Article

Journal of Sports Economics
2023, Vol. 24(7) 877-902

DOI: 10.1177/15270025231174616
journals.sagepub.com/home/jse
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When the Stars Are Out: The Impact of Missed Games on NBA Television Audiences

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Abstract

Using the 2018–2019 NBA season, we examine the causes and effects of star players missing games. Focusing on 19 star players, we find that injury, proximity to the end of season, games on consecutive days, and opponent quality lead to missed games. We then estimate a model of NBA television audience size using granular data from nationally broadcast games. Doubling the proportion of star players missing games reduces TV audience by approximately 6.5 million household viewings per regular season. A rough estimate of the advertising revenue lost due to stars missing games is between $15 and $20 million per season.

Keywords

sports demand, load management, television ratings

JEL Codes: D12, D22, Z2

Introduction

Of all the benefits professional sports provide to their consumers, certainly one of the most important is the opportunity to watch exceptionally talented individuals do what

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they do best. Whether it is Patrick Mahomes, Lionel Messi or Serena Williams, fans pay top dollar to attend their matches and television networks pay billions of dollars per year for the right to broadcast games from top professional leagues. There is considerable evidence that game attendance in several sports is positively affected by the appearance of superstar players. Not surprisingly, then, star players missing games is cause for concern for by leagues; this is particularly true of the National Basketball Association (NBA), where the absence of uninjured players has drawn the attention of league commissioner Adam Silver.[1]

Players miss games for a variety of reasons, including injuries, disagreements with their own teams, and team strategy. Injuries are an inevitable a part of sports, but otherwise healthy players missing games is something that can be controlled. In some sports, periodically resting a player is commonplace and uncontroversial; Major League Baseball players are regularly given days off, as are National Hockey League goalkeepers. In the NBA, the practice of systematically resting star players referred to as "load management" is more contentious.[2] Load management "seeks to have a team's most important contributors playing at optimal health in the biggest moments for many years" (Pelton & Arnovitz, 2019), including the end-of-season playoffs. Games missed due to load management decisions are generally not related to acute injury circumstances, but instead represent strategic decisions to sit out a player who could otherwise play to protect their physical health or conserve their energy.

In the NBA, a player's monetary reward for making the playoffs and winning the championship is relatively small.[3] Players' willingness to rest for such a small monetary reward perhaps indicates that players may be more focused on winning than on money, although there is virtually no cost to the player for sitting out. There are certainly instances of NBA star players taking lower salaries than they could otherwise get in order to improve their and their team's chances of winning a championship. For example, James Harden, a star player who has never been on a championship team, chose in 2022 to take a $14 million pay cut with the explicit goal of improving the Philadelphia 76ers chances of winning a title (see Weisfeld, 2022). Whether a *team's* willingness to have a player sit out games in order to maximize their post-season performance indicates profit-maximization or win-maximization, however, depends on the monetary benefit to the team of winning a championship. How much a championship is worth to a team in terms of future ticket and merchandise sales and so forth is difficult to determine. Moreover, if the payoff is large enough, win-maximization and profit-maximization may not be incompatible.

Leagues have a potentially valid economic reason to be concerned about players missing games generally and for strategic purposes specifically. If sports fans watch broadcasts of games in order to see the league's stars play and are inclined to tune out if they do not, players missing games will result in smaller television audiences. This is particularly true for nationally broadcast games, where the potential audience extends beyond the fans of the participating teams who would watch their local broadcasts. Load management may offer strategic benefits to teams that engage in it, but it potentially imposes an external cost on other teams in the league. Because the value of the league's national TV contracts is tied to estimated viewership, and revenue from those contracts are shared equally by the teams in the league, costs resulting from one team resting a star player are borne by all teams in the league, while the benefits accrue only to the team(s) practicing load management. Thus, the practice may be privately optimal but socially inefficient.

There appears to be an upward trend in the number of games missed by the stars of the NBA over the past two decades. Figure 1 plots the median number of games missed over the course of that season by members of the NBA All-Star teams (the 24 players selected each year by fans, coaches and the media to compete in that season's All-Star game) from the 2000–2001 to 2018–2019 seasons. While there is a fair amount of variability from year to year, an upward trend is readily discernable. These are the players most likely to attract fan attention, and therefore the type of players on which we concentrate.

In this paper, we use game-level data from the 2018–2019 NBA season to examine the causes and effects of star players missing games. First, we establish that, for a set of star players, the likelihood of missing a game is predictable. Using a linear probability model on a sample of 19 star players from the 2018–2019 NBA season, we find that some of these players' missed games for reasons

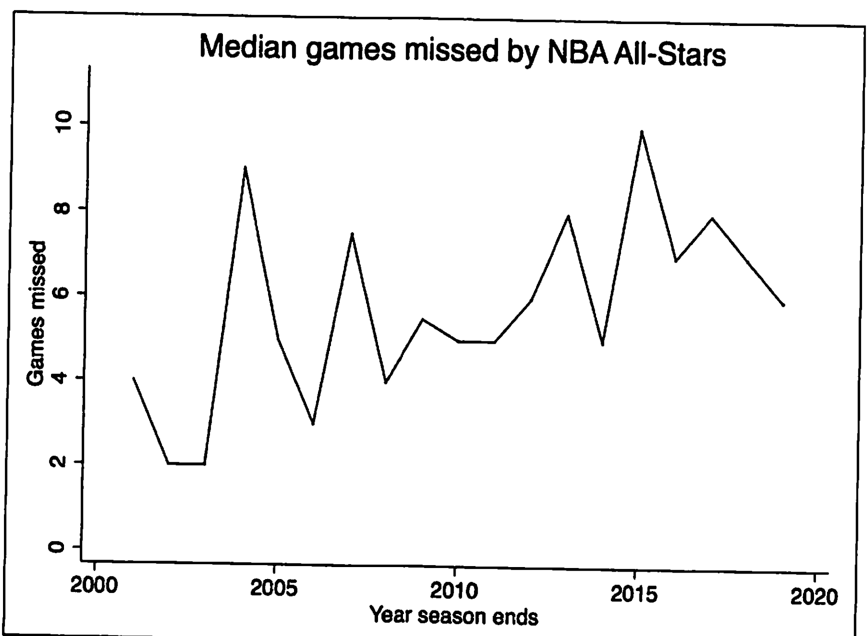

Figure 1. Median games missed by NBA All-Stars, 2000–01 to 2018–19 seasons.

that include proximity to the end of season, whether the game is part of a back-to-back sequence of games, and relative opposing team quality. Although injury is the most prominent determinant, this group of players is 6% points less likely to play in games that are part of back-to-backs. Elimination from and clinching of playoff spots are also important to their teams' decisions to rest these players. These results indicate that missed games are not merely the result of random events such as injury but that strategic decisions are being made to withhold players from games, and that the NBA's policy of assessing fines for egregious examples of load management has failed to eliminate the practice.

Second, we estimate the magnitude of the reduction in TV viewership that results from those same star players not taking part in games. We do this using a model of NBA TV audience size developed in Solow et al. (2023) that utilizes granular data from The Nielsen Company on within-game viewership of NBA games broadcast nationally on ESPN, TNT and ABC. Using OLS regressions of television viewership for 160 regular season nationally broadcast games (1738 15-min intervals) and controlling for the identity of the teams playing the game, score differentials over the course of the game, availability of substitutes, broadcasting network, day of the week and time of the broadcast, we conclude increasing the proportion of star players missing games by 100% reduces the size of the TV audience by approximately 6.5 million household viewings over the course of the regular season. A rough estimate of the advertising revenue lost by the broadcasters because of stars missing games is between $15 and $20 million over the course of the season.

Relevant Literature

The literature on the demand for sporting events is too large to summarize here.[4] Most existing studies use live attendance at events as the measure of quantity. A smaller but growing body of literature uses the size of the television viewing audience. Examples of such work include Buraimo (2008), who modeled the substitutability between attendance and television demand for English football; von Allmen and Solow (2011), who studied the impact of aggressive driving and crashes on TV spectator demand in NASCAR; and Paul and Weinbach (2015) who use betting markets to forecast TV audience size.

There are important differences between the audiences for game attendance and TV viewing. Perhaps most important from a demand perspective is that attending a live professional sports event can be expensive, while the price of watching a game on TV is, at the margin, typically zero. Consumers who attend sporting events in person tend to live relatively close to the event and are likely to be predominantly fans of the home team. Conversely, televised games are available to fans of the sport over a much wider geographical area - as wide as, in the case of national broadcasts, the entire country. Live attendance consumers and TV viewers also have very different sets of substitutes available. Someone who has purchased a ticket to a sporting event and learns shortly prior to or during the game that it will be less enjoyable (in our case, because a star player will not participate) is likely to have fewer live entertainment alternatives; the TV viewer can simply change the channel.

Using TV audience data also avoids modeling challenges that arise when using live attendance to measure demand. First, live attendance is limited by the capacity of the building while the quantity of viewers of a televised game is unconstrained. Additional fans cannot be accommodated at a live event once the capacity is reached (a "sellout"), regardless of their willingness to pay. This requires censored regression techniques to remove bias, but even those may be insufficient. Forrest et al. (2005) argue that sellouts may encourage loyal fans to substitute attendance at another, less desirable, game for the sold-out game (much like time substitution for leisure travelers). To the extent that this occurs, attendance at less desirable games is artificially inflated. Second, fans purchase tickets at widely varying times, from months before the season starts to the day of the game. The use of variable and dynamic ticket pricing (VTP and DTP respectively) strategies which allow the price of a ticket to vary depending on factors that may be known far in advance (VTP) or right up to the start of the game (DTP), now common among nearly all teams, make it harder to argue that one is estimating a single demand curve. Further dampening any price or game effects are season tickets and multi-game ticket plans. Given the ubiquity of such bundling schemes, in some cases few single game tickets may be available, leaving little room for variation in quantity.[5] Finally, the emergence of a well-organized secondary market for tickets through agencies such as StubHub make actual realized demand as measured by willingness to pay much more difficult to gauge as the same ticket can be sold multiple times. Taken together, it is clear that most tickets are not purchased at a time when fans would have current or accurate information on whether a star player will participate in the game.

A related literature tests the uncertainty of outcome hypothesis (the hypothesis that fans place higher value on games where the outcome is more uncertain) using television audience data (see Forrest et al., 2005 for English Premier League football; Coates et al., 2014 for Major League Baseball; Tainsky et al., 2014 for National Football League playoff games; Salaga & Tainsky, 2015 for U.S. college football, Solow et al., 2023 for the NBA). A recent paper in this literature by Humphreys and Pérez (2019) on Spanish football is important because, while focused on the uncertainty of outcome hypothesis, it controls for the presence of the dominant teams (Barcelona and Real Madrid) in a broadcast and uses the presence of star players on those teams, using several alternative definitions of star, as part of their robustness checks. The coefficients of those variables are not reported, but were found to have positive, statistically significant effects on TV audience size.

Very little attention has been paid to the issue of the absence of star players. Feddersen et al. (2023) find that betting odds are altered when bookmakers expect managers to rest players in European football games. The authors identify reduced "effort" or less-than-competitive personnel decisions in situations where teams' fates regarding qualification or relegation have been previously determined. Other studies, however, have examined what might be thought of as the converse question by asking how the *presence* of superstar players impacts live attendance when they play away from their home arena. In what is commonly referred to as the "superstar externality", the appearance of star players confers a positive externality on attendance, particularly at visiting stadiums. Examples include Berri et al. (2004) and Schmidt and Berri (2006) for season attendance at NBA games; Jane (2016) and Morse et al. (2008) for game attendance at NBA games; Lewis and Yoon (2018) for game attendance at Major League Baseball games; Lawson et al. (2008) and Jewell (2017) for Major League Soccer; and Brandes et al. (2008) for German soccer. Recently, Franck and Nüesch (2012) and Humphreys and Johnson (2020) extend this work for German soccer and the NBA respectively by distinguishing between stars whose status comes from performance and stars whose status is derived from popularity. Both papers note that there is some subjectivity in how one defines who counts as a superstar, an important subject we return to in the following section. Though not based on television ratings, this strand of research is important to our work in that it specifically considers the impact of superstars on demand as measured by attendance. The results generally support the idea that the presence of superstars does confer positive externalities, but results vary depending on how one defines superstar.

Buraimo and Simmons (2015) and a subsequent follow-up paper by Scelles (2017) both examined the effect of total team quality, as measured by combined team wages, on the demand for TV broadcasts of English Premier League matches between 2000–2001 and 2007–2008. Using a wide variety of controls including Derby (rivalry) games, playoff contention, day of week, availability of substitutes, and team quality, Buraimo and Simmons (2015) show that "...controlling for broadcast market conditions and team idiosyncrasies, *COMBINED RELATIVE WAGE* is all that matters to television audiences." (p. 463). The authors also estimate a probit model of which games are most likely to be shown on television, which is interesting in that it reveals those factors which sponsors are expected to positively influence demand. Scelles (2017) extends this research by considering the impact of being in contention for the championship or qualification for the champions league are also important to television ratings.

Most similar to our paper is that of Hausman and Leonard (1997), one of the first papers to examine the superstar effect by looking at TV audiences. Using Nielsen Company ratings (i.e., the fraction of households who watched a game), they examined the impact of the presence of All-Star players generally and a specific handful of superstars (Michael Jordan, Larry Bird, Magic Johnson, Shaquille O'Neal and Charles Barkley) on national over-the-air ("OTA") broadcasts for the 1990–1991 through 1992–1993 NBA seasons on NBC, the network that held the NBA broadcasting contract at that time. They similarly analyzed the effect of All-Stars and Jordan, Bird and Johnson in particular playing on national cable broadcast ratings on TNT, who had the national NBA cable broadcasting contract, for the 1989–

1990 season, and for Jordan, Bird and Johnson for local OTA and local cable broadcasts for the 1989–1990 and 1991–1992 seasons, using data disaggregated into local geographical territories (Designated Market Areas). Controlling for the season, month, day of the week and starting time of the broadcast, whether there was a competing broadcast on either the WGN or WTBS "superstations" or local OTA stations in the Designated Market Area, whether the game was part of a double-header, and the rating of the prior (lead-in) show, they concluded that total number of All-Stars had a small but significant effect on the rating of national NBA broadcasts both OTA and on cable, but that the presence of superstars, particularly Jordan, Bird and Johnson for national cable broadcasts on TNT and Jordan and Bird for national OTA broadcasts on NBC, boosted TV ratings above what a non-superstar All-Star player would add.

Identifying the Causes of Missed Games

While it would be desirable to disaggregate players' missed games according to their cause, in practice it is often difficult to identify whether a specific player's absence from a specific game is due to injury, load management or some other reason. According to the NBA, "NBA teams must report information concerning player injuries, illnesses and rest for all NBA games. By 5 p.m. local time on the day before a game (other than the second day of a back-to-back), teams must designate a participation status and identify a specific injury, illness or potential instance of a healthy player resting for any player whose participation in the game may be affected by such injury, illness or rest. For the second game of a back-to-back, teams must report the above information by 1 p.m. local time on the day of the game."[6] Such attribution is at the discretion of the team; however, while "rest" is sometimes listed as the reason for a player's unavailability, other absences attributed to a minor injury designated as "day-to-day" may also be functionally equivalent to resting.

Selection of Players

We focus our attention on 19 "star players" from the 2018–2019 regular season whose absence from a game is most likely to impact viewership. The NBA is a star-driven league; it seems unlikely that the absence of a bench player or even a regular starting player from a game would dissuade potential viewers from watching. Thus, including all players or even all starters in our data would attenuate the effect we seek to measure. Furthermore, if teams are making strategic decisions, they will rest those who are most important for a playoff run, i.e., their best players.[7]

We select a small set of players that likely influence demand for games and would have a higher propensity for load management, all else the same. While debating which players are among the league's best is a perennial fan activity, it is certainly the case that our selected set of players includes the very best and most popular

NBA talent of the 2018–2019 season. Table 1 presents our sample of players and their selection criteria. Each player in our sample is (1) a recipient of over two million fan votes for the annual All-Star game, and/or (2) among the top eleven scorers as measured by points per game in the regular season and/or (3) a recipient of a majority of possible points in the annual rookie-of-the-year voting. We collect 2018–2019 NBA season data for all-star votes, rookie-of-the-year votes, and points per game from basketball-reference.com.

Our first criterion, all-star votes by fans, is a direct measure of fan interest or demand. There are a few caveats to consider. Fan votes may reflect the size of the player's home-team fan base rather than a broader recognition of their talent. Fan voting may be biased toward favorite older stars; because of their age, these players may need more time off to recover from injury and, in turn, might be more

Table 1. Sample Selection Criteria.

	Selection Criterion Met		
	Two million + All-Star votes[a]	Top-11 points per game[b]	Top-2 Rookie of the Year voting[c]
Anthony Davis	x		
Bradley Beal		x	
Damian Lillard		x	
Derrick Rose	x		
Devin Booker		x	
Dwayne Wade	x		
Giannis Antetokounmpo	x	x	
James Harden	x	x	
Joel Embiid	x	x	
Kawhi Leonard	x	x	
Kemba Walker		x	
Kevin Durant	x	x	
Kyrie Irving	x		
LeBron James	x		
Luka Dončić	x		x
Paul George	x	x	
Russell Westbrook	x		
Stephen Curry	x	x	
Trae Young			x

Notes: [a]There were five players with between two and three million All-Star votes: Harden, Embiid, Davis, Westbrook and Wade. Wade had the fewest in this group with 2.21 million. The closest from below the two-million vote threshold were Steve Adams with 1.78 million and Klay Thompson with 1.58 million. [b]Points per game for rank 12 is 1.1 fewer than rank 11. This difference was relatively large. For context, the decrease in points per game moving from rank r to r + 1 is less than 0.7 for $r \in [2, 10]$. [c]For the rookie of the year voting, Dončić received 98% of the first-place vote and 496 points. Young received 2% of the first-place votes and 201 points, but was far ahead of 3rd place Ayrton at 66 points.

likely to partake in load management. We assume that voters of the All-Star game are representative of audiences of nationally broadcast NBA games, so that whatever home-team bias and nostalgia bias exists would be occur equally for an All-Star game and a nationally broadcast regular-season game.

Our second criterion, points per game, was selected because fan demand is offense driven. Those with more points per game will be more visible and their absence from the game more noticeable. Berri et al. (2004) find that offensive-minded players are disproportionately rewarded for their skills. Additionally, those with more points per game may put more stress on their bodies over the course of a game, all else the same, so they are good candidates for load management. We chose the top eleven as the scoring cut off because there seems to be a natural break at that point. Ordering points-per-game scoring from highest to lowest, the difference from eleventh to twelfth is the third largest points per game gap between consecutive ranks for the entire distribution.[8]

Our final criterion, rookie-of-the-year voting, captures demand due to novelty. New players provide glimpses of the NBA's future. There is a novelty and an excitement about exceptional first-year players. Luka Dončić and Trae Young were clearly above the other candidates as they received 99% and 60% of their maximum possible points respectively. The third-place vote earner, Deandre Ayton, received only 13% of his maximum points.

Table 2 provides player-specific data on missed games during the 2018–2019 regular season. It is immediately apparent that there was a great deal of variability in the number of games missed by our star players. Two of them (Beal and Walker) played in every game that season, and several others (George, Harden, Durant, Lillard, and Young) only missed a handful. Conversely, several players (Rose, James, Davis, Leonard, Booker, and Embiid) missed over 20% of their team's regular season games.

National television broadcasts do not feature our list of players evenly. For example, Curry and Durant playing for the Warriors were scheduled to participate in 30 nationally televised games while Young and Walker were only featured in one nationally televised game each. Note also that star players miss back-to-back games (games played on consecutive days) at a higher frequency than games where there is at least one day between games. Although the number of back-to-back games in the season differs only somewhat by team (e.g., 30 for Beal and Walker but only 24 for several others players), the national networks were less likely to broadcast back-to-back games than other regular season games. Thirty-one percent of all scheduled games for these players were back-to-backs, but only 20% of televised games for these players were back-to-backs.[9]

Overall, the players in our sample missed 14.44% of all games, 19.26% of back-to-back games, 13.40% of nationally-televised games and 15.38% of nationally-televised, back-to-back games. These differences in conditional means show that star players played less often in back-to-back games, even if the games were nationally televised.[10]

Table 2. 2018–2019 NBA Season: Games Missed, Back-to-Backs, and Nationally Televised Games.

	Games		Back-to-backs		National TV games		Nat'l TV × B2B	
Player	Scheduled	Missed	Scheduled	Missed	Scheduled	Missed	Scheduled	Missed
Derrick Rose	82	31	26	11	11	6	2	1
LeBron James	82	27	26	8	31	12	6	2
Anthony Davis	82	26	26	10	11	3	3	2
Kawhi Leonard	82	22	24	15	16	1	4	1
Devin Booker	82	18	24	8	3	2	0	0
Joel Embiid	82	18	26	6	27	5	5	1
Kyrie Irving	82	15	26	5	28	5	8	2
Stephen Curry	82	13	26	8	30	3	5	0
Dwayne Wade	82	10	24	2	3	0	0	0
Giannis Antetokounmpo	82	10	26	6	17	0	2	0
Luka Dončić	82	10	28	6	7	7	2	0
Russell Westbrook	82	9	24	2	28	2	7	1
Paul George	82	5	24	3	28	1	7	0
James Harden	82	4	24	1	28	1	4	0
Kevin Durant	82	4	26	2	30	2	5	0
Damian Lillard	82	2	24	1	15	0	1	0
Trae Young	82	1	24	0	1	0	0	0
Bradley Beal	82	0	30	0	6	0	3	0
Kemba Walker	82	0	30	0	1	0	1	0
Totals	1558	225	488	94	321	43	65	10
Percent, all games	100	14.44	31.32	6.03	20.60	2.76	4.17	0.64
Percent, category	100	14.44	100	19.26	100	13.40	100	16.39
Omitting Beal and Walker								
Percent, all games	100	16.14	30.70	6.74	22.53	3.08	4.38	0.72

(continued)

Table 2. (continued)

Player	Games		Back-to-backs		National TV games		Nat'l TV × B2B	
	Scheduled	Missed	Scheduled	Missed	Scheduled	Missed	Scheduled	Missed
Percent, category	100	16.14	100	21.96	100	13.69	100	13.39

Notes: Back-to-back games include both sides of the back-to-back (a pair counts as 2). We count nationally televised games as those games broadcast on ESPN, TNT, or ABC. We do not include NBA TV.

Empirical Analysis of Causes of Missed Games

We consider five possible reasons for players to miss games: injuries, and four factors which may affect a team's choice to sit its players strategically.

1. Obviously, injured players miss games until their injuries heal sufficiently. In order to identify games that are missed due to an ongoing injury, we consider whether a player who misses a given game also missed the preceding scheduled game. We create the lag of a missed game, *missed* $game_{ptg-1}$. which takes the value of 1 if player p of team t missed the game prior to game g, and 0 if player p played in the earlier game. This will partially account for longer-term injuries; although this will capture the second to n^{th} games of a stretch of games missed due to injury, it misses the first game of that sequence. We also consider the point in the regular season in which the game in question is being played, to allow for timing of injuries to vary over the course of the season. We would expect more injuries to develop as the season progresses, due to the accumulating wear and tear on players' bodies. We especially want to allow for the phenomenon of a player being "shut down" for the remainder of the season, typically as the result of an injury that occurs near the end of the regular season when a team's chances of making the playoffs is low. To this end, we create dummy variables for games in the first third of the season and the final third of the season (*first third of* $season_g$ and *final third of* $season_g$ respectively).
2. Stretches when games are concentrated over time. When a player is tired from playing a game the previous day, their bodies are physically more stressed and are more susceptible to injury (Conte et al., 2020; Morikawa et al., 2022). Load management is meant to reduce physical stress (Pelton & Arnovitz, 2019). Lewis (2018) finds that it is the concentration of playing time and associated lack of rest, rather than the aggregate amount of playing time, that explains the rate of injuries among NBA players; reducing game concentration is a natural strategy to avoid injuries. Hence, we focus on two game-concentration variables: Back-to-back games (*back to* $back_{tg}$), which takes the value of 1 if team t played game $g-1$ the previous day or if they play game $g+1$ the following day, and days of rest (*days* $rest_{tg}$), which takes the value equal to the number of games between game g and game $g-1$.
3. Games where the outcome is more certain. If teams are trying to win as many regular-season games as possible, we would expect coaches who utilize load management to rest their stars when it is less likely to change the win-loss outcome of the game. If this is true, players will be rested when the expected outcome of the games are more certain, ceteris paribus. We use the absolute value of the difference in winning percentages of the two teams (*absolute win*

pct differential$_{gt}$) as a measure of the anticipated competitiveness of the game.[11]

4. Games whose outcomes are of greater or lesser importance. This category encompasses a variety of situations where the increased probability of a loss as a result of resting a star player may be more or less important to the team. Chief among these are games that will not affect the team's chances of making the post-season playoffs. Once a team has been eliminated from playoff contention, the general manager, owner and/or coach may want to maintain the value of their assets for the following season. Similarly, once a team has secured a spot in the playoffs, they will want their players healthy for the post-season. We create dummy variables that identify games when a team has been eliminated from playoff contention (*eliminated*$_{gt}$) or has secured a playoff spot (*clinched*$_{gt}$). Since games against divisional rivals can be more important regarding playoff position, we control for whether game g involves such opponents (*divisional opponent*$_g$).
5. Potential economic impact of a missed game. We would expect profit-maximizing teams to refrain from resting players at home games, in order to maximize ticket sales and other game revenues. Thus, we control for whether game g for a star player on team t is a home game (at *home*$_{pgt}$). Similarly, while all regular season games count equally in the team's win-loss record, teams may wish to maximize their and their stars' exposure to the national audience of basketball fans. If this is the case, we might find fewer players resting during nationally televised games. Therefore, we create the variable *nationally televised*$_g$, which takes the value of 1 if a game was televised on ABC, TNT, or ESPN. We omit games that are televised on NBA TV because our television ratings data from Nielsen, used later in the analysis, does not include data for NBA TV.

Table 3 provides summary statistics for the variables related to these potential strategies. NBA data are from the NBA stats API.[12]

There are some potential issues in the estimation of missing games. Broadcasters choose which contests to broadcast. One such criterion that ABC selects on for its broadcasts is back-to-back games. So, including national broadcast is also important to avoid omitted variable bias on the estimated coefficient of back-to-back game. We also use player fixed effects to control for any unobservable, player specific, game invariant characteristics that may influence missing games. We estimate the following linear probability model:

$$missed\,game_{ptg} = \alpha + S_{tg}\beta + X_{tg}\gamma + \pi_p + \delta * missed\,game_{pt(g-1)} + \epsilon_{ptg} \quad (1)$$

where *missed game*$_{ptg}$ takes the value of 1 if player p of team t missed game g, 0 if player p played. S_{tg} is a vector of strategy related variables for each team, t, in game,

Table 3. Summary Statistics.

	Mean	Std. Dev.	Min	Max
Missed games	0.144	0.352	0	1
Regular Season games missed	11.8	9.4	0	31
Back-to-back game	0.313	0.464	0	1
Days rest	1.155	0.958	0	8
Nationally televised	0.206	0.405	0	1
Absolute win pct differential	0.232	0.220	0	1
Observations	1558			

Notes: Summary statistics for our 19 star players in their 82 game regular seasons. Back-to-back games identify either game of a back-to-back, i.e., a game that was played the day before or will be played the day after. Days rest signifies how many days since the team's last game. Nationally televised counts games broadcast on ABC, TNT of EWSPN. Absolute win percentage differential is the difference in opponents winning percentage.

g, for instance identifying back-to-back games. X_{tg} is a vector of control variables for each team t in game g, for instance, whether team t is the home team. π_p is a player specific fixed effect, and ϵ_{ptg} is the player-team-game error term that is normally distributed with mean 0, clustered by player. Clustering standard errors by player, as opposed to Huber-White robust standard errors, are appropriate here because in the presence of load management the strategy of when to rest likely varies by player. We also tried clustering by team, which resulted in slightly smaller standard errors.

Estimates of equation (1) are presented in Table 4. As expected, they indicate that injuries are the largest factor in missing a game. A player who missed the previous game, indicating a likely injury, was 0.41 to 0.45 percentage points more likely to miss the next game. That being the case, there is no evidence of games being missed less frequently during the first third of the season when injuries might be expected to be less likely, or more frequently during the final third of the season when injuries might be expected to be more likely.

There is also evidence of teams making strategic choices regarding missed games. Teams do appear to choose to rest their stars when two games are scheduled on consecutive days (back-to-back games). The parameter estimates in specifications (1) and (3) in Table 4 suggest that back-to-back games increase the likelihood of missing a game by 6 percentage points. Even if we omit Kawhi Leonard, who missed over half of the back-to-back games his team played, this result is statistically significant if somewhat reduced in magnitude. Other than these games with no days of rest between, however, the number of days of rest between games has no significant effect on missing games. This estimate suggests that players/teams regard back-to-back games as detrimental to players' success and health.[13]

The difference in the opponents' win-loss record is associated with star players missing games. A ten-percentage point increase in absolute win percentage

Table 4. Why do Players Miss Games?.

	Missed game			
	(1)	(2)	(3)	(4)
Missed last game	0.41*** (0.076)	0.45*** (0.068)	0.41*** (0.077)	0.45*** (0.069)
Back-to-back game	0.061** (0.024)	0.043** (0.016)	0.060** (0.024)	0.042** (0.016)
Nationally televised	−0.013 (0.022)	−0.00063 (0.021)	−0.0093 (0.021)	0.0016 (0.020)
Days rest	−0.010 (0.012)	−0.0051 (0.012)	−0.010 (0.012)	−0.0050 (0.012)
First third of season	−0.027 (0.033)	−0.020 (0.031)	−0.024 (0.033)	−0.018 (0.031)
Final third of season	0.0013 (0.026)	−0.0019 (0.025)	−0.029 (0.030)	−0.023 (0.028)
At home	−0.012 (0.015)	−0.0081 (0.015)	−0.012 (0.015)	−0.0076 (0.015)
Divisional opponent	−0.0073 (0.022)	−0.0043 (0.023)	−0.0076 (0.022)	−0.0042 (0.023)
Absolute win pct differential	0.090* (0.048)	0.061 (0.041)	0.052 (0.046)	0.034 (0.045)
Clinched playoff spot	0.044 (0.028)	0.063** (0.023)	0.035 (0.030)	0.058** (0.022)
Eliminated from playoffs	0.14* (0.068)	0.14** (0.063)	0.13* (0.070)	0.13* (0.065)
Final third of season × Absolute win pct differential			0.20** (0.092)	0.14* (0.078)
Player fixed effects	x	x	x	x
Observations	1532	1451	1532	1451
Omit Kawhi Leonard		x		x

Notes: Linear probability model estimating likelihood of missing a particular game given the variables listed and a player-specific fixed effect. Standard errors are clustered by player. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$. Sample limited to star players.

differential increases the likelihood of a star player missing a game by 0.9 percentage points. However, omitting Kawhi Leonard does reduce the estimated magnitude and significance. This effect is concentrated toward the end of the season as seen in specifications (3) and (4), which show the effect doubled in the final third of the season. This is evidence of strategic resting, especially toward the end of the season, in contests that are predictably less competitive.

It is also the case that players on teams that have been eliminated from post-season competition are more like to miss games, as are players on teams that have clinched spots in the playoffs. Star players on teams eliminated from playoff contention were around 14 percentage points more likely to miss a game. When omitting Kawhi Leonard, players were around 6 percentage points more likely to miss games after their team earned a playoff berth. With Kawhi in our sample, there is not significant difference, however, it is well-known that Kawhi usually sits out back-to-back games, so the playoffs being clinched might not change the calculus when it comes to load management in Kawhi's case.[14]

Conversely, several situations we considered as possibly factoring into the decision to rest star players had no discernable influence on their missing games. We find no significant impact for game location (home vs. away), games against a divisional opponent, or games played on national TV on the likelihood that star players miss games, all else equal.

The Impact of Star Players' Absence on National TV Viewing

Injuries that keep players out of games, while undesirable, are a fact of life. The fact that star NBA players are held out of games for strategic reasons also would not be of concern if their teams bear the full cost of holding them out. Any resulting reduction in demand for tickets or local broadcasts will be part of the optimizing decision by the team, to be weighed against the benefits of rest from player health during the season and possible playoff run. We make no attempt to measure those benefits here. Regardless of their magnitude, however, if the absence of otherwise healthy star players from nationally broadcast games cause fans to reduce their viewing of NBA games and if the value of a national TV contract in turn depends positively on audience size, the cost of missed games is borne in part by the rest of the league via lost national TV revenue in ensuing media contract negotiations. This externalization of cost would lead teams and players to engage in excessive load management from a league-wide perspective; this is precisely the argument advanced by the NBA against load management.

In this section, we provide evidence that the demand for TV broadcasts is in fact reduced when star players miss games. Due to the difficulty of differentiating between games missed due to load management and games missed due to injury or other reasons, we assume the impact on viewership of a star player's absence is the same regardless of the cause.

We use a model of NBA TV audience size developed in Solow et al. (2023) to study the uncertainty of outcome hypothesis within individual games. The model examines the relationship between audience size and alternative measures of the closeness of the game, controlling for a variety of other factors including the availability of other concurrently broadcast NBA games as a substitute. It utilizes estimated household viewership of nationally broadcast NBA games from the 2018–

2019 season; there were 168 national broadcasts of NBA regular season games in that season; 82 on ESPN, 67 on TNT and 19 on ABC. We obtained estimates of the number of households viewing the broadcast, broken down into fifteen-minute intervals, from The Nielsen Company. These data covered 162 of the nationally broadcast games, and we dropped one game that was broadcast simultaneously on two networks, reducing our final sample to 160 broadcasts. Those 160 games comprise 1,738 unique 15-min ratings intervals (about 11 per game).

Breaking each game into multiple consecutive broadcast intervals is valuable for several reasons. First, it allows us to control for variations in the closeness of the score as the game progresses, which is the focus of Solow et al. (2023). Secondly, it allows us to allow for smaller audience size during points in the broadcast when no action is taking place, which would otherwise be averaged in with intervals of active play. These are pregame and halftime broadcast intervals, which consist largely of advertisements interspersed with short periods during which the commentators are talking. The loss of viewers during such periods has been recognized by the NBA for some time; for example, NBA Commissioner Adam Silver noted, "Not surprisingly, we lose the highest number of fans when we move off live action, especially at halftime" in a 2018 interview.[15] Finally, the use of broadcast interval data allows us to more accurately assess the impact of competing broadcast games, which don't always start and end at the same time as the game under observation. By using the start times of each interval, we are able to match both scoring and the availability of concurrent broadcasts of NBA games to the viewing data.

How concurrently broadcast NBA games and their availability as a substitute for viewers might impact audience size requires some further discussion. First, we would expect the availability of alternative NBA broadcasts to reduce the demand for any given game, as some of the national TV audience may prefer to watch the teams playing in the alternative game or games. The TV audience for a game between the L.A. Lakers and the Golden State Warriors is likely to be smaller, all else equal, if the Utah Jazz are playing L.A. Clippers on another station than if they are not, simply because some potential viewers support the Jazz or the Clippers. This hypothesis is supported by Solow et al. (2023).

Secondly, the availability of concurrently broadcast NBA games is likely to affect the impact that a missing star player has on the audience of a game. However, the direction of that effect is ambiguous. On the one hand, in the absence of a game on another network, some fans will continue to watch a game that is missing a star player rather than not watch at all. If there is another game being broadcast, the availability of a substitute game provides some of those fans a preferable alternative to not watching. Some fans watching the Lakers-Warriors game when LeBron James is not playing might choose to switch to the Jazz-Clippers game if available but would continue to watch the Lakers and Warriors (even without James) if not. Others might choose to stop watching NBA basketball at that time altogether. Conversely, the presence of more concurrently broadcast games provides a larger audience of basketball fans who could switch to the national broadcast if they James *is* playing. These effects tend to *increase* the overall impact of the presence or absence of a star player when there are more concurrently broadcast NBA games.

On the other hand, when there are two or more games being broadcast simultaneously, we would expect their TV audiences to be different; viewers will sort themselves by watching the teams that they like, regardless of whether a star player is playing. When the Lakers-Warriors and Jazz-Clippers games are broadcast concurrently, the audience for the former will contain proportionally more Lakers and Warriors fans, who find the Jazz-Clippers game a poorer substitute, and who are more likely to continue watching the Lakers-Warriors game if James is not playing. This effect tends to *decrease* the overall impact of a missing star player when there are more concurrently broadcast NBA games. As a result, the total effect of concurrently broadcast games on the impact that absent star players have on viewership is ambiguous.

Thus, we estimate the following linear model:

$$\begin{aligned} viewership_{gi} = & \beta_1(\%\, stars\ out_g) + \beta_2(concurrent\ NBA\ games_{gi}) \\ & + \beta_3(concurrent\ NBA\ games_{gi} * \%\, stars\ out_g) + \Gamma\, \mathbf{Z}_{gi} + \epsilon_{gi} \end{aligned} \quad (2)$$

where $viewership_{gi}$ is the number of households watching nationally televised NBA regular season game g in 15-min interval i, % $stars\ out_g$ denotes the percentage of the 19 designated stars who are on the rosters of the two teams playing that are missing from game g, Γ is a vector of coefficients and $\mathbf{Z}_{gi}$ includes a measure of the absolute value of the score differential during interval i of game g, an indicator variable that takes the value 1 if no scoring took place during interval i of game g and 0 otherwise,[16] and fixed effects for the identities of the teams that are playing, the day of the week and the time of day of the broadcast and the broadcasting network.[17] Following Hausman and Leonard (1997), the start-time fixed effects consist of four dummy variables: before 5:00 pm, between 5:00 pm and 7:00 pm, between 7:00 pm and 9:00 pm, and after 9:00 pm. All start times are Eastern. ε_{gi} are mean 0 i.i.d. clustered standard errors; here, we cluster by game because the treatment variable (i.e., whether star players are missing) is assigned by game and all broadcast intervals within that game are treated identically.

We merge the game data and player specific data with the television ratings data to create a dataset of viewership for each 15-min interval of all nationally televised games, which includes data on presence of star players and other game specific variables. In addition to viewership numbers at intervals, we are also given the broadcasting network (ABC, ESPN, or TNT) and start time of the telecast. Table 5 presents summary statistics for the main variables under investigation.

In Table 6, we present OLS regression results using equation (2). The results are consistent with our expectations. Regarding star players missing games, our point estimates suggest that if the percentage of star players missing an average game increases by 100%, (from 14% to 28%), the viewership falls by 38,798 or about

2.3% of average per-game viewership, evaluating at the mean number of games being broadcast concurrently. This is an average for each time interval, not over the entirety of the game. Over a 168-broadcast regular season schedule, that translates into 6,518,064 fewer household viewings. Additional games being broadcast concurrently reduces the impact of star players' absence, suggesting that the availability of more viewing options is more than offset by the clustering of TV audiences by team preferences.

Also as expected, the number of other NBA games being played concurrently reduces viewership as audiences opt to watch their favored teams rather than the national broadcast. Evaluated at the sample mean, our point estimates indicate at that viewership of a given game drops by 49,628 households for each additional concurrent game being broadcast, which is about a 3% decline in viewership.

We can make a rough estimate of the external cost that missing stars impose on the league by estimating the advertising revenue the broadcasters lose because of smaller audiences. Television advertisements are priced according to audience size; the price advertisers pay is typically measured in cost per mille (CPM), or cost per thousand viewing households. Estimated average CPM for a 30-s commercial in 2018–2019 was $32 for broadcast TV and $17.50 for cable.[18] Private communication with management of one of the networks indicates a CPM of $30–$35 for commercials during a regular-season NBA game.[19] Hence, we use $30 as a CPM per 30-s commercial.

There are typically 13 commercial breaks during a nationally televised NBA game: two mandatory timeouts (so-called TV timeouts) during each quarter, each lasting 3.25 min, required by NBA rules;[20] additional 3.5-min breaks between quarters 1 and 2 and between quarters 3 and 4; and three commercial breaks during halftime. If 3 min of each break is dedicated to commercials with the remainder consisting of broadcaster commentary, there will roughly six 30-s commercials per commercial break or 78 commercials per game. This is a conservative estimate; other estimates run as high as 90 commercials per game.[21] Thus, the 6,518,064 fewer viewers that would result from a doubling of the percentage of stars missing from games over the course of a season translates into roughly 508.4 million fewer ad viewings or roughly $15.25 million per season at $30 per thousand viewings. Again, this is a conservative estimate; if we use the higher estimates of 90 commercials per game and a $35 CPM, the lost advertising revenue is $20.53 million.

Two caveats are in order. First, while $15.25 million or even $20.53 million is a lot of money, it is relatively small compared to the $2.7 billion annual value of the

Table 5. Sample Summary Statistics.

	Mean	Std. Deviation	Min	Max
Viewership (households)	1,620,894	894,252	194,495	8,424,265
% Stars Out	0.13828	0.27597	0	1
Concurrent NBA Games	2.108	2.1561	0	10

Table 6. Impact of Star Missing Game on National Television Viewership.

	Estimated Coefficient (Robust Standard Error)
% Stars Out	−377,304*
	(211,111)
Concurrent NBA Games	−55,917***
	(16,508)
% Stars Out × Concurrent NBA Games	45,572
	(45,421)

NBA's contract with its national TV broadcasters. Second, it is not clear how much of this lost value is passed through to the NBA and how much is absorbed by the broadcasting networks.

Conclusion

We have examined some of the causes and effects of star NBA players missing games. Our analysis provides a closer look at the characteristics of the game governing those absences, and the impact on television viewership when star players miss games. Using data from the 2018–2019 NBA regular season, we estimate a linear probability model which identifies game-specific scenarios that influence players' likelihood of missing games. Although injury is most often the cause of a player missing game action, strategic considerations also influence players' and teams' decisions to rest otherwise healthy players. Back-to-back games, end-of-season games when teams have clinched or been eliminated from the playoffs, and games toward the end of the year with large opening point spreads all increase the likelihood that players miss games.

Fans likely understand and appreciate that teams rest star players for strategic reasons, in order to pursue their playoff and championship aspirations and to protect the health of players. On the margin, however, fans appear to prefer watching games where the stars are playing. Thus, load management should have negative effects on NBA viewership and on combined teams' revenue. Our results support these statements. We find that star players' absences cost the NBA broadcasters something on the order of $15.25 million to $20.53 million of advertising revenue per season, which provides an upper bound on the cost to the NBA teams who share revenue from the national television contract. When compared to the $2.7 billion annual value of that contract, however, it is difficult not to conclude that impact of load management on the economic wellbeing of the NBA is minimal.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article

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Notes

1. Nico Martinez. Adam Silver Gets Real on Star Players Missing Games During the Season. April 6, 2022. https://fadeawayworld.net/nba-media/adam-silver-gets-real-on-star-players-missing-games-during-the-season. Accessed November 14, 2022.
2. The NBA prohibits listing "rest" as a reason to sit a player in a nationally televised game, with fines starting at $100,000, but prior to a November 2019 policy change, did allow the team to list "load management" if the team can argue that player is recovering from an injury. See Andrew Greif. NBA approves Clippers' plan to sit Kawhi Leonard as part of load management. November 6, 2019. Online at https://www.latimes.com/sports/clippers/story/2019-11-06/nba-approves-clippersplan-to-sit-kawhi-leonard-as-part-of-load-management. Accessed October 16, 2020, and Reid Goldsmith. NBA Clarifies Load management is rest in new memo. November 29, 2019. https://clutchpoints.com/nba-newsleague-clarifies-load-management-is-rest-new-memo/. Accessed October 21, 2020.
3. According to the Burd (2022), the total players' playoff pool for 2022 was slightly greater than $23 million; this was apportioned to the teams based on how far they went in the post-season tournament, with the team that wins the championship finals receiving about $4.1 million and the runner-up about $2.7 million. Each teams' reward is split equally amongst the 15 players on the team, so a player on the championship team receives about $275 thousand and a player on the runner-up about $182 thousand. While a significant amount of money, this is relatively small in the context of a league where the minimum player salary is $893,310 and the median salary is $4,347,600.
4. Cox (2012) contains a comprehensive summary of this work covering all major team sports. See also Coates et al. (2014).
5. John Lombardo. NBA Projects another season-ticket sales record. Sports Business Journal. https://www.sportsbusinessdaily.com/Journal/Issues/2015/10/26/Leagues-and-Governing-Bodies/NBAtickets.aspx. October 26, 2015.
6. See NBA Injury Report: 2021-22 Season.
7. Since our results are based on a small group of star players, they should not be extrapolated to all players. The problem of load management regarding fan demand, if there is a problem, is limited to the stars.
8. From 11^{th} to 12^{th}, the decrease is 1.1 ppg. For comparison, moving from rank r to r+1, points per game decreases by less than 0.7 ppg for $r \in [2, 10]$. Russell Westbrook to Klay Thompson, rank 17^{th} to 18^{th}, is greater at 1.4. The largest difference is rank 1 to rank 2; James Harden is far above the rest.
9. Broadcasts on ABC (weekend games) never feature teams on a back-to-back.

10. Dropping Beal and Walker who missed no games, we find players miss back-to-back games almost 22% of the time and miss nationally televised back-to-back games 16.39% of the time where televised games are missed 13% of the time.
11. We also considered use betting market point spreads as a measure of outcome uncertainty, but the opening point spread announcements takes place after player absences are announced, and therefore likely reflect that information.
12. We thank Scott Kaplan and Ryan Davis for their help locating this data.
13. One concern in interpreting the back-to-back coefficient estimates as evidence for strategic rest is that a minor injury sustained in game *g* is more likely to keep the player out of game *g+1* if the games were played on consecutive days than if the games were spaced further apart. If the only effect of back-to-back games is on the second game, we cannot confidently say that strategy is involved. We have run these same regressions while separating the first game and second game of back-to-backs. We do find that players are almost twice as likely to miss the second game relative to the first game of a back-to-back series of games, but there is still statistically significant evidence that the first game of a back-to-back is more likely to be missed (4.7 percentage points with Kawhi and 3 percentage points without Kawhi, significant at 10% level).
14. Additionally, Kawhi's Raptors were challenging for the Eastern Conference's top seed, which would mean home-court advantage in the Eastern Conference finals. They played in sixteen games after clinching a playoff spot; in thirteen they still had a chance at earning the top seed. Additionally, Kawhi played in their final three games of the season.
15. See "NBA Commissioner Adam Silver has a game plan," Strategy+Business, April 30, 2018, available at https://www.strategy-business.com/article/NBA-Commissioner-Adam-Silver-Has-a-Game-Plan.
16. These intervals are typically pregame and halftime broadcast intervals, during which the commentators are talking but no game play is taking place.
17. The variables in **Z** plus *concurrent NBA games* are the variables included in the model presented in Solow et al. (2023). In the interest of brevity, we do not discuss the magnitudes of their impacts here, but we present the estimated effects of broadcast time of day, day of week, and network in the Appendix.
18. Media Dynamics, Inc. press release.
19. For some additional context, the average cost to air a commercial on national broadcast television is $105,000 for a 30-second slot. See https://www.statista.com/statistics/302200/primetime-tv-cost-commercial-usa/
20. See the NBA Rulebook, Rule 5: scoring and timing sections II.d and section VI.c. (mandatory timeouts).
21. See Nationals Arm Race, "How much live action occurs in each sport? Ball in Play studies summarized" Available at https://www.nationalsarmrace.com/?p=475.

References

Berri, D. J., Brook, S. L., & Schmidt, M. B. (2004). Stars at the gate: The impact of star power on NBA gate revenues. *Journal of Sports Economics*, *5*(1), 33–50. doi:10.1177/1527002503254051

Brandes, L., Franck, E., & Nüesch, S. (2008). Local heroes and superstars : An empirical analysis of star attraction in German soccer. *Journal of Sports Economics*, *9*(3), 266–286. doi:10.1177/1527002507302026

Buraimo, B. (2008). Stadium attendance and television audience demand in English league football. *Managerial and Decision Economics*, *29*(6), 513–523. doi:10.1002/mde.1421

Buraimo, B., & Simmons, R. (2015). Uncertainty of outcome or star quality? Television audience demand for English Premier League football. *International Journal of the Economics of Business*, *22*(3), 449–469. doi:10.1080/13571516.2015.1010282

Burd, B. (2022). How much do NBA players make in the playoffs? The Sports Economist, April 21, 2022. Available at https://thesportseconomist.com/how-much-do-nba-players-make-in-the-playoffs/

Coates, D., Humphreys, B. R., & Zhou, L. (2014). Reference-dependent preferences, loss aversion, and live game attendance. *Economic Inquiry*, *52*(3), 959–973. doi:10.1111/ecin.12061

Conte, D., Kamarauskas, P., Ferioli, D., Scanlan, A., Kamandulis, S., Paulauskas, H., & Lukonaitiene, I. (2020). Workload and well-being across games played on consecutive days during in-season phase in basketball players. *The Journal of Sports Medicine and Physical Fitness*, *61*(4), 534–541. doi:10.23736/S0022-4707.20.11396-3

Cox, A. (2012). Live broadcasting, gate revenue, and football club performance: Some evidence. *International Journal of the Economics of Business*, *19*(1), 75–98. doi:10.1080/13571516.2012.643668

Feddersen, A., Humphreys, B. R., & Soebbing, B. P. (2023). Contest incentives, team effort, and betting market outcomes in European football. *European Sport Management Quarterly*, *23*(3), 605–621. doi:10.1080/16184742.2021.1898432

Forrest, D., Simmons, R., & Buraimo, B. (2005). Outcome uncertainty and the couch potato audience. *Scottish Journal of Political Economy*, *52*(4), 641–661. doi:10.1111/j.1467-9485.2005.00360.x

Franck, E., & Nuesch, S. (2012). Talent and/or popularity: What does it take to be a superstar? *Economic Inquiry*, *50*(1), 202–216. doi:10.1111/j.1465-7295.2010.00360.x

Hausman, J. A., & Leonard, G. K. (1997). Superstars in the National Basketball Association: Economic value and policy. *Journal of Labor Economics*, *15*(4), 586–624. doi:10.1086/209839

Humphreys, B. R., & Johnson, C. (2020). The effect of superstars on game attendance: Evidence from the NBA. *Journal of Sports Economics*, *21*(2), 152–175. doi:10.1177/1527002519885441

Humphreys, B. R., & Pérez, L. (2019). Loss aversion, upset preference, and sports television viewing audience size. *Journal of Behavioral and Experimental Economics*, *78*, 61–67. doi:10.1016/j.socec.2018.12.002

Jane, W.-J. (2016). The effect of star quality on attendance demand: The case of the National Basketball Association. *Journal of Sports Economics*, *17*(4), 396–417. doi:10.1177/1527002514530405

Jewell, R. T. (2017). The effect of marquee players on sports demand: The case of U.S. Major league soccer. *Journal of Sports Economics*, *18*(3), 239–252. doi:10.1177/1527002514567922

Lawson, R. A., Sheehan, K., & Stephenson, E. F. (2008). Vend it like Beckham: David Beckham's effect on MLS ticket sales. *International Journal of Sport Finance*, *3*(4), 189–195.

Lewis, M. (2018). It's a hard-knock life: Game load, fatigue, and injury risk in the National Basketball Association. *Journal of Athletic Training*, *53*(5), 503–509. doi:10.4085/1062-6050-243-17

Lewis, M., & Yoon, Y. (2018). An empirical examination of the development and impact of star power in major league baseball. *Journal of Sports Economics*, *19*(2), 155–187. doi:10.1177/1527002515626220

Morikawa, L., Tummala, S., Brinkman, J., Petty, S., & Chhabra, A. (2022). Effect of a condensed NBA season on injury risk: An analysis of the 2020 season and player safety. *Orthopaedic Journal of Sports Medicine*, *10*(9), 1–9. doi:10.4085/1062-6050-243-17

Morse, A., Shapiro, S., McEvoy, C., & Rascher, D. (2008). The effects of roster turnover on demand in the National Basketball Association. *International Journal of Sport Finance*, *3*(1), 8–18. doi:10.2139/ssm.1690885

NBA Injury Report: 2021–22 Season. Available at https://official.nba.com/nba-injury-report-2021-22-season/

Paul, R. J., & Weinbach, A. P. (2015). The betting market as a forecast of television ratings for primetime NFL football. *International Journal of Sport Finance*, *10*(3), 284–296.

Pelton, K., & Arnovitz, K. (2019). NBA load management: What we know and don't know. ESPN. Available at https://www.espn.com/nba/story/_/id/28066201/nba-load-management-know-know

Salaga, S., & Tainsky, S. (2015). Betting lines and college football television ratings. *Economics Letters*, *132*, 112–116. doi:10.1016/j.econlet.2015.04.032

Scelles, N. (2017). Star quality and competitive balance? Television audience demand for English Premier League football reconsidered. *Applied Economics Letters*, *24*(19), 1399–1402. doi:10.1080/13504851.2017.1282125

Schmidt, M. B., & Berri, D. J. (2006). Research note: What takes them out to the ball game? *Journal of Sports Economics*, *7*(2), 222–233. doi:10.1177/1527002504271352

Solow, J., Reilly, P., & von Allmen, P. (2023). Within-game uncertainty of outcome and the demand for professional basketball on television. Working paper.

Tainsky, S., Xu, J., & Zhou, Y. (2014). Qualifying the game uncertainty effect: A gamelevel analysis of NFL postseason broadcast ratings. *Journal of Sports Economics*, *15*(3), 219–236. doi:10.1177/1527002512457946

von Allmen, P., & Solow, J. (2011). The demand for aggressive behavior in American stock car racing. In R. Jewell (Ed.), *Violence and Aggression in Sporting Contests. Sports Economics, Management and Policy* (pp. 79–96), vol 4. Springer.

Weisfeld, O. (2022). James Harden has taken a $14 m pay cut to try to win a title. Why the hate? The Guardian, July 24, 2022. Available at https://www.theguardian.com/sport/2022/jul/25/james-harden-pay-cut-philadelphia-76ers-contract-nba-basketball

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Appendix: Estimated effects of broadcast time of day, day of week and network.

Broadcast Start Time	Estimated Coefficient (Robust Standard Error)
Before 5:00 PM	3,439,569 (947,194)
5:00 PM to 7:00 PM	4,970,578 (497,764)
7:00 PM to 9:00 PM	3,402,758 (740,294)
After 9:00 PM	3,550,249 (720,208)

F-test of equality of all coefficients is rejected at the 5% significance level.

Game Day of Week (difference from Friday)	Estimated Coefficient (Robust Standard Error)
Saturday	−255,115 (793,701)
Sunday	−717,344* (378,861)
Monday	808,969* (421,993)
Tuesday	1,241,171*** (416,649)
Wednesday	−17,756 (62,548)
Thursday	1,285,095*** (433,006)
Friday	omitted

Broadcast Network (difference from ABC)	Estimated Coefficient (Robust Standard Error)
TNT	−3,086,135*** (743,730)
ESPN	−1,595,011** (755,979)
ABC	omitted