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On the Edge of Your Seat: Demand for Football on Television and the Uncertainty of Outcome Hypothesis

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Abstract

This paper examines the relationship between the demand for English football on television and outcome uncertainty. It tests the uncertainty of outcome hypothesis by using minute-by-minute television viewership figures which avoids the problems encountered when estimating demand using match attendance. We find that although uncertainty matters, it is the progression of the match which drives viewership and as a draw looks increasingly likely, viewers are likely to switch channels. Games that end in victories have a higher average viewership than games that end in stalemates.

Keywords: sports, soccer, football, competitive balance, television

Introduction

The most fundamental issue in the study of the economics of sport is the "uncertainty of outcome" hypothesis. According to this hypothesis, the greater the uncertainty of outcome of a sporting event, the greater the demand.[1] Sports leagues have consistently justified competitive restraints on the grounds that they permit resource distribution, which in turn promotes outcome uncertainty and thereby benefits the consumer by providing a more attractive league product. Sports leagues are, on the face of it, cartels.[2] Agreements among the clubs to restrain economic competition, such as salary caps, roster limits, draft rules, transfer fee systems, or agreements to share income from ticket sales, broadcasting, or merchandising would in any other context be prohibited. Yet such agreements have been accepted by the courts[3] and even encouraged by the legislature,[4] largely on the basis of the uncertainty of outcome hypothesis.

There exists a substantial economics literature aimed at testing the hypothesis by relating game attendance to some ex ante measure of uncertainty. Such studies are fraught with diffculty for a number of reasons. First, since the majority of attendees are fans of the home team, they presumably demand a strong probability that their team will win, and so home team demand may well be decreasing in the uncertainty of outcome, at least over a significant range of the data. Second, it is often hard to disentangle the quality of the two teams from the balance of the competition, and therefore hard to identify the true impact of outcome uncertainty. Third, game attendance is often determined by factors that have little to do with the outcome uncertainty of the game in question; for example, season-ticket owners are likely to be committed to attending regardless of the current balance between the opposing teams. Fourth, many games in the major leagues are sold out and therefore observed demand cannot be explained by outcome uncertainty.

In this paper we adopt a novel approach that evades these problems and therefore offers a more plausible estimate of the impact of outcome uncertainty on demand. Instead of using game attendance we use TV viewing figures, so that all else equal, supporters of the away team are as capable of viewing the match as supporters of the home team.[5] Furthermore, we use viewing data measured on a minute-by-minute basis throughout the game. This allows us to control for game-specific factors, such as the quality of the teams, while examining the effect on demand of the evolving outcome uncertainty of the game. To do this we estimate the probability of each possible result (a home win, an away win, a no-score draw or a score draw)[6] conditional on the current score at each minute of the game, each team's form, and red cards. We examine three measures of outcome uncertainty:

1. The squared difference between the probability of the home team winning and the away team winning.
2. The probability of draws.
3. The sum of squared deviations from the initial probabilities.

We find that viewership is decreasing in the first of these measures, so that a more even game, in the sense that either side could win, attracts more viewers. This result is consistent with the uncertainty of outcome hypothesis. However, we also find that viewership is also decreasing in the probability of draw, suggesting that viewers are averse to watching games that are expected to end in a stalemate. Lastly, we find some evidence to support the proposition that viewership is increasing in the deviation of outcome probabilities during the game from the initial outcome probabilities (i.e., those at the start of the game), suggesting that viewers are attracted to the unexpected.

To the extent that we can generalize from the case of the English Premier League, these results significantly enhance our understanding of the relationship between demand and uncertainty in sport. Leagues have consistently pleaded the need to maintain competitive balance among teams as a justification for restraints on economic competition in the labor market and in the product market (e.g., collective selling of rights). While this justification is intuitively appealing, the precise kind of uncertainty that is desirable has proved diffcult to articulate. Our results do not support the idea that simply evening up resources among teams will improve the attractiveness of games; much depends on the predictability of the contests that the leagues create.

Data

Description

Television ratings data were collected for 248 English F.A. Premiership matches broadcast on television between January 1, 2002, and May 15, 2005. Data on audience size were estimates made by the Broadcasters' Audience Research Board Ltd. (BARB). Supplemental television information was collected from the Monopolies and Merger Commission (1999) report. Individual match data for all Premiership games including team fixtures, positions, goals scored, and red cards were taken from the Rothmans Football Yearbooks[7] and http://www.soccerbase.com.[8] Actual match kick-off times and injury minutes played were supplied by PA Sport.

Table 1: Summary Statistics for Premiership Games Broadcast 2002–2005

	Averages						
				Total Goals Scored			
Season	Number of Games Broadcast †	TV Rating ‡	Goal Difference	All Games	All Draws	Score Draws	Wins
2002*	30	1.79	1.60	2.80	2.40	2.67	2.41
2003	65	2.45	1.37	2.88	2.59	2.93	1.83
2004	66	2.44	1.15	2.67	1.90	3.16	3.00
2005	87	2.21	1.13	2.41	1.82	3.00	2.63

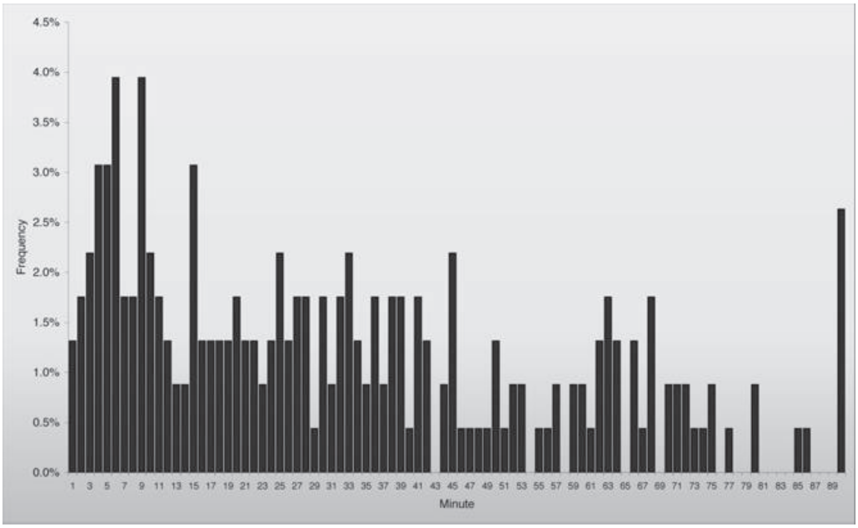
*Games between January 1, and May 11, 2002.
†Does not include Prem-Plus or pay-per-view.
‡A TV Rating is the percentage of people watching that program out of the television population.

Table 2: Summary of Match Outcomes for Games Broadcast 2002–2005

Result	Number of Games	% of Total	Average TV Rating
No-score Draw	20	8.1%	2.58*
Score Draw	45	18.1%	2.35
Home Win by 1 goal	61	24.6%	2.28
Home Win by 2 goals	29	11.7%	2.21
Home Win by 3 goals	7	2.8%	2.08
Home Win by 4 goals	5	2.0%	1.85
Home Win by 5 goals	3	1.2%	2.10
Home Win by 6 goals	1	0.4%	1.21
Away Win by 1 goal	47	19.0%	2.29
Away Win by 2 goals	17	6.9%	2.40
Away Win by 3 goals	5	2.0%	1.86
Away Win by 4 goals	6	2.4%	2.21
Away Win by 5 goals	2	0.8%	1.84

*Almost half of these were 'big' matches or derby matches.
Excluding those matches, the average was 2.04.

Figure 1: Distribution of First Goal Scored in Games Broadcast 2002–2005Averages



The tables above list summary statistics for average TV ratings, goals scored, and the distribution of goals, which give a brief overview about how most games progress, the most common types of scores, and how soon a goal is scored.

Demand and Outcome Uncertainty

Testing Outcome Uncertainty

There are at least three measures of outcome uncertainty used in the literature:

1. Match (game based measures).
2. Seasonal/ championship (measures based on the state of the championship or the dispersion of results within the season).
3. Long run (between season uncertainty, using measures of between season dispersion and persistence).

The economic analysis of the relationship between demand and outcome uncertainty goes back to Rottenberg (1956) and Neale (1964). Rottenberg (1956) first postulated the theory that attendance is a function of the quality of play and if there is a wide dispersion in quality, the contests would be more predictable, thereby reducing attendance. Neale (1964) also noted that sport is a complex product that consists not only of the match itself but also the “League-Standing Effect” where utility is generated by the excitement surrounding the standings of the clubs and the churn of those standings. The more teams alternate league positions, the more exciting the championship race.

There is a large literature dedicated to measuring the relationship between demand and outcome uncertainty which has focused on a variety of different leagues and different measures for uncertainty. Most US studies have focused on Major League Baseball or American Football (e.g., Knowles, Sherony, & Haupert, 1992; Welki & Zlatoper, 1999), whereas the majority of UK studies have centered on football (e.g., Peel & Thomas, 1988; Baimbridge, Cameron, & Dawson, 1996; Forrest & Simmons, 2002).

Empirical tests have also been extended to other sports such as rugby (Peel & Thomas, 1997) and cricket (Hynds & Smith, 1994) as well as football in other countries (Falter & Perignon, 2000; García & Rodríguez, 2002). Measures of outcome uncertainty have mostly been derived from match betting odds (Peel & Thomas, 1988; Peel & Thomas, 1992) or team positions (Baimbridge et al., 1996; García & Rodríguez, 2002).[9]

The problems in testing the relationship between demand and outcome uncertainty center on the choice of measures for uncertainty and demand. Forrest and Simmons (2002) show that UK betting odds are biased and therefore do not reflect the true probabilities of the various match outcomes. They find that the probability of a home win may be understated while an away win is overstated.[10] With respect to demand, almost all studies focusing on match uncertainty use the average gate attendance. Two problems arise when using gate attendance: (1) attendance is 'censored' because of capacity constraints and (2) stadium attendance is mostly composed of home fans, many of whom are season ticket holders. Because home fans usually want to see their team win and because season ticket holders purchase their seats in advance, these fans may be less likely to be affected by uncertainty of outcome. Using tobit estimations such as those in Welki and Zlatoper (1999) and Czarnitzski and Stadtmann (2002) gets around the first problem but not the second. To avoid both of these estimation issues, Forrest, Simmons, and Buraimo (2005) utilize television audiences as a measure of demand. Television audiences are not limited in that those who want to watch the match can do so by viewing at home or in a public place such as a sports bar. Secondly, television audience is more likely to be evenly divided between not only home and away fans, but also casual spectators. Two previous American studies, Hausman and Leonard (1997) and Kanazawa and Funk (2001) both look into the determinants of viewership with a focus on the effects of superstars and race, respectively, but neither investigate the effect of outcome uncertainty on audience size. Forrest et al. (2005) do, however, test the effect of outcome uncertainty on viewership and find that although the impact is modest, it is a significant determinant of audience size.

Our analysis builds on Forrest et al. by using previously unavailable minute-by-minute audience data. By using minute-by-minute audience estimates we are able to measure the relationship between demand and outcome uncertainty as the match progresses. To begin building our measures of outcome uncertainty, we first estimate the probabilities of a home win, an away win, and a draw as a game progresses conditional on the current score of the game.

Television Ratings

Our dataset consists of 248 matches broadcast on Sky Sports between 2002 and 2005. The formation of the FA Premier League and the broadcasting of live matches by the satellite television company BSkyB were almost concurrent. In 1992 BSkyB outbid free-to-air television broadcasters ITV and the BBC for the exclusive rights to show Premiership matches and since then all Premiership matches have been broadcast on Sky Sports channels.[11] Sky initially broadcast 60 matches out of 380 Premiership fixtures eventually expanding the schedule to the current broadcast of 138 matches where 88 are shown on Sky Sports 1, 2, or 3 and 50 are televised on Prem-Plus.[12] Sky Sports channels are subscription based and only accessible via a satellite or cable platform. We have excluded pay-per-view programming (Prem-Plus) since these games cost extra and viewing behavior may be less susceptible to outcome uncertainty. This is something to consider for future research, however.

The most widely used measure of demand for TV viewership is the TVR (or television viewership rating). A TVR is the percentage of viewers watching the program out of a potential audience, called a universe. For example, if a match has a rating of 2.53, this translates to 1.404 million viewers out of a terrestrial universe of 55.4 million.[13]

Appendix 2 provides additional definitions for television terminology.

Methodology

Stage 1: Probability Model

In order to derive our measures of outcome uncertainty, we need to estimate the probability of the four distinct match outcomes (a no-score draw, a score draw, and a home or away win) at every minute during the game. We distinguish between score draws (both teams score the same number of goals) and no score draws (neither team scores) because the former involves significant changes in the outcome probability during the game (i.e., after each goal is scored), and therefore it is possible that demand may respond to these discrete events. We also separate no-score and score draws because people may be turned off by a boring 0-0 stalemate, but entertained by a 4-4 draw. Using only one variable for a 'draw' outcome could compound the two effects and be misleading.[14]

We therefore construct a multinomial logit model of match outcome for each minute during the match. While our viewership sample may be small relative to the number of games broadcast since 1992, there is no reason to restrict our logit estimation. Thus, we utilize the entire population of games ever played in the English Premiership to get a more accurate distribution of the various possibilities and changes that occur during the game. From its inaugural season in 1992-1993 until the end of the 2004-2005 season, there were 5,186 Premiership matches, which implies over 466,740 match minutes.[15] The outcome will also be dependent on the relative strength of the two teams. We constructed a team 'form' variable using the average points earned per game for each team over the previous five games, a form variable similar to that used by Forrest et al. (2005).[16] We also condition the outcome on red cards[17] as these should have an effect on the probability of a team winning. We excluded yellow cards on the grounds that they are likely to have a relatively small impact on the outcome of a game.

A multinomial logit regression was run for each minute during a match for four possible outcomes (0=no-score draw, 1=score draw, 2=away win, 3=home win) on home and away goals, home and away red cards, and both the home and away team form. Home advantage is implicitly captured in the home win coeffcient for the probability calculation as home teams are designated separately from away teams and this is apparent by the probabilities for each outcome in minute zero (see Minute Zero in Table 8).

Our general multinomial logit model (Greene, 2000) is the following,

$$PROB(Y_i = j) = \frac{e^{\beta_i' x_i}}{1 + \sum_{k=1}^{j} e^{\beta_i' x_i}} \text{ for } j = 1, 2$$

$$PROB(Y_i = 0) = \frac{1}{1 + \sum_{k=1}^{J} e^{\beta_i' x_i}} \qquad (1)$$

where j is the outcome and an x_i vector of explanatory variables which consists of the following:

- home goals

- away goals
- home team red cards
- away team red cards
- home team form
- away team form

The results correlate well with the actual match outcomes for a given score and at a specific minute. Both the logit probabilities and actual frequencies for a no-score are highly correlated whereas there is a slight discrepancy between the two score-draw probabilities.

Using these probabilities, we construct our measures of outcome uncertainty and test whether these have any effect on demand, as measured by television ratings.

Stage 2: Viewership Model

We constructed three distinct measures of outcome uncertainty:

1. $SQOU\_W_t = (PR_t^{hwin} - PR_t^{awin})^2$
2. Draws: PR_t^{sdraw} and PR_t^{nsdraw}
3. $SQEXPECT_t = [PR_t^{hwin} - PR_0^{hwin}]^2 + [PR_t^{awin} - PR_0^{awin}]^2 + [PR_t^{nsdraw} - PR_0^{sdraw}]^2 + [PR_t^{nsdraw} - PR_0^{sdraw}]^2$

These measures capture the different aspects of outcome uncertainty. The uncertainty of outcome hypothesis states that the more uncertain the outcome of the game, the more "exciting" it is, thus driving up demand. The first variable, *SQOU Wt*, relates to the relative strengths of the two teams. It incorporates not only team quality and form but also home team advantage. As the value of this variable decreases, the more uncertain the winner. The variables *PRnsdraw jk,t* and *PRsdraw jk,t* are the probabilities at minute *t* of a draw between home team *j* playing away team *k*. Unlike US sports, football has three outcomes. The third potential outcome (the draw) *can be* independent of the balance of the winning probabilities, e.g., it may reflect different playing conditions or strategic conditions. For example, some teams may be playing for a draw, e.g., a weak team playing away at a strong team may use this strategy to avoid losing. This variable might convey some of the dissatisfaction of viewers watching defensive-minded games. Secondly, draws may not be appealing to neutral spectators who want to see lots of goals and an eventual winner. The third variable measures uncertainty relative to the initial expectations. In addition to our uncertainty measure, we hypothesize that goals should increase the excitement of a game, though too many could make the game more certain and reduce viewership. It is also apparent there is some inertia in viewership so we include lagged variables to capture this effect.

We construct a viewership model based on the 248 matches for which we have the minute-by-minute television ratings data. Dynamic panel data estimation appears to be the most appropriate model. Observation of viewing trends during a match suggest a strong inertia in viewership, therefore we will incorporate several lags of the dependent variable into the model. A common problem of panel data estimation with dynamic models is the potential for the lagged dependent variable to be correlated with the disturbance, which could encapsulate unvarying unobserved effects.[18] This correlation leads to inconsistent estimators and therefore an estimation method using instrumental variables is necessary. Anderson and Hsiao (1981) suggested first dfferencing to wipe out the unobserved fixed effects and using lagged levels of the dependent variable as instruments.[19] Arellano and Bond (1991) developed a generalized method of moments (GMM) procedure to find a more efficient estimator using additional instruments. We apply the Arellano-Bond (AB) technique for our model of television demand since we believe a dynamic model most appropriately captures viewership inertia (i.e., once people tune in, they tend to remain tuned in) and since it is likely that some effects are unobservable. Our model estimated using the AB estimator is the following (see Appendix 1 for variable definitions):

$$\Delta r_{jk,t} = \alpha_{jk} + \beta_1 \Delta r_{jk,t-1} + \beta_2 \Delta r_{jk,t-2} + \beta_3 \Delta r_{jk,t-3} + \beta_4 \Delta g_{jk,t-1} + \\ + \beta_5 \Delta tg_{jk,t} + \beta_6 \Delta SQOU\_W_{jk,t} + \beta_7 \Delta PR^{nsdraw}_{jk,t} + \beta_8 \Delta PR^{sdraw}_{jk,t} + \\ + \beta_9 \Delta SQEXPECT_{jk,t} + TimeDummies$$

The general model is presented in Table 3.

Results

Regression Estimation

The results from the Arellano-Bond one-step and two-step GMM dynamic estimations are listed in Table 3. We also estimated models with different versions of the outcome uncertainty variables. In Model (2) we do not distinguish between a no-score and a score draw, and in Model (3) we use a variation of the $EXPECT_{jk,t}$ variable where the individual terms are the absolute deviations instead of the squared terms.

Diagnostic checks for the GMM estimators include tests for serial correlation in the errors and a test that checks the instruments are not correlated with the errors. If the errors are correlated the GMM estimator will be inconsistent. Arellano and Bond state that there should be first order but no second order serial correlation. The results here indicate that this is the case for our sample. Additionally, the Sargan statistics cannot reject the null hypothesis that the instruments are not correlated with the errors.[20]

Most of the signs and significance of the outcome uncertainty variables conform to the uncertainty of outcome hypothesis. The $SQOU\ W_{jk,t}$ variable (which measures the difference in the probabilities for a home or away win) is negative[21] and significant at the 1% level, which means the greater the uncertainty about which side will win, the more viewers that will watch the game. If outcome uncertainty falls, then viewers may switch to other channels or turn off the television. However, if outcome uncertainty rises, channel hoppers may decide to stay with the game. It is also possible that potential viewers may receive updates about the state of the game from other sources such as the radio, Internet, or mobile phone texts and may decide to start watching based on the current level of outcome uncertainty.

To the extent that the $PR^{nsdraw}_{jk,t}$ and $PR^{sdraw}_{jk,t}$ variables are interpreted as measures of outcome uncertainty, the signs are perverse. However these variables may indicate other aspects of the quality of the game, e.g., “boring” characteristics such as non-attacking play, few goals, etc. which could reduce viewership. A striking result of the estimation is that score draws were also negatively signed albeit with a smaller magnitude. In our estimation sample of 248 matches, 65 games were draws of which 30% (20

Table 3: Viewership Regression: Arellano-Bond One-Step and Two-Step GMM Estimation

Explanatory Variables	Model 1 One Step	Model 1 Two Step	Model 2 One Step	Model 2 Two Step	Model 3 One Step	Model 3 Two Step
$\Delta r_{jk,t-1}$	0.6633*	0.6608*	0.6629*	0.6595*	0.6546*	0.6497*
	(0.0206)	(0.0049)	(0.0206)	(0.0043)	(0.0202)	(0.0034)
$\Delta r_{jk,t-2}$	0.0881*	0.0913*	0.0882*	0.0906*	0.0864*	0.0898*
	(0.0106)	(0.0034)	0.0106)	(0.0037)	(0.0106)	(0.0030)
$\Delta r_{jk,t-3}$	0.0205†	0.0226*	0.0206†	0.0236*	0.0193†	0.0235*
	(0.0091)	(0.0026)	(0.0091)	(0.0033)	(0.0092)	(0.0034)
$\Delta tg_{jk,t-1}$	0.0032	0.0032*	0.0056	0.0058*	0.0048	0.0067*
	(0.0046)	(0.0012)	(0.0042)	(0.0011)	(0.0042)	(0.0011)
$\Delta g_{jk,t}$	0.0089†	0.0097*	0.0089†	0.0094*	0.0089†	0.0090*
	(0.0043)	(0.0011)	(0.0043)	(0.0011)	(0.0043)	(0.0012)
$\Delta PR^{nsdraw}_{jk,t}$	−0.1558*	−0.1600*				
	(0.0433)	(0.0153)				
$\Delta PR^{sdraw}_{jk,t}$	−0.1171*	−0.1154*				
	(0.0441)	(0.0139)				
$\Delta PR^{draw}_{jk,t}$	−0.1437863*	−0.1269*	−0.1155*	−0.0996*		
	(0.0417092)	(0.0112)	(0.0413)	(0.0150)		
$\Delta SQOU\ W_{jk,t}$	−0.0843*	−0.0838*	−0.0930077*	−0.0768*	−0.0748†	−0.0617*
	(0.0289)	(0.0095)	(0.0289193)	(0.0078)	(0.0303)	(0.0108)
$\Delta EXPECT_{jk,t}$	0.0219*	0.0175*				
	(0.0143)	(0.0052)				
$\Delta SQEXPECT_{jk,t}$	0.0496†	0.0528*	0.0513136†	0.04626*		
	(0.0215)	(0.0076)	(0.0218821)	(0.0063)		
Minute 15	−0.0075†	−0.0067*	−0.0074822†	−0.0072*	−0.0084†	−0.0082*
	(0.0035)	(0.0008)	(0.0035887)	(0.0009)	(0.0037)	(0.0010)
Minute 17	0.0147*	0.0149*	0.0146918*	0.0141*	0.0138*	0.0128*
	(0.0034)	(0.0010)	(0.0034655)	(0.0009)	(0.0034)	(0.0008)
Minute 24	0.0161*	0.0155*	0.0162*	0.0159*	0.0149*	0.0157*
	(0.0031)	(0.0006)	(0.0031)	(0.0007)	(0.0032)	(0.0007)
Minute 31	–0.0127*	–0.0124*	–0.0127*	–0.0133*	–0.0140*	–0.0136*
	(0.0029)	(0.0008)	(0.0030)	(0.0007)	(0.0029)	(0.0009)
Minute 36	0.0077*	0.0074*	0.0077*	0.0070*	0.0061†	0.0052*
	(0.0025)	(0.0006)	(0.0026)	(0.0007)	(0.0025)	(0.0006)
Minute 46	–0.1868*	–0.1845*	–0.1869*	–0.1824*	–0.1879*	–0.1852*
	(0.0151)	(0.0038)	(0.0151)	(0.0039)	(0.0151)	(0.0035)
Minute 47	0.1631*	0.1622*	0.1630*	0.1584*	0.1613*	0.1586*
	(0.0122)	(0.0029)	(0.0122)	(0.0031)	(0.0121)	(0.0031)
Minute 48	0.0245*	0.0241*	0.0245*	0.0248*	0.0245*	0.0260*
	(0.0054)	(0.0016)	(0.0054)	(0.0016)	(0.0054)	(0.0018)
Minute 55	–0.0196*	–0.0197*	–0.0197*	–0.0195*	–0.0196*	–0.0201*
	(0.0047)	(0.0011)	(0.0047)	(0.0012)	(0.0047)	(0.0011)
Minute 56	0.0135*	0.0146*	0.0136*	0.0137*	0.0127*	0.0133*
	(0.0046)	(0.0013)	(0.0046)	(0.0013)	(0.0046)	(0.0012)
Minute 70	–0.0110†	–0.0126*	–0.0107†	–0.0100*	–0.0113†	–0.0125*
	(0.0051)	(0.0016)	(0.0052)	(0.0016)	(0.0051)	(0.0017)
Minute 71	0.0063	0.0072*	0.0065	0.0036†	0.0067	0.0069*
	(0.0049)	(0.0016)	(0.0049)	(0.0015)	(0.0049)	(0.0016)
Constant	0.0020*	0.0019*	0.0022*	0.0020*	0.0022*	0.0020*
	(0.0003)	(0.0001)	(0.0004)	(0.0001)	(0.0004)	(0.0001)
AR(1)	$z = -13.82$	$z = -14.19$	$z = -13.81$	$z = -14.22$	$z = -13.86$	$z = -14.19$
	$Pr > z = 0.00$	$Pr > z = 0.00$	$Pr > z = 0.00$	$Pr > z = 0.00$	$Pr > z = 0.00$	$Pr > z = 0.00$
AR(2)	$z = 0.40$	$z = 0.00$	$z = 0.43$	$z = 0.10$	$z = 0.36$	$z = 0.06$
	$Pr > z = 0.69$	$Pr > z = 0.99$	$Pr > z = 0.67$	$Pr > z = 0.92$	$Pr > z = 0.72$	$Pr > z = 0.95$
Sargan Test	χ^2 (429) = 228.81		χ^2 (429) = 224.25		χ^2 (429) = 225.87	
	$Pr > \chi^2 = 1.00$		$Pr > \chi^2 = 1.00$		$Pr > \chi^2 = 1.00$	

*Indicates Significance at 1% level
†Indicates Significance at 5% level
‡Indicates Significance at 10% level

matches) were no-score draws. In fact, out of all Premiership games (from the 1992-1993 season to the close of the 2004-2005 season) approximately 27.7% of the matches were draws.[22] One explanation for the negatively signed score-draw coefficient is that for most of the minutes, the score is level and no team is leading. For all of the score-draw matches in our sample, approximately 60% of the minutes were where the score was level. Conversely, for games where there was a winner, 60% of the minutes were where one team was leading. The longer the minutes are level, viewers may anticipate that a draw is inevitable and attacking play will subside. Table 4 below lists the proportion of 'level score minutes' in the score draw matches in our sample.

Table 4: Proportion of 'Level Minutes' in Score-Draws for Games Broadcast 2002-2005

Minute Timeband	Number of Level Minutes	Absolute Percent	Within First & Last 30 Minutes	Goal Difference	Proportion of Minutes at Goal Diff
1-5	203	90.2%		0	60.0%
6-10	163	72.4%		1	37.8%
11-15	150	66.7%		2	2.2%
16-20	132	58.7%			
21-25	126	56.0%			
26-30	113	50.2%	65.7%		
31-35	106	47.1%			
36-40	94	41.8%			
41-45	98	43.6%			
46-50	102	45.3%			
51-55	113	50.2%			
56-60	118	52.4%			
61-65	122	54.2%			
66-70	128	56.9%			
71-75	137	60.9%			
76-80	152	67.6%			
81-85	173	76.9%			
86-90	200	88.9%	67.6%		

Games=45

Even if the final result ended up as a win, viewership would have been lower on average if a goal was only scored in the dying minutes of the game. By looking matches that ended 1-0 (and 0-1), and comparing the viewership of those matches that had a 'last minute' goal versus those matches that had a goal scored earlier in the match, there are lower viewership figures for these late scoring matches. Obviously one reason could be that viewers surmise that the match will end as a no-score draw. Similarly, these games may be defensively fought matches where both sides are 'playing for the draw,' whereas in an early scoring match, the 'losing' side is forced to play more attacking football in order to get the equalizer or to achieve victory. Table 6 lists the comparison of viewership for 1-0 results.

The $SQEXPECT_{jk,t}$ variable is consistent with the outcome uncertainty hypothesis and is positively signed and significant at the 5% level, indicating that unexpected outcomes attracts viewers. A goal having occurred in the past minute boosted viewership as did total goals though the latter did not at a statistically significant level.

Table 5: Proportion of 'Level Minutes' in Score-Draws for Premiership 1993–2005

Minute Timeband	Number of Level Minutes	Absolute Percent	Within First & Last 30 Minutes	Goal Difference	Proportion of Minutes at Score
1-5	4605	94.3%		0	59.360%
6-10	4079	83.5%		1	38.166%
11-15	3648	74.7%		2	2.430%
16-20	3231	66.1%		3	0.044%
21-25	2933	60.0%			
26-30	2626	53.8%	72.1%		
31-35	2432	49.8%			
36-40	2291	46.9%			
41-45	2166	44.3%			
46-50	2118	43.4%			
51-55	2129	43.6%			
56-60	2153	44.1%			
61-65	2191	44.9%			
66-70	2384	48.8%			
71-75	2650	54.2%			
76-80	2961	60.6%			
81-85	3410	69.8%			
86-90	4188	85.7%	62.1%		

Games=977

Table 6: Comparison of Viewership for Matches Ending as 1-0 (0-1)

Goal Scored Before Minute							**Goal Scored After Minute**
	All	**21**	**26**	**29**	**74**	**79**	**84**
Rating	**2.36**	**2.91**	**2.94**	**3.00**	**2.29**	**2.28**	**2.20**
Means Test							
All 1-0 (0-1):		15.99*	18.88*	22.71*	−2.13†	−2.36†	−4.26*
Before Minute 21 :			0.99	2.52†	−16.93*	−17.06*	−18.50*
Before Minute 26 :				1.76‡	−19.48*	−19.53*	−20.94*
Before Minute 29 :					−20.51*	−20.02*	−20.68*
After Minute 74 :						−0.36	−2.43†
After Minute *79* :							−2.08†
Games	56	8	10	13	11	9	7

*Indicates Significance at 1% level
†Indicates Significance at 5% level
‡Indicates Significance at 10% level

The time dummies corrected for peaks and troughs in the data. During the 46th minute, fans are still 'away' from the half time break and take a couple of minutes to return to viewing as indicated by the large drop for minute 46 and large spike at minute 47. What may be peculiar at first are the significance minutes 15, 17, 24, 31, 36, 55 56, 70, and 71. Upon further investigation, there is a very simple explanation for these unusual increases and decreases. For specific kick-off times, these minutes correspond to a specific time in the 24-hour clock. Table 7 below should make it easier to see why these minutes are significant.

Table 7: Significance of Time Dummies

	Time after Match Minute:						
Kick-off	**15**	**17**	**24**	**31**	**36**	**55**	**70**
hh:00	hh:15	hh:17	hh:24	hh:30	hh:36	hh:15	hh:30
hh:15	hh:30	hh:32	hh:39	hh:45	hh:51	hh:25	hh:40
hh:30	hh:45	hh:47	hh:54	hh:00	hh:06	hh:40	hh:55
hh:45	hh:00	hh:02	hh:39	hh:15	hh:21	hh:55	hh:10
hh:05	hh:20	hh:22	hh:29	hh:35	hh:41	hh:15	hh:30

The times in bold indicate times when viewers are likely to be switching channels to tune in or in the case of boring matches, turning off. By looking at the average change in rating minute by minute, the general trend is steadily increasing. However for minutes listed above there was a shift in this trend. For minutes 55, 56, 70, and 71, it is expected that they might not fall exactly on the hour and half hour as half time most likely runs past the allotted 15 minutes. This is confirmed by the PA sport data which gives the second half kick-off times. By examining channel switching reports[23] there is a strong indication that new viewers do in fact tune in near the hour and half hour and that almost equal portions of these viewers either tune in from other channels or are turning on their televisions to watch the game. For minute 24, more than two thirds of the new viewers are tuning in from other satellite channels, while in minute 55 most of the viewers that decide to turn off the match are switching to other channels. Viewers may decide to turn off if the match is boring and choose to do so as another program starts on a different channel.

We also included the variable $g^{10}_{jk,t}$ (a dummy variable if a goal had been scored within the last 10 minutes) and $g^{15}_{jk,t}$ (similarly, a dummy variable if a goal had been scored within the last 15 minutes) to capture any lingering effect on viewership. These were not significant. We also estimated models which included red cards and interaction variables; none of these variables were significant.

Size of the Impact of Outcome Uncertainty on Viewership-Simulations

Given that our outcome uncertainty measures are contingent on the state of the game (in terms of the score), there is no simple way to summarize the impact of outcome uncertainty on average. Here we illustrate the effect of outcome uncertainty on viewership by simulating a hypothetical game with five possible results:

(a) A no-score draw.
(b) An away win (0-1).
(c) A home win (1-0).
(d) A score-draw where the home team scores first (1-1).
(e) A score-draw where the away team scores first (1-1).

The teams are assumed to be near-equal strength, with a slight form advantage for the away team. The initial rating is assumed to be 2.37, the average of our dataset. The first goal occurs in the 25th minute with the second goal coming in the 80th minute in the case of the score-draw. Clearly the no-score draw (case (a)) does not attract as many viewers as would a 0-1 (case (b)) or 1-0 (case (c)) result. The 1-1 (case (e)) result hurts viewership relative to case (b) but the 1-1 (case (d)) result increases viewership slightly relative to case (c). This can be attributed to the change in expectations of the away team scoring. Due to home advantage, home teams are twice as likely to win as the away team, thus an away goal occurring first generates an element of surprise. By looking at Figure 2, there is a larger jump in viewership when the away team scores first rather than if the home team leads initially, although either team scoring increases viewership over no score. However, in the case where the away team scores first and then the home team equalizes, expectations of a home win (or at least a draw) are brought back into line. This is seen in the decreasing rate viewership after the goal in the 80th minute. While it may appear that a 1-1 increases overall viewership over a no-score draw, it is not due to the draw but rather the viewership increase is driven by the away team leading. In the case where the home team scores first and the away team equalizes, it will actually shift viewership up but then level off. The average television ratings for the five results are summarized below in Table 8.

Table 8: Simulation of Five Different Results and the Impact on Viewership

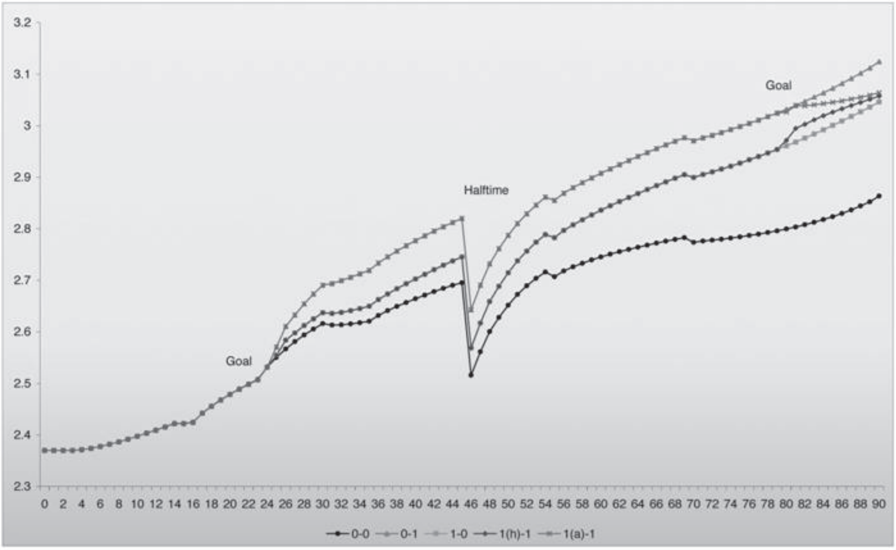
Result	**Average Rating**	**Percent Increase Over 0-0**	**Percent Increase Over 1-0**	**Percent Increase Over 0-1**
(a) 0-0	2.635			
(b) 0-1	2.750	4.39%		
		(3.88*)		
(c) 1-0	2.700	2.50%		
		(2.41)†		
(d) 1-1(ha)	2.703	2.60%	0.10%	
		(2.47)†	(0.08)	
(e) 1-1(ah)	2.747	4.26%		-0.12%
	(3.82)*		(-0.10)	

t-statistics for means test are in parentheses.
*Indicates Significance at 1% level
†Indicates Significance at 5% level

In another example we assume a very strong team (with an average of 2.4 points per game over the last 5 games) plays away at a relatively weaker team (an average of .4 points per game). Given this scenario the away team is expected to win. In this case we plot the 20 different results including the 2-2 final score that could have been reached via six different scoring patterns:

- Two home goals followed by two away goals (hhaa).
- Alternating goals with the home team scoring first (haha).
- Two away goals between two home goals (haah).
- Two home goals sandwiched between two away goals (ahha).

Figure 2: Simulation of Five Different Results and Impact on Viewership



- Alternating goals with the away team scoring first (ahah).
- Two away goals followed by two home goals (aahh).

We assume a lower initial rating of 1.00 with goals coming in the 42nd, 60th, 75th, and 82nd minutes. Tables 9, 10, and 11 compares the different results with the percentage change in rating if the match had ended differently.

Again the element of surprise raises the average rating relative to what one would have expected. Given that the away team was expected to win, average ratings are higher when the home team scores first (cases b, d, e, h, i, j, n, o, p) and win relative to the other outcomes. The scoring pattern in case (n) generates the optimal ratings for a 2-2 result. Comparing cases (i) and (j), at the 75th minute the value for $SQOUW_{jk,t}$ is lower for case (i) and $SQEXPECT_{jk,t}$ is higher which increases the average rating over that of case (j).

Discussion and Conclusions

The competitive balance of popular sport is not just an important economic issue, it has become a matter of political significance. As far back as the 1950s the United States Congress held hearings to discuss the validity of imposing competitive restraints in the players' labor market in order to achieve a desirable level of competitive balance. In 2005 the European Commission instituted a review of the governance of football to investigate, inter alia, whether European soccer leagues were sufficiently balanced and, if not, to suggest what political measures might be taken to increase that balance. Such interventions are to a significant degree motivated by the argument that a sporting contest must entail sufficient uncertainty of outcome to maintain the interest of spectators.

Empirical studies of the uncertainty of outcome hypothesis have dealt almost exclusively with this question in terms of match attendance. In this paper we have looked at television viewing. Television is rapidly becoming the principal source of revenues for

Table 9: Simulation of a 2-2 Draw and the Impact of Viewership (a)

(Case) Result	Average Rating	Percent Increase Over 0-0	Percent Increase Over 1-0	Percent Increase Over 0-1	Percent Increase Over 1(h)-1	Percent Increase Over 1(a)-1	Percent Increase Over 2-0	Percent Increase Over 0-2
(a) 0-0	1.257							
(b) 1-0	1.350	7.36%						
		(3.18*)						
(c) 0-1	1.325	5.38%						
		(2.48†)						
(d) 2-0	1.356	7.82%	0.43%					
		(3.30*)	(0.16)					
(e) 1-1(ha)	1.352	7.53%	0.16%					
		(3.24*)	(0.06)					
(f) 1-1(ah)	1.340	6.61%		1.17%				
		(2.88*)		(0.47)				
(g) 0-2	1.329	5.70%		0.30%				
		(2.57†)		(0.12)				
(h) 2-1(hha)	1.355	7.75%	0.36%				-0.06%	
		(3.28*)	(0.14)				(-0.02)	
(i) 2-1(hah)	1.358	7.99%	0.59%		0.43%			
		(3.35*)	(0.22)		(0.16)			
(j) 1-2(haa)	1.352	7.54%	0.17%		0.01%			
		(3.24*)	(0.06)		(0.00)			
(k) 2-1(ahh)	1.346	7.07%		1.61%		0.43%		
		(3.00*)		(0.63)		(0.16)		
(l) 1-2(aha)	1.340	6.62%		1.18%		0.01%		
		(2.88*)		(0.47)		(0.00)		

t-statistics for means test are in parentheses.
*Indicates Significance at 1% level
†Indicates Significance at 5% level

football leagues in Europe, and is already the dominant source for the American major leagues, most notably American football. To our knowledge Forrest et al, (2005) provide the first empirical measures of the impact of uncertainty on TV viewers, comparing average viewership of games with different levels of ex ante uncertainty. Our study is the first to analyze the impact of uncertainty on the level of viewership within a game, minute by minute.

Our findings suggest a complex picture. Uncertainty matters in the sense that viewership is decreasing in the gap in the probabilities of each side winning, but is also decreasing in the probability of a draw. This suggests that a significant proportion of viewers want something more than statistical uncertainty. The fact that our measure of the unexpected (the difference between pre-match probabilities and within match probabilities) tends to be positively associated with viewership lends weight to the idea that fans demand excitement, which is likely to be associated with eventful games in which one side wins, rather than tame draws.

Table 10: Simulation of a 2-2 Draw and the Impact of Viewership (b)

Result	Average Rating	Percent Increase Over 0-0	Percent Increase Over 1-0	Percent Increase Over 0-1	Percent Increase Over 1(h)-1	Percent Increase Over 1(a)-1	Percent Increase Over 2-0	Percent Increase Over 0-2
(m) 1-2(aah)	1.329	5.73% (2.58†)		0.33% (0.14)				0.03% (0.01)
(n) 2-2(hhaa)	1.352	7.56% (3.24*)	0.19% (0.07)				-0.24% (-0.09)	
(o) 2-2(haha)	1.355	7.80% (3.31*)	0.41% (0.16)		0.25% (0.10)			
(p) 2-2(haah)	1.352	7.57% (3.25*)	0.20% (0.08)		0.04% (0.10)			
(q) 2-2(ahha)	1.344	6.89% (2.95*)		1.43% (0.57)		0.25% (0.10)		
(r) 2-2(ahah)	1.341	6.65% (2.89*)		1.21% (0.48)		0.04% (0.01)		
(s) 2-2(aahh)	1.330	5.76% (2.59†)		0.36% (0.15)				0.06% (0.02)

t-statistics for means test are in parentheses.

*Indicates Significance at 1% level

†Indicates Significance at 5% level

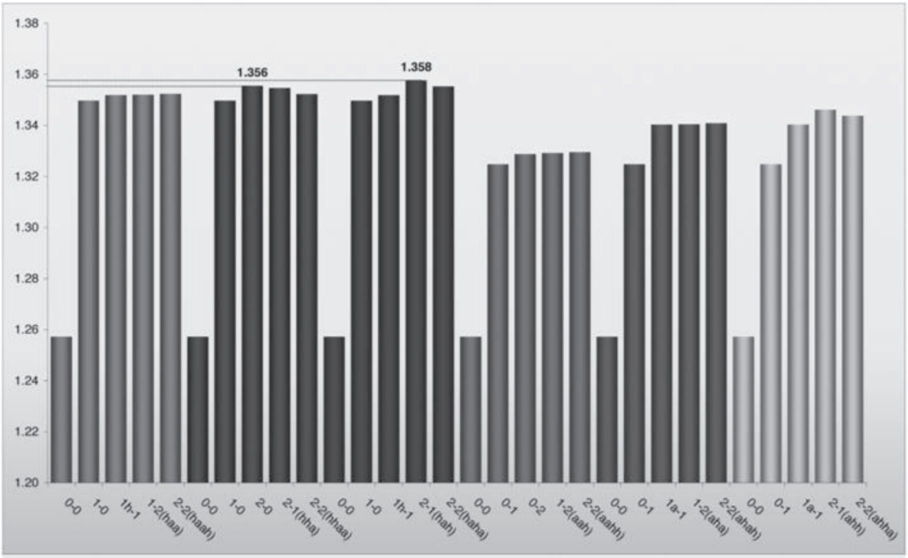
Table 11: Simulation of a 2-2 Draw and the Impact on Viewership (c)

(Case) Result	Average Rating	Percent Increase Over 2-1 (hha)	Percent Increase Over 2-1 (hah)	Percent Increase Over 2-1 (ahh)	Percent Increase Over 1-2 (aha)	Percent Increase Over 1-2 (haa)	Percent Increase Over 1-2 (aah)
(n) 2-2(hhaa)	1.352	-0.1748% (-0.07)					
(o) 2-2(haha)	1.355		-0.1744% (-0.07)				
(p) 2-2(haah)	1.352					0.03% (0.01)	
(q) 2-2(ahha)	1.344			-0.1759% (-0.07)			
(r) 2-2(ahah)	1.341				0.03% (0.01)		
(s) 2-2(aahh)	1.330						0.03% (0.01)

t-statistics for means test are in parentheses.

Our findings show that audience fluctuations within matches are significantly affected by the progress of the game. Fans may switch channels away from the game if they find the probability of a draw is increasing, or they may switch to and stick with a game that has an exciting result in prospect. We found significant evidence of fan switching at times when programs on other channels were likely to end. Games that produce a result are likely to have significantly higher audiences than games which end up as 0-0

Figure 3: Average Ratings of Games that Could End in a 2-2 Score Draw



draws. However, even games that involve goals being scored may have relatively low viewership if the game ends up as a draw. Using some simulation exercises we were able to show that in some cases a drawn match can attract a lower viewership than a match which end up with a win for one team, depending on the evolution of the game.

These results suggest that there is need for a certain amount of caution about the proposed interventions to redistribute resources in order to create an appropriate level of competitive balance. Reforms that increased the probability of a win rather than a draw could increase viewership, if the probabilities were evenly balanced between the two teams. Given that there exists a natural home advantage, some of the most well balanced and exciting games are likely to be between a strong team playing away against a relatively weak team. Given home advantage, a league of equally strong teams might even reduce viewership.

Finally, it is worth commenting on the desirability of draws. In the North American major leagues, tied games have been abolished by requiring a result (with overtime in American football and extra innings in baseball). Would measures to ensure a result, such as the penalty shoot-out, be desirable in European football? Our results suggest caution on this front as well. While a penalty shoot-out may guarantee a result, what matters for viewership is the pattern of play over the whole game, not just the end result. Teams (especially weak ones) often prefer a penalty shoot-out to taking risks during regulation time and therefore forcing a result in this way may provoke even more conservative play attracting fewer viewers.

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Endnotes

[1] The earliest statements of this hypothesis are to be found in Rottenberg (1956) and Neale (1964).

[2] According to Fort and Quirk (1995) "Professional team sports leagues are classic, even textbook, examples of business cartels."

[3] For a brief review of court cases in the US and Europe see Szymanski (2003), pp. 1178–1181; for a more detailed review of US case history see Weiler and Roberts (1998).

[4] For example, the 1961 Sports Broadcasting Act in the US permitted collective selling of broadcast rights by a league, while in Germany, parliament amended the competition act to exempt collective selling of football rights after the courts ruled collective selling anticompetitive.

[5] In the US there are often TV blackouts of home games within a certain radius of the locale of the home team. This is to encourage attendance at the stadium. Some home fans may have restricted opportunities to watch on TV. However, there is no local area blackout in English soccer. For further information on how blackouts may affect attendance see Siegfried and Hinshaw (1979), Welki and Zlatoper (1999), and Putsis and Sen (2000).

[6] No-score draws are where neither team scores; score draws are where both teams score the same number of goals.

[7] Now published as the Sky Sports Football Yearbook.

[8] An extensive football database that supplies betting and match result information to The Racing Post, The Mirror, The Sunday Mirror, The People, and the Belfast Newsletter.

[9] Borland and McDonald (2003) and Szymanski (2003) provide literature surveys about these and other studies concerning demand and outcome uncertainty.

[10] This is known in the literature as the "favorite-longshot bias." See Cain, Law, and Peel (2000).

[11] Initially, most matches were broadcast on Sky Sports, now known as Sky Sports 1. During the 1990s, the sports-dedicated channels expanded to include Sky Sports 2 (1994), Sky Sports 3 (1996), and Sky Sports Xtra (1999). A pay-per-view channel, Premiership Plus (now known as Prem-Plus), was started in 2001. Sky Sports News (2000) could be counted as a sixth channel as it shows some highlights and interviews.

[12] See Forrest, Simmons, and Szymanski (2004) for an anti-trust discussion about the restriction of games broadcast.

[13] We base our ratings on the terrestrial television universe because it is a more stable measure than a Sky-subscriber only universe. Since the late 1990s, Sky subscribers have been increasing along with the number of channels available to subscribers. If we utilized the Sky audience universe, it would give the impression that fewer people are watching when in reality it is the denominator (or universe) that is increasing. Although this will not make a difference for the minute-by-minute analysis, it could give the impression that games in 2002 were more popular and that audiences are in decline relative to the recent seasons.

[14] Additionally, the separation of draws into no-score and score draws is particularly important for betting pools. Before the National Lottery came into prominence in 1994, betting on the football pools was one of the largest and most accessible forms of gambling available in the United Kingdom. Every week, participants would try to select eight football matches whose results would maximize the bettors' points according to a specific scoring scheme. Predicting the score draws maximized the points received thereby increasing the chances of winning a percentage of the pool. In this scoring scheme, points were awarded depending if a match was a score draw, a no-score draw or a home or away win. In current pools betting, score draws are awarded three points, no-score draws receive two points, and a home or away win will get one point. (Source: http://www.littlewoodspools.co.uk.) Pools were also important because a small percentage of the entry fees went to the Football Trust, which distributed the money amongst the teams to help finance seater stadia after the Hillsborough disaster in 1989 in which 96 fans were crushed during an F.A. Cup semi-final between Liverpool and Nottingham Forest.

[15] Implicitly there are more than 90 match minutes due to injury time. However, goals are recorded in the 45th or 90th minute even if they were actually scored in injury time.

[16] An additional form variable was also calculated based on the average number of points earned over the past five home games for the home team and over the past give away games for the away team. It could be the case that some teams do well at home but fail to succeed while playing away. (Although the reverse could also be true.) Calculating the 'home-team form' based on home games and the 'away-team form' would capture this trend. Form based on 'home' or 'away' games would also account for home advantage. This did not alter the probability distribution significantly, and we chose to use the measure based on the past five games (as opposed to the past five home or away games). The form variable using the five most recent games is more likely to capture the impact of injuries or player performance than a measure incorporating games potentially played more than eight weeks prior.

[17] When a player receives a red card, he is ejected from the match and his team must play with one less player.

[18] See Greene (2000), Baltagi (1995), Wooldridge (2002), or Hsiao (2003) for a summary.

[19] For example using $y_{i,t-2}$ as an instrument for $\Delta y_{i,t-2}$.

[20] Arellano and Bond (1991) suggest using the two-step results for the Sargan test. The Sargan test has low power and the null is easily rejected if heteroskedasticity is present. Therefore, for the one-step estimation we use White's procedure for robust standard errors.

[21] The sign is negative because the more the value approaches zero (gets smaller) the more uncertain the winner.

[22] Out of all the draws that occurred in the Premiership from 1993–2005, 31.9% were no-score draws and only 17.6% were high-scoring draws (2-2 and higher).

[23] These reports indicate the source of new viewers as well as where viewers go if they change channels or switch off.

Authors' Note

The full version of this paper can be downloaded at http://ideas.repec.org/p/spe/wpaper/0631.html

Appendices

Appendix 1. Definitions

Variable	*Definition*
r_t	Television rating.
PR_t^{hwin}	Probability of a home win at time t.
PR_t^{awin}	Probability of an away win at time t.
PR_t^{nsdraw}	Probability of a non-score draw at time t.
PR_t^{sdraw}	Probability of a score draw at time t.
PR_t^{draw}	Probability of any draw at time t.
tg_t	Total number of goals (home and away) at time t.
g_{t-1}	If a goal was scored in the last minute.
$SQOU\_W_t$	$\left(PR_t^{hwin} - PR_t^{awin}\right)^2$
$SQEXPECT_t$	$\left(PR_{jk,t}^{hwin} - PR_{jk,0}^{hwin}\right)^2 + \left(PR_{jk,t}^{awin} - PR_{jk,0}^{awin}\right)^2 + \left(PR_{jk,t}^{nsdraw} - PR_{jk,0}^{nsdraw}\right)^2 + \left(PR_{jk,t}^{sdraw} - PR_{jk,0}^{sdraw}\right)^2$

Appendix 2. Television Terminology

The following television terms are according to the BARB website:

- Television Rating — The TVR (Television Rating) measures the popularity of a program, daypart, commercial break, or advertisement by comparing its audience to the population as a whole. One TVR is numerically equivalent to one per cent of a target audience.
- Reach — The net number or percentage of people who have seen a particular piece of broadcast output (e.g., a program, daypart, channel, TV advertising campaign). The BARB definition is for this to be at least three consecutive minutes.
- Share — The percentage of the total viewing audience watching over a given period of time. This can apply to channels, programs, time periods, etc.