First version: August 2010
Revised version: May 2011

Playoff Uncertainty, Match Uncertainty and Attendance at Australian National Rugby League Matches*

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Abstract

This paper develops a new simulation-based measure of playoff uncertainty and investigates its contribution to modelling match attendance compared to other variants of playoff uncertainty in the existing literature. A model of match attendance incorporating match uncertainty, playoff uncertainty, past home-team performance and other relevant control variables is fitted to Australian National Rugby League data for seasons 2004-2008. The probability of making the playoffs and home-team success are more important determinants of match attendance than match uncertainty. Alternative measures of playoff uncertainty based on points behind the leader, although more ad hoc, also appear able to capture broadly similar effects on attendance to the playoff probabilities.

JEL classification: C23, L83
Key words: playoff uncertainty, match uncertainty, sports league attendance, Australian National Rugby League, fixed effects estimation

* We are grateful to Dan Farhat, Liam Lenten, two anonymous referees, and participants at the Australian Conference of Economists ACE10, Sydney (September 2010) for helpful comments and suggestions on earlier drafts. We also thank Dan Farhat for advice on MATLAB coding.

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I Introduction

According to the ‘uncertainty of outcome hypothesis’ (UOH) (Rottenberg, 1956), close sporting contests, with more uncertain outcomes, are more attractive to fans. Empirical studies of fans’ demand for sport include a wide range of explanatory variables (Borland & Macdonald, 2003), but uncertainty of outcome is usually regarded, on a priori grounds, as one of the key factors. Moreover, the UOH is a central tenet in the economic analysis of sports leagues. Concerns about lack of competitive balance and the implications for fan interest via the UOH are often emphasized in sports antitrust cases to justify restrictive practices (such as salary caps, player drafts and revenue sharing) that would be considered anti-competitive and unlawful in other industries. Consequently, there is a substantial body of literature examining the UOH both at the aggregate level (viewing each season as an individual observation) and at a more disaggregated level (viewing each match as an observation). However, although the UOH has been around for over 50 years, it continues to be a focus for empirical testing. This is partly due to the mixed nature of the existing evidence on its relevance (Borland & Macdonald, 2003; Szymanski, 2003; Downward *et al*., 2009) and partly due to the challenges of measuring the different unobservable *ex ante* dimensions of uncertainty of outcome required to test the UOH (Sloane, 2006).

In this paper, we investigate the effects of uncertainty of outcome on match attendance in the Australian National Rugby League (NRL). Given the span of the data examined, we focus on match uncertainty and ‘playoff uncertainty’, i.e., uncertainty about which teams will finish in the top eight positions, which qualifies them for post-regular-season playoffs that determine the overall league winners. Playoff uncertainty and other aspects of seasonal uncertainty have received less attention in the literature than individual match uncertainty, but seasonal uncertainty may have a more important effect on fan interest and attendance over the course of a season as teams drop out of contention for the top positions.

Measures of seasonal uncertainty in existing studies are relatively crude, such as counting the number of games or points behind the leader. Our approach is to derive measures of both playoff and match uncertainty using a simulation model applied to data from the NRL. Simulation methods have previously been used to predict match and tournament outcomes (e.g., Clarke, 1993; Koning *et al*., 2003) and to investigate the implications for attendance of different league structures or of equalizing playing talent across teams (Dobson *et al*., 2001; Forrest *et al*., 2005). However, our study constitutes one of the first attempts, along with Bojke (2008), to use simulation methods specifically to generate *ex ante* measures of different aspects of uncertainty of outcome.

There are numerous previous studies of the determinants of attendance for different sports. However, relatively few consider rugby league, and these examine attendance at English rugby league matches (Baimbridge *et al*., 1995; Carmichael *et al*., 1999; Jones *et al*., 2000; Dobson *et al*., 2001). Australian attendance demand studies focus on the Australian Football League (e.g., Borland, 1987; Borland & Lye, 1992; Lenten, 2009a), with analysis of the NRL concentrating more on measurement of competitive balance (e.g., Booth, 2004; Lenten, 2009b). The unpublished paper by Alchin and Tranby (1995), which examines attendance demand for Australian rugby league using season-level data for 35 seasons (1960-1994), is an exception. Our paper therefore contributes to a currently sparse literature relating to attendance demand for rugby league in general and for the NRL in particular.[1]

In Section II we provide an overview of the various measures used to quantify different dimensions of uncertainty of outcome in the existing literature testing the UOH. Section III outlines a new approach to measuring both match uncertainty and playoff uncertainty

[1] The NRL was formed in 1907 as the New South Wales Rugby League with the inaugural premiership held in 1908. It is now the most important rugby league championship in the Southern Hemisphere with, from 2007, ten teams from New South Wales, three from Queensland, one from Victoria, one from the Australian Capital Territory, and one from New Zealand.

based on simulating match and end-of-season outcomes. Section IV includes the simulation-based uncertainty measures in an empirical model of attendance demand for NRL matches. Results from fitting the model to five seasons of NRL data are reported in section V, including comparisons of results for the simulation-based measure of playoff uncertainty with measures used in previous match attendance studies. Section VI concludes.

II Measuring Uncertainty of Outcome

It is usual to distinguish between (at least) three different dimensions of uncertainty of outcome relating to different relevant time spans: short-run match uncertainty, medium-term within-season uncertainty, and long-run championship uncertainty (Cairns *et al*., 1986; Borland & Macdonald, 2003; Szymanski, 2003).[2]

Match uncertainty is concerned with the predictability of individual matches. It is the most frequently examined dimension of outcome uncertainty, although there is no clear consensus on the best way to measure it (Buraimo *et al*., 2008). Measures of match uncertainty used in the literature are generally based on two main sources of information: teams' relative performances prior to a match (as summarized in relative league positions, points totals or win percentages) or match betting odds.

Match uncertainty measures based on teams' league positions (e.g., Hart *et al*., 1975; Borland & Lye, 1992; Baimbridge *et al*., 1996; Falter & Pérignon, 2000; García & Rodríguez, 2002; Benz *et al*., 2009; Madalozzo & Villar, 2009), points totals (e.g., Wilson & Sim, 1995) or win percentages (e.g., Welki & Zlatoper, 1999; Meehan *et al*., 2007) have drawbacks. They do not account for home advantage (Forrest & Simmons, 2002; Buraimo

[2] Uncertainty of outcome is closely related to competitive balance, i.e., how evenly teams are matched. Ignoring other factors, such as the extent of home advantage, a higher degree of competitive balance tends to produce more closely contested matches and, hence, higher levels of match and seasonal uncertainty. However, an important difference is that *ex post* measures (e.g., based on win percentages) are commonly used to track competitive balance, whereas uncertainty of outcome is inherently an *ex ante* concept (Kringstad & Gerrard, 2007).

et al., 2008) or the difficulty of the teams' playing schedules up to that point in the season, and do not necessarily adequately capture current form (Sandy *et al*., 2004). Win percentages and league positions are likely to display greater variability early in the season when teams have played relatively few games, so the degree to which these measures reflect teams' relative abilities will vary over the season. All these measures have also been criticized for being "entirely backward-looking" and based on partial information (Downward & Dawson, 2000, p.134).

By contrast, betting odds are regarded as incorporating a wider range of relevant information, e.g., on suspensions or injuries to players. Odds-based measures of match uncertainty are generally expressed in the form of the probability of a home-team win (Peel & Thomas, 1988, 1992; Knowles *et al*., 1992; Czarnitzki & Stadtmann, 2002; Benz *et al*., 2009; Lemke *et al*., 2010) or the ratio of the probability of a home win to the probability of an away win (Forrest & Simmons, 2002). Although odds-based measures accord more closely with an *ex ante* notion of outcome uncertainty, concerns have been raised about biases in setting odds (Forrest & Simmons, 2002; Forrest *et al*., 2005; Dawson & Downward, 2005; Buraimo *et al*., 2008).[3] Also, the historical record for such odds may not always be available for use in empirical studies.

Despite the emphasis placed on the UOH in the literature, empirical results on the significance of match uncertainty are mixed. Of 18 studies reviewed by Borland and Macdonald (2003), only four produced clear evidence of a statistically significant positive effect of match uncertainty on attendance. Difficulty in identifying significant match uncertainty effects may be partly due to measurement problems, especially as measures are

[3] Dobson and Goddard (2008) provide a succinct but comprehensive review of recent studies of the efficiency of fixed-odds betting on football; most of the studies they review suggest that betting odds are not efficient.

often based on ex post information and overlap with indicators of team quality or success.[4] In this study, as discussed in section III, our measure of match uncertainty is neither determined purely by teams' standings nor reliant on betting odds, but is based on a match's predicted outcome and the distribution of observed errors.

Seasonal uncertainty is concerned with the degree of within-season uncertainty surrounding teams finishing in some end-of-season position, e.g., winning the championship or making the playoffs. From an overall league perspective, fans are generally expected to prefer higher levels of uncertainty with many teams in contention throughout the season. Indeed, this is a primary motivation for playoffs as an element of competition design. However, playoffs redistribute the probability of eventual success over more teams, so there is a potential trade-off between increased attendance for teams kept in contention by the existence of playoffs and decreased attendance for teams whose probability of eventual success has been consequently reduced (Bojke, 2008). Overall league attendance may therefore decrease, especially if the latter are large-market teams.

Measures of seasonal uncertainty used in the literature are usually based on the number of games a team is required to win to make the playoffs or to win the championship (e.g., Jennett, 1984; Borland & Lye, 1992), the number of games (wins) or points behind the leading team (e.g., Borland, 1987; Whitney, 1988; Knowles *et al*., 1992; García & Rodríguez, 2002; Meehan *et al*., 2007; Benz *et al*., 2009; Lemke *et al*., 2010), or the significance of the match for the championship, playoffs or relegation (e.g., Jones *et al*., 2000; Dobson *et al*., 2001; Madalozzo & Villar, 2009). Matches between teams out of contention are expected to attract less interest.[5] The statistical significance of such

[4] Downward *et al*. (2009), in their review of studies of short-run uncertainty of outcome, note that league standings, rather than differences in standings or odds-based measures, tend to show up as more relevant in explaining attendance. However, actual standings are more a reflection of team success or team quality than of uncertainty of outcome.

[5] An alternative approach is to examine the effect of playoff uncertainty on average attendance for the league as a whole, rather than on attendance at individual matches. For example, Lee (2009) constructs a measure of

variables in empirical studies tends to be stronger than for measures of match uncertainty; of 19 studies reviewed by Borland and Macdonald (2003), 12 reported a statistically significant effect of seasonal uncertainty on attendance.[6]

Although useful in modelling match attendance, these variables have drawbacks as measures of *ex ante* uncertainty. Any measure based on the number of games a team needs to win to make the playoffs, or to win the championship, requires information that is not available at the time spectators decide whether to attend a match (Dawson & Downward, 2005). Counting the number of games behind provides a guide to the feasibility of a team remaining in contention, but relies entirely on the current points table, does not consider the difficulty of remaining matches in the schedule either for that team or for others in contention, and usually assesses how teams rank relative only to the current leader.[7]

Consecutive-season uncertainty refers to the absence of long-run domination by one team or a small number of teams According to the UOH, long-run domination by a few teams decreases championship uncertainty and is expected to have a negative effect on match attendance. There are relatively few empirical studies of this dimension of uncertainty of outcome and results do not provide clear conclusions (Borland & Macdonald, 2003; Downward *et al*., 2009). For attendance at the level of individual matches, as in the current study, consecutive-season uncertainty has largely been ignored, primarily due to the restricted time span of such studies.

Although there are plausible links between different dimensions of uncertainty of outcome and match attendance, existing evidence on the relevance of the relationships is

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average league-wide playoff uncertainty, based on aggregating team-specific information on games behind the leader.

[6] Downward *et al*. (2009) review a selection of studies that overlaps with those considered by Borland and Macdonald (2003). The results on seasonal uncertainty are again mixed. Overall, they conclude (p. 218) that "in the shorter run at least, a team's success is at least as important as UO for determining match attendances".

[7] In competitions with end-of-season playoffs, the number of games behind the current competition leader may not give an accurate reflection of a team's chance of making the playoffs. For example, the first-placed team may be well ahead of all the other teams; what matters then is how tight the competition is among the other teams vying for the remaining playoff positions.

surprisingly ambiguous. This may reflect the inadequate nature of commonly used measures of the different dimensions of uncertainty of outcome (Dawson & Downward, 2005; Sloane, 2006), motivating further testing of the UOH. Uncertainty of outcome, by its very nature, is concerned with the degree of predictability or unpredictability of the relevant outcome, and is therefore an *ex ante* concept. In contrast, most measures of uncertainty of outcome, apart from those based on betting odds, are backward-looking. In this paper we examine the relevance of measures of match and season uncertainty obtained from a consistent simulation framework that updates probability measures of match uncertainty and playoff uncertainty (the most relevant aspect of seasonal uncertainty in the NRL context) using information available to spectators at the time of their attendance decision. This corresponds more closely to an *ex ante* formulation of uncertainty than used in many existing studies.

III Simulation-based Measures of Playoff Uncertainty and Match Uncertainty

Our proposed measures of playoff and match uncertainty are derived by simulating the results of matches not yet played in the season. In particular, the probability of each team making the playoffs, at any point in the season, is measured by the proportion of simulated end-of-season outcomes for which that team finishes in the playoff positions. A simulation-based measure of playoff uncertainty has several advantages compared to previous measures. It is not based solely on the current state of the league points table. It reflects a team's likelihood of making the playoffs relative to all other teams in the league, not just the first-placed team. Moreover, the playoff probabilities of the various teams are consistent at every point because they are derived jointly. It takes into account the strength of the schedule, i.e., the difficulty of the remaining matches a team has to play in a season. In addition, it utilizes only information available to spectators prior to the relevant match and evolves as the season progresses.

Predicted match outcomes are required to simulate sequences of results through the season. To predict match outcomes we use a framework similar to that of Stefani and Clarke (1992) and Clarke (1993, 2005). The outcome of each match is characterized by the home team's winning margin (points scored by the home team less points scored by the away team). The predicted home team's winning margin depends on the teams' playing strengths and the extent of home advantage:

$$PM_{ij,r,y} = \lambda^H H_y + S_{i,r-1,y} - S_{j,r-1,y} \tag{1}$$

where $PM_{ij,r,y}$ is home team i's predicted winning margin against away team j, in round r of year y; λ^H is a dummy variable equal to one if the match is played at a non-neutral venue and zero otherwise; H_y is home advantage in year y, and $S_{i,r-1,y}$ is the strength rating for team i based on information up to and including round $r-1$ of year y.[8]

To allow for evolution of current form, team strength ratings are adjusted as the season progresses. For each match, the predicted outcome in equation (1) is compared with the actual match outcome, and the prediction error is calculated as

$$E_{ij,r,y} = AM_{ij,r,y} - PM_{ij,r,y}$$

where $E_{ij,r,y}$ is the error in predicting the match outcome of home team i against away team j, in round r of year y, and $AM_{ij,r,y}$ is the corresponding actual winning margin. Team strength ratings are updated using a simple exponential smoothing scheme:

$$\text{Home team: } S_{i,r,y} = S_{i,r-1,y} + \gamma E_{ij,r,y} \tag{2}$$

$$\text{Away team: } S_{j,r,y} = S_{j,r-1,y} - \gamma E_{ij,r,y}$$

where γ is a positive constant. If the home team wins a match by more than predicted, its strength rating increases, reflecting improved form, and the away team's strength rating decreases, reflecting worsened form.

[8] $PM_{ij,r,y} < 0$ corresponds to a predicted win for the away team with a points margin of $|PM_{ij,r,y}|$.

Strength ratings of all teams are set equal to zero at the beginning of the 2003 season, the season prior to the first season of observations used in fitting the attendance model in section IV, and are updated as the season progresses using equation (2).[9] The parameters in the model (γ and H) are determined by minimising $\sum E^2_{ij,r,2003}$, the sum of squared errors in prediction for match outcomes in 2003. The end-of-2003 strength ratings are used as initial values for the 2004 season. Strength ratings for 2004 matches are then updated, day-by-day, using equation (2) and 2003 values for γ and H; these strength ratings are then used in equation (1) to obtain predicted winning margins. At the end of each season, the process is repeated; i.e., the strength ratings of all teams at the beginning of season $y-1$ are set equal to zero. The parameters γ and H are obtained by minimizing the sum of squared errors in prediction in season $y-1$. The updated strength ratings provide initial values for season y. Strength ratings for season y matches are then updated (using season $y-1$ values for γ and H), and are used to generate predicted winning margins for matches in season y.

This setup assumes a homogeneous home advantage across teams within each season although this is allowed to vary between seasons. Alternative assumptions are possible (Clarke, 2005), e.g., home advantage may be different for different teams.[10] We adopt the common home advantage formulation because the key motivation is to model spectators' *ex ante* uncertainty of outcomes, not necessarily to maximize prediction accuracy. The more variation in home advantage allowed across teams and over time, the more explanatory power can be loaded onto home advantage (with parameters $H_{i,y}$; $i = 1, 2, \ldots, 16$ reflecting home advantage), especially with only 24 matches per team per season, but this is unlikely to reflect fans' *ex ante* expectations accurately. If we allow home advantage

[9] By setting all initial values of team strength ratings equal to zero, the sum of all team strength ratings, and hence the average strength rating, are also zero at any point in time. A team's strength rating can therefore be interpreted as the expected points margin resulting from a match against an average team at a neutral venue.

[10] Clarke's (2005) evidence suggests team-specific home advantages are significant in the Australian Football League, but year effects are not significant. However, his tests are based on fitting all the data and testing *ex post* for team and year effects.

to vary by team, we find the H_i terms vary considerably, for any i, from season to season; hence, last season's team-specific home advantage is not likely to be a reliable guide to this season's team-specific home advantage. We therefore incorporate an average home-advantage adjustment (based only on the previous season's results) rather than overfitting the model and reducing the apparent *ex ante* uncertainty faced by spectators.[11] Despite this, the model estimates 59 per cent of match winners correctly.[12] For the matches in our sample, actual home-team scoring margins, AM_{ij}, range from −66 to +65; 45 per cent of the matches' predicted scoring margins are within 10 points of the actual result, 62 per cent are within 15 points, 75 per cent are within 20 points, and only 9 per cent of the prediction errors are more than 30 points.

Simulated match outcomes are generated by adding a random error to the predicted match outcome:

$$SM_{ij,r,y} = \lambda^H H_y + S_{i,r-1,y} - S_{j,r-1,y} + GE_{ij,r,y}$$

where $SM_{ij,r,y}$ is home team i's simulated winning margin against away team j, in round r of year y, and $GE_{ij,r,y}$ is the corresponding generated error. The errors are randomly drawn from a normal distribution with mean zero and a standard deviation equal to that observed in the actual errors in the fitted model. The distribution of generated errors therefore approximates the distribution of observed errors.

The measure of playoff uncertainty is based on the probability of the home team making the playoffs. This varies as the season progresses and is constructed, for each round, by simulating yet-to-be-played matches to give an end-of-season points table and

[11] Year effects are maintained as the model is fitted to each season's data separately. The optimized parameter values vary across seasons (with γ values ranging from 0.047 to 0.101 and H_y values from 1.961 to 5.620).

[12] This compares favourably to the 61.4 per cent success rate in correctly predicting winning teams attained by a sports prediction website for NRL over the sample period (http://footyforecaster.com). The mean absolute value of the error in the predicted match outcome in our model is 14.37 compared to the website's 14.46.

repeating this process 1000 times. Within each simulation, strength ratings are updated based on the previous rounds' simulated results. The predicted probability of the home team making the playoffs, at that point in the season, is given by the proportion of simulated end-of-season points tables for which the home team makes the playoffs.[13] The probability of the away team making the playoffs is constructed in the same way.[14]

Our measure of match uncertainty is based on the probability of the home team winning the match. In the context of our simulation, this probability can be constructed from the predicted outcome of a match and the cumulative distribution of the observed errors in the prediction of all match outcomes. For example, suppose that the home team is predicted to win a given match by x points. Any error in prediction of less than x points will still result in the home team winning. Therefore, the proportion of observed errors greater than $-x$ will give the predicted probability of the home team winning the match.[15]

The model used to predict match and playoff probabilities was constructed using Microsoft Excel 2007. Parameter values (γ and H) were determined, on a season-by-season basis, using the Solver function to minimize the sum of squared errors in match-outcome predictions. Matlab 10 was used to simulate the results for yet-to-be-played matches as each season evolves.

This simulation-based approach provides measures of playoff uncertainty and match uncertainty jointly derived from a consistent *ex ante* framework. The playoff uncertainty

[13] For example, if there are five remaining rounds in a season containing 26 pre-playoff rounds, the 21 completed rounds will give a points table reflecting actual standings at the end of 21 rounds. A simulated end-of-season points table can be constructed by adding in simulated results for the final five pre-playoff rounds of matches. Repeating this process 1000 times gives 1000 simulated end-of-season points tables. The proportion of these points tables for which a team makes the playoffs gives a predicted probability, evaluated at the beginning of the 22nd round, of the team making the playoffs.

[14] Bojke (2008) uses a similar simulation approach to obtain predictions of end-of-season finishing positions and measures of game significance. However, his simulations are based on individual match betting odds for which there are some time-matching problems (Bojke, 2008, p.184).

[15] This method assumes there is no correlation between the predicted match outcome and the error in the predicted match outcome. Testing the correlation between these two variables reveals no significant correlation.

measure, in particular, offers a potential improvement on more ad hoc measures of playoff uncertainty used in the past.

IV Modelling Match Attendance

To assess the relevance of a measure of playoff uncertainty based on simulated probabilities, and to compare its performance with alternative measures, we include these in a model of attendance at NRL matches.[16] Comprehensive reviews of the literature on the determinants of match attendance in different sports leagues are provided by Borland and Macdonald (2003), Szymanski (2003), and Downward *et al*. (2009). Here we adopt a conventional single-equation framework, which allows us to focus on the value-added of the new simulation-based measures.

The empirical model for match attendance takes the general form

$$\ln(\textit{Attendance}) = f(\textit{Match Uncertainty}, \textit{Playoff Uncertainty}, \textit{Interactions}, \textit{WinStreak}, \textit{PreviousYrWin}, \textit{Round}, \textit{Round}^2, \textit{Sydney}, \textit{Weather}, \textit{Year}, \textit{Day of Week}, \textit{Time of Day}, \textit{Away Team}, \textit{Home Team}) + u \qquad (3)$$

The dependent variable, ln(*Attendance*), is the natural logarithm of match attendance. The semi-log functional form provides a partial response to heterogeneity in the variation in attendance levels across teams (discussed further below), although specifying the dependent variable as *Attendance* does not qualitatively alter the key results. u is a combined error term such that $u_{it} = \alpha_i + \varepsilon_{it}$, where α_i is a random individual-specific effect and ε_{it} an idiosyncratic error for home team i at time t.

[16] Most studies testing the UOH focus on match attendance. Given the importance of television revenues for professional sports leagues, including the NRL, television viewers have become a much more important group of consumers of professional sporting events. It would therefore also be desirable to test the UOH for television viewers of NRL matches to add to the few existing studies of television viewers of other sports (e.g., Forrest *et al*., 2005; Buraimo, 2008; Buraimo & Simmons, 2009; Yang & Kumareswaran, 2009; Alavy *et al*., 2010; Tainsky & McEvoy, 2011). However, television ratings data for NRL matches are not readily available, so this is not feasible in the current paper.

Match Uncertainty is modelled by including the simulated probability of a home-team win, denoted *PHomeWin*, as discussed in Section III. However, uncertainty is not a monotonic function of the home-win probability, as low or high home-win probabilities correspond to reduced uncertainty. We therefore also include the squared value of *PHomeWin*. A quadratic relationship between the simulated home-win probability and the log of attendance enables us to derive an estimate of the attendance-maximizing home-win probability (e.g., Whitney, 1988; Knowles *et al*., 1992; Peel & Thomas, 1992; Czarnitzki & Stadtmann, 2002; Owen & Weatherston, 2004a,b; Benz *et al*., 2009; Lemke *et al*., 2010). If only the linear *PHomeWin* coefficient is statistically significant, then this implies a monotonic relationship between attendance and home-win probability; this is more representative of a 'probability of success' effect than an uncertainty effect. Alternative formulations of the match uncertainty variable, discussed in Section V, are also considered to assess the sensitivity of the results.

Playoff Uncertainty is the key variable of interest in this study. Our preferred measure is based on the simulated probability of the home team making the playoffs at that stage of the season, denoted *PHomePlayoff*, as discussed in section III. To allow for a quadratic relationship between the playoff probability and attendance, we include the squared value of *PHomePlayoff*. However, if there is a turning point, we expect it to be at a home-team success probability closer to unity than for individual matches; i.e., other things equal, home teams with a high probability of making the playoffs will attract large crowds, unless fans are so sure of successful qualification that they hold off attending until the playoff matches. The corresponding probability for the away team, *PAwayPlayoff*, and its squared term are also included. In addition, the relevance of match uncertainty may depend on the probability of making the playoffs (Sloane, 2006); the effect of match uncertainty may be enhanced for teams in playoff contention, or match uncertainty may act as a substitute for a high playoff probability. To allow for these possibilities, we include interactions between match and playoff uncertainty.

For comparison, we also examine variants of playoff uncertainty measures used in previous studies (as discussed in section II): the number of points the home team is behind the current leader, the average number of points the home and away teams are behind the current leader, and the number of points the home team requires to make the playoffs.[17] These measures primarily reflect the likelihood of a team successfully making the playoffs; from this perspective, spectators are attracted to matches when the home team is closer to the current competition leader or when fewer points are required to make the playoffs. To allow for a possible quadratic uncertainty effect we also test for the relevance of squared terms for these variables.

WinStreak is defined as the number of consecutive wins (home and away) for the home team. Spectators like to see their team win; a significant positive effect of recent home-team success on match attendance is a consistent finding of previous studies (Borland & Macdonald, 2003).

PreviousYrWin is a dummy variable equal to one if the home team was the previous year's premiership winner (or zero otherwise). A positive relationship between match attendance and *PreviousYrWin* is expected, reflecting increased interest in a team that has recently shown championship winning ability.[18]

Round, represents the number of the round in the season (1, 2, …, 26) in which a match is played. Including *Round* and its squared value allows the stage of the season to affect attendance, after partialling out other factors such as team success and uncertainty

[17] Draws, in which each team receives half the available points, are feasible although relatively rare in the NRL, so the number of points behind the current leader is used instead of the number of games behind.

[18] We also examined two other variants of this variable that allow the effect of recent success to diminish as the season progresses. The first divides the *PreviousYrWin* dummy by the round in the season. The second multiplies *PreviousYrWin* by the number of rounds left in the season. All three versions give statistically significant effects, with no significant implications for the other estimated coefficients.

measures. For example, fan interest may be high initially, decline as the season progresses, but increase towards the end of the season.

Sydney is a dummy variable equal to one if both playing teams are from Sydney, and zero otherwise. A positive relationship between match attendance and *Sydney* is expected, due to greater support for the away team than usual.

Weather represents a set of six dummy variables indicating if the weather at the match location is classified as *Hot*, *Overcast*, *Windy*, *Rain*, *Showers* or *Cold*. Existing studies find positive effects of warmer, sunnier weather on attendance and negative effects of rain (e.g., García & Rodríguez, 2002; Czarnitzki & Stadtmann, 2002; Owen & Weatherston, 2004a,b; Meehan *et al*., 2007; Lemke *et al*., 2010).

Year represents a set of 1-0 dummy variables for the year in which a match took place (with 2004 as the base category). This controls for any season-specific factors influencing all teams' average attendance but not captured by the other explanatory variables (e.g., varying average ticket prices across seasons). *Day of Week* represents a set of five 1-0 dummy variables for the day of the week a match is played (*Tues*, *Wed*, *Fri*, *Sat*, *Sun*, with Monday as the base category). This is motivated by the significance of day-of-the-week effects on attendance demand in other sports (e.g., García & Rodríguez, 2002; Meehan *et al*., 2007; Lemke *et al*., 2010). *Time of Day* represents a set of 17 dummy variables for different kick-off times (with 12 noon as the base category).

Away Team consists of a set of away-team dummy variables to allow for the possibility that some visiting teams are intrinsically more appealing to home fans than others, as Lemke *et al*. (2010) find for baseball. *Home Team* represents the home-team-specific fixed effects.[19]

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[19] Fixed effects may capture factors such as teams' historical support base, different market size of catchment areas, ease of access to match venues, stadium quality, and alternative forms of entertainment available to spectators.

V Results

The data used to fit the model in equation (3) are individual match data from the NRL for seasons 2004-2008.[20] The NRL currently hosts 16 teams following the addition of the Gold Coast Titans in 2007. Each season contains 26 rounds (apart from 2007 when there were 25 rounds) of regular-season play followed by four rounds of playoffs for the eight highest-ranked teams. The empirical analysis focuses on the regular-season matches (924 matches in total). The data therefore constitute an unbalanced panel comprising 16 cross-sectional units (the home teams) with 60 'time-series' observations (i.e., home matches) for each of 15 teams, and 24 observations for the remaining team, the Titans.[21] Summary statistics for the key variables of interest are provided in Table 1.

The model in equation (3) is treated as a single-equation demand function and the parameters are estimated using the fixed effects estimator, with home-team fixed effects. For fixed effects estimation, the regressors are assumed to be uncorrelated with the time-varying component of the equation's error term, ε_{it}, but they may be correlated with the individual-specific α_i components. The random effects estimator is a feasible alternative estimator if the random effect, α_i, is distributed independently of all the explanatory variables for all t, but is inconsistent under the assumptions of the fixed effects model. A common strategy to choose the estimator is to apply a Hausman pre-test of the null hypothesis that the individual effects are random, and select the fixed or random effects estimator based on the result of this pre-test. However, Guggenberger (2010) shows that such pretesting can lead to significant size distortion in subsequent testing of parameter

[20] The data were obtained from http://stats.rleague.com and http://www.nrlstats.com.

[21] Unlike many panel data sets, the observations over time are not equally spaced (because teams do not play at home every week, or even every other week) and there is a gap between seasons. Also, the timing of the observations are not aligned for all teams, as in each round some teams play at home and others play away. Conventional methods for analysing the time-series aspects of the data are therefore not necessarily appropriate; however, timing issues do not affect most of our results, unless specifically indicated.

significance; directly using *t*-statistics based on the fixed effects estimator is therefore recommended, rather than a two-stage process involving pretesting.[22]

Exogeneity of the regressors (with respect to ε_{it}) would be an inappropriate assumption if, for example, higher attendance enhanced a team's available resources sufficiently to attract better players and improve the team's relative strength. However, any feedback from attendance to within-season performance and the simulated uncertainty measures is likely to be relatively minor in the current context given the focus on estimating the short-run effects of uncertainty on individual match attendance.[23] In addition, the operation of a salary cap, although subject to breaches of varying degrees of severity, has helped to dampen any link between revenue and on-field performance. If such feedback effects are of more significance in the longer run, these may need to be considered in studies using longer time spans of data.[24]

Table 2 reports results for the fitted model, including diagnostic tests for normality, groupwise heteroskedasticity, serial correlation and cross-sectional dependence. The null of normality of the errors is not rejected at the 5 per cent significance level based on a chi-squared test examining skewness and kurtosis. There is no obvious evidence of first-order autocorrelation, using Wooldridge's (2002, pp. 282-3) test.[25] On the basis of Pesaran's (2004) CD test, there is no evidence of cross-sectional dependence in the errors. This is

[22] A Hausman test, derived as an *F*-statistic using cluster-robust standard errors in an auxiliary regression involving demeaned time-varying regressors (Wooldridge, 2002, p.290) strongly rejects the random effects specification ($p = 0.000$). Hence, in this application, both Guggenberger's (2010) proposed strategy and the conventional approach suggest focusing on the fixed effects estimates. In any case, random effects estimates give qualitatively similar conclusions.

[23] Admission price is not included in the set of explanatory variables. As Downward *et al*. (2009) note in their review of recent attendance demand studies, this is not uncommon. Pricing in the NRL is highly uniform and regulated; consequently, admission prices within a regular season do not vary in response to match-specific factors affecting demand, such as match quality or uncertainty of outcome.

[24] Match attendance reaches stadium capacity for only 2 per cent of the regular-season matches in the sample, so any bias or inconsistency due to censoring of the dependent variable (with attendance at capacity, such that the number of spectators willing to pay to attend is not observable) is a minor issue.

[25] The time counter for the autocorrelation test results reported is based on the order of the home matches for each team. Because of the irregular nature of the time dimension of the data, 'time t' observations do not match exactly across different teams. Therefore, this result is only suggestive.

supported by the low average absolute value of the off-diagonal elements in the matrix of residuals (denoted *AvAbsCross*) and by the lack of statistical significance of the Breusch-Pagan (1980) LM test applied to a balanced panel that omits the home results for the Titans.[26] The modified Wald test for groupwise heteroskedasticity (Baum, 2001) strongly suggests that error variances differ across cross-sectional units, i.e., home teams. This is also apparent in Figure 1, which plots values for ln(*Attendance*) and their mean values for each home team. Consequently, cluster-robust standard errors are reported; these assume errors are independent across teams but allow for varying error variances across 16 clusters, i.e., by home team.[27] However, using unadjusted standard errors, based on the assumption of iid errors, gives qualitatively similar conclusions for the key variables.

Initially, we included quadratic terms for *PHomePlayoff* and *PAwayPlayoff*, but their coefficients were not statistically significant at the 10 per cent level and, due to the high correlation between the linear and quadratic terms (0.970 for both variables), their inclusion reduced the precision of estimation of the coefficients on the linear terms; the quadratic terms were therefore deleted.[28]

Our benchmark specification is reported in Table 2, column (1), with a variant containing the interaction term *PHomeWin* × *PHomePlayoff* in column (2). The main focus of interest is the size and statistical significance of the coefficients on the proxies for playoff and match uncertainty. The simulated probabilities of the home and away teams

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[26] The Breusch-Pagan test is appropriate if the time-series dimension of the panel, T, is greater than the number of cross-sectional units, N, as in our application. The Pesaran test is more appropriate for panels with large N and T fixed (De Hoyos & Sarafidis, 2006). The caveat about the irregular and unmatched timing of observations also applies to the results for both these tests; in particular, they are unlikely to fully reflect common shocks and unobserved components that lead to dependence at relatively high frequencies (e.g., less than a fortnight).

[27] Using bootstrap standard errors, with resampling over clusters, gives qualitatively similar results, apart from changes to the statistical significance of some of the time-of-match effects.

[28] Similarly, an interaction between $PHomeWin^2$, the squared value of *PHomeWin*, and *PHomePlayoff* was initially included but this term is highly correlated with *PHomeWin* × *PHomePlayoff* ($r = 0.969$) and its effect is not statistically significant at the 10 per cent level. To save space, results for models including the squared playoff probabilities and the $PHomeWin^2$ × *PHomePlayoff* interaction are not reported, but are available on request.

making the playoffs both have estimated effects that are statistically significant at the 0.1 per cent level. Based on the results in Table 2, column (1), other things equal, for every increase of 0.1 in the probability that the home team will make the playoffs, match attendance is estimated to increase by nearly 2 per cent. Equivalently, this corresponds to a 20 per cent higher attendance for a team certain of making the playoffs compared to a team having no chance of making the playoffs. An increase of 0.1 in the probability that the away team will make the playoffs, other things equal, boosts match attendance by about 1 per cent.

The simulated probability of a home win is entered in quadratic form and both terms are on the margin of statistical significance at the 5 per cent level. Based on the point estimates, the quadratic relationship between ln(*Attendance*) and *PHomeWin* has an attendance-maximizing home-win probability of 0.605, a result in line with several previous studies for other sports (Borland & Macdonald, 2003). A quadratic relationship with significant coefficients, indicative of an inverted U-shaped relationship between home-win probability and attendance, is conventionally interpreted as supportive of the UOH at the level of match uncertainty; however, previous studies do not usually examine whether the marginal effect of the home-win probability is significant throughout its range of values. The 95 per cent symmetric confidence interval for the marginal effect of *PHomeWin* can be obtained as:

$$(b_1+2b_2 \mathit{PHomeWin}) \pm 1.96[\mathrm{var}(b_1)+ 4\mathit{PHomeWin}^2\,\mathrm{var}(b_2) +4\mathit{PHomeWin}\,\mathrm{cov}(b_1,b_2)]^{1/2}$$

in which b_1 and b_2 are the point estimates on *PHomeWin* and $\mathit{PHomeWin}^2$ respectively, and var(b_1), var(b_2) and cov(b_1,b_2) are the estimated cluster-robust variances and covariance of the relevant estimated parameters (Aiken & West, 1991). The point estimates and confidence intervals for the marginal effect for the model in Table 2, column (1) are represented graphically in Figure 2. Increasing the home-win probability has a statistically significant positive marginal effect on match attendance up to approximately a value of *PHomeWin* of 0.5. Thereafter, the marginal effect, including beyond the turning point in the relationship between ln(*Attendance*) and *PHomeWin*, is not statistically significantly different from zero. The results obtained therefore provide only relatively modest support for the UOH with respect to match uncertainty.

The interaction term *PHomeWin* × *PHomePlayoff* is included in Table 2, column (2); its coefficient is negative, implying some degree of substitutability between the home team's match and playoff success probabilities; i.e., other things equal, increases in *PHomeWin* have a smaller attendance-enhancing effect at high values of *PHomePlayoff*. However, the estimated coefficient on the interaction term is statistically significant only at the 10 per cent but not the 5 per cent level.[29]

The statistical and quantitative significance of the other coefficient estimates are robust across columns (1) and (2), so we focus on results for the former. The estimated coefficient on home-team success is positive and statistically significant at the 0.1 per cent level. The point estimate suggests that a three-match increase in *WinStreak* increases attendance by 11.4 per cent. The estimated average effect of winning the premiership in the previous season is an increase in attendance of approximately 17 per cent. Each of these estimated effects assumes other things are equal; however, for a team with a successful run of wins, consequent improvements in strength ratings and league standing also enhance the probabilities of winning matches and of making the playoffs.

The coefficients on *Round* and its squared value are both statistically significant at the 0.01 per cent level and imply initially declining attendance as the season progresses, with a

[29] With the interaction term included, the playoff probabilities are still highly statistically significant and the quantitative significance of the effect of *PHomePlayoff* on attendance is enhanced. However, the coefficient on the quadratic term $PHomeWin^2$ is no longer statistically significant at even the 10 per cent level, further dampening support for the UOH applied to match uncertainty. However, the high degree of intercorrelation between the various probabilities, their squares and interactions makes it difficult to estimate some of these effects precisely.

turning point after 14 rounds, other things equal. This pattern is consistent with heightened early-season interest in matches, followed by a fall-off in interest and then a revival towards the end of the season.

Matches involving two Sydney-based teams have statistically and quantitatively significantly higher attendance, whereas rain, showers or windy weather, on average, have negative effects on attendance. Attendance in 2005 and 2008 (the NRL's centenary year) was on average higher than in the base year of 2004. Mid-week matches (Tuesday and Wednesday) attract statistically significantly higher attendance (compared to Monday matches). The identity of the away team also has statistically significant effects on attendance (not reported in Table 2) with several away teams, e.g., the Dragons and the Broncos, drawing significantly higher crowds than others.[30] Some significant time-of-day effects are also found (primarily negative effects from later kick-off times in the afternoon compared to noon, other things equal).

Given the marginal significance of the terms in the quadratic formulation involving the *PHomeWin* in Table 2, column (1), we experimented with alternative measures of match uncertainty. Columns (3) to (5) report results using *Excite50* (defined as $0.5 - |0.5 - PHomeWin|$), *Excite60* (defined as $0.6 - |0.6 - PHomeWin)|$) and *MatchUnbal* (defined as $|\ln(PHomeWin/(1 - PHomeWin))|$). None of these alternative formulations has a statistically significant effect at the 5 per cent level, although the coefficient on *Excite60* is significant at the 10 per cent level.[31]

In Table 3, we report results using alternative measures of playoff uncertainty: the number of points the home team is behind the current leader (*HomePtsBack*) in column (1), *HomePtsBack* and the number of points the away team is behind the current leader

[30] The null hypothesis of zero coefficients on all the away-team dummy variables is decisively rejected with a *p*-value of 0.0000.

[31] *Excite50* and *Excite60* have maximum values at home-win probabilities of 0.5 and 0.6 respectively, the latter closely corresponding to the turning point of the quadratic relationship in Table 2, column (1).

(*AwayPtsBack*) in column (2), the average of the number of points the home and away teams are behind the current leader (*AvPtsBack*) in column (3), and the number of points the home team requires to make the playoffs (*PtsRequired*) in column (4). Each of the four measures of playoff uncertainty has the expected coefficient sign and each is highly statistically significant.[32] Varying the definition of the playoff uncertainty measure has little effect on the size and significance of the coefficients on other variables, except for changes in the marginal significance level of *PHomeWin*. These results suggest that all the measures examined are capturing, in different ways, the effects of the playoff probabilities on match attendance.

VI Conclusions

The simulation-based approach adopted in this paper to generate measures of uncertainty of outcome in modelling sports attendance produces promising results. It has several appealing features compared to existing ad hoc methods of characterizing seasonal or playoff uncertainty; in particular, it provides a consistent set of playoff probabilities across all teams reflecting the strength of the past and future schedules and uses a wider set of relevant *ex ante* information than just current league standings. It would be feasible to apply this approach in a range of different league settings to evaluate the attendance implications of different aspects of competition design, such as different playoff structures or multiple prizes (e.g., avoiding relegation and/or qualification for other competitions, such as in European football).

The results obtained for the NRL suggest that playoff uncertainty, or more specifically a team's probability of qualifying for the playoffs, is a more significant driver of attendance than individual match uncertainty. Although we have characterized existing

[32] If quadratic terms are included in the model for each of these measures, none is statistically significant at the 5 per cent level.

points-behind-based measures of playoff uncertainty as relatively crude, and their marginal levels of statistical significance are not quite as impressive as the simulation-based measures, they do appear to capture broadly similar effects as compared to the playoff probabilities. Hence, to the extent that the NRL experience is representative, the use of such measures in other attendance demand studies may not have seriously misrepresented the role of teams' chances of end-of-season success. However, given the highly intercorrelated nature of the various relevant probabilities, separating the effects of uncertainty from the effects of the probability of success is difficult, especially for analysis at the level of match attendance. In keeping with existing results for other sports, consistent winning performances have a quantitatively greater effect on attendance than uncertainty measures.

Overall, NRL fans are attracted to winning teams; the various estimated effects reflecting the home team's past win performances and enhanced probabilities of match and playoff success combine to produce a virtuous cycle that improves match attendance.

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TABLE 1

Summary Statistics for Key Variables

	Mean	Std Dev	Min	Max
ln*Attendance*	9.576	0.413	8.340	10.832
PHomeWin	0.590	0.168	0.101	0.944
PHomePlayoff	0.550	0.389	0	1
PAwayPlayoff	0.535	0.392	0	1
WinStreak	0.910	1.459	0	11
PrevYrWin	0.065	0.247	0	1
Round	13.451	7.535	1	26
Sydney	0.207	0.405	0	1

TABLE 2

Fixed Effects Estimation Results with Alternative Match Uncertainty Measures

	(1)	(2)	(3)	(4)	(5)
PHomeWin	0.753*	0.586			
	(2.18)	(2.03)			
PHomeWin^2	–0.622	–0.352			
	(2.03)	(1.41)			
PHomePlayoff	0.194***	0.366***	0.204***	0.196***	0.205***
	(8.53)	(4.21)	(9.46)	(9.51)	(9.34)
PAwayPlayoff	0.106***	0.103***	0.0962**	0.103***	0.0947**
	(5.01)	(4.88)	(3.87)	(4.35)	(3.87)
PHomeWin × *PHomePlayoff*		–0.290			
		(1.97)			
WinStreak	0.0381***	0.0385***	0.0387***	0.0383***	0.0390***
	(4.48)	(4.54)	(4.25)	(4.32)	(4.35)
PreviousYrWin	0.168***	0.164**	0.173***	0.169***	0.174***
	(4.35)	(4.05)	(4.47)	(4.38)	(4.47)
Excite50			0.120		
			(1.32)		
Excite60				0.208	
				(1.82)	
MatchUnbal					–0.0291
					(1.56)
Round	–0.0512***	–0.0501***	–0.0511***	–0.0513***	–0.0511***
	(9.33)	(8.98)	(9.49)	(9.45)	(9.41)
Round^2	0.00176***	0.00172***	0.00175***	0.00176***	0.00175***
	(8.00)	(7.85)	(8.10)	(8.09)	(8.05)
Sydney	0.121*	0.120*	0.120*	0.121*	0.120*
	(2.23)	(2.27)	(2.23)	(2.24)	(2.24)
Hot	0.0216	0.0212	0.0182	0.0229	0.0173
	(0.18)	(0.18)	(0.16)	(0.19)	(0.15)
Overcast	–0.0150	–0.0116	–0.0147	–0.0147	–0.0144
	(0.25)	(0.19)	(0.24)	(0.24)	(0.24)
Windy	–0.109**	–0.105**	–0.109**	–0.108**	–0.109**
	(3.29)	(3.33)	(3.32)	(3.32)	(3.30)
Rain	–0.242***	–0.241***	–0.242***	–0.241***	–0.242***
	(4.27)	(4.32)	(4.27)	(4.27)	(4.27)
Showers	–0.188***	–0.184***	–0.191***	–0.189***	–0.191***
	(6.27)	(6.22)	(6.54)	(6.30)	(6.56)
Cold	–0.0559	–0.0550	–0.0582	–0.0552	–0.0577
	(1.21)	(1.15)	(1.24)	(1.19)	(1.24)
2005	0.0944**	0.0933**	0.100**	0.0960**	0.101**
	(3.59)	(3.49)	(3.68)	(3.45)	(3.74)
2006	0.00890	0.00777	0.0170	0.0111	0.0172
	(0.27)	(0.23)	(0.54)	(0.33)	(0.54)
2007	0.00630	0.00659	0.0106	0.00768	0.00919
	(0.17)	(0.18)	(0.29)	(0.21)	(0.25)

2008	0.0772*	0.0771*	0.0863*	0.0790*	0.0860*
	(2.49)	(2.51)	(2.65)	(2.47)	(2.64)
Tues	0.873***	0.868***	0.862***	0.870***	0.863***
	(6.27)	(6.32)	(6.22)	(6.30)	(6.23)
Wed	0.516**	0.525***	0.494**	0.517**	0.495**
	(3.94)	(4.13)	(3.76)	(4.00)	(3.77)
Fri	–0.160	–0.151	–0.145	–0.165	–0.147
	(0.68)	(0.63)	(0.62)	(0.69)	(0.63)
Sat	–0.285	–0.277	–0.273	–0.291	–0.274
	(1.20)	(1.15)	(1.16)	(1.22)	(1.16)
Sun	–0.0666	–0.0684	–0.0774	–0.0670	–0.0755
	(0.72)	(0.74)	(0.83)	(0.72)	(0.81)
R^2	0.697	0.699	0.696	0.697	0.696
Normality-p	0.186	0.152	0.225	0.207	0.233
Hetero-p	0.000	0.000	0.000	0.000	0.000
BP-LM-p	0.128	0.154	0.113	0.134	0.112
Pesaran CD-p	0.504	0.532	0.442	0.447	0.478
AvAbsCross	0.128	0.126	0.127	0.128	0.127
Auto-p	0.239	0.277	0.301	0.344	0.268

Notes: The dependent variable is ln(*Attendance*). Absolute *t*-statistics, based on cluster-robust standard errors, are reported in parentheses. *, ** and *** denote significance at the 5 per cent, 1 per cent and 0.1 per cent levels respectively. Dummy variables for away teams and time of kick-off are included in the models but estimates are not reported; full results are available on request. N = 924 for all models. R^2 values are obtained from equivalent least-squares dummy variable regressions that include the home-team fixed effects. Suffix *p* denotes *p*-values reported for diagnostic tests. *Normality* is a chi-squared test for normality, *Hetero* is a modified Wald test for groupwise heteroskedasticity, *BP-LM* is the Breusch-Pagan (1980) LM test for cross-sectional independence of the errors, *Pesaran CD* is Pesaran's (2004) cross-sectional dependence test, *Auto* is Wooldridge's (2002) test for first-order autocorrelation, and *AvAbsCross* is the average absolute value of the off-diagonal elements in the matrix of residuals.

TABLE 3

Fixed Effects Estimation Results with Alternative Playoff Uncertainty Measures

	(1)	(2)	(3)	(4)
PHomeWin	0.699	0.771	0.863*	0.607
	(1.95)	(2.12)	(2.20)	(1.73)
PHomeWin^2	–0.665*	–0.655	–0.656	–0.604
	(2.18)	(2.05)	(1.96)	(2.03)
HomePtsBack	–0.0156***	–0.0142***		
	(6.53)	(5.55)		
AwayPtsBack		–0.00592*		
		(2.77)		
AvPtsBack			–0.0198***	
			(7.58)	
PtsRequired				–0.0224***
				(6.50)
WinStreak	0.0358**	0.0356**	0.0383***	0.0339**
	(3.85)	(3.91)	(4.21)	(3.77)
PreviousYrWin	0.158**	0.154**	0.147*	0.152**
	(3.27)	(3.11)	(2.94)	(3.21)
Round	–0.0423***	–0.0401***	–0.0408***	–0.0782***
	(7.78)	(7.69)	(8.01)	(9.61)
Round^2	0.00169***	0.00170***	0.00172***	0.00190***
	(7.91)	(7.96)	(8.10)	(7.87)
R^2	0.685	0.687	0.685	0.691
Normality-p	0.075	0.044	0.035	0.074
Hetero-p	0.000	0.000	0.000	0.000
BP-LM-p	0.177	0.225	0.331	0.035
Pesaran CD-p	0.185	0.077	0.097	0.482
AvAbsCross	0.122	0.120	0.118	0.127
Auto-p	0.228	0.122	0.117	0.293

Note: see *Notes* to Table 2. Dummy variables for weather characteristics, Sydney teams, year and day effects, away teams and time of kick-off are included in the models, but estimates are not reported; full results are available on request.

FIGURE 1

Heterogeneity in ln(Attendance) Across Home Teams

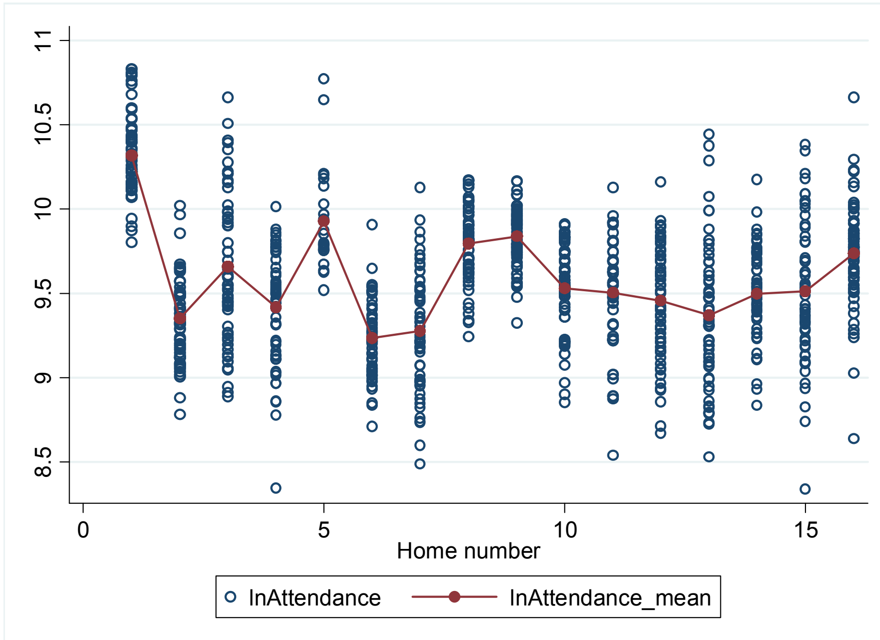

FIGURE 2

Marginal Effect of Simulated PHomeWin on ln(Attendance)