

Article

The Effect of the Crowd on Home Bias: Evidence from NBA Games During the COVID-19 Pandemic

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Abstract

The present study examines a specific type of referee biases, home bias, and analyzes how the presence of fans affects home bias by using NBA games played in empty arenas during the COVID-19 pandemic in the 2020–2021 season and matches played before the pandemic from 2017 to 2020. This research also uses a unique data set from NBA Last Two Minute Reports to assess referees' performance at the play level. The findings show crowd support does not cause referees to treat home and away teams differently in crucial situations during the NBA regular season, contrary to the results in most prior studies.

Keywords

referee bias, home bias, COVID-19, crowd support

1. Introduction

Referees are appointed to make impartial decisions in sports competition. Yet, a wide range of biases may exist to distract referees from making correct decisions, such as biases based on race (e.g., Price and Wolfers, 2010), star status (e.g., Caudill et al., 2014), nationality (e.g., Pope and Pope, 2015), etc. Home bias, which occurs when referees favor home teams over away teams, is another source of referee bias

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(Garicano et al., 2005). It is often believed that home bias contributes to home advantage with referees consistently favoring home teams over their opponents (Boyko et al., 2007). Despite the strong belief of home bias among fans, it is less clear how home bias occurs in sports competition. Prior research has proposed a variety of plausible causes of home bias, such as crowd support (e.g., Dohmen, 2008), heterogeneity in referees (e.g., Boyko et al., 2007), stake size (e.g., Garicano et al., 2005). Among these possibilities, the home crowd factor seems to draw the most attention in scholarship (Nevill et al., 2002; Sutter & Kocher, 2004).

The theoretical explanations of the impact of the crowd on home bias are well documented in the literature. Several studies pointed out that social pressure created by home crowds causes referees to make favorable calls to home teams (Akerlof, 1980; Becker & Murphy, 2000; Bernheim, 1994). In sports competition, home crowds form a social environment to support home teams. Any actions against the home crowds may face strong social pressure. As a result, referees may make some decisions that they would not have made to gain social awards or avoid social sanctions in front of the home crowd (Dohmen & Sauermann, 2016).

Resting on theoretical foundations, a plethora of research sought to develop empirical evidence regarding the impact of the crowd on home bias (Nevill et al., 2002; Sutter & Kocher, 2004). Despite extensive research, prior studies lag in three areas that motivate our study. First, most prior research employed game-level and minute-level data, such as the number of yellow and red cards and penalty kicks, to investigate the impact of crowd support on home bias (Boyko et al., 2007; Buraimo et al., 2010; Buraimo et al., 2012). By comparing the frequency of game statistics in matches with and without fans, scholars drew conclusions regarding the effect of crowd support on home bias. Yet, these game statistics may be simultaneously affected by player and referee behavior. Without a clear identification strategy, it is difficult to conclude the change in game statistics is solely caused by the change in referee behavior (Buraimo et al., 2017). Second, prior studies largely utilized the variation in attendance or the distance between the stand and the field to study how the crowd affects referee behavior (e.g., Dohmen, 2008). Few studies considered the case where fans were completely removed from the stands. This is largely due to the lack of incidents where teams restrict fans from attending live events (e.g., Pettersson-Lidbom and Priks, 2010). However, the absence of the crowd may create additional effects on referees' performance that were not captured before. Thus, additional analysis is needed to further investigate how the missing crowd will affect referee behavior. Lastly, a wealth of studies of the impact of the crowd on home bias focused on European football (Buraimo et al., 2017). Little attention is paid to other sports and sports leagues (Dohmen & Sauermann, 2016). Yet, prior research has noted that even within the same sport, referees may exhibit different behaviors across various leagues and divisions (Bryson et al., 2021). Thus, it is necessary to study other sports and leagues in order to develop a more comprehensive understanding of the effect of the crowd on home bias.

The present study uses a natural experiment from the 2020–2021 National Basketball Association (NBA) regular-season games played during the COVID-19 pandemic and games played before the pandemic to study the effect of the crowd on home bias. This research also employs a unique data set from NBA Last Two Minute Reports (L2Ms) to analyze how the crowd impacts home bias. The data set is unique in that it does not only include the count of foul calls and non-calls, but also the correctness of these calls and non-calls, information that was not available in most prior research examining home bias. With data specifically related to referees' performance, our research can plausibly separate referee behavior from player behavior, producing more accurate estimation of the impact of the crowd on home bias. The play-by-play nature of the data set also allows us to examine referee behavior at the play level, rather than at the game level and minute level that were often observed in prior research.

2. Literature Review

2.1 Home Bias

Early studies of home bias largely focus on developing evidence that referees favor home teams over away teams in sports competition. A lineage of studies relied on European football as the context to study home bias. Dohmen and Sauermann (2016) summarized numerous forms of home bias in European football. First, a few studies showed referees assigned more stoppage time to home teams than away teams. The different treatments by referees are particularly salient when home teams are trailing toward the end of the game (Garicano et al., 2005). Second, a range of studies investigated whether referees were more likely to award goals to home teams than away teams. By using data with the correctness of the referring decisions, Dohmen (2008) found that more incorrect goals were awarded to home teams than away teams, implying strong favoritism toward home teams. Third, a few studies investigated whether home teams tended to receive more penalty kicks than their opponents (Boyko et al., 2007; Constantinou et al., 2014). Among these inquiries, Dohmen's (2008) study using the correctness of penalty kicks in Bundesliga to investigate home bias is particularly relevant to the present research. Specifically, he found that incorrect or disputable penalty kicks were more likely to be awarded to home teams, suggesting the existence of home team favoritism. Lastly, a number of studies compared the number of yellow cards awarded to home and away teams in studying home bias. Most research concluded that visiting teams were more likely to receive yellow cards than home teams, implying that referees favor home teams through penalizing away teams more (Buraimo et al., 2010; Dawson et al., 2007; Goumas, 2014; Pettersson-Lidbom & Priks, 2010).

Home bias was also examined in other sports. Of particular relevance to the study is the referee behavior in the NBA. Price et al. (2012) extracted referee calls from

play-by-play data to examine home bias in the NBA. They used non-discretionary turnovers, calls that do not involve referees' discretion, as the control group, and discretionary turnovers, calls that need subjective judgment from referees, as the treatment group. They found strong evidence that NBA referees favored home teams by calling fewer discretionary turnovers on home teams than away teams, relative to non-discretionary calls. Deutscher (2015) employed NBA L2Ms from the 2014–2015 season and examined home bias in the NBA. Unlike Price et al.'s (2012) study, Deutscher (2015) did not find strong evidence of home bias in the NBA. Despite the contradictory conclusions, it is crucial to note that NBA L2M data used in Deutscher; (2015) research only track referees' performance late in a close game and may not capture home bias exhibited early in a match. Interestingly, Price et al. (2012) did find some evidence that home bias was reduced in the fourth quarter of the NBA games, partially echoing the findings from Deutscher's (2015) study.

2.2 *Causes of Home Bias*

While home bias seems common in sports competition, perhaps a more interesting question to ask is what factors cause home bias (Buraimo et al., 2017; Pollard, 2008). A wide range of possible causes of home bias has been proposed and studied in prior research. For example, Boyko et al. (2007) found out that home bias might depend on individual referees. They examined matches in the English Premium League and discovered the variability of home bias across referees. In other words, certain referees were more likely to favor home teams than their peers. In addition, stake size may affect home bias. For example, Garicano et al. (2005) noted that home teams were strongly favored toward the end of the season when the stake of games is high. On the other hand, Price et al. (2012) reported that home bias was reduced in the fourth quarter of a basketball game where referees' decisions might significantly influence game outcomes.

Another possible source of home bias that has been widely studied is the presence of the home crowd. With home fans cheering loudly for home teams, referees may face strong social pressure, and thus are likely to make biased decisions in favor of home teams. Based on this hypothesis, previous research used the variation in the size of the home crowd to test whether home fans contribute to home bias. For example, Garicano et al. (2005) noted that home bias was positively related to attendance in Spain soccer leagues. Other research extends the previous work by examining how the composition of the home crowd will affect home bias. Specifically, a few studies calculated the ratio of attendance to capacity to gauge the proportion of away team fans in the crowd as they argued the ratio would be higher if more away fans were present (Dohmen, 2008; Garicano et al., 2005; Goumas, 2014). These studies found consistent evidence that home bias was mitigated when more away fans joined the crowd. Pettersson-Lidbom and Priks (2010) took advantage of the absence of the crowd in Italian football leagues, due to hooligan violence in 2007.

They developed evidence that games without spectators involved less home bias. Prior research also used the distance to the field to study home bias. For example, Dohmen (2008) and Scoppa (2008) compared the home bias in stadiums with and without running tracks and found the bias is weaker when games were played in stadiums with running tracks.

2.3 COVID-19, Home Advantage, and Home Bias

The COVID-19 pandemic forced sports leagues and teams to play games without fans in the stands. This setting has created an opportunity to study whether the crowd drives the home advantage. While not always the case, numerous studies have found the reduced home advantage in games played behind closed doors across the world, showing evidence that the home advantage depends on crowd support (Benz & Lopez, 2021; Cueva, 2020; Ferraresi & Gucciardi, 2021; Ponzo & Scoppa, 2018). Among research that is particularly relevant to our study, Higgs and Stavness (2021) analyzed the home advantage in the NBA bubble where all games were played in empty arenas. They found that the NBA home advantage was significantly reduced in the bubble. In addition, Leota et al. (2021) examined the NBA 2020–21 season where a significant portion of games was played without fans and other proportions of games were played in partially filled areas. They also found that the absence of the crowd reduces the home advantage in the NBA.

In observing the reduced home advantage in sports leagues, a range of studies also take advantage of games played behind closed doors during the COVID-19 pandemic to investigate whether the crowd affects the home advantage through pressuring referees to favor home teams over away teams (Endrich & Gesche, 2020; Fischer & Haucap, 2021). Specifically, these studies analyzed how home bias will differ when fans are allowed in games, compared to games without fans (Bryson et al., 2021). As of this writing, numerous investigations have shown the absence of the crowd did significantly reduce home bias. For example, Bryson et al. (2021); Endrich and Gesche (2020), Scoppa (2021), and Sors et al. (2021) examined European football games played during the COVID-19 pandemic, showing that there was less home bias (particularly the gap between home and away teams in yellow cards) when teams were played in empty stadiums. Reade et al. (2020) used closed-door games played before the pandemic and found similar evidence of reduced home bias in European football leagues.

Despite extensive investigations of the effect of crowd support on home bias using games played during the COVID-19 pandemic, most studies were conducted in the context of European football (Reade et al., 2020). Evidence from North American professional sports leagues seems scant. Prior studies noted the importance of examining different leagues and counties as research found conflicting results regarding the impact of the empty stadiums on home bias across European football leagues.

(Bryson et al., 2021; Reade et al., 2020). Therefore, there is a need to further explore the effect of crowd support on home bias in other sports and leagues.

It is also worth noting that most recent research studying the effect of the crowd on home bias relied on comparing game-level or minute-level statistics, such as fouls, penalty kicks, and yellow cards, in games with and without fans in the stands (Bryson et al., 2021; Endrich & Gesche, 2020). One possible issue with such a comparison is that the difference may be caused by the change in player behavior rather than referee behavior as the absence of fans may also affect how players compete (Fischer & Haucap, 2021; Russell, 1983). These studies rejected the idea that the reduced home bias stemmed from the change in player behavior through two methods. First, prior studies incorporated player statistics, such as goals, tackles, shots, passes, fouls, etc., into statistical models to control for player behavior (Endrich & Gesche, 2020; Price et al., 2012). Second, a few studies compared player statistics in games with and without fans and noted the player statistics differences between the two games were not significant (Bryson et al., 2021; Pettersson-Lidbom & Priks, 2010). Based on this observation, they argued that the change in game statistics, such as the number of fouls and penalty kicks, must come from the change in referee behavior, not player behavior. Despite these efforts, prior studies cannot completely rule out the possibility that both player and referee behavior contribute to the change in games statistics when fans are absent. Therefore, more precise estimation of referee behavior is needed in order to reveal how the missing crowd affects home bias during the COVID-19 pandemic.

3. Methodology

To better estimate the impact of the crowd on home bias, our research uses NBA L2M data from 1,679 NBA regular-season games played between the 2017–2018 and 2020–2021 seasons. We excluded all games that happened in the NBA bubble during the 2019–2020 season from analysis as these games played in a neutral site and settings were significantly different from regular NBA arenas. The unit of observation is a foul play in NBA L2Ms. In total, our research analyzes 30,695 foul plays from 1,679 games.

3.1 Data

An NBA L2M (see Figure 1) is a play-by-play document that tracks the correctness of calls and non-calls for actions in the last two minutes of the fourth quarter or the last two minutes of any overtime in qualified games (National Basketball Association [NBA], n.d.a). If a game is qualified for the L2M, the NBA league office will review game videos after matches to determine the correctness of every officiating decision (NBA, n.d.a). The first L2M report was released in March 2015 (Deutscher, 2015). Since the 2017–2018 season, the NBA has provided L2Ms for any game in which







Heat (109) @ Trail Blazers (115) February 9, 2020						
Period	Time	Call Type	Committing Player	Disadvantaged Player	Review Decision	
						
	02:08.1	To	01:49.0			
	Q4	01:57.0	Foul: Personal	CJ McCollum	Goran Dragic	CC
	Comment:	McCollum (POR) makes body to body contact with Dragic (MIA) prior to his upward shooting motion.				
	Q4	01:52.0	Foul: Loose Ball	Jae Crowder	Hassan Whiteside	CNC
	Comment:	Crowder (MIA) makes slight contact with Whiteside (POR) during the rebound.				
						
	01:49.1	To	01:30.0			
	Q4	01:34.0	Foul: Personal	Andre Iguodala	Trevor Ariza	INC
	Comment:	After the pick, Iguodala (MIA) continues to move into and affects Ariza's (POR) FOM.				
	Q4	01:34.0	Foul: Offensive	Trevor Ariza	Andre Iguodala	CNC
	Comment:	Ariza (POR) is firming up and makes marginal contact with Iguodala (MIA) during the pick.				
	Q4	01:30.0	Foul: Personal	Bam Adebayo	Hassan Whiteside	IC
	Comment:	Adebayo (MIA) cleanly dislodges the basketball, any additional contact to Whiteside's (POR) arm is deemed incidental.				

Figure 1. Example of the NBA L2M.

Table 1. Summary of ICs and INCs from the 2017-2018 to 2020-2021 Seasons.

Season	IC Percentage	IC per period	INC Percentage	INC per period
2017-2018	2.9%	0.096	6.0%	0.809
2018-2019	4.0%	0.126	6.7%	1.020
2019-2020	3.8%	0.125	6.3%	0.836
2020-2021	5.1%	0.168	4.6%	0.578
Average	3.9%	0.127	6.0%	0.817

one team’s lead over the other is three points or fewer at any point during the last two minutes of the fourth quarter or overtime (NBA, n.d.a). While the league first launched L2Ms in 2015, it made significant changes to the report before the beginning of the 2017–2018 season (NBA, n.d.a). Thus, to ensure the consistency of our analysis, the present study utilizes L2M data from the 2017–2018 to 2020–2021 seasons. In addition, our research will focus on foul calls and non-calls, given the fact that 88% of the actions reported in L2Ms are related to fouls.¹ The second most frequent action is turnovers, but a large number of turnover plays do not rely on referees’ judgment, such as 24-second violations. For these reasons, this article will center on examining foul actions in L2Ms. L2M data are available at official.nba.com.

We consider two sets of officiating decisions documented in NBA L2Ms, Correct Call (CC) versus Incorrect Call (IC) and Correct Non-Call (CNC) versus Incorrect Non-Call (INC), as our dependent variables in statistical models. Specifically, CCs and ICs represent the correctness of foul calls, while CNCs and INCs relate to foul calls missed by referees. The frequency and percentage of these calls and non-calls by season can be found in Table 1. It is important to note that although the percentage

of ICs (3.9%) and INCs (6.0%) are close, INCs occur more frequently in an NBA game than ICs. For example, the average number of INCs per period is 0.817, suggesting one incorrect foul non-call is expected to occur almost every period. On the other hand, the average number of ICs is equal to 0.127, implying one incorrect foul call is expected to happen every eight periods. Figures 2 and 3 also visualize the percentage of ICs and INCs and frequency of ICs and INCs per period from the 2017–2018 to 2020–2021 seasons.

In addition to data from L2Ms, we also collect NBA player and team data from basketball-reference.com. As displayed in Figure 1, each play in L2Ms is linked to a player who may commit a foul on the court. We match player names with player and team information found on Basketball-Reference in order to identify whether a player is from the home or away team. The dummy variable *Home* is equal to 1 if a foul committing player is from the home team and 0 otherwise. We also use game attendance collected from basketball-reference.com to determine whether a given game has fans in the stands or not. The dummy variable *Fan* contains the value of 1 for games with fans and 0 for games without fans. It is critical to note that, unlike prior studies, we do not include game attendance as one of the predictors

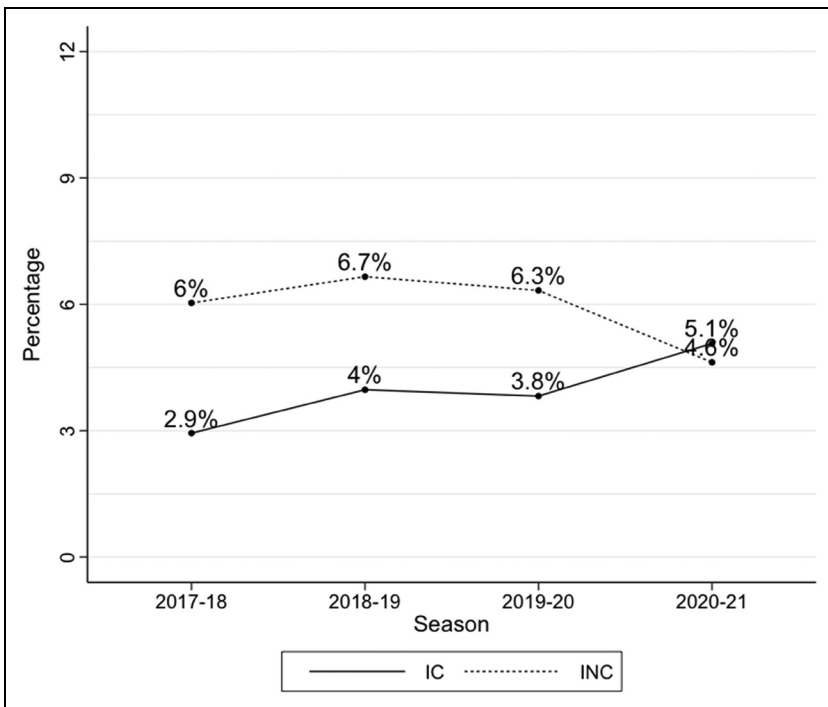


Figure 2. Percentage of ICs and INCs from the 2017–2018 to 2020–2021 seasons.

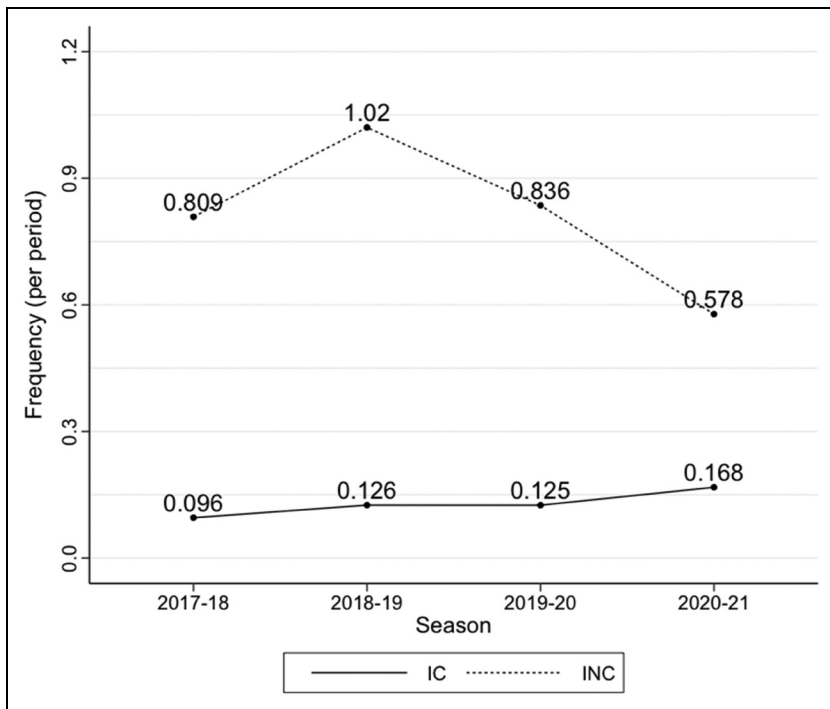


Figure 3. Frequency of ICs and INCs per period from the 2017-2018 to 2020-2021 seasons.

in our models due to its high correlation with the variable *Fan*. Figures 4 and 5 show the average weekly attendance for all games played between the 2017–2018 and 2020–2021 season and how teams gradually allowed fans in NBA arenas during the 2020–2021 pandemic season.

We also gather data for a range of control variables that may affect referees' officiating decisions. First, prior research noted that referees might favor all-star players over normal players (Caudill et al., 2014). Thus, we find the all-star status for all players documented in L2Ms. The all-star status is determined by players being selected into all-star teams in a given season. The variable *Star* is equal to 1 if the observed player has the all-star status and 0 otherwise. In addition to the all-star status, referees may make biased calls or non-calls based on players' nationality (Dawson & Dobson, 2010; Page & Page, 2010; Pope & Pope, 2015). To control for this bias, we collect nationality data from basketball-reference.com and assign all players to one of the two categories, non-U.S. and U.S. players based on their born places. The dummy variable *Nationality* is equal to 1 for all U.S. players and 0 for non-U.S. players. Along with player data, we also count seconds left for each action in L2Ms as referees may change their officiating behavior toward the end of the game with a few seconds left on the clock (Deutscher, 2015).

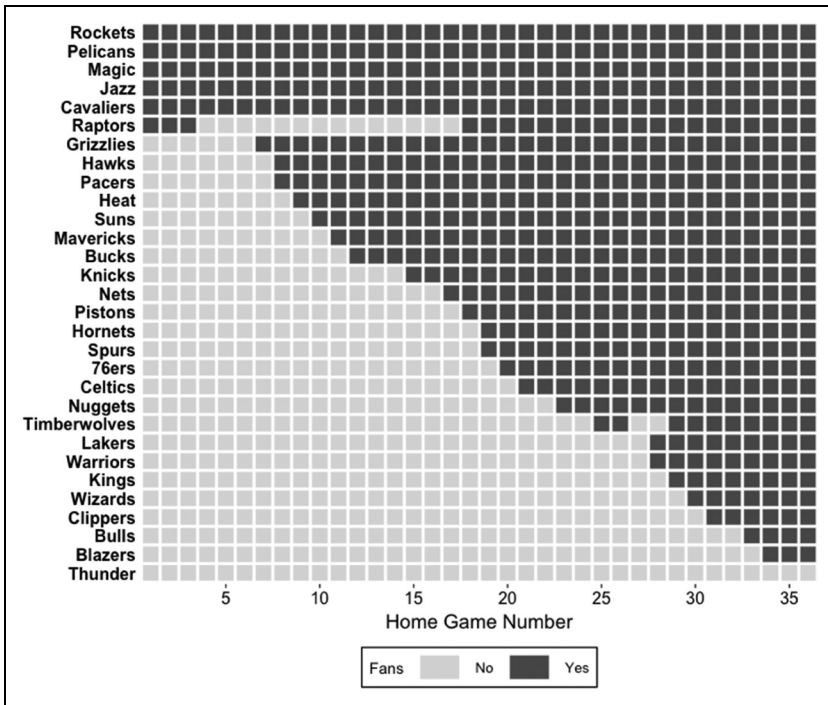


Figure 4. The presence of fans in home games during the 2020-2021 season.

Several variables related to game information are included in models. We use the variable *National TV* with the value of 1 to indicate games that were broadcast on national television based on data collected from espn.com. These nationally televised games are under special scrutiny and thus may change how referees make decisions on the court (Rocha et al., 2013; Yewell et al., 2014). Point spread data from covers.com is used to measure the relative strength between two competing teams. Prior research suggested that underdogs are more likely to receive favored calls than other teams (Dawson et al., 2007). Lastly, we calculate score differentials for all plays in L2Ms by using the home team score minus the away team score at the time of the play. Team scores are collected from NBA play-by-play data on basketball-reference.com. The prior literature suggests referees may officiate games differently when home teams are behind their opponents (Garicano et al., 2005).

We also gather referee data to control for heterogeneity in referees. Specifically, we consider referees' age and experience as both of them are likely to affect their officiating performance (Weston et al., 2011). We calculate the referee's age by using a given NBA game date subtracting referee's birthdate. Experience is estimated by counting the number of games referees have officiated in prior seasons. Since all

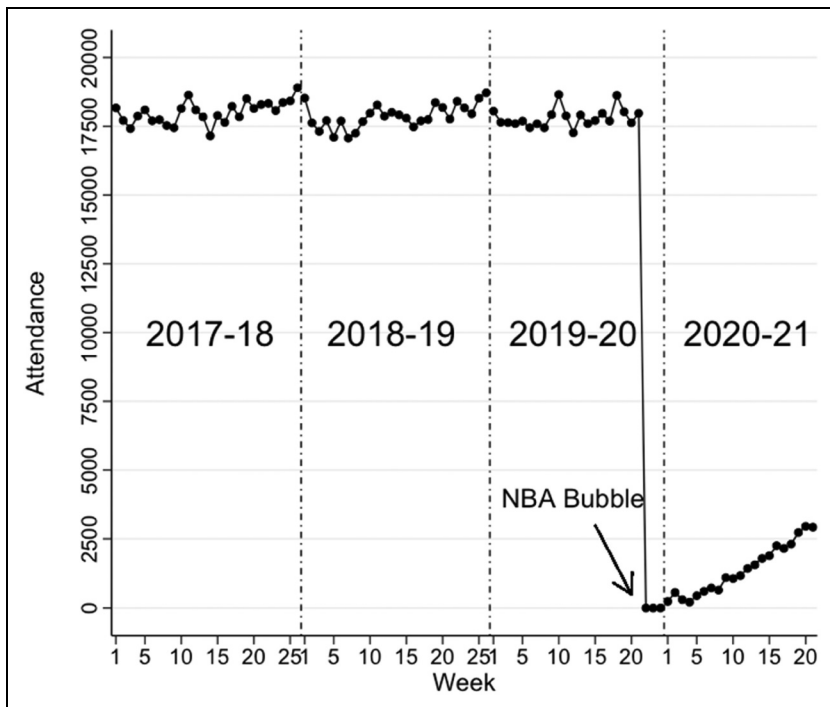


Figure 5. Average weekly attendance from the 2017-2018 to 2020-2021 seasons.

NBA games are officiated by three referees, we average their ages and count their total number of officiated games to construct the variables *Age* and *Experience* for a given play in L2Ms.

3.2 Empirical Strategy

One of the key challenges in identifying the impact of the crowd on home bias is to differentiate player and referee behavior as both of them are likely to be affected by crowds (Price et al., 2012). Without accounting for the change in player behavior, econometric models may suffer from endogeneity issues, resulting in biased estimation regarding the effect of crowd support on home bias.

We address the aforementioned issue by analyzing the correctness of foul calls and non-calls from NBA L2Ms at the play level. By assuming that the probability of ICs and INCs is independent of player behavior, we expect NBA referees will officiate games at the same level of accuracy regardless of how hard players compete. This assumption allows us to directly test the impact of the home crowd on home bias, without worrying that the change in referees' performance is caused by players.

Overall, our analysis takes two steps. We first explore the existence of home bias and the overall impact of the crowd on the probability of ICs and INCs in the NBA by using the following model specification:

$$Y_{it} = \beta_0 + \beta_1 Home_{it} + \beta_2 Fan_{it} + X'_{it}a + \sigma_{rhv} + \tau_{yw} + \varepsilon_{it} \quad (1)$$

where Y_{it} takes the value of 1 for ICs and INCs in play i at game t and 0 otherwise. $Home_{it}$ is a dummy variable with 1 indicating the foul committing player in play i is from the home team in game t and 0 otherwise. Fan_{it} is also a dummy variable with 1 meaning fans are allowed in play i at game t and 0 otherwise. X_{it} contains a set of control variables, including the player all-star status, nationality, seconds left, national TV game, favorite, score differential, etc. The term σ_{rhv} includes referee, home team, and visiting team fixed effects. τ_{yw} represents season and week fixed effects. ε_{it} is an error term capturing unobserved effects on referees' performance. Consider the natures of foul calls and non-calls in L2Ms, we analyze the probability of ICs and INCs in two separate models, one for ICs and CCs and the other one for INCs and CNCs.

After exploring the existence of home bias and the overall effect of the crowd on referees' officiating performance, we then study the effect of the crowd on home bias. Specifically, our second model, Equation (2), extends Equation (1) by adding the interaction term between the $Home_{it}$ and Fan_{it} variables in order to estimate how home bias may change when arenas are filled with fans, relative to empty venues.

$$Y_{it} = \beta_0 + \beta_1 Home_{it} + \beta_2 Fan_{it} + \beta_3 Home_{it} * Fan_{it} + X'_{it}a + \sigma_{rhv} + \tau_{yw} + \varepsilon_{it} \quad (2)$$

We estimate both Equations (1) and (2) using the linear probability model with the Ordinary Least Squares (OLS) estimation method. While other models are available, we choose the linear probability model in this study because its estimators are relatively easy to interpret (Ai & Norton, 2003). We also cluster standard errors at the game level as the accuracy of foul calls or non-calls may be correlated in each game (Wooldridge, 2015).

To further study whether the estimation results from Equations (1) and (2) are driven by a specific type of fouls, we pay attention to various types of foul calls and non-calls documented in L2Ms. Specifically, we employ the same specifications in Equations (1) and (2) to perform separate regression analyses for each of the four most frequent foul types, personal, shooting, offensive, loose ball fouls. While L2Ms track more than 20 types of fouls, 96% of fouls can be found in one of the four fouls noted above.² Thus, we only explore these four foul types here instead of all of them. The detailed descriptions of these foul types can be found in Table 2.

Table 2. Foul Type Definitions.

Foul Type	Definition
Personal Foul ^a	Illegal personal contact with an opponent.
Shooting Foul	A player is fouled in the act of shooting. Free throws should be awarded regardless of the penalty situation.
Offensive Foul	Illegal personal contact initiated by an offensive player.
Loose Ball Foul	A foul committed when no team has the control of the ball.

Note. Detailed descriptions of fouls can be found here: <https://official.nba.com/rule-no-12-fouls-and-penalties/>.
^aSince shooting, offensive, and loose ball fouls can all be considered personal fouls and the NBA does not specify what constitutes personal fouls in L2Ms, we treat personal fouls here as common defensive fouls.

Table 3. Summary Statistics.

Variable	N	Mean	St. Dev.	Min	Max
IC	5,876	0.039	0.193	0	1
INC	24,819	0.060	0.237	0	1
Home	30,695	0.497	0.500	0	1
Fan	30,695	0.896	0.306	0	1
All-star	30,695	0.149	0.356	0	1
Seconds Left	30,695	51.5	36.2	0	123
Score Differential	30,695	0.224	3.7	-14	14
Nationality	30,695	0.728	0.445	0	1
National TV	30,695	0.238	0.426	0	1
Favorite	30,695	0.493	0.500	0	1
Age	30,695	45.3	4.9	32.5	62
Experience	30,695	696.1	240.9	171	1558

4. Results

Table 3 provides summary statistics. Overall, ICs account for 3.9% of 5,876 foul calls in L2Ms, while INCs make up 6% of 24,819 foul non-calls. Among a total of 30,695 plays examined in the present study, 49.7% of foul committing players are from home teams. About 15% of the plays involve all-star players, and 72.8% of the plays are related to U.S. players. Approximately half of the plays include players from favorite teams, according to betting odds data. The average seconds left for actions in L2Ms are 51.5 s, and the average score differentials are 0.224 points. Of all plays used in our research, almost 90% of the plays occurred in games with spectators in the stands, while the rest appeared in matches without fans. It is also important to note that all games played behind closed doors in our analysis are from the 2020–2021 pandemic season. We did not include NBA bubble games as these

games took place in a site that is vastly different from regular NBA facilities. The summary statistics table also shows approximately 23.8% of plays occurred in national TV games. The average age of referees is 45.3 and total officiating experience is 696 games.

4.1 Home Bias and Crowd Support

We first report the estimation results for Equation (1) in Table 4. Recall that Equation (1) considers the evidence of home bias and the overall impact of crowd support on referees' officiating performance. Column 1 of Table 4 contains the results for the model using INCs and CNCs as the dependent variable. The estimated coefficient on *Fan* is not statistically significant. This is evidence that crowd support may not affect referees' overall performance in foul non-calls. The parameter estimate on *Home* is not significant, indicating that referees do not favor home teams over away teams in foul non-calls during clutch time in the NBA regular season.

Table 4. Foul Non-Call Models Without the Interaction Term (INC vs. CNCs).

Variable	(1) All	(2) Personal	(3) Shooting	(4) Offensive	(5) Loose Ball
Home	0.000 (0.003)	-0.002 (0.006)	0.008 (0.007)	-0.004 (0.005)	0.024* (0.011)
Fan	0.012 (0.007)	0.006 (0.012)	-0.005 (0.013)	0.023* (0.011)	0.030 (0.024)
All Star	-0.001 (0.004)	-0.006 (0.008)	0.002 (0.009)	-0.002 (0.007)	-0.000 (0.015)
Seconds Left	-0.0001* (0.0000)	-0.0001 (0.0001)	0.0003*** (0.0001)	-0.0003*** (0.0001)	-0.0004* (0.0001)
Score Differential	0.000 (0.000)	0.001 (0.001)	-0.002* (0.001)	0.001 (0.001)	-0.001 (0.001)
Nationality	0.005 (0.004)	0.009 (0.006)	0.001 (0.007)	0.015** (0.005)	-0.014 (0.012)
National TV	-0.001 (0.004)	0.005 (0.008)	-0.010 (0.009)	0.010 (0.007)	-0.026 (0.014)
Favorite	-0.003 (0.000)	0.002 (0.002)	-0.011 (0.008)	-0.003 (0.004)	0.004 (0.011)
Age	-0.144 (0.314)	-0.276 (0.588)	1.095 (0.586)	-0.736 (0.526)	-1.363 (1.001)
Experience	-0.000 (0.000)	-0.001 (0.001)	-0.000 (0.001)	-0.000 (0.000)	0.002 (0.001)
N	24819	7071	6945	7168	3011
R ²	0.017	0.051	0.054	0.054	0.124

Note. Standard errors in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01.

Columns 2 to 5 of Table 4 report the regression analysis results for Equation (1) across four foul types in the model using INCs and CNCs as the dependent variable. Specifically, the estimated parameter on *Fan* is significant only in the Offensive foul model, but not in the other three models. This result implies that the presence of fans will increase the probability of INCs in offensive fouls by 2.3%, compared to empty arenas. Another interesting finding from Columns 2 to 5 of Table 4 is that the estimate on *Home* is significant in the Loose Ball foul model. Specifically, the model shows referees are 2.4% more likely to miss loose ball foul calls on home teams than away teams, providing some evidence of home team favoritism in the NBA. This finding is also evident in Figure 6 that shows the probability of INCs in loose ball fouls for home teams is consistently higher than away teams over the four seasons examined in the present study.

We now turn to report the estimation results for Equation (1) using ICs and CCs as the dependent variable in Table 5. The insignificant estimate on *Home* in Column 1 implies that referees do not favor home teams by calling more incorrect calls on away teams than home teams. The parameter estimate on the *Fan* variable is not significant

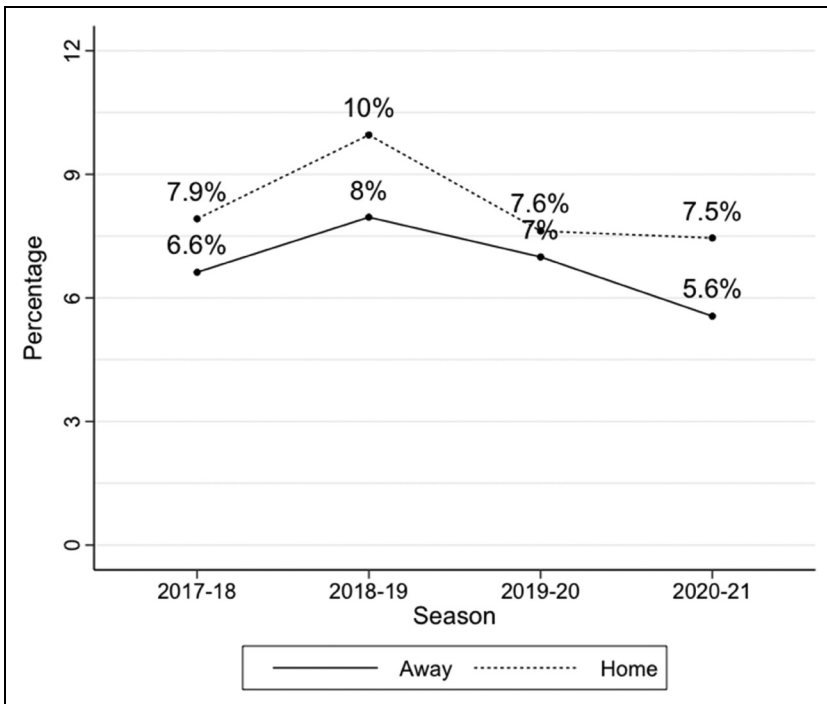


Figure 6. Percentage of loose ball foul INCs for home and away teams from the 2017-2018 to 2020-2021 seasons.

Table 5. Foul Call Models Without the Interaction Term (ICs vs. CCs).

Variable	(1) All	(2) Personal	(3) Shooting	(4) Offensive	(5) Loose Ball
Home	0.006 (0.006)	0.002 (0.008)	0.013 (0.014)	0.151 (0.319)	-0.165 (0.330)
Fan	0.001 (0.012)	0.007 (0.015)	0.013 (0.036)	-23.760 (39.353)	-1.290 (2.761)
All Star	0.009 (0.009)	0.004 (0.010)	-0.004 (0.022)	0.244 (0.636)	0.021 (0.430)
Seconds Left	0.0003*** (0.0001)	0.0004*** (0.0001)	-0.0003 (0.0002)	0.002 (0.009)	-0.001 (0.004)
Score Differential	0.001 (0.001)	-0.000 (0.001)	0.001 (0.002)	0.089 (0.168)	-0.021 (0.085)
Nationality	-0.013 (0.007)	-0.005 (0.008)	-0.008 (0.016)	-0.026 (0.647)	-0.090 (0.237)
National TV	0.001 (0.007)	-0.007 (0.008)	0.029 (0.021)	-3.664 (7.562)	0.395 (0.797)
Favorite	0.008 (0.006)	0.003 (0.007)	0.021 (0.016)	-0.054 (0.443)	0.186 (0.342)
Age	0.092 (0.485)	-0.046 (0.588)	1.915 (1.397)		
Experience	0.000 (0.000)	0.001 (0.001)	0.000 (0.001)		
N	5876	3276	1652	224	271
R ²	0.058	0.113	0.198	0.924	0.875

Note. Standard errors in parentheses. * $p < 0.5$; ** $p < 0.01$; *** $p < 0.001$.

either, indicating that crowd support does not generally increase the probability of ICs.

Columns 2 to 5 of Table 5 report the results for four foul types from the foul call model using the specification in Equation (1). None of the estimates on *Home* are statistically significant, consistent with the finding in Column 1. These results suggest home bias related to foul calls may not exist during clutch time in the NBA regular season. The same insignificant results can be observed on the *Fan* variable from Columns 2 to 5. These findings are consistent with the results in Column 1, showing that fans cheering in arenas does not cause referees to make more ICs.

4.2 The Effect of the Crowd on Home Bias

So far, we have reported analysis results for the models examining home bias and the overall impact of the crowd on referees' performance. We now show the analysis results for the models using the specification in Equation (2). Recall that the interaction term between the *Fan* and *Home* variables is added to Equation (2) in order to

investigate whether crowd support is a source of home bias. Table 6 presents the analysis results for the models with INCs and CNCs as the dependent variable. Columns 1 reports the results for the model using the full data set of foul non-calls and Columns 2 to 5 contain the analysis results for four foul types. All estimated coefficients on the interaction term between *Home* and *Fan* are not statistically significant, meaning referees do not treat home and away teams differently in foul non-calls when fans are present, relative to the absence of the crowd.

We now report the estimation results on control variables from the foul non-call models in Table 6. Among all control variables included in the model, the *Seconds Left* variable has a significant impact on the probability of INCs. Interestingly, the relationship between seconds left and the probability of INCs varies across different foul types. For example, seconds left do not seem to matter to the occurrence of personal foul INCs. On the other hand, the Offensive and Loose Ball foul models present a negative relationship, meaning referees are more likely to miss offensive and loose

Table 6. Foul Non-Call Models with the Interaction Term (INC vs. CNCs).

Variable	(1) All	(2) Personal	(3) Shooting	(4) Offensive	(5) Loose Ball
Home	0.003 (0.008)	0.004 (0.015)	0.022 (0.016)	-0.016 (0.012)	0.025 (0.034)
Fan	0.014 (0.008)	0.010 (0.014)	0.003 (0.015)	0.017 (0.013)	0.031 (0.028)
Home × Fan	-0.003 (0.009)	-0.007 (0.016)	-0.016 (0.017)	0.013 (0.013)	-0.001 (0.036)
All Star	-0.001 (0.004)	-0.006 (0.008)	0.002 (0.009)	-0.002 (0.007)	-0.000 (0.015)
Seconds Left	-0.0001* (0.0000)	-0.0001 (0.0001)	0.0003*** (0.0001)	-0.0003*** (0.0001)	-0.0004* (0.0001)
Score Differential	0.000 (0.000)	0.001 (0.001)	-0.002* (0.001)	0.001 (0.001)	-0.001 (0.001)
Nationality	0.005 (0.004)	0.009 (0.006)	0.001 (0.007)	0.015** (0.005)	-0.014 (0.012)
National TV	-0.001 (0.004)	0.005 (0.008)	-0.010 (0.009)	0.010 (0.007)	-0.026 (0.014)
Favorite	-0.003 (0.003)	0.002 (0.006)	-0.011 (0.006)	-0.003 (0.005)	0.004 (0.011)
Age	-0.144 (0.314)	-0.276 (0.588)	1.099 (0.585)	-0.728 (0.527)	-1.363 (1.001)
Experience	-0.000 (0.000)	-0.001 (0.001)	-0.000 (0.001)	-0.000 (0.000)	0.002 (0.001)
N	24819	7071	6945	7168	3011
R ²	0.017	0.051	0.054	0.054	0.124

Note. Standard errors in parentheses. *p < 0.5; **p < 0.01; ***p < 0.001.

ball foul calls toward the end of the period. Furthermore, the Shooting foul model suggests that the probability of referees missing shooting foul calls will significantly increase with a few seconds left on the game clock.

Score differentials also affect the probability of INCs in the Shooting foul model. Recall score differentials are calculated by using the home team score minus the away team score at the occurrence of a foul call or non-call. The positive and significant parameter estimate on *Score Differential* suggests the more the home team leads, the less likely referees will miss shooting foul calls. The positive and significant estimate on *Nationality* in the Offensive foul model presents another interesting finding. Recall the *Nationality* variable takes the value of 1 for U.S. players and 0 for non-U.S. players. The results from the Offensive foul model suggest referees are 1.5% more likely to miss an offensive foul call on U.S. players than non-U.S. players. None of the other control variables are statistically significant in affecting the probability of INCs.

Table 7. Foul Call Models with the Interaction Term (ICs vs. CCs).

Variable	(1) All	(2) Personal	(3) Shooting	(4) Offensive	(5) Loose Ball
Home	0.017 (0.018)	0.003 (0.026)	-0.035 (0.041)	-0.112 (0.468)	0.106 (1.081)
Fan	0.006 (0.015)	0.007 (0.019)	-0.014 (0.041)	-21.175 (40.833)	-0.976 (4.037)
Home × Fan	-0.012 (0.019)	-0.001 (0.026)	0.054 (0.044)	0.296 (0.426)	-0.294 (1.207)
All Star	0.009 (0.009)	0.004 (0.010)	-0.003 (0.022)	0.256 (0.629)	0.065 (0.520)
Seconds Left	0.0003*** (0.0001)	0.0004*** (0.0001)	-0.0003 (0.0001)	0.002 (0.010)	-0.001 (0.004)
Score Differential	0.001 (0.001)	-0.000 (0.001)	0.001 (0.002)	0.089 (0.175)	-0.032 (0.137)
Nationality	-0.013 (0.007)	-0.005 (0.008)	-0.008 (0.016)	-0.027 (0.670)	-0.079 (0.248)
National TV	0.001 (0.007)	-0.007 (0.008)	0.029 (0.021)	-3.225 (7.875)	0.492 (1.082)
Favorite	0.008 (0.006)	0.003 (0.007)	0.020 (0.016)	-0.093 (0.435)	0.174 (0.338)
Age	0.092 (0.485)	-0.046 (0.587)	1.936 (1.393)		
Experience	0.000 (0.000)	0.001 (0.001)	0.000 (0.001)		
N	5876	3276	1652	224	271
R ²	0.058	0.113	0.199	0.926	0.877

Note. Standard errors in parentheses. *p < 0.5; **p < 0.01; ***p < 0.001.

Table 7 reports the findings for the model using the specification in Equation (2) with ICs and CCs as the dependent variable. Similar to foul non-call models, we report the results for the full model in Column 1 and four foul types in Columns 2 to 5. None of the estimated coefficients on the interaction term are statistically significant, offering consistent evidence that the gap in the probability of ICs between home and away teams does not change with and without fans in the stands.

Moving to the control variables from the foul call models in Table 7, the estimated coefficient on *Seconds Left* is positive and significant in Column 1, offering evidence that referees are less likely to make ICs toward the end of the game. The estimation results in Columns 2 to 5 also suggest that the positive relationship between *Seconds Left* and the probability of ICs largely exists in personal fouls. None of the other control variables are statistically significant in affecting the probability of ICs.

4.3 Robustness Checks

We perform a series of robustness checks in order to test the robustness of the analysis results for the variable of interest, which is the interaction term between the *Fan* and *Home* variables in Equation (2). First, we conduct several placebo tests that examine whether estimation results will change when they ought not to. We also address some endogeneity concerns due to the pandemic effect. Then, our robustness checks re-examine the estimation results by using the data only from the 2020–2021 season in which all games were played during the COVID-19 pandemic. We also consider how different levels of crowd size and the timing of the competition will affect estimation results. The last few robustness checks analyze INCs at the game level, coach's challenge and instant replay (NBA, n.d.b), as well as outliers in model estimations.

Overall, the results from robustness checks are consistent with our main findings, which suggest that crowd support does not cause referees to treat home and away teams differently in late-game situations during the NBA regular season. The full analyses of the robustness checks can be found in Appendix A.

5. Discussion

The present study aims to study the impact of the crowd on home bias in the NBA. To do this, we first check the existence of home bias and examine the overall impact of the crowd on NBA referee performance by using L2M data through Equation (1). Our research offers evidence that home bias may not widely exist in crucial situations during the NBA regular season, except for INCs in loose ball fouls. Figure 6 visualizes the probability of INCs in loose ball fouls between home and away teams from the 2017–2018 to 2020–2021 seasons. This finding is expected as among the four foul types examined in the present study, judging the side that commits loose ball fouls requires the most referees' discretion. According to the NBA league office, loose ball fouls occur when no team has control of the ball (NBA, n.d.c). Our analysis

results showing home teams are more likely to receive INCs in loose ball fouls than away teams illustrate that referees may favor home teams through missing more loose ball fouls that should be called on home teams.

Apart from loose ball foul INCs, our research is largely in line with two prior research that shows little evidence of home bias in the NBA. For example, Price et al. (2012) found some evidence of home bias in the NBA, but also noted that such bias was significantly mitigated in the fourth quarter. Their findings may be consistent with our results from NBA L2Ms, which only document foul calls and non-calls in the last two minutes of the fourth quarter and the last two minutes of over-times. Our analysis also echoes the study of home bias conducted by Deutscher (2015) who analyzed NBA L2M data from the 2014–2015 season. After analyzing foul calls and non-calls, the author did not find home team favoritism in the NBA. With conclusions from prior research and the present study, it is safe to summarize that home bias is not common in late-game situations during the NBA regular season.

In addition to testing the existence of home bias in the NBA, our research also offers analysis of the overall impact of the crowd on referees' performance. On the INC side, we show that referees are 2.3% more likely to miss calls in offensive fouls when fans are present. The correctness of other foul non-calls does not seem to be affected by the presence of the crowd. This finding is also expected as offensive fouls are often considered the most difficult foul to judge in basketball. This is evident in our data set where the offensive foul calls have the lowest accuracy rate among four foul types. As a result, it is not surprising that the presence of the crowd may pressure referees to miss more offensive foul calls. For ICs, our analysis does not find evidence that crowd support results in a higher probability of ICs. This finding is different from previous research that examines the correctness of referees' decisions in European football. For example, Dohmen (2008) used data from the German soccer league and found when fans were closer to the field, referees became more likely to grant wrong or disputable penalty kicks.

Through Equation (2), our analysis reveals that crowd support does not cause referees to favor home teams over away teams in foul calls and non-calls, relative to the absence of the crowd in NBA games. Our finding is in line with a few studies examining the effect of the crowd on home bias (e.g., Fischer and Haucap, 2021) but contradicts most prior research that concluded the missing crowd leads to reduced home bias in European football leagues during the COVID-19 pandemic (e.g., Bryson et al., 2021; Endrich & Gesche, 2020; Scoppa, 2021; Sors et al., 2021).

While our study offers a different conclusion regarding the relationship between crowd support and home bias than prior research, it is critical to recognize a few differences between our study and previous work. First, our research employs play-level data that are not used in most prior work. In particular, the present research employs play-by-play data from NBA L2Ms that track the correctness of foul calls or non-calls at the end of close games, whereas existing research often analyzes data, such as the number of yellow, red cards, fouls, penalty kicks, at the game level or minute level. The availability of play-level data allows us to control for more factors that can

potentially affect refereeing decisions, and thus produces more precise estimation of the influence of the crowd on home bias. Another possible reason that our analysis draws a different conclusion than most prior research may relate to the nature of L2M data. As noted before, L2Ms only document the plays in the last two minutes of the fourth quarter and overtimes in qualified games. Referee behavior in other periods of the game and games with large score differentials are not documented by L2Ms. Thus, it is possible that referees are influenced by crowds when making officiating decisions on home and away teams in periods or games that are not covered by L2Ms. The last possible reason for our finding is that referees may be well aware that their actions are closely monitored in the last two minutes of the fourth quarter and overtimes in close games, since their foul calls and non-calls will be reported and evaluated in L2Ms. Thus, NBA referees may exercise extra caution in officiating during these periods as their refereeing performance could be linked to their promotion and contract extension (Deutscher, 2015; NBA, n.d.d.).

Our study also offers evidence that the home crowd may not contribute to the home advantage through pressuring referees to favor home teams in the NBA. A wealth of studies has argued that one mechanism of how the home advantage is created is through home crowds pressuring referees to give favorable treatments toward home teams. (Boyko et al., 2007; Goumas, 2014; Johnston, 2008; Sors et al., 2021). If the crowd does help create the home advantage through affecting referees' judgment, then referees should be more biased toward home teams in games with fans than matches without fans. Yet, our study shows that while NBA referees seem to favor home teams over their opponents in loose ball foul non-calls, the gap in the probability of loose ball foul INCs between home and away teams does not change when teams compete in empty NBA arenas during the COVID-19 pandemic. In other foul types and call types, we do not find evidence of home bias in the NBA nor do we detect any change in the relative difference of the probability of ICs and INCs between home and away teams in games with and without fans.

6. Conclusion

The present study investigates the effect of the crowd on home bias by comparing NBA games played in empty arenas during the COVID-19 pandemic and games played before the pandemic. Using data from NBA L2Ms, our research provides consistent evidence that the presence of fans does not lead referees to treat home and away teams differently in clutch time during the NBA regular season. In the meantime, our research offers evidence that crowd support will increase the probability of INCs in offensive fouls by 2.3% late in a game, indicating fans can affect referees' decision-making process in general. The present study also reveals some evidence of home bias in loose ball foul non-calls. Data analysis shows that referees are 2.4% more likely to miss a loose ball foul on home teams than away teams. Other foul calls and non-calls do not present home team favoritism.

Consider these findings, our research makes three significant contributions to the home bias literature. First, our study takes advantage of the games played during the COVID-19 pandemic, almost half of which do not have fans in the stands. This setting creates a natural experiment to examine whether fans contribute to home bias. The majority of prior research studying how crowd support affects home bias relies on investigating the change in attendance as attendance data are often observable in most sporting events (e.g., Garicano et al., 2005; Sutter & Kocher, 2004). Our research advances the existing work by comparing games with fans completely removed from the stands to games with fans in the stands.

Second, our analysis employs play-by-play data from NBA L2Ms to isolate referee behavior from player behavior, producing more accurate estimation of the relationship between the crowd and home bias. Most prior research used game-level and minute-level data, such as stoppage time, penalty kicks, and yellow cards, to study the impact of fans on home bias (Boyko et al., 2007; Buraimo et al., 2010). Despite the use of numerous control variables, prior research may not fully rule out the possibility that the reduced home bias in empty stadiums is caused by the change in player behavior (Buraimo et al., 2012). Our research addresses this issue by examining the correctness of foul calls and non-calls at the play level, which allows us to directly test the impact of fans on referees' officiating decisions.

Third, most prior inquiries on home bias center on European football (Dohmen & Sauermann, 2016). The present study advances prior studies by examining home bias in one of the most popular North American sports leagues, the NBA. Our research draws different conclusions from previous studies, highlighting the importance of considering home bias in different sports and leagues (Bryson et al., 2021).

A few limitations of the present study need to be noted. First, our research examining the effect of the crowd on home bias only considers close games in which score differentials between two teams are equal or fewer than three points at any point during the final two minutes of the fourth quarter or overtime (NBA, n.d.a). Thus, the findings from our study may not apply to all NBA games. In addition, the data set used in the present study, NBA L2Ms, only documents foul calls and non-calls that happened late in a game. Late-game situations are significantly different from other periods of the game, especially when a single foul call or missed foul call may dictate game outcomes toward the end of the games or in overtimes. Therefore, our analysis may not predict how referees will behave in other game situations.

Future research may further explore home bias and the effect of the crowd on home bias under more complicated situations. With the availability of NBA L2Ms, scholars may consider examining referee bias in the playoffs. It is believed that the intensity and stake of playoff games are drastically different from regular-season games (Price et al., 2012). Thus, referees may face more social pressure or scrutiny in playoff games. Future studies may investigate whether home bias will occur during the playoffs or how the playoff crowd will affect home bias in the NBA.

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Supplemental material

Supplemental material for this article is available online.

Notes

1. Other call types include turnovers, instant replay, violation, stoppage, ejection, etc.
2. The rest includes defensive 3-second, personal take, away from play, technical, etc.

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