)	(0.0052)	(0.0053)	(0.0053)	(0.0053)
	[1.1216]	[1.1218]	[1.1211]	[1.1240]	[1.1241]	[1.1237]
ASTH	0.037***	0.036***	0.036***	0.043***	0.043***	0.044***
	(0.0081)	(0.0081)	(0.0081)	(0.0087)	(0.0087)	(0.0087)
	[1.0373]	[1.0364]	[1.0363]	[1.0442]	[1.0442]	[1.0450]
STLH	0.16***	0.16***	0.16***	0.16***	0.16***	0.16***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
	[1.1699]	[1.1689]	[1.1688]	[1.1691]	[1.1689]	[1.1689]
BLKH	0.12***	0.11***	0.11***	0.11***	0.11***	0.11***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
	[1.1226]	[1.1210]	[1.1209]	[1.1183]	[1.1180]	[1.1178]

TOVH	-0.056***	-0.056***	-0.057***	-0.050***	-0.050***	-0.050***
	(0.0081)	(0.0081)	(0.0081)	(0.0083)	(0.0083)	(0.0083)
	[0.9460]	[0.9453]	[0.9450]	[0.9509]	[0.9509]	[0.9508]
PFH	-0.11***	-0.11***	-0.11***	-0.12***	-0.12***	-0.11***
	(0.0077)	(0.0077)	(0.0076)	(0.0079)	(0.0079)	(0.0079)
	[0.8919]	[0.8918]	[0.8944]	[0.8906]	[0.8905]	[0.8930]
Constant	-15.2***	-15.1***	-14.3***	-15.4***	-15.4***	-14.8***
	(0.47)	(0.46)	(0.44)	(0.49)	(0.49)	(0.46)
Observations	7,059	7,059	7,059	7,059	7,059	7,059
Pseudo R^2	0.283	0.282	0.279			
Number of home_team_id				30	30	30
Likelihood-ratio test of $\rho = 0$[b]				87.78***	93.44***	102.34***

Notes:

[a] Values in brackets are odds ratios.

[b] The null hypothesis of the likelihood-ratio test is H_0: The panel-level variance component is unimportant when ρ is zero. The chi-squared statistics reject the null hypothesis, indicating that the panel estimator is different from the pool estimator.

Single, double, and triple asterisks (*,**,***) denote coefficients are statistically different from zero at the 10%, 5%, and 1% levels, respectively. Values in parentheses are standard errors.

In addition, home team's shots (*FGH*), three-point shots (*3PFGH*), penalty shots (*FTH*), rebounds (*TRBH*), assists (*ASTH*), steals (*STLH*) and blocks (*BLKH*) are positively associated with the probability of the home team winning whereas home team's total turnovers (*TOVH*) and the number of fouls made by home team (*PFH*) in a single game appear to be negatively associated with the probability of the home team winning. All findings are significant at the 1% significance level. For example, when home team's shots increase by one in a single game, the probability of the home team winning increases by 0.18-0.19 percentage points. When home team's turnovers in a single game increase by one, the probability of the home team winning decreases by 0.05-0.06 percentage points.

This study has a panel data structure. It is, therefore, necessary to identify unobservable factors using a random effects logistic regression model for analysis. The analysis results are shown in Models (4)-(6) in Table 2 in which the estimated coefficients of audience size and its proxy variables are mainly positive. For example, when the number of audiences in arena (*Audience*) increases by 1,000, the probability of the home team winning increases by 3 percentage points. When the arena occupancy rate (*Audience%*) increases by 1%, the probability of the home team winning increases by 0.91 percentage points. Without audience in arenas (*Post*), home court advantage decreases and consequently home team's performance is affected negatively. In Model (6), compared to that prior to the implementation of the no fans policy, the probability of the home team winning decreases by 0.53 percentage points after the implementation of the no fans policy. Moreover, home team's shots, three-point shots, penalty shots, rebounds, assists, steals and blocks affect its winning percentage positively and significantly, while its turnovers and fouls affect the winning percentage negatively and significantly. These findings support our results state above.

Table 3 presents the coefficient estimates of using the DiD method in Equation (2) to examine the impact of the no fans policy on home court advantage measured by the points earned from a single game. In addition, this study employed the Durbin–Wu–Hausman test to determine either a random or fixed effects model is optimal in the DiD. Given that the Hausman chi-square test statistic is not significant (0.21 and 1.12, respectively in Models (2) and (4)), a random effects model is more suitable. However, when we additionally control for year fixed effects and team fixed effects, the Hausman chi-square test statistic appears to be significant, meaning a fixed effects model is more suitable. Therefore, the results of the fixed effects model are presented in columns (6) and (8).

Table 3 The impact of the no fans policy on home court advantage measured by the points earned from a single game (Dependent variable: *Points*)

	OLS	RE	OLS	RE	OLS	FE	OLS	FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Home	2.54***	2.54***	2.54***	2.54***	2.56***	2.57***	2.57***	2.58***
	(0.22)	(0.22)	(0.22)	(0.22)	(0.21)	(0.21)	(0.21)	(0.21)
Post	6.19***	6.26***	6.13***	6.18***	2.56***	2.38***	2.58***	2.36***
	(0.50)	(0.51)	(0.51)	(0.51)	(0.59)	(0.57)	(0.59)	(0.57)
*Home*Post*	-2.33***	-2.33***	-2.38***	-2.38***	-2.46***	-2.54***	-2.49***	-2.59***
	(0.71)	(0.71)	(0.71)	(0.72)	(0.70)	(0.68)	(0.71)	(0.68)
Average_player_age	-0.19**	-0.18**	-0.064	-0.038	0.56***	0.66***	0.71***	0.81***
	(0.088)	(0.091)	(0.087)	(0.089)	(0.086)	(0.093)	(0.086)	(0.092)
Coach_age	0.075***	0.075***	0.087***	0.085***	0.038***	0.029**	0.045***	0.032**
	(0.012)	(0.013)	(0.012)	(0.013)	(0.012)	(0.013)	(0.012)	(0.013)
Salary_ratio	251***	243***			183***	152***		
	(24.1)	(24.9)			(21.7)	(24.3)		
Salary_hhi			21.8***	19.4***			9.49***	6.02**
			(2.78)	(2.76)			(2.64)	(2.74)
Constant	99.0***	99.1***	101***	100***	80.5***	78.8***	81.2***	79.1***
	(2.18)	(2.29)	(2.19)	(2.31)	(2.24)	(2.41)	(2.27)	(2.44)
Year Dummy					Yes	Yes	Yes	Yes
Team Dummy					Yes	Yes	Yes	Yes
Observations	14,118	14,118	14,118	14,118	14,118	14,118	14,118	14,118
R-squared	0.033	0.033	0.030	0.030	0.137	0.127	0.134	0.125
Number of home_team_id		30		30		30		30
Hausman test		0.21		1.12		274.75***		291.35***

Notes: Single, double, and triple asterisks (*,**,***) denote coefficients are statistically different from zero at the 10%, 5%, and 1% levels, respectively. Values in parentheses are standard errors.

In Table 3, all models consistently demonstrate that the coefficients of the dummy variable of home team (*Home*) are positive and significant. In Models (1)-(4), home teams earn 2.54 points more as opposed to guest teams in a single game at the 1% significance level. According to Models (5)-(8), with fixed effects controlling for time-invariant unobservable factors and individual team characteristics, home teams earn 2.56-2.58 points more as opposed to guest teams at the 1% significance level. Our finding in supporting home court advantage is consistent with Entine and Small (2008). The coefficients of *Post* appear to be consistently positive and significant. An additional 2.36-6.26 points will be scored in a single game at the 1% significance level after the implementation of the no fans policy. Our findings suggest that both home and guest teams play better behind closed doors.

The main coefficient of interest in this study is the coefficient of the interaction term (*Home*Post*), found to be consistently and significantly negative in Table 3. Home teams earn 2.33-2.59 points less as opposed to guest teams in each game when the games are played without audience in arenas at the 1% significance level, suggesting that home court advantage decreases and home team earns fewer points when the no fans policy is implemented. Our findings are consistent with Ferraresi and Gucciardi (2020) who observed that home court advantage declines behind closed doors without supportive audience in the main five football leagues of Europe.

The teams with high salaries are attractive to outstanding players, resulting in improving their performance and earn more points in each game. According to Table 3, the ratio of teams' total salaries to the conference's total salaries appears to be positive and significant, which conforms to the research results of Peeters and van Ours (2021). The degree of dispersion of teams' salaries (*Salary_hhi*) also appears to be positive and significant, meaning the higher degree of a team's salaries the more points earned by the team, which is helpful for the team to win the games (Halevy et al., 2012).

Table 4 contains the coefficient estimates of using the DiD method in Equation (3) to examine the impact of the no fans policy on referee bias measured by total fouls in single games. OLS, random and fixed effects model were employed. In Model (2), since the Hausman chi-square test statistic is insignificant (0.29), a random effects model is more suitable whereas in Model (6), a fixed effects model is more suitable, since the Hausman chi-square test statistic is significant (304.78).

The results in Table 4 consistently indicate that the dummy variable of home team (*Home*) is negative at the 1% significance level. The number of home team's fouls in a single game decreases by 0.59-0.6 as opposed to the guest team. Similar to the findings in previous studies (Bryson et al., 2021; Dawson & Dobson, 2010; Dohmen, 2008; Dohmen & Sauermann, 2016; Endrich & Gesche, 2020; Pettersson-Lidbom & Priks, 2010; Scoppa, 2021), referees are likely to show favoritism toward home teams which results in home team's fewer fouls, indicating the existence of referee bias. The coefficients of *Post* consistently appear to be significantly positive in Models (1)-(6). In Model (6), the regression results of the fixed effects model indicate that, fouls increase by 0.76 in a single game after the implementation of the no fans policy. Apparently, referees are relieved from pressure in the games played without audience and thereby make their decisions fairly.

Table 4 The impact of the no fans policy on referee bias measured by fouls of a team in a single game (Dependent variable: *Fouls*)

	OLS	RE	FE	OLS	RE	FE
	(1)	(2)	(3)	(4)	(5)	(6)
Home	-0.60***	-0.60***	-0.60***	-0.59***	-0.59***	-0.59***
	(0.075)	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)
Post	0.72***	0.75***	0.76***	0.74***	0.74***	0.76***
	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)	(0.20)
*Home*Post*	0.48**	0.48**	0.48**	0.44*	0.44*	0.45*
	(0.25)	(0.24)	(0.24)	(0.24)	(0.24)	(0.24)
Constant	20.5***	20.5***	20.5***	20.9***	20.9***	20.7***
	(0.054)	(0.15)	(0.053)	(0.22)	(0.21)	(0.24)
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Team Dummy				Yes	Yes	Yes
Observations	14,118	14,118	14,118	14,118	14,118	14,118
R-squared	0.023	0.023	0.024	0.052	0.052	0.040
Number of home_team_id		30	30		30	30
Hausman test		0.29				304.78***

Notes: Single, double, and triple asterisks (*,**,***) denote coefficients are statistically different from zero at the 10%, 5%, and 1% levels, respectively. Values in parentheses are standard errors.

The coefficients of the interaction term (*Home*Post*) are found to be consistently and significantly positive in Table 4. These results indicate that home team's fouls increase by 0.44-0.48 in a single game as opposed to guest team when the no fans policy is implemented and the games are played without audience in arenas. Our findings are consistent with Bryson et al. (2021) who observed that when games are played without audience in arenas, referees are free from audience's pressure and thus home team's fouls increase.

4.1 Robustness Checks

The number of fouls is used as a dependent variable in Equation (3) for analyzing how referee bias was affected by the implementation of the no fans policy. However, since the number of team fouls is a count data involving discontinuity, a Poisson regression (PR) model is a more suitable option and therefore used for the robustness checks. The results of PR with random and fixed effects are presented in Table 5.

Table 5 The impact of the no fans policy on referee bias measured by fouls of a team in a single game in a Poisson Model (Dependent variable: *Fouls*)

	Poisson	Poisson RE	Poisson FE	Poisson	Poisson RE	Poisson FE
	(1)	(2)	(3)	(4)	(5)	(6)
Home	-0.030***	-0.030***	-0.030***	-0.030***	-0.030***	-0.030***
	(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0039)	(0.0039)
Post	0.037***	0.038***	0.038***	0.038***	0.038***	0.038***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
*Home*Post*	0.024*	0.024*	0.024*	0.024*	0.024*	0.024*
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Constant fouls		3.01***			3.04***	
		(0.0077)			(0.011)	
Constant lnalpha		-6.58***			-23.0	
		(0.28)			(105)	
Constant	3.01***			3.04***		
	(0.0037)			(0.011)		
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Team Dummy				Yes	Yes	Yes
Observations	14,118	14,118	14,118	14,118	14,118	14,118
Number of home_team_id		30	30		30	30
Pseudo R^2	0.004			0.009		
Likelihood-ratio test of ρ = 0[a]		313.58***			8.9e-04	
Hausman test		11.00			0.00	

Notes:

[a] The null hypothesis of the likelihood-ratio test is H_0: The panel-level variance component is unimportant when ρ is zero. The chi-squared statistics reject the null hypothesis, indicating that the panel estimator is different from the pool estimator.

Single and triple asterisks (*,***) denote coefficients are statistically different from zero at the 10% and 1% levels, respectively. Values in parentheses are standard errors.

Consistent with our previous findings in Table 4, the coefficients of interaction term (*Home*Post*) are found to be significantly positive in Table 5, which supports our previous findings that referees are less biased without audience in arenas. As to the coefficients of *Home* and *Post*, the number of home team's fouls in a single game decreases opposed to the guest team, and fouls increase in a single game after the implementation of the no fans policy. These robustness check findings reinforce our previous findings.

4.2 Discussions

This study at first evaluates the impact of audience size on NBA home court advantage. According to the empirical results, a large audience in arenas or a high arena occupancy rate will positively and significantly affect the probability of the home team winning. Apparently, a large audience in arenas or a high arena occupancy rate will create psychological support for players and thereby improve players' performance, same as the research results of Boudreaux et al. (2017) who support for the social support hypothesis and suggest that the crowd effect increases the likelihood of the home team winning by 21-22.8 percentage points. Home team's shots, three-point shots, penalty shots, rebounds, assists, steals and blocks positively and significantly affect its winning percentage while its turnovers and fouls negatively and significantly affect home team's winning percentage. Our findings are consistent with the research results of Berri et al. (2009).

Next, this study discusses the impact of games played without audience in arenas (the no fans policy) on home court advantage by employing the DiD method and reveals some interesting findings. First of all, home teams have scored 2.54-2.58 points more than guest teams from games, which means the existence of home court advantage in NBA games. This finding is consistent with Entine and Small (2008) who found that home teams had won 3.24 points more than guest teams. Secondly, both home and guest teams have won higher scores in a single game after the implementation of the no fans policy that required teams played without audience in attendance. Better performance without pressure from audience after the implementation of the policy tend to support for the hypothesis of choking under pressure when performing skill-based tasks. Our finding is consistent with the research results of Böheim et al. (2019) in NBA and Jane (2022) in MLB who observed that supportive audiences induce choking under pressure, resulting in home teams' lower performance.

Most interestingly, this study finds that the implementation of the no fans policy negatively affects home court advantage. On average, guest teams have earned more points whereas home teams have earned fewer points when games are played without audience in arenas. Home teams earn 2.33-2.59 points less as opposed to guest teams when the games are played behind closed doors. Our findings are consistent with Ferraresi and Gucciardi (2020) who pointed out that in the main five football leagues of Europe, during the lockdown and without supportive fans, a home team gets 0.223 fewer points, which is equivalent to a 14% decrease with respect to the points achieved by home teams.

Higher salaries are attractive to outstanding players, and with outstanding players, teams tend to have won more points from games, same as the research results of Peeters and van Ours (2021). According to Halevy et al. (2012), a higher dispersion of players' salaries can motivate players work closely with one another and thereby improve teams' performance, which is beneficial for coaches to guide the teams to victory. This study also found a positive correlation between the dispersion of players' salaries and the scores earned, which is beneficial for the teams to win the games with a high group performance.

Lastly but not the least, this paper discussed the impact of the no fans policy on referee bias. According to the previous studies (e.g., Bryson et al., 2021; Dawson & Dobson, 2010; Dohmen, 2008; Dohmen

& Sauermann, 2016; Endrich & Gesche, 2020; Pettersson-Lidbom & Priks, 2010; Scoppa, 2021), referees are likely to show favoritism toward home teams which results in fewer (more) fouls for home (guest) teams, indicating the existence of referee bias. Reversely, when games are played without audience in arenas, referees' decisions are more objective and fairer presumably because referees are relieved from psychological pressure in the games without audience. Our evidence indicates that in the games played without audience, referee bias decreases and home teams' fouls increase. The finding corresponds to the results in Bryson et al. (2021) who observed home (guest) teams had received 0.07 more (0.29 fewer) yellow cards when games were played in empty stadiums.

5. Conclusion and Policy Implication

The COVID-19 pandemic provides a unique natural experiment opportunity to allow this study to discuss the impact of the no fans policy on home court advantage and referee bias, simultaneously. According to our results, the implementation of no fans policy reduces both home court advantage and referee bias. From the study of home court advantage and referee bias, we can learn the complicated social psychology and confirm that audience is an important factor to affect home court advantage and referee bias.

Home court advantage can lead to increase ticket sales, merchandise purchases and fan engagement, all of which contribute to the overall economic success of a sports franchise (Wolfers, 2006). According to statistics from Nielsen-Research in 2018, NBA fans' direct and indirect related spending (fan engagement) in the stadium was worth approximately USD 425 million. When home teams try to impose pressure on referees through players and audiences' behaviors either intentionally or unintentionally, they have a good chance to improve their winning percentage. However, referee bias seriously affects the game outcomes, thereby affecting the economic achievement of the NBA. A nine-year USD 24 billion (USD 2.7 billion/year) television deal with ESPN, ABC and Turner Sports began with the 2016–17 season and will run through the 2024–25 season. NBA is seeking as much as USD 75 billion in media rights fees in its next negotiations. Referees must act fairly and neutrally so they can ensure high quality games for fans and those who buy season tickets and pay TV subscription fees. Moreover, Americans have placed more than $220 billion on sports bets in five years since legalization in 2018. Sports betting industry is highly concerned about referees' fairness because the outcomes of the games and referees' decisions affect substantial betting profits. The positive impact of home court advantage, coupled with policy considerations regarding the possible impacts of referee bias, will contribute to the economic success of the sports industry. Understanding these impacts is important for sports franchises, sponsors and policymakers to improve economic returns while ensuring the integrity and fairness of competitions.

One limitation of the research should be mentioned. There are three on-court referees effectively randomly assigned to each NBA game. Different combinations of referees with different individual characteristics may change the course of a game, and its outcome. Inasmuch as this study focuses on the impact of the NBA games played without audience in arenas on referee bias. Some characteristics of referees, such as ages, experience and disciplines are not included in the empirical models. The robustness of our findings could be further validated by including this type of information.

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