Identifying the Impact of A Decrease in Attendance on Home Court Advantage*

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Abstract

Fan support is a critical component in establishing home court advantage across many sports. Whether the impact is on referee decision making or psychologically affecting opposing teams, fans influence the outcome of games. Due to varying degrees of local and state ordinances, the 2020-2021 college basketball season created the opportunity to explore the impact of home court advantage when fans were not allowed to attend some matches. We exploit differences in conference-level policies to measuring the impact of fan attendance on home advantage before and during the pandemic with attendance restrictions. Our results suggest that policies restricting attendance during the Covid-19 pandemic more strongly impacts the home advantage (measured by score differential) for teams in power conferences relative to those in mid-major and low-major conferences.

JEL Classification: I18, L83, M54, Z20
Keywords: attendance; college basketball; Covid-19 pandemic; home advantage

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1 Introduction

Home advantage, the propensity of the home team to win more often than the away team, in sports has been well documented over the past few decades, but researchers haven't always been able to separate the specific factors impacting that advantage. The Covid-19 pandemic, coupled with various state and organizational policies across the United States which led to unprecedented restrictions on mass gatherings like sports events, has created an opportunity to measure the impact fans have on home advantage. The first wave of the pandemic impacted professional leagues in the United States and forced many to operate in a "bubble." Bubbles were isolation zones created for teams in professional sports leagues to reside and quarantine in during the season, providing protection to players during the Covid-19 pandemic. By the start of fall 2020, some major collegiate conferences, like the PAC-12 and Big 10, announced the cancellation of the football season due to the pandemic. After other major conferences, notably the SEC, continued with its football season, the PAC-12 and Big 10 reversed course and played a reduced schedule. At the Football Championship Subdivision (FCS) level, some teams and leagues opted to play a fall schedule while others deferred to the spring. Because football is the first intercollegiate season of the academic year, conferences scrambled to determine attendance policies. Intercollegiate basketball starts later in the Fall and most conferences opted to play a slightly modified schedule that limited the amount of travel for teams.[1].

Across most of the United States, there are 351 Division I basketball programs organized in 32 different conferences.[2] At the end of the season, 68 of those programs are selected to play in a tournament to determine a national champion. Teams often boast of the impact of their student section and the importance of playing at home, but the literature is varied on which part of the game day experience is responsible for home advantage. Successful collegiate sports program, more broadly speaking, play a role in furthering its university's

[1] During the summer of 2020, eight conferences announced their intent to cancel Fall 2020 sports, but only the Ivy League actually canceled their season.

[2] Alaska is the only state without a Division I basketball program.

mission. Perez (2012) found that successful Division I college basketball programs significantly increased the size of a university's incoming freshman class from the region, and Smith (2008) found a positive relationship between success on the court and the SAT scores of the incoming first-year class.

Some researchers lament that sports detract from the teaching mission of a university, but Smith (2008) found relatively inconclusive impacts of college basketball programs on academic success while Lindo et al. (2012) and Hernández-Julián and Rotthoff (2014) find negative impacts on academic success following successful football seasons. These results are consistent even for teams that experience unexpected success in the end-of-year playoff tournament (Collier et al., 2020). When teams experience a high level of success and earn a spot in the national championship tournament, White et al. (2019) find that binge drinking increased 47% by male students. There is a negative impact on student quality if teams are caught engaging in extralegal activity to improve (e.g. engaging in academic fraud or providing improper benefits) due to the associated negative publicity and post-season bans (Eggers et al., 2020). While athletic events may not have a significant academic impact on students, Insler and Karam (2019) finds causal evidence of decreased academic performance associated with athletic participation.

The present article analyzes the impact of playing on a familiar court by exploiting attendance restrictions during the 2020-2021 NCAA college basketball season. Carlin et al. (2021) estimate that counties hosting an additional NCAA Division I men's game in March 2020 resulted in 34 additional deaths. After the United States became more aware of the severity of the eventual pandemic, counties and states responded with significant restrictions on in-person gatherings. Because of the pandemic-related protocols, teams played home games in front of very limited crowds or without any spectators at all in the 2020-2021 season. Fans are often credited with being one of the primary components of home advantage, and the removal of this significant factor allows us to quantify how much of home court advantage can be attributed to fan attendance.

2 Literature Review

Home advantage has been studied and analyzed across multiple disciplines. The general consensus is that home advantage is driven by a set of game-specific factors related to crowd size, the players' familiarity with the facilities, and the impact of travel. Schwartz and Barsky (1977) was one of the earliest works to focus on home advantage, looking at professional leagues for baseball, football, hockey, and five college basketball teams in the Pennsylvania area. The authors found that home advantage was magnified for basketball and hockey, relative to football and baseball, which was attributed primarily to the elimination of weather as a factor. In the decades that followed, other studies have focused on various factors surrounding the game itself and what effect the crowd plays in that outcome, particularly with respect to referee bias.[3] Home advantage is not limited to team sports but can also be found in individual sports as unique as skeleton (Chun and Park, 2021) or biathletes (Harb-Wu and Krumer, 2019).

The inconvenience of traveling can negatively impact players by interrupting their daily routines, affecting classroom expectations, and fatigue related to time zone changes (Snyder and Purdy, 1985; Pace and Carron, 1992; Smith et al., 2000). Another outcome often studied in home advantage looks at referee bias (Sutter and Kocher, 2004), even though the results are inconclusive (Johnston, 2008). Regarding home advantage in basketball specifically, early studies by Varca (1980) and Snyder and Purdy (1985) focused on the Southeastern Conference and Mid-American Conference. Both find significant effects of home advantage for teams, but the studies analyze only one conference each. The notion of parity within one league is rare, except in the case of "basketball-rich" conferences, such as the Big East Conference[4]. The authors note that other factors may also affect the home team's winning percentage, including officiating bias, familiarity with the area, audience size, and density.

[3] For a broader review of factors influencing stadium attendance, see Schreyer and Ansari (2021).

[4] In 2011, the Big East Conference sent 11 (of their 16) teams to the NCAA tournament, with the lowest team receiving an 11 seed. In 2018, the Atlantic Coast Conference (ACC) sent 9 of their 15 teams to the tournament, with the lowest as an 8 seed.

Sport psychologists suggest that a favorable crowd impacts both player performance and officiating in favor of the crowd's preference. Previous work by Boudreaux et al. (2017) attempts to isolate the impact of a sympathetic crowd by analyzing the Lakers-Clippers rivalry in the National Basketball Association to control for non-crowd factors. The present study exploits the unprecedented opportunity represented by the pandemic to investigate presence versus absence of fans across Division I college basketball venues across the United States.

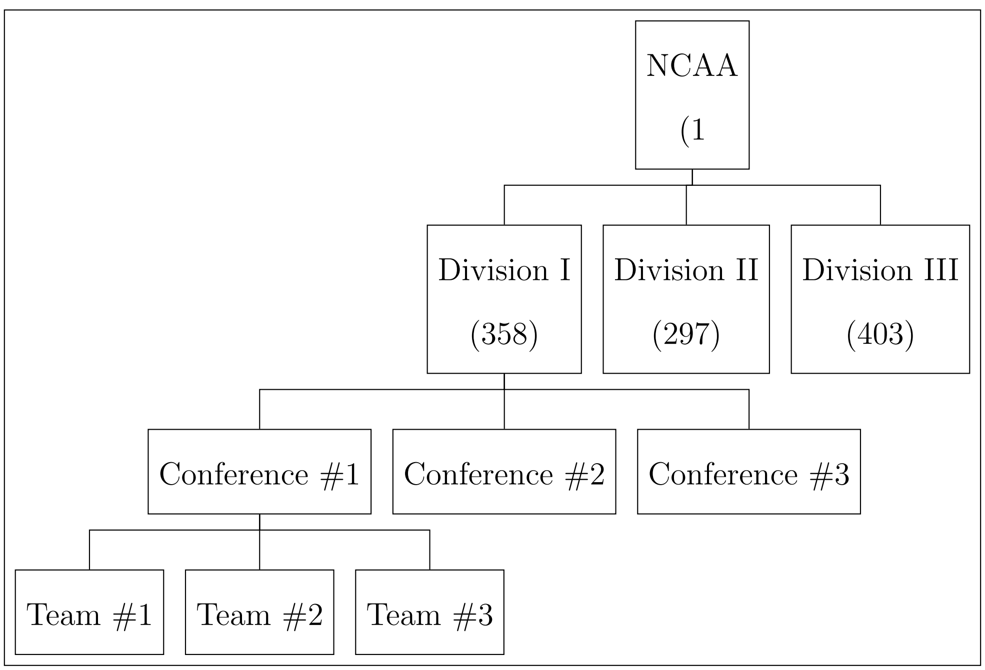
Nearly all of the previous work has focused to some extent on the impact of crowds on game outcomes, but the present study works in the opposite direction by focusing on "ghost games" in which crowds are not present. The first round of pandemic-related research in this area focused on association football (soccer), particularly in Germany. Losak and Sabel (2021) appear to be the first to look at how home advantage is impacted when playing "behind closed doors" in North America. Looking at data from Major League Baseball, Losak and Sabel (2021) find no statistically significant impact of attendance policies on home field advantage. Similar results were found in "ghost games" played in the German Bundesliga when Covid-19 restrictions unexpectedly restricted the number of fans allowed to attend matches (Dilger and Vischer, 2020). This contradicts findings associated with "ghost games" played in German association football (Fischer and Haucap, 2021) and the impact of officiating bias across European leagues during the pandemic restrictions (Bryson et al., 2021; Hill and Van Yperen, 2021). For collegiate football, McMahon and Quintanar (2021) find that the pandemic-induced restrictions on crowd sizes negatively impacted home advantage.

3 The Structure of American College Basketball

The NCAA is the governing body for the majority of collegiate sports in America, especially at the highest level of competition. The NCAA has divided all universities that sanction sports into three distinct divisions, which are based on the number of scholarships that a program is allowed to issue to its student athletes. The highest-ranked division of the NCAA is Division I (DI), while lower-ranked schools compete in Division II (DII), Division III (DIII), or outside the NCAA in a different association (such as the NAIA). Nearly all basketball games shown on major television networks each year are Division I games. We focus solely on Division I basketball games because of the similarities in scholarship requirements and other institutional characteristics across teams.

In Division I, there are 358 teams arranged into 32 conferences (NCSA Sports), but each conference contains varying numbers of teams. Men's college basketball is a nested framework in which **teams** are arranged in **conferences**, which are arranged in **divisions** by the organizing body, the National Collegiate Athletic Association (NCAA):

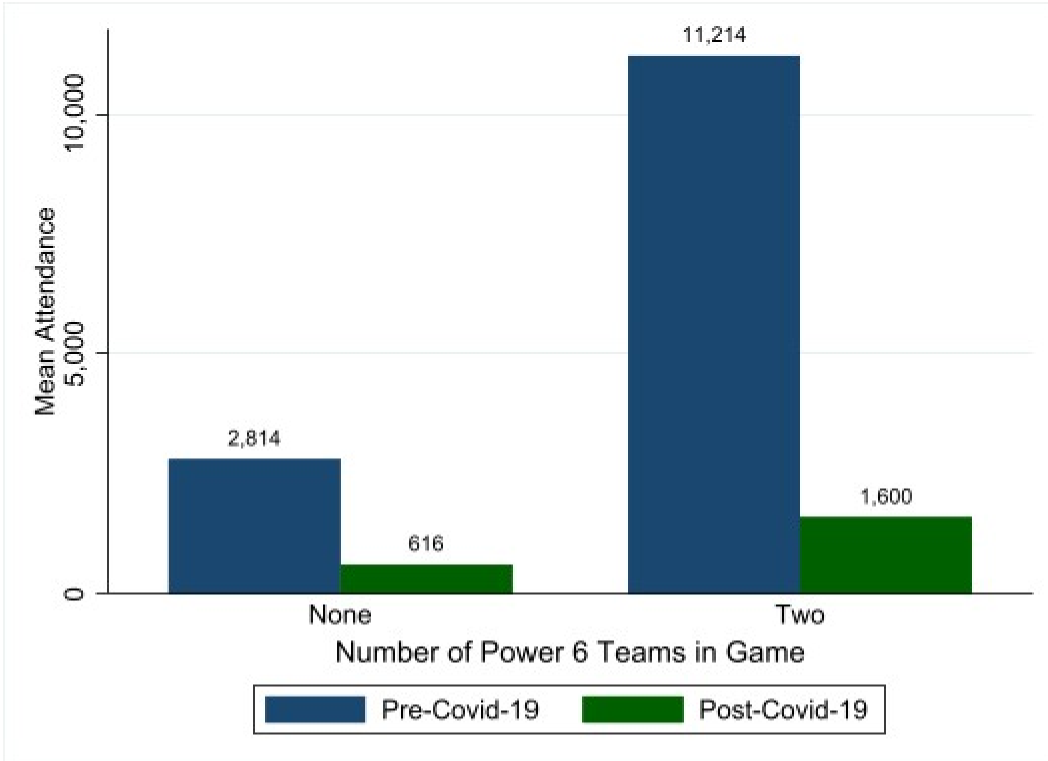
Figure 1: NCAA hierarchical relationship between teams, conferences, and divisions



Division I teams are classified into conferences, which are clusters of teams that are grouped for various reasons, including geography, academic prestige, media market power, alumni support, and overall athletic competitiveness. Over the past decade, conferences have become less about geographic proximity, and more about athletic competitiveness. If a team wishes to change conferences, it is often a multi-year process. While conference choice may be endogenous, including each conference as a control would deflate the standard errors of a linear regression. Using mixed effects modeling allows us to cluster conferences as a level to account for any random effects specific to conference selection. We divide our sample into two subgroups based on the quality of play that occurs at the conference level. The best conferences are often referred to as the “major” conferences while the remaining conferences are grouped together and referred to as “mid-major” conferences. The major conferences are often referred to as “Power 6” conferences because there are six major conferences in this group. Figure 2 shows the change in average home attendance during our sample when both teams in a game are from one of the non-Power 6 conferences and when each teams play in one of the Power 6 conferences. Appendix A1 lists the conferences associated with these two groupings.

In Figure 2, we notice two important differences. First, The average attendance between games played between two non-Power 6 teams and two Power 6 teams is significant in magnitude and statistically in the Pre-Covid-19 season. Mean attendance for games played between two non-Power 6 teams in the Pre-Covid-19 season is 2,814 and between two Power 6 teams is 11,214. Second, the change in average attendance due to pandemic restrictions was much greater for games played between two Power 6 teams. The mean pre-post-Covid-19 difference in attendance for games played between two non-Power 6 teams is 2,197 compared to 9,614 for games played between two Power 6 teams.

Figure 2: Average attendance before and after Covid-19 restrictions



Note: The difference in mean attendance (before and during Covid-19 restrictions) in competitions between two Power 6 teams and two non-Power 6 teams is statistically significant at the 1% level.

Unlike professional sports, college sports programs have the ability to make scheduling decisions years in advance along with a requirement to play a predetermined conference schedule. During the course of a basketball season, games are divided into two specific types: non-conference and conference games. Non-conference games are scheduled by the athletic department prior to the start of the season. As the name implies, these games involve teams from two different conferences competing against each other. There are few rules regarding who teams schedule for their non-conference opponents, but the most common is a limit on the number of teams below DI level. For this study, we only consider games played between two DI teams. For conference games, which usually occur in the second half of the season, games are scheduled at the conference level. These games often feature teams alternating between home and away games. Each conference has its own specification for scheduling its games, but each conference attempts to balance the number of home and away games for its teams each year. Because opponent choice in non-conference games is an endogenous variable, we cluster at the team level to account for opponent selection. As a robustness check, we estimate our model by looking only at conference games. In most conferences, teams play each other twice in a season–once at home and once away.

4 Data and Methods

4.1 Data Summary and Motivation

In order to investigate the impact of attendance on home court advantage in NCAA DI men's college basketball, we utilize the exogenous variation in attendance from the Covid-19 shock. Thus, we have a pre-Covid-19 period (the 2019-2020 season which abruptly ended in March 2020 when the virus surged in the U.S. and restrictions were implemented) and a post-Covid-19 period (the 2020-2021 season) that did not allow many or any fans in attendance at most games.

We assembled a data set of 14,634 observations (7,317 games) that occurred in the 2019-2020 season and the 2020-2021 season.[5] Because each game is played by two teams, the data set has two observations for each game to account for each variable's impact on the outcome variables for both the home and away teams. All games in the sample were regular season games played between two NCAA Division I teams at non-neutral locations, prior to any conference or national post-season tournament. Data were collected on game score, competition site, attendance, and season win percentage for each team at the time of game from Sports Reference[6] and cross-checked with the NCAA's online statistics archive.[7] To compute the distance between the away team's home court and playing location, we calculated

[5]Data for the 2019-2020 season began on November 5, 2019 and lasted until March 8, 2020 totaling 4,241 games and 8,482 observations. Data for the 2020-2021 season began on November 25, 2020 and was collected through March 7, 2021 totaling 3,076 games and 6,152 observations.

[6]https://www.sports-reference.com/cbb

[7]http://web1.ncaa.org/stats/StatsSrv/rankings?sportCode=MBB

straight-line distances between the two teams' arenas using geocoded stadium addresses from Google Maps.[8]

The conferences in NCAA Division I basketball are commonly separated into two groups based, non-Power 6 and Power 6, based on historical eliteness, success, and level of competition. Although the NCAA does not officially make this distinction, for the purposes of this study, it is important to differentiate between the two levels. In the Appendix, Table A1 lists the groupings of conferences into these two categories. We expect there to be a differential impact of the exogenous change in attendance due to Covid-19 for game outcomes between Power 6 and non-Power 6 conferences. Thus, we split the sample into two groups: games played between two Power 6 teams and games played between two non-Power 6 teams.[9] Figure 3 shows the differences in the attendance distribution of games played between two teams from a Power 6 conference and two teams from a non-Power 6 conference.[10] From this histogram, we can that the lowest levels of attendance have by far the highest frequency in games played between two non-Power 6 teams. Conversely, high levels of attendance are more common in games played between two Power 6 teams.[11]

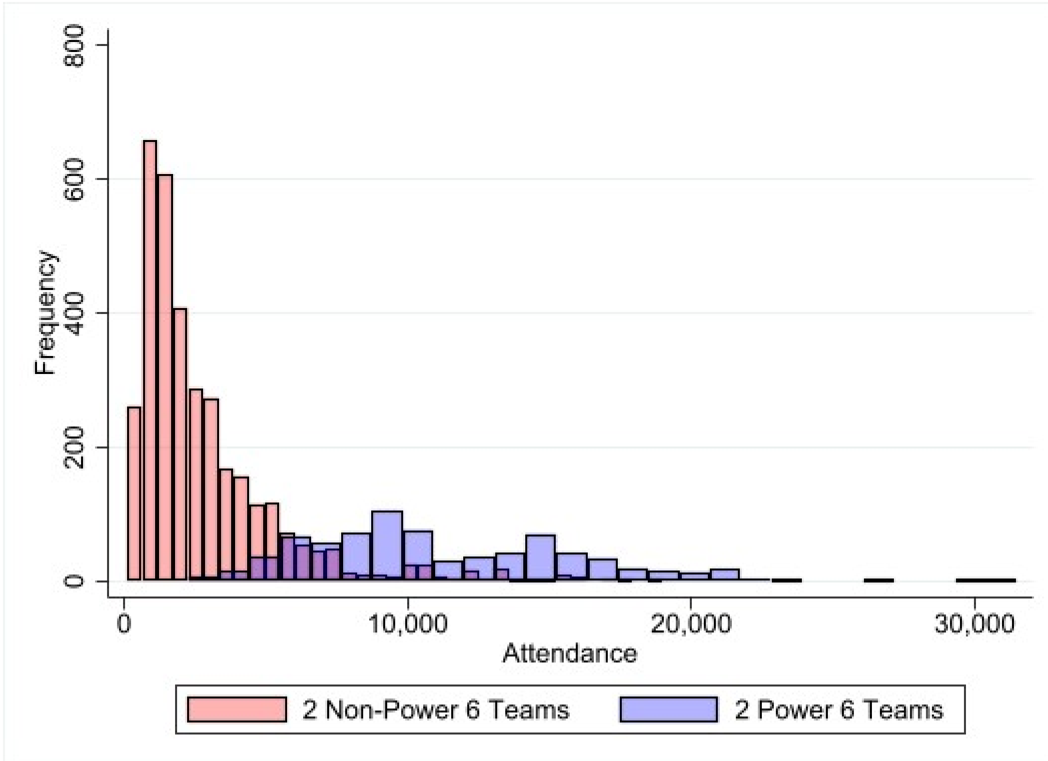
[8]There are some teams with a home venue that is not on campus, however, most are located within a couple of miles of campus.

[9]We drop all games played between a Power 6 team and non-Power 6 team. The score differential for these games is much higher and represents a different level and type of competition.

[10]As noted in Figure 2, the difference in mean attendance (before and after Covid-19) in competitions between two Power 6 teams and non-Power 6 teams is statistically significant at the 1% level. The color not indicated in the key shows the part of the distribution for the two non-Power 6 teams that overlap with the two Power 6 teams.

[11]It is also important to note here that since there are far more teams and conferences in the non-Power 6 category, the total number of games represented in the two distributions are not equal. There are 4,551 games played between two non-Power 6 teams and 1,177 between two Power 6 teams

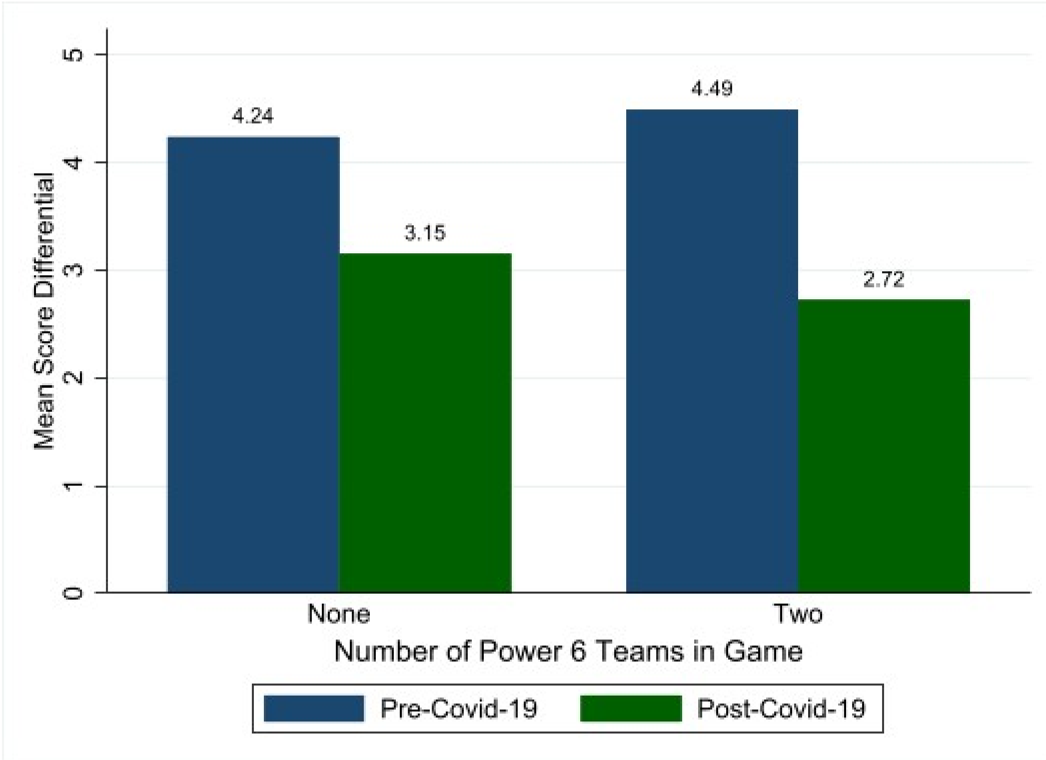
Figure 3: Game attendance distribution by conference classification



To further motivate the analysis, we examine how the score differential changed before and during Covid-19 in games played between two Power 6 teams and two mid-major teams.[12] The score differential is calculated as the difference between the home team's final score and the away team's final score. Therefore, a positive score differential implies that the home team scored more points (thus, winning the game) than the away team. Figure 4 shows the average score differential between two mid-major teams fell from 4.2 points before Covid-19 to 3.2 points after Covid-19. However, the average score differential between two Power 6 teams fell by more from 4.5 points before Covid-19 to 2.7 points after Covid-19. The pre- and post-Covid-19 mean differences are statistically significant at the 1% level for both groups.

[12]Here, "after" and "post-"Covid-19 refers to the start of the pandemic restrictions and virus surge in the United States (March 2020).

Figure 4: Average score differential before and after Covid-19 restrictions



Note: The difference in mean score differential (before and during Covid-19 restrictions) in competitions between two Power 6 teams and two non-Power 6 teams is statistically significant at the 1% level.

Figure 4 shows that there is a home court advantage in terms of score differential in both seasons. In addition, we can see that for all conference classifications, the average score differential change pre- and post-Covid-19 is significantly different. Furthermore, the change is much larger for two Power 6 teams. for games between two mid-major teams and games between two Power 6 teams. The mean score differential changes from 4.24 to 3.15 (a difference of 1.09) for games played between two non-Power 6 teams when the number of fans is reduced. This is smaller than the average score differential change in games played between two Power 6 teams which falls from 4.49 to 2.72 (a difference of 1.77) when attendance decreases due to Covid-19 restrictions. We hypothesize that the primary difference in games pre- and post-Covid-19 is the absence of fans in basketball arenas. Thus, we can examine the impact of fans (or lack thereof) on home court advantage by analyzing the change in score differential before and after Covid-19.

The primary outcome variable of interest is score differential; however, we also consider whether the home team won or lost, free throw percentage differential, and field goal percentage differential as additional measures of home court advantage. Each has been considered a measure of home advantage in past literature. A perfunctory glance at the game-level data shows some interesting facts about college basketball during our sample period. Table 1 shows the summary statistics for each dependent variable used in the analysis for the home team.[13]

Table 1: Dependent Variable Summary Statistics for Home Teams

Variable	Mean	Std. Dev.	N
Score Differential	3.769	13.677	7,317
Won	0.614	0.487	7,317
Field Goal PCT Differential	1.598%	10.174	7,317
Free Throw PCT Differential	1.208%	17.908	7,313

Note: Data are based on two seasons of data for all home games.

The home team wins approximately 61.4% of games played in our sample. Across all games, home teams attempt an average of 1.8 additional free throws and have a free throw percentage differential of 1.2% during the game.[14] These additional free throw attempts may indicate that visiting teams are assigned more fouls in a game; however, this may or may not be a causal link to the overall final point differential.[15] Because home teams have a higher winning percentage, the losing (visiting) team may purposely foul the winning (home) team at the end of the game in an attempt to get the ball back in the waning minutes of the game. Home teams also have a higher average field goal percentage by 1.6%. Finally, the home team wins, on average, by about 3.8 points.

[13]Note, summarizing the data for both home and away teams would be meaningless and result in a zero mean score, free throw, and field goal differential. The proportion of games won would be exactly 0.5.

[14]Home teams attempted an average of 19.4 free throws and visiting teams attempted 17.6 free throws.

[15]This statistic is consistent with the results from Moskowitz and Wertheim (2012).

Table 2 shows the dependent variable summary statistics for home teams and in the pre-pandemic or "Pre-Covid" (2019-2020) season and during the pandemic or "Post-Covid" (2020-2021) season with few or no fans.[16]

Table 2: Dependent Variable Summary Statistics for Home Teams (Pre- and Post-Covid-19)

	Variable	**Mean**	**Std. Dev.**	**N**
Pre-Covid	Score Differential	4.288 ***	13.333	4,241
	Won	0.632 ***	0.482	4,241
	Field Goal % Differential	1.776% *	10.081	4,241
	Free Throw % Differential	1.425%	17.531	4,239
Post-Covid	Score Differential	3.054 ***	14.107	3,076
	Won	0.589 ***	0.492	3,076
	Field Goal % Differential	1.354% *	10.297	3,076
	Free Throw % Differential	0.909%	18.414	3,074

Note: Statistically significant differences are reported across the pre- and post-Covid-19 time periods. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

As noted in Figure 4, the mean score differential falls from 4.29 points to 3.05 points for the home team (becomes less positive) in the season with no or few fans. In other words, the home team wins by fewer points in the absence of an audience. The same is true for field goal percentage differential. The average probability that the home team wins also declines (while still remaining above 0.50) from 0.63 pre-pandemic to 0.59 during the pandemic. The free throw percentage differential also decreases, but this change is not statistically significant.

[16]Note that the home and away team means are simply the opposite of one another and sum to zero. Thus, the away team summary statistics are not reported.

4.2 Empirical Specification

We explore the impact of "ghost games" on home court advantage in NCAA DI college basketball by looking at games played under Covid-19 policies that restricted attendance at most collegiate sporting events. The primary outcome variable of interest is the final score differential between home and away teams. The data are a repeated cross section of games played during the 2019-2020 and 2020-2021 seasons. Our estimation strategy is similar to Ferraresi and Gucciardi (2020), where we identify the home team as "treated" and the away team as a "control." We then exploit the exogenous variation in attendance between the pre-Covid-19 (2019-2020) and the post-Covid-19 pandemic seasons (2020-2021). This allows us to compare the point differential between home and away teams before the pandemic (with fans) to the point differential between home and away teams during the pandemic (with few or no fans). We estimate the following differences in differences (DiD) model separately for games between two Power 6 teams and games between two non-Power 6 teams:

$$y_{ij}^{k} = \beta_0 + \beta_1 Home_{ij} + \beta_2 PostCovid_{ij} + \beta_3 Home_{ij} * PostCovid_{ij} + \gamma X_{ij} + \mu_j + e_{ij} \quad (1)$$

where i represents game and j represents team. The index k indicates the four dependent variables: score differential, win or loss, free throw percentage differential, and field goal percentage differential. In what follows, we focus on the interpretation of dependent variable score differential. The μ_j term are fixed effects that control for unobserved home time-invariant team-level heterogeneity.[17] The variable $Home$ is a dummy variable equal to 1 if the team is the home team and equal to 0 if the team is the visiting team. The variable $PostCovid$ is also a dummy variable equal to 1 if the game was played in the 2020-2021 season during the pandemic with no (or few) fans and equal to 0 if the game was played in the 2019-2020 season with fans before Covid-19 caused the NCAA to end the season in

[17] A Hausman test shows that we reject the null hypothesis that the team-level effects are adequately modeled with random effects at the 1% level.

March 2020.

The coefficient β_1 represents the score differential between the home and away teams before the Covid-19 pandemic, where fans could freely attend games. The coefficient of interest, β_3, shows the differential effect of home court advantage when games were played with few or no fans during the 2020-2021 season. So, $\beta_1 + \beta_3$ is the score differential of the home team in the post-Covid-19 period.

Hypothesis 1 (H1): *Home court advantage.*

> Pre-pandemic evidence of "home court advantage" would be represented by $\beta_1 > 0$. If there is still home court advantage during the pandemic with few or no fans, then we would find $\beta_1 + \beta_3 > 0$.

Hypothesis 2 (H2): *Home choke.*

> Evidence of a "home choke"pre-pandemic would be indicated by $\beta_1 < 0$. During the pandemic season with few or no fans, results of a home choke effect would be $\beta_1 + \beta_3 < 0$.

The existing literature already explores H1 and H2 as referenced in Section 2. Thus, the contribution of this work is to examine H3 and H4, the degree to which fans impact home court advantage.

Hypothesis 3 (H3): *Lack of fans decreases home court advantage.*

> If fans increase home court advantage, we would expect $\beta_3 < 0$. In other words, during the pandemic when there were few or no fans, home court advantage would decrease (either disappear or become smaller).

Hypothesis 4 (H4): *Lack of fans increases home court advantage.*

> If fans decrease home court advantage, we would expect $\beta_3 > 0$. Under this hypothesis, fans would cause the home team to perform worse. So, during the pandemic when there were few or no fans, we would see home court advantage become more positive.

Finally, $\underline{X}$ represents a vector of control variables commonly used in the literature. Summary statistics for the control variables can be found in Table 3.[18]

Table 3: Control Variable Summary Statistics

		Home			**Away**		
	Variable	**Mean**	**Std. Dev.**	**N**	**Mean**	**Std. Dev.**	**N**
Pre-Covid	Season Win %	50.389	18.605	4,241	48.917	18.452	4,241
	Distance	0.830	32.784	4,228	504.451	499.511	4,228
Post-Covid	Season Win %	50.827	19.628	3,076	49.169	19.640	3,076
	Distance	1.932	29.105	3,057	450.667	443.984	3,057

Note: Data are based on two seasons for home and away teams. Because winning percentage is captured at the time of each game, the average home and away team winning percentage will not sum to one because teams are allowed to play teams from other divisions, which aren't included in this sample.

Since most teams in our sample are playing each other throughout the season, the season win percentage at time of the game averages to around 50% in all cases. Mean distance to the arena (in miles) for the home team is less than 2 miles for both seasons. The average distance traveled for the away team is lower during the pandemic season by about 54 miles and this difference is statistically significant at the 1% level. However, the away team still traveled an average of 451 miles even during the Covid-19 outbreak. We control for log distance (due to the skewness of this variable) to take this into account in our specifications.

[18]Similarly, Wang et al. (2011) use game location, end-of-season winning percentage differential, and travel distance as control variables. We use season winning percentage at time of game and logged travel distance to account for skewness in the distribution of this variable. We omit the whether the team and a team's opponent are from a BCS conference (analogously, to the Power 6) in basketball since we split our sample. Finally, we also do not explicitly consider attendance since this is proxied by our time variable, pre- and post-Covid-19 seasons or the interaction terms. Boudreaux et al. (2017) primarily consider only winning percentage differential and the distance traveled for the away team to get from their previous game to the home site. College basketball teams play fewer games than professional teams and have a longer window between games during the season, so we consider only travel between two stadiums instead of the visiting teams previous game since college players are more likely to return home before traveling again.

5 Results

In what follows, we show results of Model 1 estimation for four dependent variables: score differential, win or loss, field goal percentage differential, and free throw percentage differential.

5.1 Score Differential

Table 4 shows the results of the differences-in-differences with team-level fixed effects.

Table 4: Dependent Variable: Score Differential

	(1) All	(2) All	(3) Non-Power 6	(4) Power 6	(5) Non-Power 6	(6) Power 6
Home	8.189***	6.058***	7.995***	9.049***	5.602***	8.974***
	(0.274)	(0.841)	(0.306)	(0.615)	(0.910)	(2.310)
PostCovid	1.175***	1.240***	1.054***	1.656***	0.927***	2.384***
	(0.300)	(0.297)	(0.341)	(0.632)	(0.337)	(0.634)
Home*PostCovid	-2.485***	-2.469***	-2.220***	-3.583***	-2.240***	-3.397***
	(0.421)	(0.416)	(0.479)	(0.892)	(0.472)	(0.883)
Season Win %		0.257***			0.262***	0.245***
		(0.0118)			(0.0132)	(0.0277)
Distance		-0.366***			-0.415***	-0.00928
		(0.139)			(0.151)	(0.374)
Constant	-4.066***	-14.77***	-3.974***	-4.460***	-14.03***	-18.98***
	(0.194)	(1.016)	(0.217)	(0.435)	(1.089)	(2.820)
Observations	14,634	14,570	11,662	2,972	11,616	2,954
Number of Teams	357	357	282	76	282	76

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5 summarizes the marginal effect of being the home team on score differential for games played between two Power 6 teams and two non-Power 6 teams for the pre- and post-Covid-19 time periods. The marginal effect is given by

$$\frac{\partial y_{ij}}{\partial Home_{ij}} = \beta_1 + \beta_3 PostCovid_{ij} \tag{2}$$

evaluated at PostCovid=0 (PreCovid) and PostCovid=1 (PostCovid)

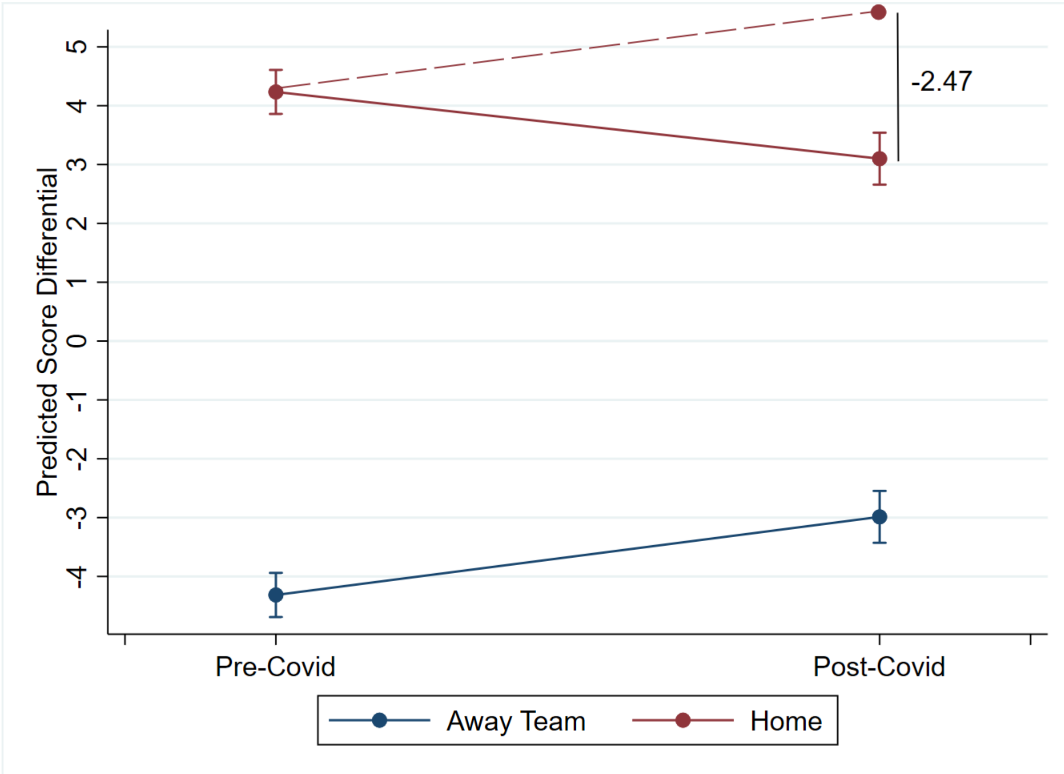
Table 5: Marginal Effects Dependent Variable: Score Differential

	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	Non-Power 6	Power 6	Non-Power 6	Power 6
PreCovid	8.19	6.06	8.00	9.05	5.60	8.97
PostCovid	5.70	3.59	5.78	5.47	3.36	5.58
Difference	-2.49	-2.47	-2.22	-3.58	-2.24	-3.40
		with controls			with controls	with controls

All statistically significant at the 1% or 5% level.

First, in the full sample, our results are consistent with H1. We find evidence of a home court advantage (as defined by score differential) in NCAA DI men's college basketball. Pre-pandemic, on average, the home team won by 6.06 points when controlling for season win percentage and travel distance. During the pandemic with few or no fans, the home team still shows an advantage of 3.59 points.

Figure 5: Predicted Score Differential



Second, we find that home court advantage is larger for games played between two teams from Power 6 conferences compared to two teams from non-Power 6 conferences. In games featuring two teams from non-Power 6 conferences, the score differential falls from 5.60 points pre-pandemic to 3.36 points during the pandemic after including various controls. For two teams from Power 6 conferences, after controlling for various factors, home court advantage falls from 8.97 points pre-pandemic to 5.58 during the pandemic.

Third, we find evidence in favor of H3, that the lack of fans decreases home court advantage. For all games in the sample, home court advantage falls by 2.47 points in the absence of fans (or with very few fans). Again, this effect is larger for games played between two Power 6 teams at 3.40 points compared to games played between two non-Power 6 teams at 2.24 points. As discussed previously, we hypothesize that since games played between two Power 6 teams have significantly more fans than games played between two non-Power 6 teams, the effect of losing fans on home team performance in more high-profile games is larger.

5.2 Win or Loss

To determine the probability of winning or losing for the home team and away team in pre- and post-Covid-19 seasons, we estimate Model 1 as a logit. The dependent variable is equal to 1 if the team wins and equal to 0 if the team loses. Table 6 shows the results.

Table 6: Dependent Variable: Win or Loss

	(1) All	(2) All	(3) Non-Power 6	(4) Power 6	(5) Non-Power 6	(6) Power 6
Home=1	1.158***	0.721***	1.119***	1.328***	0.613***	1.494***
	(0.0480)	(0.151)	(0.0531)	(0.112)	(0.162)	(0.423)
PostCovid=1	0.196***	0.202***	0.194***	0.221**	0.163***	0.361***
	(0.0515)	(0.0532)	(0.0582)	(0.112)	(0.0601)	(0.116)
Home*PostCovid=1	-0.385***	-0.384***	-0.373***	-0.467***	-0.376***	-0.439***
	(0.0725)	(0.0747)	(0.0817)	(0.159)	(0.0842)	(0.163)
Season Win %		0.0493***			0.0495***	0.0503***
		(0.00220)			(0.00243)	(0.00526)
Distance		-0.0818***			-0.0946***	0.0231
		(0.0249)			(0.0270)	(0.0683)
Observations	14,667	14,603	11,695	2,972	11,649	2,954
Number of Teams	357	357	282	76	282	76

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

To draw meaning from these results, we estimate the predicted probability of winning and how that changes for the home and away teams pre-pandemic and during the pandemic with no or few fans.

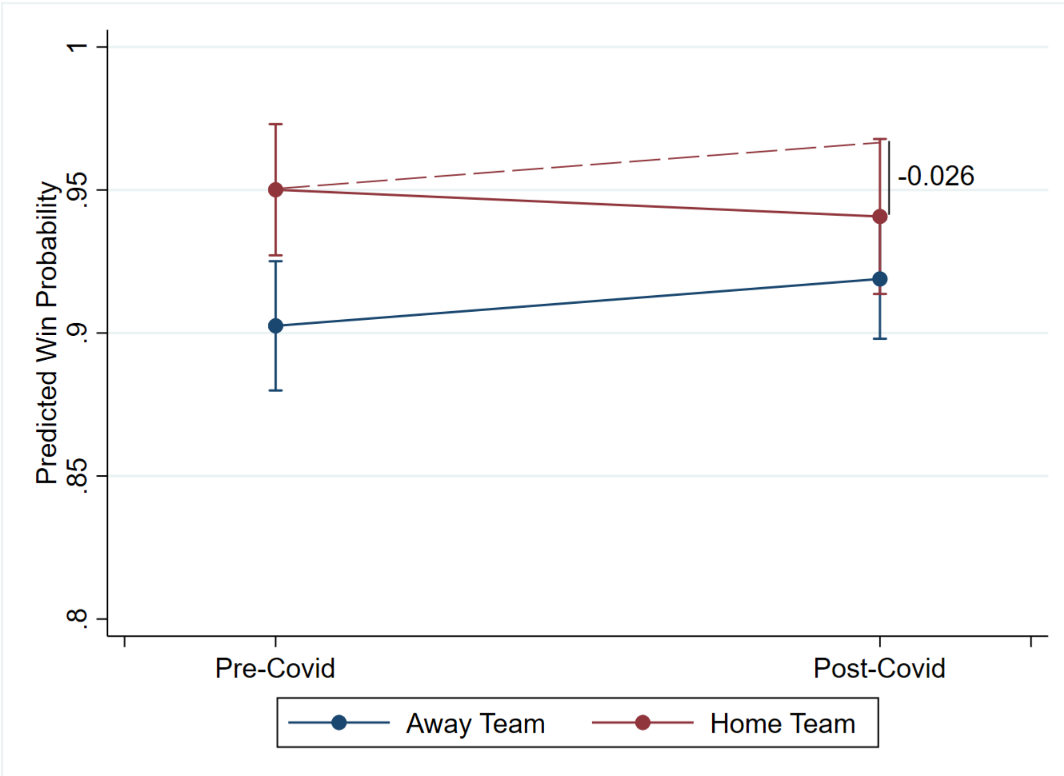
Table 7: Dependent Variable: Win or Loss

	(1) All	(2) All	(3) Non-Power 6	(4) Power 6	(5) Non-Power 6	(6) Power 6
PreCovid	0.261	0.048	0.254	0.291	0.047	0.037
PostCovid	0.176	0.022	0.171	0.192	0.018	0.022
Difference	-0.085	-0.026	-0.083	-0.099	-0.029	-0.015
		with controls			with controls	with controls

All statistically significant at the 1% or 5% level.

In all cases, the change in the probability of the home team winning during the pandemic with few or no fans compared to the pre-pandemic season is negative. Again, the pre- and post-Covid-19 marginal effects of the home team winning being positive provide evidence in favor of H1. Furthermore, the change in the probability of winning being negative for the home team during the pandemic supports H3. Column 2 shows the increase in the probability of winning for the home team compared to the away team for the pre-pandemic and during pandemic seasons after controlling for season win percentage and travel distance. These results are shown in Figure 6.

Figure 6: Predicted Probability of Winning



The navy blue line shows the change in the predicted win probability for the away team in the pre-Covid-19 season and during the pandemic (Post-Covid) with few or no fans. Few or no fans increases the probability of the away team winning. Conversely, the red line shows the predicted probability of winning for the home team pre-pandemic and during the Covid-19 outbreak. The red dashed line shows the counterfactual if the home team had been impacted by the absence of fans in the same way as the away team. In the case of the home team, few or no fans decreases their probability of winning (by about 2.6%).

5.3 Field Goal Percentage Differential

Table 8 shows the results of Model 1 with field goal differential as the dependent variable rather than using score differential. Score differentials may be influenced by home teams potentially taking more 3-point shots compared to field goals, which would increase the score differential despite two teams shooting equally well and being unaffected by missing crowds.

Table 8: Dependent Variable: Field Goal Percent Differential

	(1) All	(2) All	(3) Non-Power 6	(4) Power 6	(5) Non-Power 6	(6) Power 6
Home	3.364***	3.493***	3.358***	3.395***	3.370***	4.455**
	(0.212)	(0.656)	(0.234)	(0.494)	(0.703)	(1.868)
PostCovid	0.387*	0.415*	0.370	0.413	0.311	0.824
	(0.232)	(0.231)	(0.262)	(0.508)	(0.260)	(0.512)
Home*PostCovid	-0.856***	-0.820**	-0.817**	-0.996	-0.829**	-0.789
	(0.326)	(0.324)	(0.367)	(0.717)	(0.365)	(0.714)
Season Win %		0.138***			0.137***	0.151***
		(0.00923)			(0.0102)	(0.0224)
Distance		0.0222			0.00183	0.178
		(0.108)			(0.117)	(0.303)
Constant	-1.665***	-8.704***	-1.664***	-1.657***	-8.182***	-11.71***
	(0.150)	(0.792)	(0.166)	(0.350)	(0.841)	(2.279)
Observations	14,634	14,570	11,662	2,972	11,616	2,954
Number of Teams	357	357	282	76	282	76

*** p<0.01, ** p<0.05, * p<0.1

Again, home court advantage in field goal percentage differential still exists pre-pandemic and during Covid-19 showing evidence in favor of H1 general, we still find that the removal of fans has a negative impact on home court advantage, now defined as the field goal differential. On average, the field goal differential between the home and away team goes down by about 0.79 and 1.00 percentage points (although, this is not statistically significant for games played between two Power 6 teams) continuing support for H3.

5.4 Free Throw Percentage Differential

Table 9 shows the results of estimating Model 1 with free throw percentage differential as the outcome variable. Free throws are the only in-game activity that is consistent across all courts across the country. Looking at free throw percentage controls for differences in shot selection during a game or shot preferences across teams.

Table 9: Dependent Variable: Free Throw Percentage Differential

	(1) All	(2) All	(3) Non-Power 6	(4) Power 6	(5) Non-Power 6	(6) Power 6
Home	2.752***	2.347*	2.939***	1.952**	2.168*	2.642
	(0.386)	(1.205)	(0.426)	(0.908)	(1.289)	(3.454)
PostCovid	0.479	0.545	0.395	0.598	0.358	1.036
	(0.423)	(0.425)	(0.476)	(0.934)	(0.478)	(0.947)
Home*PostCovid	-1.046*	-1.105*	-0.873	-1.433	-0.874	-1.647
	(0.594)	(0.596)	(0.667)	(1.318)	(0.669)	(1.320)
Season Win %		0.0867***			0.0857***	0.0926**
		(0.0170)			(0.0187)	(0.0414)
Distance		-0.0658			-0.132	0.127
		(0.199)			(0.214)	(0.560)
Constant	-1.358***	-5.303***	-1.453***	-0.919	-4.768***	-7.174*
	(0.273)	(1.455)	(0.302)	(0.643)	(1.543)	(4.215)
Observations	14,626	14,562	11,656	2,970	11,610	2,952
Number of Teams	357	357	282	76	282	76

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In this set of results, home court advantage still exists pre-pandemic and during the pandemic with no or few fans. However, in most cases, the interaction between *Home* and *PostCovid* is negative it is not statistically significant. Thus, we cannot claim support for H3 with respect to free throw differential.

Section A.2 presents several robustness checks including clustering the standard errors, adding free throw attempts as a control variable, and limiting the sample to only in-conference games. Our main results are robust to these changes in the specification.

6 Conclusion

Home advantage spans a wide variety of sports from around the globe, and nearly all studies find that fans play a vital role in that advantage. In our primary estimation of fans' impact, we find that a lack of fans results in a 38-40% reduction in score differential for college basketball games. The percentage impact is consistent when looking at Power 6 and non-Power 6 teams, however the impact is felt the most in major conferences where crowd size is significantly larger.

While the pandemic limited the ability of all teams and conferences to allow fans to attend games, it raises an interested policy question surrounding tournament play at the end of the season. Many conferences host neutral site tournaments and the national championship tournament rarely includes teams playing in the same city as their university. In early rounds of the tournament, most games are sparsely attended and likely result in more "Cinderella" outcomes because of the lack of home advantage. Not only are teams playing on unfamiliar courts, but they also do not have an overwhelmingly supportive crowd. If the purpose of a tournament setting is to advance the best team then this method may be appropriate. If the goal, however, is to advance the most marketable team then this method might result in smaller (non-Power 6 conference) teams advancing in the tournament.

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A Appendix

A.1 Classification of Division I Conferences

Table A1: Classification of NCAA Division I Men's Basketball Conferences

Power 6 Conferences
Atlantic Coast Conference (ACC)
Big 12 Conference
Big East Conference
Big 10 Conference
Pacific 12 Conference (Pac-12)
Southeastern Conference (SEC)

Non-Power 6 Conferences
American East Conference
Atlantic 10 Conference (A-10)
Atlantic Sun Conference
Big South Conference
Big Sky Conference
Colonial Athletic Conference
Conference USA
Great West Conference
Ivy League
Horizon League
Metro Atlantic Athletic Conference (MAAC)
Mid-American Conference (MAC)
Mid-Eastern Athletic Conference (MEAC)
Missouri Valley Conference (MVC)
Mountain West Conference (MWC)
Northeastern Conference (NEC)
Ohio Valley Conference (OVC)
Patriot League
Southern Conference (SoCon)
Southland Conference (SLC)
Southwestern Athletic Conference (SWAC)
Sunbelt Conference (SBC)
The Summit League
Independents
West Coast Conference (WCC)
Western Athletic Conference (WAC)

A.2 Robustness Checks

In this section, we explore several robustness checks in our main specification with score differential as the dependent variable. Following Ferraresi and Gucciardi (2020), we estimate a specification that clusters standard errors at the team level. As shown in Table A2, the statistical significance of the main results are unchanged.

Table A2: Dependent Variable: Score Differential Clustered SE

	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	Non-Power 6	Power 6	Non-Power 6	Power 6
Home	8.189***	6.058***	7.995***	9.049***	5.602***	8.974***
	(0.274)	(0.947)	(0.310)	(0.568)	(1.026)	(2.551)
PostCovid	1.175***	1.240***	1.054**	1.656**	0.927***	2.384***
	(0.362)	(0.278)	(0.421)	(0.699)	(0.312)	(0.600)
Home*PostCovid	-2.485***	-2.469***	-2.220***	-3.583***	-2.240***	-3.397***
	(0.416)	(0.416)	(0.477)	(0.859)	(0.477)	(0.860)
Season Win %		0.257***			0.262***	0.245***
		(0.00956)			(0.0103)	(0.0231)
Distance		-0.366**			-0.415**	-0.00928
		(0.158)			(0.175)	(0.395)
Constant	-4.066***	-14.77***	-3.974***	-4.460***	-14.03***	-18.98***
	(0.187)	(1.029)	(0.213)	(0.379)	(1.092)	(2.844)
Observations	14,634	14,570	11,662	2,972	11,616	2,954
Number of Teams	357	357	282	76	282	76

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We also considered adding free throw attempts to the model as a control variable. Table A3 shows these results.

Table A3: Dependent Variable: Score Differential with FTA

	(1) All	(2) All	(3) Non-Power 6	(4) Power 6	(5) Non-Power 6	(6) Power 6
Home	7.694***	5.859***	7.518***	8.500***	5.399***	8.762***
	(0.274)	(0.837)	(0.306)	(0.620)	(0.905)	(2.302)
PostCovid	1.182***	1.246***	1.051***	1.669***	0.932***	2.365***
	(0.298)	(0.295)	(0.339)	(0.629)	(0.335)	(0.631)
Home*PostCovid	-2.181***	-2.197***	-1.908***	-3.287***	-1.954***	-3.148***
	(0.419)	(0.414)	(0.476)	(0.889)	(0.470)	(0.881)
Season Win %		0.248***			0.253***	0.236***
		(0.0118)			(0.0131)	(0.0277)
Distance		-0.323**			-0.374**	0.0368
		(0.138)			(0.150)	(0.373)
FTA	0.203***	0.183***	0.210***	0.173***	0.191***	0.152***
	(0.0148)	(0.0146)	(0.0166)	(0.0320)	(0.0164)	(0.0317)
Constant	-7.636***	-17.82***	-7.698***	-7.413***	-17.25***	-21.33***
	(0.324)	(1.039)	(0.365)	(0.698)	(1.117)	(2.852)
Observations	14,634	14,570	11,662	2,972	11,616	2,954
Number of Teams	357	357	282	76	282	76

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

While free throw attempts do appear to be a statistically significant predictor of score differential, the magnitude and significance of the main results are largely unchanged. Table A3 still supports H1 and H3.

Finally, we consider to what degree the treatment (playing home or away) is truly exogenous). To do so, we estimate the main regression specification with only in-conference play. Typically, every team plays each team in their respective conference once at home and once away during a season and cannot determine when they're assigned those particular games. Table A4 shows these results.

Table A4: Dependent Variable: Score Differential In-Conference

	(1) All	(2) All	(3) Non-Power 6	(4) Power 6	(5) Non-Power 6	(6) Power 6
Home	6.622***	6.366***	5.856***	9.283***	5.844***	10.09***
	(0.306)	(1.010)	(0.347)	(0.646)	(1.113)	(2.449)
PostCovid	0.847***	0.976***	0.550	1.871***	0.505	2.530***
	(0.322)	(0.318)	(0.370)	(0.656)	(0.365)	(0.658)
Home*PostCovid	-1.839***	-1.839***	-1.248**	-3.978***	-1.316**	-3.771***
	(0.453)	(0.447)	(0.519)	(0.925)	(0.512)	(0.917)
Season Win %		0.244***			0.249***	0.233***
		(0.0128)			(0.0143)	(0.0289)
Distance		-0.0450			-0.00212	0.136
		(0.168)			(0.186)	(0.398)
Constant	-3.278***	-15.32***	-2.895***	-4.584***	-14.75***	-19.25***
	(0.217)	(1.185)	(0.247)	(0.458)	(1.288)	(2.971)
Observations	11,582	11,522	8,850	2,732	8,806	2,716
Number of Teams	357	357	282	76	282	76

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Again, the main results are not meaningfully impact. However, the magnitude of the change in home court advantage due to no or few fans for the Power 6 teams is actually larger. Specifically, home court advantage falls by 3.77 points for games between two Power 6 teams when there are no or few fans.