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Abstract

Contests that are designed to be *consumed* for entertainment by non-contestants are a fixture of economic, cultural and political life. In this paper, we examine whether individuals prefer to consume contests that have more uncertain outcomes. We look to professional sports and exploit injury-induced changes to teams' line-ups to estimate the effect of outcome uncertainty on spectator demand for contests. Drawing on multiple seasons of game-level data from the Australian Football League, we find that game outcome uncertainty has a large effect: a one standard-deviation increase in the outcome uncertainty of a game *causes*, on average, an 11.2% increase in attendance. We show that this effect is greater: 1) when there is more at stake on the outcome of the contest; and, 2) for teams that have larger, more-dispersed fan bases. Our results extend research on contest design and information preferences by suggesting that spectators are strongly drawn to evenly-balanced contests, behavior consistent with people deriving entertainment utility from suspense and the resolution of uncertainty.

JEL classification: Z20, L82, L83, M55

Keywords: Contest design, information preferences, consumer demand

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1 Introduction

Many economic, cultural, and political institutions use contests to determine how to allocate outcomes between agents. Examples of such contests include relative reward schemes within firms, innovation challenges, political elections, and standardized tests for college admissions. A large body of research in economics studies how these types of contests can serve as efficient mechanisms for resolving agency problems and eliciting innovation (Lazear and Rosen, 1981; Prendergast, 1999; Fullerton and McAfee, 1999; Terwiesch and Xu, 2008). However, in practice there is a diverse and economically-significant class of contests - one that prominently includes professional sports events, competitive 'reality' television programs, and 'game' shows - designed to serve an additional purpose: to be consumed as entertainment by non-contestants.

The American Time Use Survey reveals that adults in the United States spend roughly one-fifth of each day consuming entertainment (Aguiar et al., 2013). To give some sense of the economic importance of just one form of contest-based entertainment, in 2019, the estimated revenue of the North American sports market was $73 billion, with gate revenue alone estimated at $20 billion (PricewaterhouseCoopers, 2019). Furthermore, according to Nielsen, of the top 20 most-watched primetime telecasts of 2019, 15 were live sports broadcasts and 3 were live 'award' contests (e.g., Academy Awards, Golden Globes, etc) (Variety, 2019).

In this paper, we examine the idea that people derive entertainment utility from suspense and the resolution of outcome uncertainty, an explanation the economics literature commonly puts forward to explain the popularity of contest-based forms of entertainment. To achieve this, we look to professional sports and use injury-induced changes to team line-ups as a source of plausibly exogenous variation in contest outcome uncertainty. Specifically, we construct a data set that contains attendance, team line-up, injury, betting, and performance information for all regular season games played in the Australian Football League (AFL) for the period 2013-2018. Our data set is unique because we are able to link injuries and line-up changes in the sample to betting, attendance and performance data at the game level.[1]

A number of empirical papers in economics study contest-based forms of entertainment - in particular professional sports and game shows - to understand how contest design choices shape the incentives and behavior of *contestants* (Ehrenberg and Bognanno, 1990; Post et al., 2008; Brown, 2011; Genakos and Pagliero, 2012). Whilst this work has improved our understanding of the incentive effects of contests, the literature,

[1] The focus of this paper - and much of the literature in sports economics on the demand for sports - is *game* outcome uncertainty. However, as Borland and MacDonald (2003) discusses, both intra-seasonal and inter-seasonal outcome uncertainty also impact consumer interest in sporting contests. The former refers to the number of teams in contention for the playoffs at a given point in the season; the latter refers to the number of teams that are likely to win titles across seasons.

however, provides scant insight into the behavior of *spectators* - i.e., the non-contestants that consume these contests.

In contrast, there is an extensive literature in sports economics and marketing that examines the *outcome uncertainty hypothesis* - the contention that sports fans prefer contests that have more uncertain outcomes (Rottenberg, 1956; Neale, 1964). At the core of this hypothesis is the idea that individuals are drawn to sources of information that gradually resolve uncertainty (Caplin and Leahy, 2001; Ely et al., 2015). While administrators of major sports competitions have implicitly used the outcome uncertainty hypothesis to justify the implementation of labor market regulations and other competitive balance policies with non-trivial welfare implications (e.g., salary caps and drafts, free-agency restrictions), empirical evidence on the relationship between outcome uncertainty and spectator demand for contests is at best mixed (Szymanski, 2003; Borland and MacDonald, 2003).[2] As few, if any, of the papers examining this topic exploit plausibly exogenous variation in outcome uncertainty, it is difficult to evaluate the extent to which the empirical inconsistencies in this literature are driven by omitted variables bias and other forms of endogeneity.[3]

In this paper, we use an instrumental variables (IVs) research design to address these endogeneity concerns and thereby identify the causal effect of outcome uncertainty on spectator demand for contest-based entertainment. Following the sports economics literature, we measure spectator demand using stadium attendance. Furthermore, we employ a measure of contest outcome uncertainty based on game-level betting odds. Our identification strategy separately employs two different injury measures as instruments: 1) the total number of injury-induced line-up changes made by a team for an upcoming game; and, 2) the aggregate loss of playing 'talent' represented by these injury-induced line-up changes (as captured by quantitative player ratings sourced from the league's data provider).

To ground our paper in earlier empirical work in sports economics and marketing, we generate regular ordinary least squares (OLS) estimates of the effect of game outcome uncertainty on spectator demand for sporting contests. We find that a one standard deviation increase in game outcome uncertainty is associated, on average, with a 5.4% increase in stadium attendance. OLS estimates also suggest that attendance at a game is maximized when the home team is a 61% chance of winning. These results are similar in magnitude and direction to findings previously reported in the literature (Szymanski, 2003; Borland and MacDonald, 2003; Schreyer et al., 2018).

Given our concern that these OLS estimates are biased, we use IVs to study the

[2]The wide-spread use of non-disclosure agreements for contestants on competitive reality television programs and games shows is also grounded in the idea that the primary appeal of contest-based entertainment is suspense - or the facilitation and eventual resolution of outcome uncertainty.

[3]We discuss the source and severity of these endogeneity concerns at length in Section 3.1 of this paper.

impact of outcome uncertainty on spectator demand for contests. We focus on variation in game outcome uncertainty arising from game-to-game changes to the line-ups fielded by teams competing in the AFL. Specifically, we exploit injuries to the team that enters the week of a game as non-favorite as exogenous shocks that lower the win probability of the non-favorite team. In turn, this decreases game outcome uncertainty (i.e., the non-favorite becomes even less of a chance to win the upcoming game). We observe but do not exploit as an instrument the injuries suffered by the team that enters the week of a game as favorite as these line-up changes are not monotonically related to changes in game outcome uncertainty.

We show that the announcement of injury-induced line-up changes are strongly correlated with changes in the probability of a team winning a game, and, by extension, changes in game outcome uncertainty. To suggest that injury-induced line-up changes are unlikely to affect attendance through channels other than game outcome uncertainty, we show that games with greater numbers of injury-induced line-up changes (vis-a-vis games with fewer numbers of injury-induced line-up changes) involve teams of similar quality, are played during similar time slots during the week, and occur no later or earlier in the season. We also show that *future* injury-induced changes to the line-up of the non-favorite team are not associated with game and team attributes at period t. These results strongly suggest injury-induced line-up changes are a plausible instrument for game outcome uncertainty.

Turning to our main results, we find that the relationship between game outcome uncertainty and spectator demand is strong and economically large: a one standard deviation increase in game outcome uncertainty *causes*, on average, an increase in stadium attendance of at least 11.2% - an effect equivalent to an additional 3,700 spectators per game. Our IV results are at least twice as large as those obtained using OLS, which suggest large negative biases in OLS estimates. We also employ our empirical strategy to estimate the 'optimal' level of outcome uncertainty. We find that attendance is maximized when the home team has a win probability of approximately 53% - close to the theoretical inflection point that would arise if spectators cared purely about game uncertainty of outcome.

Next, we explore two different sources of heterogeneity in the effect of game outcome uncertainty on spectator demand. First, we show that outcome uncertainty and attendance are very strongly associated for games where a play-off position is likely to still be at stake for at least one of the competing teams (we label these 'significant' games in the context of the championship race). We do not observe that outcome uncertainty increases spectator demand for games featuring only teams that have very likely already secured a place in the finals or very likely already been ruled out of contention for play-offs.

Second, we show that game outcome uncertainty causes particularly large increases in attendance for established teams that have larger, more-dispersed supporter bases (i.e., teams most likely to have higher proportions of casual fans). We also show that newer, less-established clubs - teams more likely to have smaller supporter bases made up of higher proportions of die-hard fans - face relatively inelastic demand with respect to game outcome uncertainty.

To establish the validity of our identification strategy, we conduct a number of robustness checks. Specifically, we show that our results are unlikely to arise due to endogenous 'misreporting' of injuries (e.g., teams resting players). We also show that our injury instruments appear unlikely to be violated by superstar effects or consumer preferences for high scoring games. As a final check of our identification strategy, we show that our results also hold up when we use league-enforced line-up changes ('suspensions') as an alternative instrument.

The rest of the paper reads as follows. Section II discusses the literature related to this study. Section III describes the setting and data. Section IV outlines our empirical strategy. Section V presents our main results. Section VI documents a series of robustness checks. Section VII provides additional cross-sectional analysis of our main results. Section VIII offers concluding remarks.

2 Related Literature

Our study most directly contributes to the literature on contest design (Lazear and Rosen, 1981; Green and Stokey, 1983; Nalebuff and Stiglitz, 1983). This body of research has focused on examining the incentive effects of tournaments and understanding how a range of contest design parameters - e.g., prize size, information disclosure policy, entry conditions - affect the behavior of contestants (Ehrenberg and Bognanno, 1990; Becker and Huselid, 1992; Knoeber and Thurman, 1994; Moldovanu and Sela, 2001; Casas-Arce and Martínez-Jerez, 2009). A number of papers in this literature exploit settings in professional sports to consider how outcome uncertainty affects the behavior of contestants. Examining the adverse incentive effects of competing with superstars, Brown (2011) uses data from professional golf tournaments to show that the introduction of large skill differences between competitors (i.e., decreases in outcome uncertainty) reduce contestant effort and lower performance. Conversely, in studying weightlifters' behavior in multi-round tournaments, Genakos and Pagliero (2012) shows that leaders take greater risks but perform worse when competition is more intense (i.e., when outcome uncertainty is greater). We extend research on contest design by identifying how uncertainty affects the behavior of spectators, a group of stakeholders whose behavior has not been explicitly studied in this literature. By showing that spectators have strong preferences for contests that have uncertain outcomes, our paper suggests that administrators who design contests that are consumed for entertainment need to consider both the 'incentive effects' of outcome uncertainty (i.e., the impacts on the behavior of contestants) and the 'consumption effects' of outcome uncertainty (i.e., the impacts on the behavior of spectators). Consideration of only the former may lead administrators to design contests that have desirable incentive properties but that are sub-optimal from a consumer demand perspective (e.g., unbalanced contests where competitors maximize aggregate effort but spectators 'tune out').

Relatedly, this paper's findings are especially relevant to the design of innovation contests. For these types of contests, audience interest is crucial for attracting contestants from a wide-range of technology areas - e.g., DARPRA and X-prize 'grand challenges' (Murray et al., 2012; Galasso et al., 2018). A number of studies on innovation challenges show that contestants are motivated by social distinction and respond strongly to public recognition (Frey and Gallus, 2017; Gallus et al., 2020). Our paper suggests that the designers of innovation challenges may be able to use outcome uncertainty to better engage spectators, and thereby attract contestants seeking public recognition.

Our paper also provides empirical evidence that complements theoretical research in the literature on belief-based utility and information preferences (Golman et al., 2017). A stream of this research formalizes preferences over the resolution of uncertainty (Kreps and Porteus, 1978). Caplin and Leahy (2001) applys a framework that suggests agents bet on their favourite team so as to increase the amount of suspense they will experience while watching a sports game. Relatedly, Ely et al. (2015) introduces a framework in which a Bayesian audience derives entertainment utility from anticipated changes in beliefs about outcomes (i.e., suspense). We extend this literature by showing empirically that individuals actively seek out suspense and consume sources of information that gradually resolve uncertainty - e.g., attending a high-stakes game in person, rather than simply looking up the outcome of a game upon its completion. More broadly, we show that preferences for suspense, rather than simply inscrutable tastes, drive demand for contest-based entertainment.

Finally, our paper contributes to the sports economics literature on uncertainty of outcome (Rottenberg, 1956; Neale, 1964; Borland and MacDonald, 2003; Szymanski, 2003). Whilst a large body of empirical research has tested the outcome uncertainty hypothesis in a range of different settings (Forrest and Simmons, 2002; Benz et al., 2009; Coates and Humphreys, 2012; Cox, 2018), this literature has yet to robustly identify the effect of outcome uncertainty on spectator demand for contest-based entertainment. We build on this research by exploiting a source of plausibly exogenous variation in outcome uncertainty. To the best of our knowledge, we provide the first causal estimates of the effect of game outcome uncertainty on spectator demand for contests. From a policy perspective, by showing that outcome uncertainty causes increased attendance at live sports, our paper lends support to the competitive balance policies implemented by many sports leagues around the world. The findings in our paper also inform the broader legal debate around the trade offs between consumer and labor welfare, and the antitrust implications of competitive balance policies in professional sports (Szymanski, 2003; McKeown, 2010; McCann, 2010).

3 Setting & Data Description

3.1 The Australian Football League

Founded in 1897, the Australian Football League is the world's premier Australian-rules football competition. Australian-rules football is the most popular sport in Australia, and the AFL is by the far the country's most commercially-successful and well-supported sports competition.[4] AFL games typically draw crowds of 30,000-35,000 supporters, comparable to match day attendance for the major European soccer leagues.[5] Furthermore, AFL teams have some of the largest fan bases in professional sports, with the league's largest clubs having up to 100,000 season-ticket holders. Whilst a large portion of individuals in attendance at a given game are season-ticket holders, single entry tickets may also be purchased for a game. Teams vary the price of these tickets from game to game, and these prices are typically set at the start of each season. A small, 'legitimate' secondary market for tickets also exists, but the AFL requires all tickets to be re-sold at face value.

The AFL season runs annually from March to September, with each of the League's 18 teams playing a total of 22 regular season games over 23 weeks. All games are broadcast on television.[6] Free-to-air television screens several games a week (with this fixture set prior to the start of the season), whilst cable stations and streaming services show all games live.[7] Winning a game earns a team 4 points, and upon completion of

[4] As per its annual report, the AFL generated $668 million AUD in revenue during the 2018 season. For comparison, the National Rugby League - the second-largest sports league in Australia - reported $500 million AUD in revenue for the 2018 season.

[5] AFL teams play out of large capacity, multi-use stadiums. As such, sell outs during the regular season are very uncommon in the AFL. This is not the case in other major sports leagues (e.g. NFL, EPL, etc) where sell outs occur frequently and attendance-based measures of demand are likely to be censored from above (i.e. 'desired' attendance and 'actual' attendance depart due to supply constraints).

[6] The literature has primarily looked at the association between game outcome uncertainty and attendance. However, more recent work has sought to estimate the effect of game outcome uncertainty on other forms of consumption - i.e. TV viewership (Forrest et al., 2005; Allan and Roy, 2008; Dang et al., 2015). Consistent with the former approach, this study takes as its measure of interest consumer demand as proxied by attendance.

[7] These broadcast arrangements remained stable for the period of the sample examined in this study. This alleviates the concern that changes to the screening of live games may at least partially be driving the results documented in this paper (i.e. consumers substituting television consumption for live consumption - or vice versa - due to some structural change).

the regular season, the top 8 teams in the standings (as per total points accumulated) qualify for the finals. The league employs a four-week playoff tournament in the finals, culminating in a 'grand final', the winner of which is awarded the 'premiership' (i.e. the league title).

The 'evenness' of the AFL as a competition has been widely attributed to the league's aggressive implementation and maintenance of competitive balance policies, most notably player drafts, free agency restrictions, revenue sharing, and strictly-enforced salary caps. Many of these policies are similar to the competitive balance measures employed in the major North American sports competitions (e.g., NFL, NBA, etc). Reflected in the words of the league's CEO, the AFL has justified these policies on the grounds that spectators strongly prefer more even contests (Australian Football League, 2016):

> We have pursued a managed competition with these policies instead of one left to free market forces so that every club has the opportunity to be successful on-field and to give their members and supporters hope. Having a competition in which there are uncertain outcomes each week with every club capable of beating the other on any given day or night is fundamental to driving interest in our game and building attendances, club memberships and national television and digital media audiences.

Nonetheless, these policies have faced resistance from a range of different stakeholders.[8]. The competition's 'mega clubs' (teams like Richmond, Collingwood, and West Coast, who have upwards of 85,000 season-ticket holders) have at times been vocal proponents of deregulating the competition - the thinking being that attendance is best maximized when the most popular teams enjoy continued success (The Australian, 2016). Whilst generally supportive of competitive balance, the AFL Players' Association has also raised concerns over the manner in which the AFL's trade regulations and salary cap may dampen wages and redistribute rents from players to owners/teams.[9]

3.2 Team Announcements, Injuries, and Betting Markets

AFL policy requires clubs to announce their team line-up several days prior to an upcoming game.[10] This involves each team identifying the 22 players they have selected to

[8]Dabscheck and Opie (2003) write at length about issues related to legal regulations in Australian sporting labor markets. The authors specifically address the topic of industrial relations in the AFL.

[9]Theoretical models in economics show that the distributional effects of free agency and player drafts on the player market as a whole are not clear (Zimbalist and Storey, 1992). For example, increased expenditure on free agents caused by competition for their services might lead to a reduction of investment in the development of rookie talent or lower salaries on average for players bound by labor restrictions.

[10]For Thursday games, line-ups are announced on Wednesday. For Friday and Saturday games, line-ups are announced on Thursday. For Sunday games, line-ups are usually announced on Friday.

play in that week's game.[11]

When line-ups are announced, teams explicitly identify two 'sets' of players: 'ins' and 'outs'. 'Ins' are players that did not feature in the previous week's line-up and have been brought into the team for the upcoming week's game. Typically, these are players that are returning from injury, or have been promoted from the club's 'feeder' (or reserve) teams. 'Outs' are players that featured in the previous week's line-up but are not in the team named for the upcoming week's game. Typically, these are players that have been injured in the previous week's game or during mid-week training in preparation for the upcoming week's game. These players may also be uninjured athletes who have been dropped due to poor form.

In addition to explicitly identifying each of the 'outs', teams must also disclose the reason for the line-up change. If a player is injured, the specific injury or illness is disclosed. If a player is dropped, he is listed as 'omitted'. As such, a player who the team was unable to select (due to injury) can be distinguished from a player who the team chose not to select (due to form).

Weekly team line-up announcements are closely followed by the public (line-ups are discussed intensely on local sports television programs and on the Internet) and by bookmakers. Sports betting in Australia is legal and betting on the outcome of individual AFL games is extremely active.[12] Bookmakers set their 'opening odds' for an upcoming AFL game at the start of each week (typically, this occurs each Monday during the season). Over the course of the week, bookmakers will adjust these odds in response to market forces and the disclosure of information material to the outcome of the upcoming game (e.g., weather forecasts, interviews and press conferences with players and coaches, etc). In this way, the betting odds come to impound the information contained in line-up announcements. In particular, the disclosure of injuries to specific players can lead to large changes in the betting odds for a specific game. These changes reflect shifts in the public's expectations of which team will win the upcoming game. Bookmakers continue to take bets and adjust the odds up until the start of each game, at which point the 'closing' odds are set.

3.3 Measures

We use game-level data on all regular season AFL games played between 2013-2018. This data set contains information on game-day attendance, betting odds, team line-ups, player performance ratings, and game results. The data set was constructed from three

[11] Teams also declare a set of 'emergency' players, who can be brought into the line-up in the event that any of the starting 22 players are required to pull out prior to the game. Prior to 2018, teams named 3 emergency players; from 2018, teams have been required to name 4 emergency players.

[12] According to Australian Gambling Research Centre (2017), sports betting generated \$1.06 billion AUD worth of winnings for the industry in 2016. Per capita gambling in Australia is more than double the level observed in the U.S. Around 7% of all sports bets made in Australia are placed on AFL games.

different sources: official AFL match reports, online bookmaking sites, and performance data generated by the AFL's data provider, Champion Data (see Appendix - Data for details). Given our study exploits the announcement of game-to-game line-up changes induced by injuries, we drop from our sample all games from the first week of each season (by definition, there are no 'changes' at the start of the season). As such, our data set has a total of 1,133 game-level observations.[13]

In this paper, the outcome measure of interest is $attendance_{ijs}$, the total number of spectators ('000) in attendance at the game between home team i and away team j in season s. Based on game-day swipe-in data from entry gates at each of the league's stadiums, these figures are sourced from official AFL match reports.

To proxy for uncertainty of game outcome, we employ a construct based on Theil's inequality measure. This is a widely-used game uncertainty of outcome proxy that is based on the distribution of a game's possible outcomes (Peel and Thomas, 1996; Benz et al., 2009; Pawlowski and Anders, 2012; Schreyer et al., 2018). Specifically, we calculate the measure as follows:

$$\text{outcome uncertainty}_{ijs} = \text{prob}_{ijs} \log\left(\frac{1}{\text{prob}_{ijs}}\right) + \left(1 - \text{prob}_{ijs}\right) \log\left(\frac{1}{1 - \text{prob}_{ijs}}\right)$$

where $prob_{ijs}$ is the probability of home team i defeating away team j in season s. As draws are very uncommon in Australian rules football (unlike soccer), we only consider the probability of a home win/loss in our construction of this measure. Our proxy is increasing in game outcome uncertainty, with a value of 0 indicating a certain home team win (loss), and a value of 0.7 indicating a '50-50' game (i.e. the home and away teams are equal favorites to win).

We use the average closing odds on the betting market for a home team win as our estimate of the home team's expected win probability.[14] Consistent with the use of this measure in the literature, we calculate the bookmaker's margin and then deduct this from the closing odds to arrive at an unbiased estimate of the home team's win probability (Benz et al., 2009). We classify the non-favorite as the team that started the week of the game with an opening-odds-implied win probability of below 50%. The

[13]We have 6 seasons of data with 18 teams competing each season in 11 'unique' games. This give us 6*11*18 = 1,188 observations. We drop games from the first round of each season: 1,188 - (6*9) = 1,134. Finally, due to a cancelled game in 2015 season (the fixture between Adelaide and Geelong was called off due to the death of Adelaide coach, Phil Walsh), we have 1,134-1 = 1,133 observations.

[14]Betting odds are averaged over the largest bookmakers in the Australian sports betting market (e.g. Sportsbet, Bet365, etc). For games that occur early in our sample, the betting market contains 10 bookmakers; for games that occur later in our sample, the betting market contains 12 bookmakers (2 bookmakers entered the market in the period 2013-2018). See Appendix - Odds for further discussion of betting odds data.

implicit assumption here is that the team that starts the week as non-favorite remains so at least up until the moment line-ups are announced for the upcoming game.

To capture injury shocks, we employ two measures. The first of these measures is defined as follows: $\textit{Number of injuries}_{ijs}$ is the total number of injury-induced line-up changes made by the non-favorite for the game between home team i and away team j in season s. To reiterate, by injury-induced line-up changes, we mean players who appeared for the non-favorite in game $t-1$ but due to injury were not selected for game t. This measure is constructed using data sourced from the official team line-up announcements.

We also use an alternative injury shock measure that is designed to capture differences in the quality of players that are lost due to injury. The use of this measure is motivated by the idea that not all injury-induced line-up changes will impact game outcome uncertainty to the same extent. For instance, an injury to an average player will not lower the affected team's probability of winning to the same degree as an injury to an above average or star player. This measure uses the game-level player performance ratings generated by Champion Data - the AFL's official data and sports analytics provider.[15]

Specifically, we calculate the average performance rating received by a player over the course of each season and sum together these ratings for the players from the non-favorite who due to injury withdrew from game ijs. This results in a summary measure of the total playing talent that is missing due to injury. This alternative injury shock measure is defined as follows: $\textit{Rating of injuries}_{ijs}$ is the total number of player rating points 'lost' by the non-favorite due to injury-induced line-up changes for the game between home team i and away team j in season s.

We also employ a number of control variables in our analysis. To capture competition between specific teams, we employ an indicator variable in our analysis that controls for local rivalries between clubs. This measure is defined as follows: $\textit{rivals}_{ij}$ is equal to one if the home team i and away team j are football clubs based in the same city. Known as 'derbies', games between teams from the same city are typically fiercely contested and draw especially large crowds. To control for the time-varying quality (or form) of the teams involved in each game, we also construct and use Elo-based team performance ratings for the home and away teams.[16] These ratings are updated after each game and take into account the historical performance of each team.

[15] Champion Data rates player performance using a single metric that is tied to a large number of quantitative performance measures. The objective of this rating is to capture a player's overall contribution to his team's performance. More information on the player rating can be found at `https://www.afl.com.au/news/453167/player-ratings-frequently-asked-questions`.

[16] First developed to rank players in chess, Elo ratings are commonly used in games and sport to measure the quality of participants. A contestant's Elo rating is represented by a number which increases or decreases depending on the outcome of games between rated contestants.

4 Empirical Strategy

4.1 Identification

In this section, we develop an empirical approach to identify the effect of contest outcome uncertainty on spectator demand.[17] The standard approach used in the literature to evaluate the impact of uncertainty of outcome on attendance is to regress attendance on game outcome uncertainty after conditioning on a vector of game-level covariates and including a range of fixed effects - for examples see Forrest and Simmons (2002), Benz et al. (2009), Coates and Humphreys (2012), Cox (2018). This approach is typically implemented by estimating the following type of reduced-form equation:

$$\log(\text{attendance})_{ijs} = \alpha_0 + \alpha_1 \text{outcome uncertainty}_{ijs} + \alpha \mathbf{X}_{ijs} + \phi_i + \omega_j + \chi_w + \epsilon_{ijs}$$

where $attendance_{ijs}$ is the total number of people that attended the game between home team i and away team j in season s.[18] $outcome\ uncertainty_{ijs}$ is a measure of the uncertainty of the outcome of the game between home team i and away team j in season s, $\mathbf{X}_{ijs}$ is a vector of game-level covariates, ϕ_i is a home-team fixed effect, ω_j is an away-team fixed effect, $\chi_w$is a week-of-season (or round) fixed effect, and ϵ_{ijs} is an idiosyncratic error term.

For the above empirical specification to identify α_1, the effect of uncertainty of outcome on attendance, $outcome\ uncertainty_{ijs}$ and ϵ_{ijs} must be uncorrelated. This assumption is challenging, as uncertainty of outcome is likely to be endogenous, even when attendance is conditioned on a large number of covariates and fixed effects.[19]

A range of unmeasured confounders may give rise to this endogeneity problem. For instance, if increased advertising and promotion activity boost attendance, competition administrators or the teams themselves might more heavily promote games that are

[17]There are only two prior studies that explore this topic in the context of the AFL. Borland and Lye (1992) looks at the association between game outcome uncertainty and attendance. This study fails to find a relationship between attendance and game outcome uncertainty (as measured using the absolute difference in league standings of the competing teams). In contrast, Dang et al. (2015) documents a strong positive association between game outcome uncertainty and TV viewership. Neither papers' estimates are 'causally identified'.

[18]Attendance is strictly positive, typically takes large integer values, and usually heavily right-skewed. As such, models of attendance in the literature work with the natural logarithm of attendance. This serves to reduce the influence of extreme values or outliers on the estimates produced by the model. Log-linear models also generate coefficients with an appealing interpretation: $\%\Delta y = 100 * (e^{\alpha_1 * \Delta x} - 1)$

[19]Szymanski (2003) notes that "there have been relatively few attempts to analyze causality empirically in the sports literature". Szymanski (2001) is perhaps the only prior study that provides a causal estimate of the effect of *seasonal* outcome uncertainty (or championship inequality) on fan interest. Our paper is distinct from Szymanski (2001) in that we provide causal estimates of the effect of *game* outcome uncertainty on attendance.

expected to not be especially close (McDonald and Rascher, 2000). As many of these promotions and advertising campaigns are unobservable (from the perspective of an empiricist looking to employ a research design), these marketing practices might serve to bias downwards estimates of the effect of game uncertainty of outcome on attendance.[20] Alternatively, if not controlled for, weather may may lead to a correlation between uncertainty of outcome and the error term - e.g., forecasted wet weather may make games closer in expectation but reduce attendance as spectators do not wish to potentially sit or stand in the rain) (Cairns, 1984). This would also lead OLS estimates to underestimate the effect of outcome uncertainty on attendance.

Selection on observables may also be violated through other channels. Known as load management, teams occasionally rest star players for games that are likely to be 'blow outs' (Soligard et al., 2016). As the presence of star players is associated with attendance as well as the uncertainty of the outcome of a game, load management likely acts to positively bias estimates of the effect of game outcome uncertainty on demand (Hausman and Leonard, 1997; Ormiston, 2014). Game outcome uncertainty will also be endogenous if administrators schedule games that are expected to be close in time slots that are more attractive to spectators (Jakee et al., 2010). This would also positively bias estimates of the effect of game outcome uncertainty on attendance. Alternatively, ticket prices - on either the primary or secondary markets - may also vary with game outcome uncertainty (Diehl et al., 2016). If teams or individual ticket sellers expect demand to be dampened for games that are unlikely to be close, we should expect to see prices lowered for tickets to these particular games. This would negatively bias OLS estimates of the effect of game uncertainty of outcome. As these examples highlight, $\textit{outcome uncertainty}_{ijs}$ may be correlated with ϵ_{ijs} in a variety of ways that may work to either negatively or positively bias estimates of the effect of game outcome uncertainty on spectator demand for contests.

In this paper, we use instrumental variables (IVs) to overcome this problem. The main advantage of using IVs is that we are explicit about the source of variation used to evaluate the impact of game uncertainty of outcome on attendance. Specifically, we use the announcement of injury-induced changes to the line-up of the non-favorite team to instrument for the uncertainty of a game's outcome.[21]

A valid IV is required to meet two criteria: 1) the instrument must be relevant; and, 2) the instrument must meet the exclusion restriction (Angrist and Krueger, 2001). Regarding the former, for our instrument to be relevant it must affect game outcome

[20] Taking advantage of settings where specific types of promotional events are observable, a literature in marketing studies the association between game-day promotions and attendance at sports events (McDonald and Rascher, 2000; Bovd and Krehbiel, 2003).

[21] A small literature in economics exploits injury shocks in professional sports to examine predictions from tournament theory. For instance, Brown (2011) uses injury-induced changes to Tiger Woods' playing schedule on the PGA Tour to identify the adverse effects of superstars in tournaments.

uncertainty (in our case, by impacting the likelihood of a non-favorite team win). Regarding the latter, for our instrument to meet the exclusion restriction it must not affect attendance through any channel except for its direct effect on uncertainty of game outcome.

With respect to the relevance condition, injuries force a team to field a weakened playing line-up; one containing players that absent injuries would not be named to start. As such, injury-induced line-up changes decrease the likelihood that the affected team will win the game. If the team that is the non-favorite suffers injuries, this then serves to decrease the uncertainty of the outcome of the upcoming game in that the non-favorite is now perceived by the public to be even less of a chance of winning.

The effect of injuries to the favorite team on game outcome uncertainty is more complicated. Whilst injury-induced line-up changes to the favorite decrease the likelihood of the favorite winning, this does not strictly increase game outcome uncertainty. For instance, if a team is only marginally favorite (or if a moderate favorite suffers a large number of injuries), the announcement of injury-induced line-up changes to the favorite could in fact work to decrease game outcome uncertainty (i.e. the injury shock makes the favorite more of a non-favorite than the non-favorite was prior to the disclosure of the team line-ups). As such, injury-induced changes to the line-up of the favorite fail to meet the monotonicty condition, an additional technical assumption that is required to hold for IV methods to identify the local average treatment effect (Angrist et al., 1996). For this reason, although we observe injury-induced line-up changes for both the favorite and the non-favorite teams, we only exploit the latter in our identification strategy.[22]

The exclusion restriction requires that injuries cannot be related to attendance outside of their effect on game uncertainty of outcome. This assumption cannot be empirically tested, and must instead be evaluated on the basis of theory and an understanding of the setting and any relevant institutional details. We argue that conditional on the specific teams involved in a game, injury-induced line-up changes are exogenous.

Given the nature of Australian-rules football as a sport, this seems a reasonable assumption. For instance, two of the most common forms of injury to occur to AFL players are blunt force injuries (e.g. head or body knocks from tackles and collisions) and joint injuries (e.g. torn knee ligaments) (Hrysomallis, 2013). These injuries typically do not occur in any sort of systematic fashion, but usually arise due to random on-field events (e.g. a player slips in a contest and receives a blow to the head, a player tears an anterior-cruciate ligament in a tackle). Even if we allow for injuries to be more likely to occur in closer games or in especially important contests when players might

[22] A failure of monotonicity means the instrument pushes some games into treatment while pushing others out. These 'defiers' complicate the link between the local average treatment effect and the reduced form. Specifically, we might have a scenario where the reduced form is zero when the effect on compliers is cancelled out by the effect on defiers.

exert themselves excessively, the exclusion restriction is not violated as we are exploiting injuries as negative shocks on the line-up fielded by a team for the *following* game - i.e., we are not analyzing outcome uncertainty and attendance for the game in which the injuries occurred. Furthermore, we do not expect there to be correlation between the characteristics of games from week to week (e.g., the AFL does not design the fixture so that a team will face a good team in one week and poor team the following week). This lends further credence to the argument that injury-induced line-up changes are plausibly exogenous.

That being said, our identification strategy acknowledges that specific teams are likely to be better (or worse) at managing injuries. This could arise because more successful teams have better-resourced sports science and medical departments, which in turn allows these teams to better manage and prevent injuries (McCall et al., 2014). Given that successful teams will also be more likely to have greater numbers of supporters (and thus higher levels of attendance), there is the danger that line-up changes due to injury are confounded by the level of resources a team has at its disposal. For this reason, in our empirical design, we use fixed effects for both the home and away teams.

4.2 Estimation

To implement our IV approach and thus mitigate bias introduced by the endogeneity of uncertainty of outcome, we estimate a two-stage least squares model of attendance on uncertainty of outcome. The model starts with the following first stage:

$$\text{outcome uncertainty}_{ijs} = \pi_0 + \pi_1 \text{injuries}_{ijs} + \pi_2 \mathbf{X}_{ijs} + \gamma_i + \rho_j + \theta_s + u_{ijs}$$

where *outcome uncertainty*$_{ijs}$ is the Theil Index of the game between home team i and away team j in season s, injuries$_{ijs}$ is our measure of injury-induced changes to the line up of the non-favorite in the game between home team i and away team j in season s, $\mathbf{X}_{ijs}$ is a vector of game-level covariates, γ_i is a home-team fixed effect, ρ_j is an away-team fixed effect, θ_s is a season fixed effect, and u_{ijs} is an idiosyncratic error term. For our instrument to meet the relevancy condition, our injury measure must be strongly correlated with game uncertainty of outcome.

The second-stage equation estimates the relationship between uncertainty of outcome and attendance:

$$\log(\text{attendance})_{ijs} = \beta_0 + \beta_1 \text{outcome } \widehat{\text{uncertainty}}_{ijs} + \beta_2 \mathbf{X}_{ijs} + \psi_i + \eta_j + \upsilon_s + e_{ijs}$$

where $attendance_{ijs}$ is the total number of people that attended the game between home team i and away team j in season s, $outcome\widehat{\ } uncertainty_{ijs}$ is the fitted value from the first-stage, $\mathbf{X}_{ijs}$ is a vector of game-level covariates, ψ_r is a home-team fixed effect, η_j is an away-team fixed effect, υ_s is a season fixed effect, and e_{ijs} is an idiosyncratic error term. For our instrument to meet the exclusion restriction, our injury measure must be uncorrelated with e_{ijs}. If this assumption holds, β_1 identifies the effect of game outcome uncertainty on attendance.

5 Results

5.1 Descriptive Statistics

We present summary statistics for the games in our sample in table 1. In terms of our outcome measure, the average game in our sample was attended by 32,602 spectators. The least-well-attended game was attended by 4,370 spectators and the most-well-attended game attended by 93,370 spectators.[23] Based on average closing odds, for the average game in our sample, the favorite team was a 73% chance of winning. Based also on average closing odds, for the average game in our sample, the home team was a 55% chance of winning. This suggests that for the typical game the home team was usually favorite. Looking at measures of dispersion, we see considerable variation in the win probability of the favorite team, with our sample containing games where the favorite was considered a near certainty to win (Max = 0.98) and games where the competing teams were evenly split (Min = 0.50). Naturally, this variation is reflected in our uncertainty of outcome measure. The average game in our sample had a Theil index of 0.54. The minimum Theil index is 0.02 and the maximum is 0.69 (by construction, the Theil index has a lower bound of 0 and an upper bound of 0.70). Therefore, our sample contains games that have very high and very low levels of outcome uncertainty, and a mass of games that are expected to have fairly close outcomes.

[23] Consistent with the AFL's use of large capacity, multi-use stadiums, sell outs are uncommon in our sample. For instance, median attendance is 59% of stadium capacity. Furthermore, attendance was above 90% (95%) capacity for only 6% (2%) of games in our sample. As we are not concerned that our dependent variable is in practice censored from above, we employ OLS and 2SLS estimation procedures in our analysis, rather than the types of censored regression models employed by studies elsewhere in the literature that deal with settings where sell-outs are common (Benz et al., 2009; Coates and Humphreys, 2012; Cox, 2018). As fewer than 1% of the games in our sample have attendance below 20% capacity (and no game in our sample has attendance at under 5% capacity), we are even less concerned that our dependent variable is bound from below.

Turning to the properties of our instruments, the average game in our sample featured 1.23 injury-induced changes to the line-up of the team that was non-favorite. We observe in our sample games where teams had as few as zero injury-induced line-up changes, and as many as 11 injury-induced line-up changes.[24] In terms of measuring the quality of the players lost to injury, for the average game in our sample, the line-up of the team that was non-favorite was typically absent due to injury player(s) worth 86.50 player rating points. Again, we see considerable variation in this measure. For context, the average AFL player has an average performance rating of 62.60. For further comparison, figure 1 plots the distribution of average performance ratings for all active players in the AFL between 2013-2018 against the distribution of average performance ratings for all injured players over the same period. Figure 1 highlights two features of the data. First, playing talent within the AFL appears to be approximately normally distributed. Thus, there is considerable variation in player quality within teams and across the league. Second, the distribution of average performance ratings of injured players stochastically dominates the distribution of average performance ratings for all players. This suggests that injured-induced line-up changes act as negative shocks to the quality of the affected team (i.e., injured players are replaced, on average, by lower quality players).

Overall, table 1 shows that attendance in the AFL varies considerably from game to game in the AFL. Similarly, there is a high degree of variability in terms of game uncertainty of outcome. The extent to which the former is a function of the latter - and the role that injuries play in helping us explore this - is the focus of the remainder of our empirical analysis.

5.2 Univariate Analysis

Next, we compare the characteristics of high uncertainty of outcome games and low uncertainty of outcome games (i.e., games that have above- and below-median scores on the Theil Index).

In table 2, we begin by comparing attendance across high and low uncertainty of outcome games. Consistent with the uncertainty of outcome hypothesis, we see that average attendance is greater for high uncertainty of outcome games than for low uncertainty of outcome games: 35,874 spectators and 29,362 spectators, respectively. This difference - 6,512 spectators - is significant at the 1% level.

Turning to the matter of covariate balance, table 2 provides evidence that low outcome uncertainty games (compared to high outcome uncertainty games) typically involve

[24]In untabulated results, we observe that the median game in our sample features 1 injury-induced change to the line-up of the non-favorite. Furthermore, we observe that over two-thirds (68%) of games in our sample feature at least 1 injury-induced line-up change; whilst 15% of games in our sample feature at least 3 injury-induced line-up changes. This suggests our injury instrument displays considerable variation.

a team that is perceived as a much stronger favorite and typically occur earlier in the season. Table 2 also suggests that high uncertainty of outcome games are much more likely to be played during 'marquee' time slots (Thursday and Fridays, and during the evening). Finally, table 2 also shows that high uncertainty of outcome games vis-a-vis low uncertainty outcome games typically involve less dominant teams as favorites and relatively stronger teams as non-favorites. Taken together, the differences reported in table 2 indicate that game uncertainty of outcome is not random; it is in fact correlated with a range of observable characteristics of games that are also determinants of match-day attendance.

However, the larger concern is that high outcome uncertainty and low outcome uncertainty games likely also differ across a variety of unobservable attributes. As a result, it is not obvious that high uncertainty of outcome and low uncertainty of outcome games are a fair counterfactual for each other, even when such analysis is conditioned on a rich set of covariates. This casts considerable doubt on the ability of selection on observables (and other matching style identification strategies) to identify the effect of uncertainty of outcome on attendance.

5.3 Instrumental Variables Analysis - Plausible Exogeneity

To address the endogeneity of contest outcome uncertainty, we provide instrumental variables estimates. Specifically, we instrument for game outcome uncertainty using the disclosure of injury shocks to the line-up of the team that enters the week of the game as non-favorite. We provide evidence that suggests injuries in the AFL are plausibly exogenous. To do so, we compare 'pre-treatment' characteristics of games that have high numbers of injury-induced line-up changes and games that have low numbers of injury-induced line-up changes.

In table 3, we show across a range of pre-treatment characteristics that games where the non-favorite team faced a higher number of injury-induced line-up changes cannot be distinguished using difference-in-means tests from games where the non-favorite team faced a low number of injury-induced line-up changes. Specifically, games that have above-median injury-induced changes to the non-favorite team line-up do not appear to be played any earlier or later in the season, do not appear to be played earlier or later in the week, do not appear to be played at different times of the day, and do not appear to involve teams of higher or lower quality. The former of these results is particularly interesting, as it appears to suggest that teams do not consistently 'use' injuries to strategically rest players for upcoming games against especially good or especially poor teams. This is further supported by the fact that the average likelihood of a favorite team win as of the beginning of the week of the game (i.e., before the line-ups for the game have been announced) does not differ across high versus low injury games. Overall, by showing that games impacted by high versus low numbers of injury-induced changes to the line-up of the non-favorite are balanced on pre-treatment outcomes, table 3 lends support to the idea that injuries are plausibly exogenous.

5.4 Instrumental Variables Analysis - First Stage

Next, we formally test the relevance of injury shocks as instruments for game outcome uncertainty. In table 4, we report the results from a model where we regress the probability of a favorite team win (as implied by the average bookmakers' closing odds) on our injury shock measures. Specifically, table 4 allows us to trace out the mechanism by which injury-induced line-up changes impact game outcome uncertainty by increasing the likelihood that the favorite team will win.

In table 4 columns 1-2, we see that an increase in the number of injury-induced line-up changes to the non-favorite substantially increases the win probability of the favorite. Specifically, an additional injury-induced change to the non-favorite team line-up increases the probability of a favorite team win by approximately 2.0 percentage points - a result that is significant at the 1% level. In table 4 columns 3-4, we show that when the non-favorite's line-up loses an 'average' player due to injury (an individual that has a player rating of 70 points), the probability of the favorite team winning increases by 2.1 percentage points - a result that is significant at the 1% level.

As documented in table 4, these results are robust to the inclusion of home-team, away-team, and season fixed effects. Encouragingly, our results change very little when we include these fixed effects, which further supports the exogeneity of injury-induced line up-changes. Taken together, the results in table 4 suggest that injury-induced line-up changes affect the relative strength of the teams involved in a game.

Building off of these results, we next look directly at the relationship between injury-induced line-up changes and game outcome uncertainty. In table 5, we estimate our first-stage model by regressing game outcome uncertainty on our measures of non-favorite team injury-induced line-up changes.

In table 5, we observe F-statistics > 10. This suggests that injury-induced line-up changes are unlikely to be a weak instrument. As a result, our IV estimates are unlikely to be biased towards those produced by OLS (Staiger and Stock, 1994; Stock et al., 2002). In terms of interpreting the specific coefficients, in table 5 columns 1-2, we observe that an additional injury-induced change to the non-favorite team's line-up is associated with a 0.024 unit decrease in our game outcome uncertainty measure. This association is significant at the 1% level, and reflects a 0.16 standard deviation decrease in game outcome uncertainty. In columns 3-4, we present similar findings using our alternative injury shock measure. The loss of an average player due to injury from the line up of the non-favorite team is associated with a 0.023 unit decrease in our game outcome uncertainty measure. This association is statistically significant at the 1% level.

In sum, the first-stage results indicate that injury-induced changes to the line-up of the non-favorite team have a strong, negative impact on game outcome uncertainty. Moreover, the robustness of the estimated coefficients to the inclusion of a range of fixed effects - as well as the use of alternative injury measures - suggests that the effect of injury shocks on game outcome uncertainty does not appear to be affected by game characteristics and other unobservable factors.

5.5 Instrumental Variables Analysis - Reduced form

Having documented the strong impact of our instruments on game outcome uncertainty, we turn to analyzing the direct relationship between injury-induced line-up changes and attendance. We do so by exploring the reduced-form correlation between our injury measures and stadium attendance at AFL games, our dependent variable of interest. This analysis identifies the *intention-to-treat* effect (Angrist et al., 1996).

The results are presented in table 6, where we find a strong negative correlation between attendance and injury-induced changes to the line-up of the non-favorite team. The estimated coefficients show that a one standard-deviation increase in the number of injury-induced changes to the line-up of the non-favorite team is associated with a decrease in attendance in the range of 2.1-4.9% (columns 1-2). For reference, we observe similar results using our alternative injury shock measure that takes the sum of the average performance ratings of the injured players (columns 3-4). The estimates reported in columns 1-4 are significant at the 1% level.

The reduced-form results documented in table 6 provide strong evidence that decreased game outcome uncertainty causes lower attendance. However, the magnitude of these estimates needs to be scaled to reflect the fact that the reduced-form result is driven by the subset of games that have lower levels of game outcome uncertainty due to the instrument.

5.6 Instrumental Variables Analysis - Two-stage Least Squares

In table 7 we examine the impact of game outcome uncertainty on attendance using a number of alternative specifications. To facilitate comparison between OLS and IV estimates, in columns 1-2 we provide OLS estimates of the effect of game outcome uncertainty on attendance. As suggested by our univariate analysis, game outcome uncertainty is positively associated with attendance. In column 2, we follow the standard selection-on-observables design employed in the literature and include home team and away team fixed effects and season fixed effects. Consistent with the endogeneity of game outcome uncertainty, we observe a significant reduction in the size of the association between game outcome uncertainty and attendance. OLS estimates suggest that a one standard-deviation increase in game outcome uncertainty is associated with an increase in game attendance of approximately 1,700 spectators (equivalent to 5.4% increase in attendance at the average game in our sample).[25]

Columns 3-6 of table 7 present the estimated coefficients from our IV method. Consistent with theory and the results of our univariate analysis, the impact of game outcome uncertainty on attendance is positive and statistically significant. This holds regardless of the specific injury shock measure we employ. This result also holds when we control for team rivalries and employ home team, away team, and season fixed effects.[26] Focusing on our preferred specifications, reported in columns 5-6, we see that a one-standard deviation increase in game outcome uncertainty leads to an increase in attendance of approximately 3,800 spectators. This is equivalent to an average increase in game-day attendance of at least 11.2%.[27] These coefficients, statistically significant at the 5% level, suggest that spectators have strong preferences for contests that have more uncertain outcomes.

Across each of the specifications reported in table 7, the magnitude of the coefficient estimated using IV is larger than the coefficient estimated using OLS. In fact, comparing the most conservative estimates generated using each technique, our IV estimates suggest that OLS underestimates the effect of game uncertainty of outcome on attendance by at least 5.8 percentage points (this difference is significant at the 1% level). This implies that the actual impact of game outcome uncertainty on attendance is likely to be at least twice as large as the estimates generated using OLS.[28]

The large gap between IV and OLS estimates suggests that game outcome uncertainty is more pronounced in situations where unobserved game characteristics dampen attendance. As a result, OLS heavily underestimates the effect of game outcome uncertainty on attendance. As discussed earlier in this paper, a number of factors could be

[25] For log-linear models: $\%\Delta y = 100 * (e^{\alpha_1 * \Delta x} - 1)$. Therefore, for a one standard deviation increase in game outcome uncertainty, we get $100 * (e^{0.353*0.15} - 1) = 0.054$

[26] In untabulated results (available upon request), we also control for lagged attendance from the previous game between the home and away teams and include round-of-season and time-slot fixed effects. We employ the latter to address potential confounding driven by the timing of when games occur during the season. For example, players may be more likely to get hurt later in the season, when attendance may also be lower. Similarly, players usually have fewer rest days (and thus may be more likely to pull out injured) leading into Thursday and Friday night games, the AFL's 'marquee' (i.e., best attended) time slot. However, when we include these additional controls and fixed effects, our estimates change very little and remain similar to those reported in columns 5-6 of table 7.

[27] To provide a sense of the economic significance of these effect sizes, a one standard deviation increase in game outcome uncertainty is equivalent to the win probability of the favorite team falling from 77% to 55% - or from 90% to 81% - for a given game.

[28] In untabulated results (available upon request), we also evaluate the sensitivity of our results to the use of different measures for game outcome uncertainty. Specifically, following the literature, we proxy for game outcome uncertainty using the absolute difference in win probabilities of the teams, the ratio of the win probabilities of the teams, and the closing line/spread for the game. When doing so, our results change very little from those reported in table 7 - i.e., when we proxy for game outcome uncertainty using the Theil index. Using these alternative measures, we continue to see that OLS underestimates the effect of game outcome uncertainty on attendance by a factor of at least 2.

driving this downward bias. For instance, the AFL (or the teams themselves) may more heavily promote games that are expected to be uneven. Alternatively, wet weather may make the outcome of games more uncertain whilst also keeping fans away. OLS estimates of the effect of game outcome uncertainty on attendance will also be downward biased if ticket prices are lowered prior to the start of the season for games that are expected to be one-sided.

5.7 Estimating the optimal level of game outcome uncertainty

In addition to estimating the effect of outcome uncertainty on spectator demand for contests, we also estimate the optimal level of outcome uncertainty. To do so, rather than directly instrumenting for game outcome uncertainty, we instrument for the probability of a home team win using the announcement of injury-induced changes to the line-ups of both the home and away teams. The former works to strictly lower the probability of a home team win, the latter works to strictly increase the probability of a home team win. Using this modified empirical design, we estimate the following first stage:

$$\begin{aligned} \text{win prob}_{ijs} = {} & \pi_0 + \pi_1 \text{home injuries}_{ijs} + \pi_2 \text{away injuries}_{ijs} + \pi_3 \mathbf{X}_{ijs} \\ & + \gamma_i + \rho_j + \theta_s + u_{ijs} \end{aligned}$$

where *win prob*$_{ijs}$ is the closing-odds-implied probability of home team i defeating away team j in season s, *home injuries*$_{ijs}$ is our measure of injury-induced changes to the line-up of home team i for the game against away team j in season s, *away injuries*$_{ijs}$ is our measure of injury-induced changes to the line-up of the away team j for the game against home team i in season s, $\mathbf{X}_{ijs}$ is a vector of game-level covariates, γ_i is a home-team fixed effect, ρ_j is an away-team fixed effect, θ_s is a season fixed effect, and u_{ijs} is an idiosyncratic error term.

In our second stage, we then specify a quadratic relationship between the probability of a home team win and attendance:

$$\begin{aligned} \log(\text{attendance})_{ijs} = {} & \beta_0 + \beta_1 \ \text{win} \widehat{\text{prob}}_{ijs} + \beta_1 \ \text{win} \widehat{\text{prob}}^2_{ijs} + \beta_2 \mathbf{X}_{ijs} \\ & + \psi_i + \eta_j + \upsilon_s + e_{ijs} \end{aligned}$$

where *attendance*$_{ijs}$ is the total number of people that attended the game between home team i and away team j in season s, $\widehat{winprob}_{ijs}$ are predicted values from the first-stage, $\mathbf{X}_{ijs}$ is a vector of game-level covariates, ψ_r is a home-team fixed effect, η_j is an away-team fixed effect, υ_s is a season fixed effect, and e_{ijs} is an idiosyncratic error term.

In line with the uncertainty of outcome hypothesis, we expect attendance to be greatest at games where both the home and away teams have a reasonable chance of victory (i.e., when game outcome uncertainty is heightened). However, it may not necessarily be the case that this optimization point arises precisely when the home team has a 50% chance of winning. For instance, attendance may be greatest when the home team is favorite, but not so heavily that there is only a trivial chance of an upset. This maps on to the idea that supporters prefer a likely but uncertain home team victory (Szymanski, 2003). Alternatively, perhaps supporters have very strong preferences for a home team victory. In this case, attendance will be maximized when the probability of a home team win is very high.

In table 8, we report the results from this analysis. Again, to facilitate comparison, in columns 1-2 we provide OLS estimates of the relationship between home team win probability and attendance. Consistent with the idea that spectators prefer more uncertain games, we observe a statistically-significant quadratic relationship between home team win probability and attendance. In column 2, we add home-team, away-team, and season fixed effects. Here we observe a 'turning point' when the home team has a 61.1% chance of winning. We interpret this estimate as follows: when the home team has a win probability below 61.1%, an increase in the likelihood of a home team win leads to an increase in attendance, whilst a decrease in the likelihood of a home team win leads to a decrease in attendance. Alternatively, when the home team has a win probability above 61.1%, an increase in the likelihood of a home team win leads to a decrease in attendance, whilst a decrease in the likelihood of a home team win leads to an increase in attendance. This inflection point implies that attendance is maximized when the home team is almost twice as likely to win as the away team. This suggests that spectators strongly prefer home team wins. Nonetheless, this result is consistent with prior findings in the literature that use OLS or, more generally, selection-on-observables designs (Szymanski, 2003; Schreyer et al., 2018).

In table 8 columns 3-6, we seek to address the endogeneity of home win probability by employing IV estimates. In columns 5-6, in addition to instrumenting for home team win probability with injury-induced line-up changes, we also include home-team, away-team, and season fixed effects. Employing these specifications, we continue to see a concave relationship between home team win probability and attendance. The estimates remain significant at the 1% level. Furthermore, our IV estimates provide a far less conservative estimate of the outcome uncertainty-attendance turning point. Across columns 3-6, we consistently observe an inflection point that corresponds to a home team win probability of between 51-54%. Considerably lower than the turning point implied by the OLS estimates, this threshold suggests supporters prefer to attend games where the home team is expected to win, but where there is a still a sizeable chance that the away team will cause an upset. This difference in estimates of the turning point are again consistent with OLS underestimating the effect of game outcome uncertainty on attendance. As such, this finding is further evidence that spectators strongly prefer close and uncertain contests.[29]

For the approach in table 8 to identify the optimal level of outcome uncertainty we must assume demand for live sports is purely a function of the behavior of home team supporters (i.e., supporters of the away team do not attend games, or if they do attend, this decision is made independent of the likelihood of the away team winning). This assumption allows us to say that if the outcome of a game where the home team starts as favorites becomes more uncertain, any associated increase in attendance is driven by home team fans wanting to see a closer game (albeit one where their team is now less likely to win), and not just a result of away team fans wanting to see a game where their side is now more likely to win.

Whilst likely to hold for competitions made up of single-city teams, this assumption is potentially problematic in the AFL, where all but one team share a 'hometown' with at least one other side (the most extreme example is Melbourne, 'home' to nine teams). As such, there is a sizeable subset of games in the AFL where the 'away' team is actually playing in its home city (and in many cases, the same stadium in which it plays its own home games). This raises the concern that with our empirical design we may observe that a 50-50 game maximizes attendance not because home team supporters have a preference for games that have more uncertain outcomes, but because these games attract a large number of away supporters hoping to see their own team win.

To address this concern, we re-estimate our model on a restricted sample that only includes games where the away team is visiting from interstate (i.e., we assume supporters reside in their team's home city and do not travel interstate to attend games). For this subsample of games, if we observe that attendance increases as a game becomes more uncertain (e.g., if the home team becomes less of a favorite), then it is highly likely that this occurs because supporters of the home team - or neutral fans - prefer to attend games that have more uncertain outcomes (and not because supporters of the away team simply wish to potentially see their own team win).

Employing this restricted sample of games, our results change very little. In fact, as documented in table 8 columns 7-8, we find that the optimal home win percentage for

[29] Here it is also worth noting that this threshold is in fact very close to the mean/median home team win probability in the AFL (see table 1). This lends support to the AFL's competitive balance policies and the grounding of these policies in the argument that supporters prefer games that have uncertain outcomes.

games that feature inter-state away teams is approximately 51% - again very close to the theoretical inflection point suggested in the game outcome uncertainty literature. As such, our main results do indeed appear to be picking up the preference of home team supporters for more uncertain games, rather than away team supporters' preferences for games where their own team is a higher chance of winning.

6 Robustness

In this section, we conduct a series of empirical tests to evaluate the robustness of our main results.

6.1 Controlling for the 'form' of contestants, and team rivalries

One concern with our empirical design is that we may simply be picking up spectators' preferences for the quality (or form) of the teams involved in a game. Spectators likely prefer to watch games involving higher quality teams or sides that are 'in form'. Furthermore, higher quality teams or sides that are in form may be more or less likely to suffer injuries (or report suffering injuries). For instance, teams that experience a poor run of form and cannot qualify for the play-offs may rest their best players (under the guise of injuries) or field a team of young players to 'blood' young playing talent. Likewise, the same may occur with a team that is playing very well and, having secured a play-off position, wishes to minimize the risk of their best players getting injured. In both scenarios, the quality of both teams will determine the number of injury-induced line-up changes affecting a game and the level of attendance at a game. As such, our injury measures will not be valid instruments.

To address this concern, we undertake a series of robustness checks where we explicitly control for the quality (or form) of the teams involved in a game. We do so by conditioning both stages of our 2SLS model on the home and away teams' Elo rating (in addition to home-team, away-team, and season fixed effects). We report the results from this analysis in table 9. In columns 1-2, we control for team quality using an Elo rating trained on historical performance data going back until 1997.[30] Overall, we find that a one standard deviation increase in game outcome uncertainty leads, on average, to a 11.6% and 11.8% increase in attendance, respectively. These estimates are significant at 5% level. In columns 3-4, we control for team quality using an Elo rating trained on historical performance data going back until 2009.[31] Here, we find that a one standard deviation increase in game outcome uncertainty leads, on average, to a 11.4% and 11.6% increase in attendance, respectively. These estimates are significant at the 5% level.

[30]This version of the measure is less sensitive to week-to-week fluctuations in form.

[31]This version of the measure is more sensitive to week-to-week fluctuations in form.

For added robustness, we also address the concern that teams - when faced with 'marginal' injuries - might be less likely to make line-up changes leading into games against competitors with whom they have strong rivalries - games which are also typically better attended. To achieve this, we add to our baseline model a binary variable that indicates whether or not the teams competing in a game are based in the same city.[32] We report the results from this specification in columns 5-6 of table 9. Here, we find that a one standard deviation increase in game outcome uncertainty causes, on average, a 11.7% and 10.6% increase in attendance, respectively. These estimates are significant at the 1% and 5% level, respectively.

As documented in table 9, when we explicitly control for the quality or form of the teams involved in a game, outcome uncertainty continues to be positively related to attendance. This result also holds when we control for team rivalries. We present these findings as further evidence that injury-induced line-up changes are plausibly exogenous.

6.2 Dealing with 'endogenous' injuries

To further scrutinize the assumption that injury-induced line-up changes are exogenous, we exploit the fact that we are able to observe the specific types of injuries filed by the teams when line-ups are announced. This allows us to focus only on those injuries that are more likely to be 'genuine', and thus, truly random (i.e. not some strategic line-up change made under the guise of an injury). Specifically, as an additional robustness check, we drop all line-up changes that cite a vague or non-specific injury (e.g., teams will sometimes list injuries as 'soreness', 'illness', or 'tightness'). We then re-run our analysis using only those line-up changes linked to 'acute' injuries (e.g., hamstring strains, head wounds, cartilage tears, etc). These types of injuries are typically fairly severe, occur unpredictably during passages of play, and are less likely to be 'faked' by teams.[33]

We report the results from this analysis in table 10. In columns 1-2, we instrument for game outcome uncertainty using only those line-up changes made due to acute injuries. In columns 3-4, we employ this same IV approach whilst conditioning on our fixed effects. Here, our estimates suggest that a one standard deviation increase in game

[32] In untabulated results, we re-run this specification using an alternative, more tightly-defined indicator for team rivalries, where all same-city non-Victorian teams are classified as rivals, and only the 'Big Four' Victorian teams are classified as rivals. Our results are also robust to the use of this alternative measure.

[33] The validity of this robustness check hinges on teams truthfully disclosing the types of injuries suffered by their players (conditional on those players being reported as injured). If teams are misreporting minor injuries or resting players under the guise of more severe injuries, the assumption that injury-induced line up changes are exogenous will still be violated. However, there is little evidence to suggest that AFL club statements overstate the severity of injuries. The AFL publishes a public annual injury report coauthored by the AFL Doctors Association and AFL Physiotherapists Association. Closely scrutinized by sports science and medical professionals, this document records season-to-season changes in the different types of injuries suffered by AFL players (Saw et al., 2018). As such, systematic misreporting of injury type is unlikely to go undetected.

outcome uncertainty increases attendance by 14.8% and 15.5%, respectively. Significant at the 1% level, these effect sizes are very similar to - if slightly larger than - our main results reported in table 7. We take this as further evidence that our IV estimates are unlikely to be biased due to teams strategically resting players under the guise of injury.

6.3 Preferences for star players and high scores

Our identification strategy assumes that injury-induced line-up changes impact attendance only through their affect on game outcome uncertainty. However, if spectators have preferences for watching star players compete, injuries to these players may affect attendance directly, independent of the impact of the injuries on game outcome uncertainty. Specifically, as injuries to superstars will likely lower attendance, there is the potential that our IV estimates of the effect of game outcome uncertainty on attendance will be exaggerated by this bias.

To allay concerns about this specific violation of the exclusion restriction, we explicitly control for the absence of star players. We do so by conditioning both stages of our 2SLS model on a set of measures that count the number of star players removed due to injury from the non-favorite team's starting line-up.[34] In doing so, we exploit for identification only those injury-induced line-up changes that are associated with 'non-star' players. We report the results from this analysis in table 11. In columns 1-3, we observe that a one standard deviation increase in game outcome uncertainty leads to an increase in attendance of between 9.6% to 10.6%. These estimates - significant at either the 5% or the 10% level - are very similar to our main IV estimates.

Injury-induced line-up changes may also impact attendance through spectators' preferences for high-scoring games. Specifically, injury changes may make a team play more conservatively in an upcoming game. This may result in lower scoring, an issue if spectators prefer games that have higher total scorelines. To address this concern, in table 11 columns 4-5, we control for spectators' expectations of the total level of scoring in a game by including the closing total over/under from the sports betting market.[35] In doing so, our results again change very little and remain significant at either the 5% or 10% level. Taken together, the results in table 11 provide further support for the instrumental validity of our injury measures.

[34]For robustness, we employ three different measures to proxy for star quality. The first classifies a player as a star if their average performance rating sees them fall in the 90th percentile of the league at the the time of their injury. The second version of this measure uses a stricter classification, and defines a player as a star if their average performance rating sees them fall in 95th percentile of the league at the time of their injury. The final measure classifies a player in the 99th percentile as a star.

[35]Compared to our main results, we have fewer observations for this analysis as data on the closing total over/under is not available for a handful of the earliest games in our sample

6.4 Falsification tests

We also perform a number of falsification tests to evaluate the validity of our instrumental variables approach. Broadly speaking, we look at the relationship between the attributes of game t and *future* injury-induced line-up made changes by the non-favorite team. If we observe an association between game attributes and future injury-induced line-up changes then it is unlikely that current injuries meet the exclusion restriction. Furthermore, such an association would suggest that unobservable attributes of the non-favorite team - characteristics that are also potentially correlated with our outcomes of interest - are likely driving our results.

In figure 2, we plot the estimated coefficients from regressions of the probability of favorite win at t on either current or future injury-induced line-up changes by the non-favorite team. In figure 3, we plot the estimated coefficients from regressions of game outcome uncertainty at t on either current or future injury-induced changes to the line-up of the non-favorite team. And, finally, in figure 4, we plot the estimated coefficients from regressions of attendance on either current or future injury-induced changes to the line-up of the non-favorite team. Across each of these figures, we can clearly see that only current injuries - and not future injuries - display a statistically-significant relationship with our outcomes of interest for game t. Taken together, these figures provide further evidence that injury-induced line-up changes are plausibly exogenous.[36]

6.5 Exploiting league-enforced line-up changes

As a final piece of analysis to evaluate the validity of our instrumental variables approach, we exploit another source of plausibly exogenous variation in game outcome uncertainty. In addition to line-up changes brought about by injury, teams are forced to replace players in their starting line ups when individuals are suspended by the league for on-field misconduct.[37]

In effect, suspensions serve as league-enforced line-up changes. This addresses many of the endogeneity concerns related to injury-induced line-up changes (e.g., a team may

[36]In an additional, untabulated robustness check, we also conduct placebo analyses whereby for each game we randomly assign injury-induced line-up changes to the non-favorite team. To do so, we sample without replacement from the empirical distribution of the number of injury-induced line-up changes observed in our sample. We then repeat the analysis performed in tables 4-6 using these 'placebo treatments'. For each regression, we perform 1,000 replications of this procedure to produce an empirical distribution of the placebo treatment effects. Using density plots, we show that these placebo treatment effects are normally distributed with a mean non-distinguishable from zero at the 5% level.

[37]A player may be suspended by the league for a variety of different indiscretions. These include illegal physical contact (head-high tackles, punching, tripping, etc), physical or verbal assault of an official, and unsportsmanlike conduct. Typically, the offending player will be cited by an umpire during the game for misconduct. The player is then required to appear in front of the AFL disciplinary tribunal, which decides if the player has in fact violated the rules of the game, and, if so, the severity of the punishment received by the player. The AFL tribunal meets at the start of the week. As such, when teams announce their line-ups later in the week, they are aware if a player is eligible or not to play.

rest a player and list them as injured in the lead up to a game that is less important, expected to be easily won or lost, etc). As such, we can use the announcement of suspension-induced line-up changes as an alternative source of plausibly exogenous variation in game outcome uncertainty.

In table 12, we report the results from a 2SLS model where we instrument for game outcome uncertainty using the announcement of suspension-induced changes to the line-up of the non-favorite team. Significant at either the 5% or 1% level, these estimates are slightly lightly larger than the estimates generated when instrumenting for game outcome uncertainty with injury-induced line-up changes. Nonetheless, these results suggest that the IV coefficients we report in this paper are robust estimates of the causal effect of outcome uncertainty on spectator demand for contests.

7 Extensions

To conclude this paper, we explore how the effect of outcome uncertainty on spectator demand varies in the cross-section.

7.1 The interaction between outcome uncertainty and contest 'significance'

A key feature of the AFL - and most major sports competitions - is that individual games take place within a broader contest - i.e., the season title or championship. As such, fans may be interested in a game not only for its own outcome but the implications that the result may have for the likelihood a given team will appear in the finals or win the title (Borland and MacDonald, 2003). This suggests that demand for games that have uncertain outcomes may be moderated by the 'significance' of the outcome of the game in determining the final standings of the league, championship, or season. For instance, fans may be especially drawn to contests that have uncertain and highly-significant outcomes, but be less interested in games that are also expected to be close but have little bearing on who ultimately wins the championship.

As such, we expect to observe an interaction between game outcome uncertainty and the significance of the game (as captured by the standings of the teams competing in the game, and when the game occurs during the season). Games that occur earlier in the season are more likely to involve teams that are still actively vying for positions in the standings that ensure qualification for the finals (i.e., in the early rounds of a season, poor teams have yet to lose a sufficient number of games to be theoretically ruled out of contention for a finals position, whilst good teams have yet to secure enough wins to guarantee a finals position). As such, the outcomes of games that occur early in the season are more likely to have greater significance in terms of a league-standing effect.

This suggests that fans should be interested, on average, in games that have uncertain outcomes that occur early in the season.

In contrast, games that occur late in the season can range from the highly significant to the largely meaningless. For instance, late-season games may involve teams still actively vying for a position in the standings that ensures qualification for the finals. However, late-season games may also involve teams at the top of the standings that have either already secured a spot in the finals or teams at the bottom of the standings that can no longer make the finals. This suggests that there will be considerable heterogeneity in spectator demand for games that have uncertain outcomes that occur late in the season. Specifically, fans should be especially interested in games that have uncertain outcomes that involve at least one team still trying to secure a place in the finals. Alternatively, outcome uncertainty will likely matter much less to fans when the game in question involves teams that have either already secured their place in the finals or are unable to secure a place in the finals regardless of the outcome of the game.

To explore the above and examine the interaction between outcome uncertainty and the significance of a game, we estimate our IV model on several different subsamples of our data set. First, we separately run our IV model on only games from the first half of each season in our sample and on only games from the second half of each season in our sample. Second, we separately run our model on games from the second half of each season that feature at least one team around the 'margin' of qualifying for finals, which we define as a team sitting between 6th and 10th on the ladder when the game takes place, and on games from the second half of each season that feature only teams away from the 'margin' of qualifying for finals, which define as a team sitting between 1st-5th or 11th-18th when the game takes place.[38]

In table 13, we report the results from this cross-sectional analysis. In column 1, for reference, we report our main result - i.e., the coefficient produced by estimating our IV model on the full set of games in our sample. In column 2, we report the result produced when we estimate our model on games from the first half of the season. This estimate - significant at the 5% level - suggests that, for games in the first half of the season, a one standard deviation increase in game outcome uncertainty causes, on average, a 20% increase in attendance. In column 3, we report the result produced when we estimate our model on games from the second half of the season. Comparing the coefficients reported in columns 2-3, we see that uncertainty of outcome only appears to have an effect on attendance for games that occur in the first half of the season - i.e., when all games involve teams that are still theoretically vying for a place in the finals.[39]

[38]In the AFL, at the end of the regular season, the teams occupying the top 8 positions of the standings go through to the finals.

[39]In untabulated analysis, we also further decompose games from the first half of the season into fixtures based on the finishing position of the competing teams in the prior season. Specifically, we

We unpack this result further in the remainder of table 13. In column 4, we report the coefficient produced when we estimate our IV model on games from the second half of the season that feature at least one team positioned in the standings around the 'margin' of qualifying for finals. This result - significant at the 1% level - suggests attendance is increasing in game outcome uncertainty. In column 5, we report the result produced when we estimate our IV model on games from the second half of the season that feature only teams from outside the 'margin' of qualifying for finals. For this subsample of games, we see that outcome uncertainty does not appear to be related to attendance. Overall, the results reported in table 13 suggest that the effect of game outcome uncertainty on spectator demand is moderated by the contest's broader significance.

7.2 Local effects: The marginal attendee, season-ticket holders, and fair-weather fans

A common caveat in interpreting the estimated results using IVs is that the approach only identifies the average treatment effect for compliers. As such, the results of this paper so far do not necessarily tell us about the behavior of the 'average' fan but rather the behavior of the 'marginal attendee'. This begs the question: In our setting, who is the marginal attendee, and how generalizable is their behavior?

Our IV estimates capture the behavior of fans that decide whether or not to attend a game in response to mid-week changes in outcome uncertainty. As such, it is not clear how much our estimand tells us about the preferences of fans who commit a week or more in advance to attend games. For instance, many AFL fans hold reserved-seat season tickets for their team. Purchased at the start of each season, these tickets guarantee the holder a seat at all home games. Given the large sunk costs incurred by reserved-seat season-ticket holders, injury-induced changes in game outcome uncertainty seem unlikely to affect the attendance behavior of these fans (these supporters can be thought of as 'never takers' in the potential outcomes compliance framework). As such, the main results reported in this paper may not reflect the effect of game outcome uncertainty on attendance for this important segment of AFL fans.

However, certain teams may possess fan bases made up of greater or fewer numbers of marginal attendees. The avidity of a team's supporter base is useful for understanding this heterogeneity in demand. For instance, some of the more established teams in the competition have dispersed supporter bases made up of a large numbers of casual

compare the effect of game outcome uncertainty on attendance for games involving at least one team that finished the previous season in the 'middle' of the standings vs. games involving teams that finished the prior season either near the top of the standings or near the bottom of the standings. We show that the effect of game outcome uncertainty on attendance is larger for games from the first-half of the season involving teams that finished the prior season in the middle of the standings (i.e., teams for whom fans may be keen to see play early in the season so as to establish whether or not the club has improved over the off-season and are now more likely to be 'contenders' in the current season.)

supporters and general admission members.[40] Viewing sport as an exciting communal event or social outing, these types of fans may be especially responsive to changes in game outcome uncertainty. As such, our IV estimates are likely to do a reasonable job of reflecting the preferences of supporters of these teams. In contrast, less-established teams - particular those operating in non-traditional Australian-rules football markets - may be followed by only small groups of 'die hard' supporters. These types of teams may face very inelastic demand with respect to game outcome uncertainty. As such, for the fans of these teams, our IV estimates are likely to overestimate the strength of preferences for close and uncertain contests.

To better understand the generalizability of our IV estimates, we would ideally decompose game-level attendance data into reserved-seat and non-reserved-seat ticket holder components (or alternatively, die-hard and fair-weather fan components) and compare the attendance behavior of these different groups of supporters. However, as we only have access to game-level aggregate attendance data, we must instead examine how the effect of game outcome uncertainty on attendance varies across teams that have supporter bases composed of broadly different 'types' of fans.

First, we estimate the effect of game outcome uncertainty on attendance for home games featuring the largest, most-well established teams in the AFL. Referred to as the 'Big Four' (Collingwood, Carlton, Essendon, Richmond), these teams - based in inner-suburban Melbourne and founded in the earliest years of the competition - have national profiles and are widely-followed across the country (the Big Four are akin to 'national' franchises in US sports like the New York Yankees, Dallas Cowboys, and Los Angeles Lakers). Whilst these teams have many 'hard core' fans that regularly attend games, the Big Four Melbourne clubs also have very large numbers of dispersed 'fair weather' supporters and casual followers who hold general admission memberships - individuals who typically only purchase one-off tickets to high-profile games or use their memberships to attend games primarily for social purposes.[41] Second, we estimate the effect of game outcome uncertainty on attendance for the smaller, less-established teams (Brisbane, Gold Coast, Greater Western Sydney, Sydney). These clubs were introduced into the AFL as expansion teams designed to help grow the sport of Australian-rules football in markets that have historically followed other sports like rugby union or rugby league. In general, these teams are less-well supported than the AFL clubs based in the south and

[40] Commonly priced below $AUD100 a season, general admission memberships allow individuals to access a subset of their team's games (the most popular types of general admission memberships are valid for 3-5 home games). These tickets do not guarantee an individual a specific seat, but rather access to a general admission seating area.

[41] Based on average annual aggregate membership figures (a reasonable proxy for the size of a team's supporter base), Collingwood and Richmond had the greatest numbers of members in the AFL between 2013-2018. Whilst less successful in recent years, Essendon had the fifth-most members in the competition (and the fourth-most for a Melbourne team), and Carlton had the ninth-most members in the competition (and the fifth-most for a Melbourne team).

west of Australia. That being said, the expansion teams are typically followed by small groups of 'die hard' fans - highly-loyal supporters, most often season-ticket holders, who show up week to week.

We report the results of this cross-sectional analysis in table 14. For reference, in columns 1-2 we report the estimates produced when we run our IV models on the full set of games in our sample. In columns 3-4 we estimate our IV model on the subsample of games where the home side was one of the Big Four teams. We see that game outcome uncertainty is very strongly related to attendance for these teams: a one standard deviation increase causes attendance at Big Four home games to increase, on average, by approximately 25%. Considerably larger than the effect size reported in columns 1-2, these estimates are consistent with the idea that fans of the AFL's largest teams - many of whom are casual supporters - are very sensitive to changes in game outcome uncertainty.[42] In table 14 columns 5-6, we estimate our IV model on the subsample of games where the home side was one of the AFL's expansion teams. These coefficients - not statistically significant - suggest that game outcome uncertainty does not appear to be associated with attendance for the AFL's expansion teams. As such, the smaller, less-heavily followed teams in the AFL appear to face relatively inelastic demand with respect to game outcome uncertainty - likely reflective of the fact that these teams' supporter base are composed of a higher proportion of die-hard fans and a smaller proportion of causal supporters and marginal attendees.

In summary, table 14 sheds some light on the generalizability of our main IV estimates and suggests that there is considerable heterogeneity in the effect of outcome uncertainty on spectator demand for contests.

8 Conclusion

In this paper, we use a unique data set from the Australian Football League to estimate the effect of outcome uncertainty on demand for contests. The main contribution of this paper is to shed light on the design features and popularity of contest-based entertainment and examine a question largely overlooked in the contest design literature: Do individuals prefer to consume contests that have more uncertain outcomes?

Using variation in game outcome uncertainty associated with the announcement of injury-induced line-up changes, we show that contest outcome uncertainty has a large, positive causal effect on stadium attendance in the AFL. We show that this effect is greater: 1) when there is more at stake on the outcome of the game in the broader

[42] Due to prolonged on-field success, Hawthorn has been characterized as an 'emerging powerhouse' in the AFL (over the period 2013-2018, Hawthorn had the third-most members in the AFL). In untabulated results, if we reclassify our Big Four to include Hawthorn (and drop Carlton, a team who has been starved of on-field success over the last two decades), our estimates change very little.

context of the season; and, 2) for teams that have larger, more-dispersed fan bases.

Overall, our estimates of the effect of game outcome uncertainty on attendance are significantly larger than prior estimates in the literature. This suggests that addressing endogeneity and omitted variable concerns is extremely important for understanding the impact of outcome uncertainty on demand for contest-based forms of entertainment.

In conclusion, our results provide direct evidence that individuals do in fact prefer to consume contests that have more uncertain outcomes. This lends support to the idea that audience interest in contest-based entertainment is strongly driven by expected suspense and the resolution of uncertainty. Whilst caution should be exercised drawing an equivalence between injury-induced competitive parity and equalization stemming from explicit contest-design policies (the latter of which may be viewed by fans as artificial and obtrusive), the results reported in this paper also potentially lend support to the competitive balance regulations implemented by many sports leagues around the world. Our results also suggest that contest designers need to consider how outcome uncertainty affects not just the behavior of individuals competing in contests, but the behavior of non-contestants who consume contests for entertainment. Open questions remain over how contest designers can optimally trade off these incentive and consumption effects. Future research that combines contest design theory and evidence from the field may shed light on this issue.

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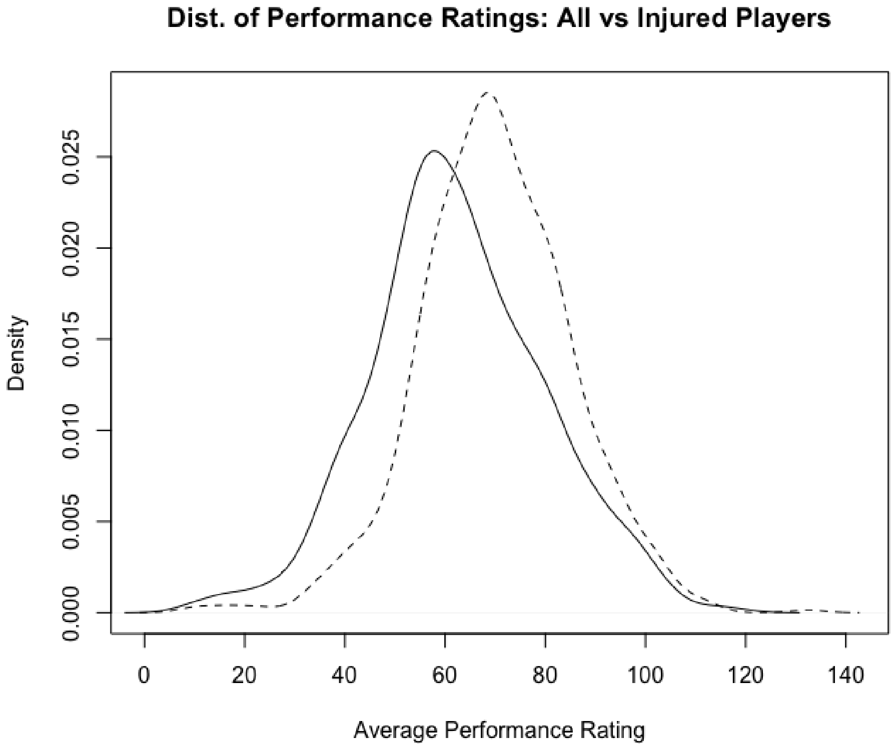
Appendix - Data

Variable	Description	Source
Attendance	The total number of spectators (in thousands) in attendance. Measured using game-day swipe in data from entry gates at the stadium.	Official AFL match reports.
Outcome Uncertainty	Theil index measure of game outcome uncertainty that is constructed using *Prob of Home Win (closing odds)* . This measures takes a minimum value of 0 (i.e., a '50-50' game) and a maximum value of 0.7 (i.e., a certain result).	Theil (1976), Peel & Thomas (1996). See Section 3.3 for more information on how this measure is constructed.
Prob of Favorite Win (closing odds)	The betting-odds implied probability that the favorite team will win the game. The favorite is defined as the team that starts the week of the upcoming game as favorite (conversely, the non-favorite is the team which starts the week as non-favorite). We use the average closing odds offered by the major bookmakers in the sports betting market in Australia. We remove the bookmaker's margin to arrive at an unbiased measure of the favorite's win probability.	Betting data was scaped from the following site, which collects and aggregates information on historical betting odds offered by Australian bookmakers: http://www.aussportsbetting.com/data/historical-afl-results-and-odds-data/
Prob of Home Win (closing odds)	The betting-odds implied probability that the home team will win the game. We use the average closing odds offered by the major bookmakers in the sports betting market in Australia. We remove the bookmaker's margin to arrive at an unbiased measure of the favorite's win probability.	See above.
Total score (closing odds)	The expected total score (or 'under-over') for the upcoming game. We use the average under-over offered by the major bookmakers in the sports betting market in Australia.	See above.
No. of injuries (non-fave/home/away)	The total number of injury-induced line-up changes made by the non-favorite/home/away team for the upcoming game.	Official AFL match reports.
Rating of injuries (non-fave/fave/away)	The total number of player rating points 'lost' by the non-favorite/home/away team for the upcoming game due to injury-induced line-up changes. Champion Data's player ratings are designed to capture a player's overall contribution to their team's performance. We use a player's average game-level rating for the season as our measure of player quality.	Official AFL match reports; Champion Data/AFL Player Ratings
No. of 'acute' injuries (non-fave)	The total number of 'acute' injury-induced line-up changes made by the non-favorite team for the upcoming game. Acute injuries exclude injuries that are non-specific or vague (e.g., soreness, illness, tightness, etc).	Official AFL match reports.
Rating of 'acute' injuries (non-fave)	The total number of player rating points 'lost' by the non-favorite/home/away team for the upcoming game due to 'acute' injury-induced line-up changes.	Official AFL match reports; Champion Data/AFL Player Ratings

Appendix - Data (cont.)

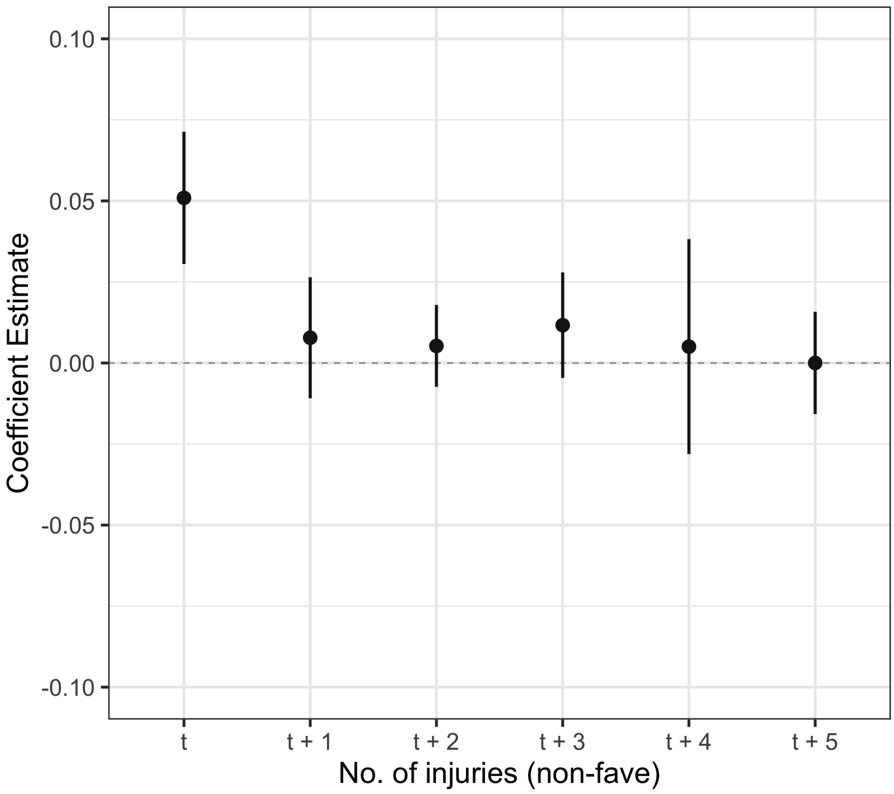
Variable	Description	Source
No. of suspensions (non-fave)	The total number of suspension-induced line-up changes that the non-favorite team was forced to make for the upcoming game.	Official AFL match reports.
Rating of suspensions (non-fave)	The total number of player rating points 'lost' by the non-favorite team for the upcoming game due to suspension-induced line-up changes.	Official AFL match reports; Champion Data/AFL Player Ratings
No. of 'star' injuries (99th/95th/90th)	The total number of injury-induced changes to 'star' players made by the non-favourite team for the upcoming game. A star player is defined as an individual with an average rating in the 99th/95th/90th percentile for the league, as per Champion Data's player performance ratings.	Official AFL match reports; Champion Data/AFL Player Ratings
Rivals	An indicator variable equal to 1 if the home and away teams competiting in a game are football clubs located in the same city (i.e., the game is a 'derby').	
Fav/Non-fav Team Elo (1997-)	The Elo rating of the favorite/non-favorite team in the game. The rating incorporates historical results dating from the start of the 1997 season onward. This version of the Elo rating is less sensitive to short-term flucations in team performance.	Official AFL match reports. See Section 3.3 for further discussion of this measure.
Home/Away Team Elo (1997-)	The Elo rating of the home/away team in the game. The rating incorporates historical results dating from the start of the 1997 season onward. This version of the Elo rating is less sensitive to short-term flucations in team performance.	Official AFL match reports. See Section 3.3 for further discussion of this measure.
Home/Away Team Elo (2009-)	The Elo rating of the home/away team in the game. The rating incorporates historical results dating from the start of the 2009 season onward. This version of the Elo rating is more sensitive to short-term flucations in team performance.	Official AFL match reports. See Section 3.3 for further discussion of this measure.

Figure 1: The distributions of average performance ratings for injured players and for all players in the AFL.



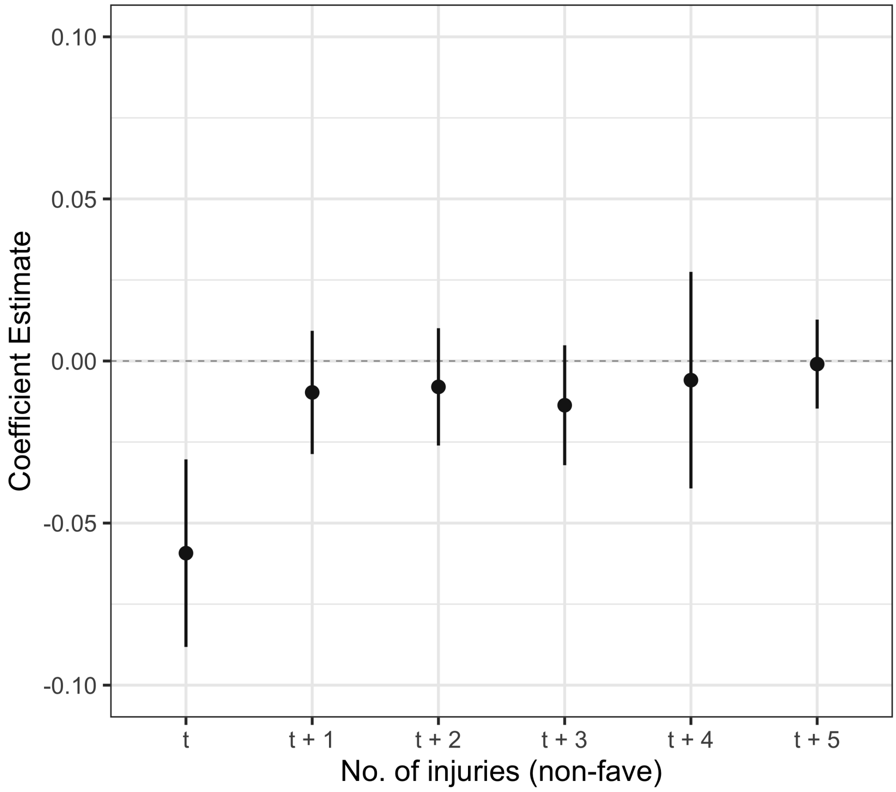
Note: This figure compares the kernal density plots of the average performance rating of players in the AFL between 2013-2018 that missed at least one game due to injury (dashed line) and the average performance rating of all players that made at least one appearance in the AFL between 2013-2018 (solid line). Performance ratings are averaged across games at the player-season level (each observation is the average of a player's game performance rating in a given season). The mean (median) average performance rating for injured players is 70.11 (69.50). The mean (median) average performance rating for all players is 62.60 (61.75).

Figure 2: Future injuries to the non-favorite are unrelated to the probability that the favorite will win at t.



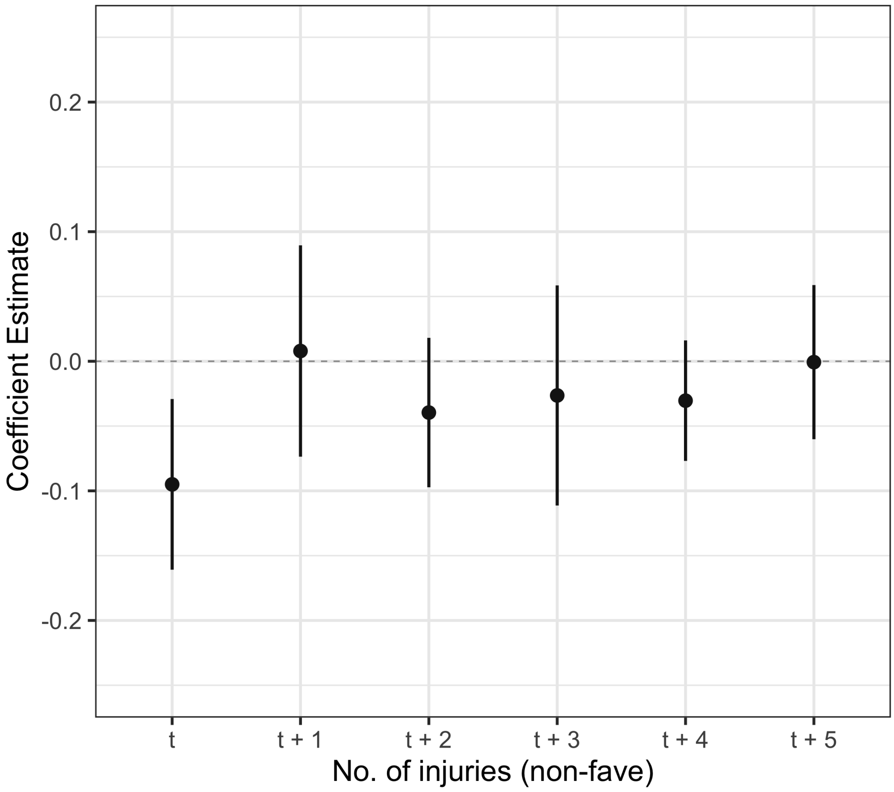
Note: This figure shows the estimated coefficients from regressions of the probability that the favorite will win game t on either current or future injury-induced changes to the line-up of the non-favorite team. 95% confidence intervals are constructed using White-robust standard errors. Regression disturbance terms are clustered at the round-season level.

Figure 3: Future injuries to the non-favorite are unrelated to the outcome uncertainty of game t.



Note: This figure shows the estimated coefficients from regressions of the outcome uncertainty of game t on either current or future injury-induced changes to the line-up of the non-favorite team. 95% confidence intervals are constructed using White-robust standard errors. Regression disturbance terms are clustered at the round-season level.

Figure 4: Future injuries to the non-favorite are unrelated to attendance at game t.



Note: This figure shows the estimated coefficients from regressions of attendance at game t on either current or future injury-induced changes to the line-up of the non-favorite team. 95% confidence intervals are constructed using White-robust standard errors. Regression disturbance terms are clustered at the round-season level.

Table 1: Descriptive statistics

	N	Mean	St. Dev.	Min	Max
Endogenous variables					
Attendance ('000)	1,133	32.62	16.16	4.37	93.37
Prob. of Favorite Win (closing odds)	1,133	0.73	0.13	0.50	0.98
Prob. of Home Win (closing odds)	1,133	0.55	0.26	0.02	0.98
Outcome Uncertainty	1,133	0.54	0.15	0.08	0.69
Injury measures					
No. of injuries (non-fav.)	1,133	1.23	1.22	0	11
No. of injuries (home)	1,133	1.07	1.09	0	7
No. of injuries (away)	1,133	1.20	1.19	0	11
Rating of injuries (non-fav.)	1,133	86.50	88.98	0.00	907.19
Ave. rating of injured player (non-fav.)	773	70.11	15.19	9.50	132.33
Rating of injuries (home)	1,133	74.60	77.92	0	493
Rating of injuries (away)	1,133	85.53	88.87	0.00	907.19
No. of 'acute' injuries (non-fav.)	1,133	1.15	1.10	0	7
Rating of 'acute' injuries (non-fav.)	1,133	80.80	79.77	0.00	513.36
No. of suspensions (non-fav.)	1,133	0.71	0.51	0	3
Rating of suspensions (non-fav.)	1,133	49.94	39.90	0.00	295.72
No. of 'star' injuries (99th)	1,133	0.06	0.26	0	2
No. of 'star' injuries (95th)	1,133	0.02	0.14	0	2
No. of 'star' injuries (90th)	1,133	0.07	0.27	0	2
Controls					
Rivals	1,133	0.33	0.47	0	1
Fav. Team Elo (1997-)	1,133	1,557.19	158.83	1,173.41	1,847.98
Non-fav. Team Elo (1997-)	1,133	1,442.48	146.54	1,169.98	1,844.99
Home Team Elo (1997-)	1,133	1,500.00	163.35	1,170.56	1,844.99
Away Team Elo (1997-)	1,133	1,499.67	163.10	1,169.98	1,847.98
Total score (closing odds)	944	176.76	12.73	117.50	212.50

Note: This table shows the descriptive statistics for the variables used in this paper. Appendix - Data contains a full list of variable definitions.

Table 2: Differences in Means - High vs. Low Outcome Uncertainty Games

	High OU	Low OU	Diff.	t-stat	p-value
Outcome Uncertainty	0.651	0.426	0.224	35.826	0.000
Attendance	35.874	29.362	6.512	6.918	0.000
Prob. of Fav. Win (closing odds)	0.624	0.832	-0.208	-44.638	0.000
Prob. of Home Win (closing odds)	0.562	0.543	0.019	1.246	0.213
Round	12.170	12.884	-0.714	-1.855	0.064
Afternoon	0.629	0.700	-0.071	-2.543	0.011
Evening	0.371	0.300	0.071	2.543	0.011
Thurs-Fri	0.178	0.109	0.069	3.326	0.001
Saturday	0.495	0.561	-0.066	-2.233	0.026
Sunday	0.307	0.319	-0.012	-0.428	0.669
Other Day	0.019	0.011	0.009	1.225	0.221
Fav. Team Elo (1997-)	1541.359	1572.997	36.658	3.799	0.000
Non-Fav. Team Elo (1997-)	1494.467	1390.579	103.888	12.752	0.000
Home Team Elo (1997-)	1518.346	1481.688	36.658	3.799	0.000
Away Team Elo (1997-)	1517.480	1481.887	35.592	3.693	0.000

Note: This table presents results from difference-in-means tests to compare the characteristics of high and low outcome uncertainty games. High (Low) outcome uncertainty (OU) games have above-median (below-median) Theil index values. Appendix - Data contains a full list of variable definitions.

Table 3: Balance on Covariates - Injury-induced line-up changes to the non-favorite

	High Inj.	Low Inj.	Diff.	t-stat	p-value
Prob. of Fav. Win (open odds)	0.728	0.716	0.012	1.497	0.135
Round	12.807	12.247	0.560	1.455	0.146
Afternoon	0.671	0.658	0.013	0.482	0.63
Evening	0.329	0.342	0.013	-0.482	0.63
Thurs-Fri	0.140	0.148	0.008	0.411	0.681
Saturday	0.542	0.513	0.029	0.983	0.326
Sunday	0.306	0.321	-0.015	0.556	0.578
Other Day	0.012	0.018	-0.006	-0.7291	0.466
Fav. Team Elo (1997-)	1558.674	1555.713	2.961	-0.316	0.754
Non-Fav. Team Elo (1997-)	1440.428	1444.522	-4.094	-0.470	0.638

Note: This table presents results from difference-in-means tests to compare the characteristics of games affected by a high number of injury-induced line-up changes and games affected by a low number of injury-induced line-up changes. High (Low) injury games have above-median (below-median) numbers of injury-induced changes to the line-up of the non-favorite team. Appendix - Data contains a full list of variable definitions.

Table 4: Probability that the favorite will win and injury-induced line-up changes

	Dependent variable:			
	Prob. of Favourite Win (closing odds)			
	(1)	(2)	(3)	(4)
No. of injuries (non-fav.)	0.021***	0.020***		
	(0.004)	(0.005)		
Rating of injuries (non-fav.)			0.0003***	0.0003***
			(0.0001)	(0.0001)
Robust SEs	Yes	Yes	Yes	Yes
Season FEs	No	Yes	No	Yes
Home team FEs	No	Yes	No	Yes
Away team FEs	No	Yes	No	Yes
Observations	1,133	1,133	1,133	1,133
R^2	0.033	0.162	0.032	0.163

Note: Estimated coefficients in columns (1)-(4) are from least squares regressions of the probability of that the favorite will win game t on injury-induced changes to the line-up of the non-favorite. White-robust standard errors are in parentheses. Regression disturbance terms are clustered at the round-season level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 5: Outcome uncertainty and injury-induced line-up changes

	Dependent variable:			
	Outcome Uncertainty			
	(1)	(2)	(3)	(4)
No. of injuries (non-fav.)	-0.024^{***}	-0.024^{***}		
	(0.006)	(0.006)		
Rating of injuries (non-fav.)			-0.0003^{***}	-0.0003^{***}
			(0.0001)	(0.0001)
Robust SEs	Yes	Yes	Yes	Yes
Season FEs	No	Yes	No	Yes
Home team FEs	No	Yes	No	Yes
Away team FEs	No	Yes	No	Yes
Observations	1,133	1,133	1,133	1,133
R^2	0.037	0.195	0.035	0.194
F-stat	16.13	13.21	15.12	12.75

Note: Estimated coefficients in columns (1)-(4) are from least squares regressions of the outcome uncertainty of game t on injury-induced changes to the line-up of the non-favorite. White-robust standard errors are in parentheses. Regression disturbance terms are clustered at the round-season level. *p<0.1; **p<0.05; ***p<0.01

Table 6: Attendance and injury-induced line-up changes

	Dependent variable:			
	Log(Attendance)			
	(1)	(2)	(3)	(4)
No. of injuries (non-fav.)	-0.039^{***}	-0.017^{***}		
	(0.014)	(0.006)		
Rating of injuries (non-fav.)			-0.001^{***}	-0.0002^{***}
			(0.0002)	(0.0001)
Robust SEs	Yes	Yes	Yes	Yes
Season FEs	No	Yes	No	Yes
Home team FEs	No	Yes	No	Yes
Away team FEs	No	Yes	No	Yes
Observations	1,133	1,133	1,133	1,133
R^2	0.007	0.692	0.007	0.692

Note: Estimated coefficients in columns (1)-(4) are from least squares regressions of attendance at game t on injury-induced changes to the line-up of the non-favorite. White-robust standard errors are in parentheses. Regression disturbance terms are clustered at the round-season level. *p<0.1; **p<0.05; ***p<0.01

Table 7: Estimates of the effect of outcome uncertainty on spectator demand for contests

	Dependent variable:					
	Log(Attendance)					
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome Uncertainty	0.601***	0.353***	1.602***	1.575***	0.728**	0.707**
	(0.088)	(0.091)	(0.539)	(0.552)	(0.330)	(0.343)
Robust SEs	Yes	Yes	Yes	Yes	Yes	Yes
Season FEs	No	Yes	No	No	Yes	Yes
Home team FEs	No	Yes	No	No	Yes	Yes
Away team FEs	No	Yes	No	No	Yes	Yes
Instrumental Variables						
No. of injuries (non-fav.)			Yes	No	Yes	No
Rating of injuries (non-fav.)			No	Yes	No	Yes
F-stat			16.13	13.21	15.12	12.75
Observations	1,133	1,133	1,133	1,133	1,133	1,133

Note: Estimated coefficients in columns (1)-(2) are from least squares regressions of attendance at game t on outcome uncertainty. Estimated coefficients in columns (3)-(6) are from IV-2SLS regressions, where the first stage is a regression of outcome uncertainty on injury-induced line-up changes to the non-favorite, and the second stage is a regression of attendance on the fitted value of outcome uncertainty generated by the first stage. White-robust standard errors are in parentheses. Regression disturbance terms are clustered at the round-season level. *p<0.1; **p<0.05; ***p<0.01

Table 8: Estimates of the level of outcome uncertainty that maximizes spectator demand for contests

	Dependent variable:							
	Log(Attendance)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prob. of Home Win	2.305***	1.214***	7.447***	7.304***	3.598***	3.683***	3.442***	3.061***
	(0.317)	(0.203)	(2.811)	(2.684)	(0.637)	(0.194)	(0.749)	(0.680)
Prob. of Home Win^2	−1.911***	−0.993***	−7.180***	−7.043***	−3.395***	−3.436***	−3.367***	−3.023***
	(0.250)	(0.203)	(2.085)	(1.881)	(0.740)	(0.313)	(0.741)	(0.317)
Optimal Home Win Prob. (%)	60.3	61.1	51.9	51.9	53	53.6	51.1	50.6
Robust SEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season FEs	No	Yes	No	No	Yes	Yes	Yes	Yes
Home team FEs	No	Yes	No	No	Yes	Yes	Yes	Yes
Away team FEs	No	Yes	No	No	Yes	Yes	Yes	Yes
Instrumental Variables								
No. of injuries (home & away)			Yes	No	Yes	No	Yes	No
Rating of injuries (home & away)			No	Yes	No	Yes	Yes	No
Sample	All	All	All	All	All	All	Interstate	Interstate
Observations	1,133	1,133	1,133	1,133	1,133	1,133	755	755

Note: Estimated coefficients in columns (1)-(2) are from least squares regressions of attendance at game t on both the probability that the home team will win the game and the square of this probability. Estimated coefficients in columns (3)-(8) are from IV-2SLS regressions, where the first stage is a regression of outcome uncertainty on both the probability that the home team will win the game and the square of this probability, and the second stage is a regression of attendance on the fitted value of outcome uncertainty generated by the first stage. 'Interstate' refers to the subsample of games where the home team was hosting an away team from another state. White-robust standard errors are in parentheses. Regression disturbance terms are clustered at the round-season level. *p<0.1; **p<0.05; ***p<0.01

Table 9: Robustness of estimates when controlling for contestant quality and team rivalries

	Dependent variable:					
	Log(Attendance)					
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome Uncertainty	0.730**	0.743**	0.719**	0.733**	0.737***	0.673**
	(0.323)	(0.352)	(0.324)	(0.351)	(0.272)	(0.281)
Home Team Elo (1997-)	0.001***	0.001***				
	(0.0001)	(0.0001)				
Away Team Elo (1997-)	0.0002	0.0002				
	(0.0002)	(0.0003)				
Home Team Elo (2009-)			0.001***	0.001***		
			(0.0001)	(0.0001)		
Away Team Elo (2009-)			0.0002	0.0002		
			(0.0002)	(0.0003)		
Rivals					0.348***	0.349***
					(0.015)	(0.014)
Robust SEs	Yes	Yes	Yes	Yes	Yes	Yes
Season FEs	Yes	Yes	Yes	Yes	Yes	Yes
Home team FEs	Yes	Yes	Yes	Yes	Yes	Yes
Away team FEs	Yes	Yes	Yes	Yes	Yes	Yes
Instrumental Variables						
No. of injuries (non-fav.)	Yes	No	Yes	No	Yes	No
Rating of injuries (non-fav.)	No	Yes	No	Yes	No	Yes
Observations	1,133	1,133	1,133	1,133	1,133	1,133

Note: Estimated coefficients in columns (1)-(6) are from IV-2SLS regressions, where the first stage is a regression of the outcome uncertainty of game t on injury-induced line-up changes to the non-favorite, and the second stage is a regression of attendance at game t on the fitted value of outcome uncertainty generated by the first stage. In columns (1)-(4), we control in both stages for home and away team quality. In columns (5)-(6), we control in both stages for rivalries between local teams. White-robust standard errors, in parentheses, are clustered at the round-season level. *p<0.1; **p<0.05; ***p<0.01

Table 10: Robustness of estimates when instrumenting for outcome uncertainty with 'acute' injuries

	Dependent variable:			
	Log(Attendance)			
	(1)	(2)	(3)	(4)
Outcome Uncertainty	2.375***	2.478***	0.923***	0.963***
	(0.775)	(0.767)	(0.352)	(0.350)
Robust SEs	Yes	Yes	Yes	Yes
Season FEs	No	No	Yes	Yes
Home team FEs	No	No	Yes	Yes
Away team FEs	No	No	Yes	Yes
Instrumental Variables				
No. of 'acute' injuries (non-fav.)	Yes	No	Yes	No
Rating of 'acute' injuries (non-fav.)	No	Yes	No	Yes
Observations	1,133	1,133	1,133	1,133

Note: Estimated coefficients in columns (1)-(4) are from IV-2SLS regressions, where the first stage is a regression of the outcome uncertainty of game t on 'acute' injury-induced changes to the line-up of the non-favorite, and the second stage is a regression of attendance at game t on the fitted value of outcome uncertainty from the first stage. Line up changes due to 'acute' injuries exclude instances where a player was withdrawn from a team's line-up for a vague or non-specific injury (e.g., soreness, tightness, etc). White-robust standard errors are in parentheses. Regression disturbance terms are clustered at the round-season level. *p<0.1; **p<0.05; ***p<0.01

Table 11: Robustness of estimates when controlling for spectator preferences for star players and for high scores

	Dependent variable:				
	Log(Attendance)				
	(1)	(2)	(3)	(4)	(5)
Outcome Uncertainty	0.652*	0.674**	0.610*	0.683*	0.701**
	(0.375)	(0.337)	(0.352)	(0.356)	(0.323)
No. of 'star' injuries (90th)	−0.023				
	(0.051)				
No. of 'star' injuries (95th)		−0.041			
		(0.106)			
No. of 'star' injuries (99th)			−0.045		
			(0.043)		
Total Score (closing odds)				0.005***	0.005***
				(0.001)	(0.001)
Robust SEs	Yes	Yes	Yes	Yes	Yes
Season FEs	Yes	Yes	Yes	Yes	Yes
Home team FEs	Yes	Yes	Yes	Yes	Yes
Away team FEs	Yes	Yes	Yes	Yes	Yes
Instrumental Variables					
No. of injuries (non-fav.)	Yes	Yes	Yes	Yes	No
Rating of injuries (non-fav.)	No	No	No	No	Yes
Observations	1,133	1,133	1,133	944	944

Note: Estimated coefficients in columns (1)-(5) are from IV-2SLS regressions, where the first stage is a regression of the outcome uncertainty of game t on injury-induced changes to the line-up of the non-favorite, and the second stage is a regression of attendance at game t on the fitted value of outcome uncertainty from the first stage. In columns (1)-(3), we control in both stages for injuries to star players. In columns (4)-(5), we control in both stages for the expected total score. White-robust standard errors are in parentheses. Regression disturbance terms are clustered at the round-season level. *p<0.1; **p<0.05; ***p<0.01

Table 12: Robustness of estimates when instrumenting for outcome uncertainty with suspensions

	Dependent variable:			
	Log(Attendance)			
	(1)	(2)	(3)	(4)
Outcome Uncertainty	2.116*	1.775	1.179**	1.142***
	(1.202)	(1.121)	(0.502)	(0.393)
Robust SEs	Yes	Yes	Yes	Yes
Season FEs	No	No	Yes	Yes
Home team FEs	No	No	Yes	Yes
Away team FEs	No	No	Yes	Yes
Instrumental Variables				
No. of suspensions	Yes	No	Yes	No
Rating of suspensions	No	Yes	No	Yes
Observations	1,133	1,133	1,133	1,133

Note: Estimated coefficients in columns (1)-(4) are from IV-2SLS regressions, where the first stage is a regression of the outcome uncertainty of game t on league-enforced line-up changes ('suspensions') to the non-favorite, and the second stage is a regression of attendance at game t on the fitted value of outcome uncertainty from the first stage. White-robust standard errors are in parentheses. Regression disturbance terms are clustered at the round-season level. *p<0.1; **p<0.05; ***p<0.01

Table 13: Heterogeneous effects - Outcome uncertainty and preferences for ‘significant’ games

	Dependent variable: Log(Attendance)				
	Full sample	1st half of season	2nd half of season	Finals ‘margin’	Outside finals ‘margin’
	(1)	(2)	(3)	(4)	(5)
Outcome Uncertainty	0.728**	1.221**	0.425	0.805***	0.504
	(0.341)	(0.532)	(0.282)	(0.170)	(0.679)
Robust SEs	Yes	Yes	Yes	Yes	Yes
Season FEs	Yes	Yes	Yes	Yes	Yes
Home team FEs	Yes	Yes	Yes	Yes	Yes
Away team FEs	Yes	Yes	Yes	Yes	Yes
Instrumental Variables					
No. of injuries (non-fav.)	Yes	Yes	Yes	Yes	Yes
Observations	1,133	564	569	277	283

Note: Estimated coefficients in columns (1)-(5) are from IV-2SLS regressions, where the first stage is a regression of the outcome uncertainty of game t on injury-induced line-up changes to the non-favorite, and the second stage is a regression of attendance at game t on the fitted value of outcome uncertainty from the first stage. Finals ‘margin’ is the subsample of games where at least either the home or away team is on the margin of qualifying for finals (i.e, the team is sitting between 6th and 10th on the ladder during the second half of the season when the game takes place). Outside finals ‘margin’ is the subsample of games where this is not the case (i.e., neither the home or away team is sitting between 6th and 10th on the ladder during the second half of the season when the game takes place). White-robust standard errors are in parentheses. Regression disturbance terms are clustered at the season level. *p<0.1; **p<0.05; ***p<0.01

Table 14: Heterogeneous effects - Outcome uncertainty and spectator 'types'

	Dependent variable: Log(Attendance)					
	Full sample	Full Sample	Big Four	Big Four	Expansion	Expansion
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome Uncertainty	0.728^{**}	0.707^{**}	1.630^{***}	1.471^{***}	0.502	0.498
	(0.341)	(0.360)	(0.615)	(0.564)	(0.622)	(0.668)
Robust SEs	Yes	Yes	Yes	Yes	Yes	Yes
Season FEs	Yes	Yes	Yes	Yes	Yes	Yes
Home team FEs	Yes	Yes	Yes	Yes	Yes	Yes
Away team FEs	Yes	Yes	Yes	Yes	Yes	Yes
Instrumental Variables						
No. of injuries (non-fav.)	Yes	No	Yes	No	Yes	No
Rating of injuries (non-fav.)	No	Yes	No	Yes	No	Yes
Observations	1,133	1,133	254	254	252	252

Note: Estimated coefficients in columns (1)-(6) are from IV-2SLS regressions, where the first stage is a regression of the outcome uncertainty of game t on injury-induced line-up changes to the non-favorite, and the second stage is a regression of attendance at game t on the fitted value of outcome uncertainty from the first stage. Big Four is the subsample of games where the home team is either Carlton, Collingwood, Essendon, or Richmond. Expansion is the subsample of games where the home team is either Brisbane, Gold Coast, Greater Western Sydney, or Sydney. White-robust standard errors are in parentheses. Regression disturbance terms are clustered at the season level. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$