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Do Scheduling Elements Make a Difference?

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Abstract

This study examines factors impacting sport attendance at non-conference NCAA Division I men's college basketball games. Non-conference college basketball games are relatively unique because athletic department personnel control many of the scheduling variables related to event popularity, including opponent, game day, and start time. As such, it is valuable for administrators to know which elements might maximize their event revenue. The current study is also distinctive because it examines both reported attendance (tickets disseminated) and actual attendance (tickets scanned at the venue). A total of 48 schools provided ticket scan rate data for their non-conference home basketball games over three seasons (2017-2020), with a total of 964 observations. Results revealed a no-show rate of 37%. Several factors affecting reported attendance were significantly different than those affecting actual attendance, including weekend games, geographic distance between schools, and home team winning percentage. Results were also different between Power Five institutions and non-Power Five institutions.

Keywords: attendance; basketball; college sports; consumer behavior; revenue

Background and Literature Review

Men's National Collegiate Athletics Association (NCAA) Division I college basketball is one of the most popular spectator sports in the United States and, for most university athletics departments, men's basketball games are also a key revenue generator. Maximizing attendance at home games is important because ticket sales, as well as the ancillary revenue streams affiliated with spectatorship such as concessions, parking, and merchandise sales, assist in meeting growing departmental expenditures (McEvoy et al., 2013).

Men's college basketball also is unique compared to many other major spectator sports in the U.S., such as professional basketball, football, baseball, soccer, hockey, or even college football, in one significant way; college basketball programs themselves determine a large portion of their game schedule. Unlike major professional team sports, where competition schedules are created by leagues or conferences, college basketball programs set their own home non-conference schedule (typically five to nine games a season), determining, among other factors, opponents, game times, and game dates (Watkins, 2013). Major college football programs also have the ability to determine some aspects of their non-conference schedule, but that portion of the schedule is generally comprised of only a couple of games and such schedules are typically set many years in advance. In addition, nearly all non-conference college football games are played on Saturdays, with game times frequently determined by television partners, meaning administrators have little control over several key event attributes.

Because athletics departments control the scheduling of non-conference basketball games, it is in their best interest to develop a schedule most beneficial to the home team. Factors affecting team development, on-court success, and the opportunity to qualify for the NCAA men's basketball tournament are typically given the highest consideration (Shapiro et al., 2009; Watkins, 2013), but a schedule that maximizes attendance would allow athletics administrators to also gain financial advantages by maximizing ticket and ancillary product sales (Coates & Humphreys, 2007).

Numerous studies have examined variables predicting demand at live sporting events, such as economic, environmental, team performance, spectator demographic, and marketing/promotional factors (Borland & MacDonald, 2003; Schreyer & Ansari, 2022). In nearly all of these studies, however, the dependent variable of interest is the attendance publicly reported by event organizers and managers. This figure is typically the number of tickets disseminated for an event, not the actual number of spectators present, a practice commonly employed within college athletics (Bachman, 2018; Brown, 2011; Cooper, 2019; Davies et al., 2010; Kleps, 2015; Milewski, 2013; Shaikin, 2005). In fact, prior academic work by Schreyer et al. (2018) identified a no-show rate of nearly 12% in European football matches, while Popp et al. (2023) suggested a 29% no-show rate across NCAA Division I college football games. The Los Angeles Times reported a 19% no-show rate for MLB's Los Angeles Angels during the 2004 season (Shaikin, 2005) and Orlando SC admitted a 28% no-show rate during the 2016 season (Baxter, 2016). At the University of Wisconsin, no-show rates for all ticketed sports, including football, basketball, hockey, and volleyball, amounted to 25% of reported attendance (Milewski, 2013). No-shows among season ticket holders or others who possess but do not use tickets are a significant issue for sport marketers because empty seats mean less ancillary revenue and can adversely impact gameday atmosphere or sponsor perceptions (Popp et al., 2023).

A handful of prior studies have examined factors influencing no-show rates at sport events in the contexts of German Bundesliga matches (Schreyer & Dauper, 2018; Schreyer et al., 2016, 2017, 2018, 2019), National Football League (NFL) contests (Siegfried & Hinshaw, 1979; Zuber & Gandar, 1988), and NCAA college football games (Popp et al., 2023). In the latter study, Popp et al. (2023) found the factors significantly related to reported attendance were not the same as those related to actual attendance, which is an important distinction. Although the intent of the early NFL studies (Siegfried & Hinshaw, 1979; Zuber & Gandar, 1988) was to determine whether television blackouts impacted spectator decisions to attend games, those investigations found factors such as weather and team success did predict no-show fan behavior. More recent work by Schreyer has found numerous statistically significant links between no-shows and a variety of factors including: (a) venue capacity, (b) game outcome uncertainty, (c) day of the week, and (d) geographic distance between ticket-holder residence and venue. We argue no-show behavior studies in the context of college basketball may have even greater practical importance to practitioners than prior studies because sport managers exert greater control over scheduling factors. In many other spectator sports, a governing body determines schedule components such as the opponent, start times, and the day of the week in which a game is played. In college basketball, however, team administrators determine these factors for a relatively large portion of their schedule, meaning if such variables are related to attendance, administrators could leverage such factors to increase spectatorship.

One other important consideration when examining college basketball attendance is the gap in spectator support between athletics departments belonging to one of the previously labeled “Power Five” conferences (i.e., Big Ten, Southeastern Conference, Big 12, Atlantic Coast Conference, and Pac 12) and those belonging to “non-Power Five” conference. (We acknowledge the changing landscape in college athletics will likely change this “Power Five” nomenclature, but the point remains the same; there is a significant gap in popularity of top-tier athletics programs and second-tier departments.) Prior research has suggested ticket revenue for Power Five institutions has grown more significantly than non-Power Five universities (Wanless et al., 2019). Among the top 30 college basketball attendance leaders during the 2021–22 basketball season, 24 belonged to a Power Five conference, and when looking at which schools drew the most fans combined between home and road contests, 18 of the top 20 schools were members of Power Five leagues (NCAA, 2022).

Thus, the purpose of the current study is two-fold. The primary objective is to determine what factors are related to reported and actual attendance as well as determine if any of those significant factors are different. In other words, are variables related to individuals obtaining a ticket (reported attendance) the same factors influencing whether they attend a game (actual attendance)? The secondary goal is to determine if factors related to both measures of sport demand (reported and actual attendance) are different between Power Five programs and non-Power Five programs within men’s college basketball.

Methods

Data were collected over the three men’s college basketball seasons directly before the Covid pandemic affected game play and spectatorship (2017–2020). Utilizing Freedom of Information Act (FOIA) requests, the research team asked public NCAA Division I athletics departments to provide ticket scan rate data from all home basketball games during the seasons within the sample (no private universities were solicited for data). For each school and year in the dataset, conference games were removed. Among the games in the dataset, 14 additional variables were collected related to those contests. They included: (a) reported attendance from the official box score, (b) day of the game (month, day, and weekday/weekend, holiday), (c) game time (afternoon vs. night game) (d) home and away team performance indicators (win percentage, Ratings Percentage Index [RPI] scores, tournament appearances), (e) betting line (money line was used for this variable), and (f) distance between schools. Six OLS regression models were built to determine which of the collected variables were statistically related to the two variables of interest, namely reported and actual attendance, using three sets of data: (a) all games, (b) only Power Five schools, and (c) only non-Power Five schools.

Descriptive statistics and a correlation matrix were examined initially to assess normality of the data and variable relationships. Six fixed-effects ordinary least squares (OLS) multiple regression models were developed to empirically examine the factors influencing reported and actual attendance in total and broken down by Power Five and non-Power Five programs. The fixed effects models were used to account for the data being in panel form. The data were observed across three time periods, creating a cross-sectional time series. Multiple regression assumptions and multicollinearity were examined, after which reduced final regression models were created. A significance level of .05 was established a priori in analyzing the regression model and related variable correlations.

Results

In total, 48 athletics departments complied with the FOIA requests at the time of data analysis. After removing all conference games from the dataset, 964 total observations remained, an average of 6.7 non-conference games per school, per season. Descriptive statistics are provided in Table 1. Of these observations, 304 (31.5%) were from home games of Power Five institutions and 660 (68.5%) came from home games of non-Power Five institutions. The average reported basketball attendance for games in the dataset was 5,743 whereas the actual attendance for those games was 3,626, a no-show rate of 36.9%. The maximum reported attendance for a non-conference game was 24,387, and the minimum was 276.

Table 1

Summary Statistics

Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
Reported Attendance	5,743.26	5,444.80	276	24,387
Actual Attendance	3,626.47	4,019.33	48	22,067
Day of the Week	4.40	1.91	1	7
Weekend	1.54	.499	1	2
Month	2.63	.813	1	7
Holiday	1.67	.469	1	2
HomeWinPct	0.693	0.279	0	1
Home RPI	152.79	103	1	353

Home NCAA Appear	15.04	15.12	0	59
Tounry Prior Yr	1.68	.466	1	2
AwayWinPct	0.509	0.286	0	1
Away NCAA Appear	5.04	7.06	0	59
BettingLine	12.11	8.74	-8.0	43
DistanceBetweenTeams	577.85	587.53	.8	3,282
Game time (Military)	1760.9	234.31	1100	2130

The first regression model, which included all schools, explained 85.8% of the variance in reported attendance, $F(17,575) = 205.196$, $p < .001$, with seven significant variables in the model, as shown in Table 2. Most of these variables were performance indicators (home and away team winning percentage, home and away team tournament appearances, whether the home team made the NCAA tournament in the prior year, and home team RPI). Playing more successful home and road opponents increased attendance. Additionally, betting line was a significant, positive determinant of reported attendance, meaning the greater the expected margin of victory, the greater reported attendance.

Table 2

All Schools Reported Attendance

Variables	***Coefficients***	***Std. Error***	***Sig.***
Weekend	572.23	386.35	0.14
Holiday	15.32	191.32	0.94
Time	0.20	0.49	0.69
Home Win %	863.06	421.83	0.04*
RPI	-3.94	1.25	0.00*
Home NCAA App.	225.45	8.00	<.001*
Tourney Last Year	-1406.83	262.88	<.001*
Away Win %	1360.72	378.60	<.001*
Away NCAA App.	96.11	11.84	<.001*
Betting Line	112.20	15.49	<.001*
Distance Btw. Schools	0.08	0.15	0.58
Day of Week 1	-68.59	471.00	0.88
Day of Week 3	-275.80	339.96	0.42
Day of Week 4	77.49	410.91	0.85
Day of Week 5	-23.82	396.74	0.95
Day of Week 6	-18.20	289.54	0.95
R-Squared	0.858		

The second model examining actual attendance among all teams explained 83.1% of the variance, $F(17,593) = 171.216$, $p < .001$. This model included seven significant variables, as seen in Table 3. Many of the performance indicators and betting line remained significant in this model, although home team winning percentage was not significant. Weekend games significantly impacted actual attendance. Based on the unstandardized beta coefficient, weekend games accounted for approximately 653 more fans.

Table 3

All Schools Actual Attendance

Variables	***Coefficients***	***Std. Error***	***Sig.***
Weekend	652.90	316.62	0.04*
Holiday	-175.40	156.19	0.26
Time	-0.12	0.40	0.76
Home Win %	405.32	348.02	0.25
RPI	-2.71	1.03	0.009*
Home NCAA App.	117.09	6.61	<.001*
Tourney Last Year	-964.69	207.78	<.001*
Away Win %	782.62	309.62	0.012*
Away NCAA App.	98.52	9.78	<.001*
Betting Line	54.19	12.56	<.001*
Distance Btw. Schools	-0.07	0.12	0.57
Day of Week 1	69.62	376.35	0.85
Day of Week 3	-304.00	279.68	0.28
Day of Week 4	96.75	332.44	0.77
Day of Week 5	386.00	323.35	0.23
Day of Week 6	202.46	236.41	0.39
R-Squared 0.831			

The third model, which only examined Power Five institutions, was significant and explained 83.4% of the variance in reported attendance, $F(18,194) = 54.252$, $p = <.001$. Four of the variables in this model were significant at the $p < .05$ level, while a fifth factor had a p-value of .053 and a sixth factor had a p-value of .066. All significant variables were related to the quality of the home or away team. Complete results are listed in Table 4.

Table 4

Power Five Schools Reported Attendance

Variables	***Coefficients***	***Std. Error***	***Sig.***
Weekend	838.68	614.02	0.17
Holiday	180.76	327.60	0.58
Time	-0.45	0.79	0.57
Home Win %	830.03	824.93	0.32
RPI	-7.50	2.68	0.00*
Home NCAA App.	245.03	12.22	0.00*
Tourney Last Year	-923.64	474.52	0.05
Away Win %	1264.30	682.79	0.07
Away RPI	0.42	2.09	0.84
Away NCAA App.	114.25	17.20	0.00*

Betting Line	134.26	27.48	0.00*
Distance Btw. Schools	-0.34	0.27	0.21
Day of Week 1	-719.20	688.17	0.30
Day of Week 3	-492.25	600.60	0.41
Day of Week 4	712.03	771.57	0.36
Day of Week 5	-657.44	579.75	0.26
Day of Week 6	-171.80	478.41	0.72
R-Squared	0.834		

The fourth model examined only non-Power Five institutions and was significant, explaining 65.6% of the variance in reported attendance, F(18,338) = 35.779, p = <.001. Five independent variables were significant. Four of them were again related to team or opponent quality, but the fifth was a new factor, distance, which had a significant positive relationship with reported attendance. This means for non-Power Five schools, playing an opponent in closer proximity results in lower reported attendance. Based on the interpretation of the unstandardized beta coefficient, for roughly every two miles of distance between schools, one fewer fan would attend the game. Complete results of this model are listed in Table 5.

Table 5

Non-Power Five Schools Reported Attendance

Variables	***Coefficients***	***Std. Error***	***Sig.***
Weekend	420.08	439.43	0.34
Holiday	340.17	210.83	0.11
Time	-0.25	0.57	0.66
Home Win %	1290.58	446.25	0.00*
RPI	-4.19	1.36	0.00*
Home NCAA App.	159.37	11.61	0.00*
Tourney Last Year	-338.25	319.19	0.29
Away Win %	667.00	468.59	0.16
Away RPI	-0.60	1.30	0.64
Away NCAA App.	84.92	16.70	0.00*
Betting Line	36.45	18.99	0.06
Distance Btw. Schools	0.46	0.16	0.00*
Day of Week 1	468.24	574.58	0.42
Day of Week 3	152.38	359.81	0.67
Day of Week 4	283.54	432.62	0.51
Day of Week 5	-106.64	493.91	0.83
Day of Week 6	-290.27	333.94	0.39
R-Squared	0.656		

The fifth model, which again only examined Power Five schools, explained 84.1% of the variance in actual attendance, $F(18,209) = 61.334$, $p = <.001$. Six factors in the model were significant at the $p < .05$ level, as seen in Table 6. Four of those factors were related to the strength of the teams (home RPI, both home and away team tournament appearances, and betting line). The other two variables were weekend games (positive relationship) and geographic distance (negative relationship). According to the unstandardized beta coefficients, among Power Five schools, a non-conference weekend game resulted in 1,573 additional spectators, while every 2 miles separating the opposing schools meant one less attendee (e.g., opponents 200 miles apart would draw 100 fewer actual attendees).

Table 6

Power Five Schools Actual Attendance

Variables	***Coefficients***	***Std. Error***	***Sig.***
Weekend	1572.98	507.89	0.00*
Holiday	-264.10	268.55	0.33
Time	-0.22	0.65	0.74
Home Win %	1036.41	680.58	0.13
RPI	-9.16	2.23	0.00*
Home NCAA App.	214.41	10.26	0.00*
Tourney Last Year	-548.66	340.88	0.11
Away Win %	203.80	552.54	0.71
Away RPI	-1.36	1.74	0.43
Away NCAA App.	125.79	14.41	0.00*
Betting Line	70.89	22.40	0.00*
Distance Btw. Schools	-0.50	0.22	0.03*
Day of Week 1	22.90	565.24	0.97
Day of Week 3	-370.21	499.63	0.46
Day of Week 4	973.57	596.32	0.10
Day of Week 5	-78.59	474.06	0.87
Day of Week 6	-126.53	393.13	0.75
R-Squared	0.841		

The final model examined non-Power Five schools and actual attendance. This model was also significant and explained 63.2% of the variance in actual attendance, $F(18,341) = 32.484$, $p = <.001$. Only two factors were significant at the $p < .05$ level in this model; home team NCAA tournament appearances and the betting line for the game, which both had positive relationships with the independent variable. Every additional all-time NCAA tournament appearance by the home team equated to 32 additional spectators.

Table 7

Non-Power Five Schools Actual Attendance

Variables	***Coefficients***	***Std. Error***	***Sig.***
Weekend	297.30	329.82	0.37
Holiday	175.99	158.08	0.27
Time	-0.45	0.43	0.30
Home Win %	243.24	335.41	0.47
RPI	-3.69	1.02	0.00*
Home NCAA App.	115.70	8.77	0.00*
Tourney Last Year	-386.69	240.35	0.11
Away Win %	522.97	352.49	0.14
Away RPI	-0.40	0.98	0.69
Away NCAA App.	65.95	12.64	0.00*
Betting Line	15.91	14.33	0.27
Distance Btw. Schools	0.39	0.12	0.00*
Day of Week 1	406.41	412.80	0.33
Day of Week 3	-93.95	271.06	0.73
Day of Week 4	22.21	325.05	0.95
Day of Week 5	-57.97	370.86	0.88
Day of Week 6	-51.89	249.53	0.84
R-Squared	0.632		

Discussion & Implications

Numerous sport demand studies have examined factors related to event attendance (Borland & MacDonald, 2003; Schreyer & Ansari, 2022). The current study differs from nearly all of those studies in two significant ways. First, the current investigation accounts for the "no-show" factor in sport attendance by examining both reported attendance (tickets disseminated for an event) and actual attendance (tickets scanned/validated at the venue). Second, the current study only examined non-conference scheduling in college basketball, which is not determined by a conference or league, but rather by the athletics department itself, meaning department administrators possess control over when games are schedules and against whom.

Our results identified a massive 37% no-show rate for non-conference Division I college basketball games. Although it is possible some of this no-show rate is due to artificial inflation by schools, it is also likely that much of the gap is due to non-use of tickets by either season ticket holders or perhaps groups who receive a large quantity of tickets but do not distribute all of them or distribute them to people who do not plan to use them (Popp et al., 2023). As the current results attest, factors affecting reported attendance are not necessarily the same as those affecting actual attendance. Weekend games, for example, did not have a significant relationship with reported attendance, but did demonstrate a relationship with actual attendance. Similarly, geographic distance between schools was not significantly related to reported attendance when including all schools (and, oddly, was negatively related to reported attendance when isolating non-Power Five teams), but was significantly related to actual attendance, particularly among Power Five teams. Interestingly, home team winning percentage was related to reported attendance, but not actual attendance. If athletics departments wish to maximize actual attendance, which in turn would maximize ancillary revenue streams, as well as create a better game atmosphere, they should consider how they schedule non-conference opponents. The results also suggest marketers (and academicians) should be cautious when using reported attendance figures to assess the impact of scheduling and promotional tactics when their goal is drawing greater numbers of spectators present at the event, as opposed to the goal of disseminating the greatest numbers of tickets.

As a hypothetical example to illustrate the findings, during the 2022–23 season, Georgia Tech's men's basketball team played seven non-conference home basketball games. Two of those games included a Thursday game against Northern Illinois, a team with three all-time NCAA tournament appearances, and a Friday game against Northeastern, a team from Boston with nine all-time NCAA tournament appearances. In both instances, George Tech did not have a game scheduled for the ensuing Saturday. Had Georgia Tech instead scheduled more regional but similarly competitive opponents Mercer (three NCAA tournament appearances) and UT-Chattanooga (12 NCAA tournament appearances), and played those games on Saturdays, our model suggests a boost in actual attendance of nearly 4,000 additional spectators for those two games combined. Even if those hypothetical attendees did not buy additional tickets, Georgia Tech would capture nearly \$80,000 in additional ancillary revenue with a per cap of \$20.

Decisions regarding non-conference scheduling within high-level college basketball cannot be made in a vacuum. Other factors impacting such decisions include opponent quality (which can determine NCAA tournament eligibility and coaching tenure), facility availability, other activities on campus or in the community, relationships between coaches, and television demands. However, the impact of scheduling on marketing and fan attendance decisions should not be left out of the equation. Fans who possess a ticket but do not utilize it represent a lost opportunity for sport organizations to not only capture additional revenue but also develop stronger relationships with those (potential) attendees.

The results of the current study also demonstrate differences in demand for collegiate sport between Power Five institutions and non-Power Five institutions. These results are somewhat perplexing. In the models, geographic distance between schools had a significant but positive relationship with actual attendance among non-Power Five schools. This suggests opponents from further away actually draw more fans. At the same time, the betting line before a game, which indicates how closely the opponents are matched and would seem to indicate which games are going to be competitive, had no relationship with actual attendance among non-Power Five schools. Prior work has demonstrated Game Outcome Uncertainty (GOU), of which betting line serves as a proxy, does seem to play a role in fans actually deciding to attend a game (Schreyer et al., 2016). These two results seem to insinuate either these factors are not important in the attendance decision-making process for fans of non-Power Five programs or that other unaccounted for factors are at play. Further exploration in this area is certainly warranted.

Conclusion

This study provides valuable insights into factors affecting reported and actual attendance for non-conference college basketball games. Although college athletics administrators must balance many factors when establishing a non-conference basketball schedule, including level of competition, venue availability, and athlete practice/rest time, they should also consider the financial ramifications. Developing a schedule which also maximizes attendance and revenue is important for cash-strapped athletics departments. Yet while administrators have the ability to manipulate non-conference college basketball scheduling, no prior academic research has investigated how the schedule impacts consumer behavior. The current study, for example, indicates that scheduling more regional opponents on Saturdays, rather than more distant opponents on weekdays, could lead to a significant boost in actual attendance. The results also highlight the need for college athletics marketers to improve efforts to ensure individuals with tickets are actually attending events or are getting tickets which might go unused into the hands of spectators who would actually utilize them. A no-show rate of 37% is the largest rate observed among similar studies.

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