NATIONAL RESEARCH UNIVERSITY
HIGHER SCHOOL OF ECONOMICS

Petr A. Parshakov, Kseniya O. Baydina

BRANDS OR UNCERTAINTY? AN EMPIRICAL TEST OF THE UNCERTAINTY OF OUTCOME HYPOTHESIS IN RUSSIAN FOOTBALL

BASIC RESEARCH PROGRAM
WORKING PAPERS

SERIES: ECONOMICS
WP BRP 163/EC/2017

Petr A. Parshakov[1], Kseniya O. Baydina[2]

BRANDS OR UNCERTAINTY? AN EMPIRICAL TEST OF THE UNCERTAINTY OF OUTCOME HYPOTHESIS IN RUSSIAN FOOTBALL

This study estimates an attendance demand model in a reduced form, with uncertainty as one of the determinants of demand, to test the Uncertainty of Outcome Hypothesis (UOH), using data from the Russian Football Premier League (RFPL). These data fit our requirements for two reasons. First, there are few sellout matches, so demand for tickets in the RFPL is not restricted by stadium capacity. Secondly, there have hitherto been no articles devoted to the study of outcome uncertainty in the RFPL. The results indicate that the UOH does not explain the behavioural pattern of attendees in the RFPL. The dependence between the attendance and uncertainty is found to be U-shaped or even declining. We explain the U-shaped dependence by the visiting team effect; an attendee's utility in the RFPL depends more on seeing a top team coming to the city than on the uncertainty of the outcome of the match.

JEL Classification: Z2, D81.

Keywords: Football, Attendance, the UOH, Uncertainty, Russian Football Premier League

[1] National Research University Higher School of Economics-Perm. International Laboratory of Intangible-driven Economy. E-mail: pparshakov@hse.ru

[2] National Research University Higher School of Economics-Perm. Faculty of Economics, Management, and Business Informatics. Student. E-mail: baydinaksusha59@yandex.ru

Introduction

The issue of determinants of demand for various goods and services has gained significant attention from economists. For instance, Ye et al. (2011) studied the impact of consumers' reviews published online on hotel bookings while Nelson and Glotfelty (2012) investigated the role of a star cast in movies' box offices. Considering the sphere of sports economics, many researchers have investigated the determinants of attendance of sports events, and, particularly, a significant number of studies have focused on outcome uncertainty as a factor influencing the demand for sports matches.

Rottenberg (1956) was the first author to address the effect of outcome uncertainty on ticket demand. Using baseball attendance data, he concluded that a greater level of competition between teams results in larger attendance. This relationship between attendance and uncertainty was formulated as the uncertainty of outcome hypothesis (UOH), which has been further tested by many authors. Borland (1987) proved the UOH using data from Australian Rules football; Rascher and Solmes (2007) found significant uncertainty of outcome in the National Basketball Association, and Soebbing (2008) did so in Major League Baseball. However, evidence for the UOH is not always convincing: Coates and Humphreys (2010) tended to reject it, while Falter et al. (2008) found that it showed no significant impact on attendance.

Despite the lack of consistent evidence for the positive effects of outcome uncertainty on demand, active competition between teams is perceived to be the key to professional leagues' prosperity [Buraimo and Simmons, 2015]. In this regard, the practice revenue sharing in US sports leagues, which allows the relative balance of win prospects between wealthy and poor teams increases consumer interest in the competition. No such system exists in the Russian sports market, however, in some matches when top-ranked teams do not play at full strength or leave strong players on the bench it can be supposed that teams do so deliberately to reduce their chances of winning. There are two possible reasons for this. Firstly, these teams want to rest key players for more difficult matches, and, secondly, they can try to maintain outcome uncertainty. These attempts equalize the chances of winning, and this means that the Russian sports market assumes the positive effect of outcome uncertainty on demand.

This study estimates an attendance demand model in a reduced form, with uncertainty as one of the demand determinants, in order to test the UOH using Russian Football Premier League (RFPL) data. These data fit our requirements for two reasons. Firstly, since there are few sellout matches, ticket demand in the RFPL is not restricted by stadium capacity. Secondly, the majority of previous studies have concentrated on developed sports leagues such as Major League Baseball, while developing sports markets, like the Russian one, have received less attention. In fact, there yet have been no studies investigating outcome uncertainty in the RFPL.

Our key finding is that the RFPL attendance pattern contradicts the UOH: the higher the probability of the home team winning, the lower the attendance. We explain this by the visiting team effect – the lower probability of the home team winning implies a more powerful visiting team. Fans may be more interested in watching a superior visiting team than a very competitive game.

Literature Review

The first work in this sphere was carried out by Rottenberg (1956), who formulated the UOH. He suggested fans prefer closer competition between teams; that is, increasing the uncertainty of the outcome leads to higher attendances. This hypothesis was tested in further studies, but the results have been inconclusive.

First, there are various types of outcome uncertainty. Cairns (1987) distinguished game uncertainty, playoff uncertainty and consecutive season uncertainty. A similar division can be found in Sloane (1976) (short-run and long-run uncertainty) and Borland and Macdonald (2003) (match, seasonal and long-run uncertainty). According to Cairns et al. (1986), short-run or match uncertainty relates to the outcome of a particular match; seasonal (playoff) uncertainty refers to championship results and matches qualifying for international leagues; and long-run (consecutive season) uncertainty tells us about the level of domination of several strong teams in the league. Our study focuses on game uncertainty.

In addition, it is important to distinguish between “competitive balance”, “competitive intensity” and “uncertainty of outcome”. Scelles et al. (2013) provided the following definitions for these notions: “competitive balance” refers to the domination of a team over one or more seasons; “competitive intensity” is regarded as the importance of a match in the framework of qualification in higher competitions or relegation in lower ones; “uncertainty of outcome” is the teams’ probability of winning a match. The present study focuses on uncertainty of outcome as a determinant of match attendance.

Borland and Macdonald (2003) summarized research on the UOH and investigated two approaches to measure outcome uncertainty: 1) through differences in league positions or the share of games won, and 2) through betting odds. Research based on betting odds seems to be more appropriate for tracking match outcome uncertainty, since the first approach does not take into account facing strong and powerful teams in previous matches and describes team success rather than uncertainty. Moreover, Sauer (1998) noted that the betting market analyses various factors affecting outcomes, and forecasts game results based on this information.

Table 1 presents a studies considering match outcome uncertainty. Some studies, for example, Borland and Lye (1992), and Peel and Thomas (1997), used match attendances or their logarithm as the dependent variable. The studies of Whitney (1988) and Soebbing (2008) regarding outcome uncertainty in Major League Baseball were based on attendance figures over a full season or annual average attendances per game. The same dependent variable was used in Mills and Fort (2014). However, such aggregated numbers do not react to changing conditions on a game-by-game basis. In order to track game uncertainty data, match attendances are more appropriate.

Table 1. Summary of related literature

Authors	Uncertainty measure	Data	Dependent variable	Relationship
Borland (1987)	(a) difference in number of games won between the first and last teams; (b) the sum of coefficients of variation of the number of games won by each team; (c) the average number of games behind the leader; (d) the number of teams that are in the final five, or only two games outside it	Australian Rules football (1950-86)	P_a = attendance per round per capita; $\ln(P_a/(1-P_a)$	(a) not significant; (b) not significant; (c) negative (the UOH support); (d) not significant
Whitney (1988)	home team winning percentages	Major League Baseball (1970-84)	Home attendance over a full season; logarithm of home attendance over a full season	positive (the UOH rejection)
Peel and Thomas (1992)	home team win probability/betting odds	English football league (1986-87)	logarithm of match attendance	U-shaped relationship (the UOH rejection)
Peel and Thomas (1997)	handicap spread (absolute handicap value)/betting odds	British rugby league (1994-95)	match attendance	negative (the UOH rejection)
Forrest and	home team win probability/away	English Premier League	logarithm of	U-shaped

Authors	Uncertainty measure	Data	Dependent variable	Relationship
Simmons (2002)	team win probability/betting odds	(1st, 2nd, 3rd divisions) (1997-98)	match attendance	relationship (the UOH rejection)
Forrest et al. (2005)	the ratio of the probability of a home win to the probability of an away win/ proportion of wins, draws, losses	English league (1st, 2nd, 3rd divisions) (1997-98)	logarithm of match attendance	U-shaped relationship (the UOH rejection)
Buraimo and Simmons (2008)	(a) Theil index/betting odds; (b) home team win probability/betting odds	English Premier League (2000-2006)	logarithm of match attendance	(a) negative (the UOH rejection); (b) U-shaped relationship (the UOH rejection)
Falter et al. (2008)	difference in points per game	French Soccer First League (1997-2000)	logarithm of match attendance and percentage of stadium fullness	not significant
Lee and Fort (2008)	winning percentage distribution	Major League Baseball (1901-2003)	average attendance per game in particular year	not significant
Benz et al. (2009)	(a) absolute difference in league standings; (b) difference in points per game; (c) Theil index/betting odds; (d) the home team winning probability/betting odds	1st division of professional German football (1999-2004)	logarithm of match attendance	(a) negative (the UOH support); (b) negative (the UOH support); (c) not significant; (d) inverse U-shaped relationship (the UOH support)
Tainsky and Winfree (2010)	home team win probability (p) and $\sqrt{p(1-p)}$/winning percentages	Major League Baseball (1996-2009)	logarithm of match attendance	not significant
Coates and Humphreys (2010)	(a) winning percentages of home and visiting teams; (b) absolute point spread	National Football League (1985-2008)	logarithm of match attendance	(a) positive (the UOH rejection) (b) positive (the UOH rejection)
Lemke et al. (2010)	home team win probability/betting odds	Major League Baseball (2007)	logarithm of match attendance and match attendance	inverse U-shaped relationship (the UOH support)
Pawlowski and Anders (2012)	Theil index/betting odds	German first football division (2005-06)	logarithm of match attendance	negative (the UOH rejection)
Coates and Humphreys	home team win probability/betting odds	National Hockey League (2005-10)	logarithm of match	positive (the UOH

Authors	Uncertainty measure	Data	Dependent variable	Relationship
(2012)			attendance	rejection)
Coates et al. (2014)	home team win probability/betting odds	Major League Baseball (2005-2010)	logarithm of match attendance	U-shaped relationship (the UOH rejection)
Mills and Fort (2014)	distribution of winning percentages	(a) National Basketball Association (1950-2000), (b) National Football League (1930-2000), (c) National Hockey League (1930-2000)	annual average attendance per game	(a) positive (the UOH Support); (b) not significant; (c) not significant
Sacheti et al. (2014)	difference in points	International cricket/England, Australia, New Zealand (1980-2012)	average daily attendance during the match and logarithm of average daily attendance during the match	not significant
Pawlowski and Nalbantis (2015)	Theil index/betting odds	Swiss and Austrian 1st division football leagues (2008-2013)	logarithm of match attendance	not significant

No consensus emerges from the results of these studies. Some studies did not detect a connection between match outcome uncertainty and attendance numbers [Lee and Fort, 2008], [Falter et al., 2008]; other studies did, but draw varying conclusions.

The studies can be divided into two groups. The first group regards the level of outcome uncertainty directly as the independent variable, and this is measured through the Theil index or through differences in winning percentages and league standings. For example, Buraimo and Simmons (2008), Pawlowski and Anders (2012) and Pawlowski and Nalbantis (2015) used the Theil index, while Borland (1987), Borland and Lye (1992), Lee and Fort (2008) and Cox (2015) included the difference in winning and probability percentages. Benz et al. (2008) and Mills and Fort (2013) report a positive correlation with uncertainty of outcome, which is consistent with the UOH; Buraimo and Simmons (2008), Coates and Humphreys (2010), and more recently Martins and Cro (2016) claim that higher uncertainty has negative impact on attendance; Lee and Fort (2008) and Benz et al. (2009) find no significant correlation.

The second group, including Peel and Thomas (1992), Forrest and Simmons (2002) and Rascher and Solmes (2007), investigates game outcome uncertainty through the home team win probability. These studies have the advantage of allowing a more thorough investigation of the particular point where the curve of the home win probability changes its direction. When using the Theil index, it is possible only to detect an increase or decrease in the uncertainty. However, a fall in outcome uncertainty can occur because an increase in the probability of the home or visiting team winning. In order to address this, some authors use the home win probability. Szymansky (2003) and Borland and Macdonald (2003) analysed the UOH literature and investigated the consensus that attendance is maximized when the home win probability is equal to 0.66. However, studies by Peel and Thomas (1992), Forrest and Simmons (2002) and Forrest et al. (2005) are not consistent with such results, and report a U-shaped relationship between attendance and the home team win probability.

Coates et al. (2014) pointed out that the U-shaped curve is observed only in cases when the marginal utility of winning is greater than the marginal utility of losing. The authors develop a model of attendance using a reference-dependent preferences approach.

Some studies have contributed to the UOH literature by identifying the fans' feelings and emotions about outcome uncertainty. Pawlowski (2013) and Pawlowski and Budzinsky (2013) conducted surveys of football fans in Germany, the Netherlands and Denmark, and discovered that they were looking for closer competition between teams. Higher match outcome uncertainty is associated with growing expected satisfaction from a game and increased attendance. However, the results of inquiries do not always reflect actual behaviour, which may account for the models which reject the UOH.

In the past few years, the UOH and even the idea of uncertainty as a determinant of attendance has been criticized. Salaga and Tainsky (2015) pointed out the following disadvantages of using attendance data:

1) There is no difference between season ticket holders and those who buy tickets for particular matches.

2) If demand exceeds stadium capacity, real demand cannot be observed. Meehan et al. (2007) and Coates and Humphreys (2012) resolve this problem using a censored normal regression, and Coates et al. (2012) include dummy variables for sellout matches.

3) Home attendance data do not distinguish interest in uncertainty from interest in a home team win.

Alavy et al. (2010) identified the same difficulties with the analysis of attendance data. Instead of using this variable, Salaga and Tainsky (2015), Alavy et al. (2010) and Paul and Weinbach (2007) studied TV ratings. In order to measure outcome uncertainty, Salaga and Tainsky (2015) used current game margin, which allowed them to construct changes in uncertainty within a game. They also included measures for pre-game uncertainty of outcome through pre-game point spread. Alavy et al. (2010) used a wider approach to capture the dynamic uncertainty of outcome; these authors used red cards and estimated minute-by-minute changes in ratings. They concluded that, with a rise in outcome uncertainty during the game, broadcasting ratings increase. Salaga and Tainsky (2015) produced the same results, but also found that, at the beginning of the game, consumers prefer less uncertainty. Cox (2015) compared stadium attendance in his article on TV demand for matches. He concluded that, in the first case, more certain outcomes attract more spectators, while higher TV ratings are observed for matches with unpredictable results. However, Buraimo and Simmons (2015) showed that there was no interaction between TV demand and outcome uncertainty since the 2002/03 season of the English Premier League although this connection was investigated in previous seasons. The authors explained this fact by a shift in audience priorities towards team quality from outcome uncertainty.

As mentioned, the literature reports divergent results: even the same authors, for example Borland (1987) and Borland and Lye (1992), Pawlowski and Anders (2012) and Pawlowski and Nalbantis (2015), and different authors working on data from the same leagues, such as Whitney (1988), Lee and Fort (2008) and Soebbing (2008), are inconsistent in their results. This opens up new space for revision and further research on other samples from different sports leagues.

A large body of research has been conducted in developed leagues with significant fan interest and a high demand for sports events. There is a lack of attention to developing sporting competitions, such as the RFPL. No studies have investigated the impact of outcome uncertainty on attendances in Russian sport championships. This study is the first investigate the behaviour of customers under uncertainty in the RFPL.

The sample from the RFPL allows us to answer the research question more fully, as firstly, there are few sellout matches. The demand for football matches in the RFPL is not restricted by stadium capacity. Secondly, there are generally six teams in the RFPL competing for the trophy, which makes the concentration index sufficiently low and increases uncertainty of outcome. Thirdly, the RFPL is not commercially developed in comparison with North American sports leagues and, consequently, uncertainty of outcome is particularly important. For contests such as the NBA and

NHL, commercial factors can be more important than outcome uncertainty for consumers when they make a decision about visiting a match.

Methodology

The following model is estimated:

$$attendance_i = \beta_0 + \beta_1 htwp_i + \beta_2 htwp_i^2 + \beta_3 temperature_{\ i} + \beta_4 precipitation_{\ i} + \beta_5 stadium\_capacity_i + \beta_6 distance + \beta_7 not\_home\_stadium_i + \beta_8 h\_t\_goal\_per\_game_i + \beta_9 v\_t\_goal\_per\_game_i + \beta_{10} h\_t\_goal\_allowed\_per\_game_i + \beta_{11} v\_t\_goal\_allowed\_per\_game_i + \beta_{12} derby + \varepsilon_i \quad (1)$$

where *attendance* is the number of people who attended the game; *htwp* is the constructed probability of the home team winning. The remaining indicators are control variables: *temperature* (in celsius) and *precipitation* (equal to one if there was any type of precipitation) means weather conditions, which are important in Russia; *stadium capacity* is the total capacity of the stadium; *distance* is the number of kilometres between the city of the visiting team and the city of the home team; *h_t_goal_per_game* and *v_t_goal_per_game* are the average number of goals per game scored in previous games of the season by the home team and visiting teams; *h_t_goal_allowed_per_game* and *v_t_goal_allowed_per_game* are the average number of goals allowed by the home and visiting teams; *not home stadium* indicates games that are not played at the usual home team stadium; *derby* defines games of teams from the same city and ε is the error term. The estimation uses OLS with heteroscedasticity-robust standard errors.

The rationale for the inclusion of these variables can be found in previous studies. Regarding the variable of interest, Coates et al. (2014) presented validation for the use of the squared home team winning probability to track the influence of outcome uncertainty on attendance. It is also important to control for team quality; for this, we use variables indicating goals scored and allowed by both teams, following Coates et al. (2014) and Coates and Humphreys (2010). Another important indicator is the quality of the stadium, which can be observed through its age [Soebbing, 2008] or its capacity, as in Borland and Lye (1992). We use stadium capacity as an explanatory variable, since stadiums with larger capacity tend to be better equipped.

In addition, we include distance between the cities of teams and temperature. The control for temperature allows for the possibility of not including dummy variables for certain months, as in Buraimo and Simmons (2008). Also since Pawlowski and Nalbantis (2015) and Lemke et al. (2010)

investigated the quadratic relationship distance and temperature, and attendance, we tested this specification in models not presented in this article. These results showed that squared distance and temperature were insignificant and worsened the quality of the model.

The *derby* is used to detect teams from the same cities. *Derby* is partially captured in the “distance between cities” variable, however, distance helps to test how the remoteness of cities affects attendance while “derby” variable helps to reveal how the necessity to travel to another city influences match attendance. We expect a significant positive impact from this variable on attendance.

Because of lack of data about ticket prices we estimate the model in a reduced form.

Data

This paper focuses on football clubs that participated in the RFPL, 2012-2014. There are 16 teams in the RFPL that play each other twice; once at home and once away. The last two teams of the final standings are relegated to the lower division. The RFPL was founded in 1992 and traditionally ran in summer, from March to November. In 2010, it was decided to shift the schedule to the autumn-to-spring model, so the 2011/12 season was a transitional one. Since the 2012/13 season, the RFPL has followed the new model, in line with the top European leagues.

During the 2012/13 season, Spartak and Zenit participated in the UEFA Champions League, and CSKA and Zenit took part during the 2013/14 season. Spartak and CSKA share the largest stadium, which has a capacity of 84,745. Other stadiums have significantly lower capacity: the second-largest stadium is situated in Krasnodar (35,200) and serves the Krasnodar and Kuban teams. Apart from these cases, teams generally do not share stadiums. There is also the Russian Cup contest, which is held partially during the same period as the RFPL. However, fans are typically more interested in the RFPL as it is considered more prestigious.

Our data for attendances are presented on a match-by-match basis, which allows us to detect instant changes in demand. Observable attendances clearly reflect real demand for matches, since there are few sellouts. All matches were televised through a subscription channel, while only a few key games were shown on widely available channels. Unfortunately, because of difficulties of data collection is impossible to include TV broadcasting as an explanatory variable in the model. However, the work of Martins and Cro (2016) includes a variable showing that TV broadcasting does not have a significant impact on attendance. The other variables of temperature, probability of the home team winning, previous goals per game and not home stadium were also calculated individually for every game. The data about goals before the match and stadium where it was played were received from the website www.championat.com, and bets were derived from livetv.ru, which is unavailable today.

The probability of the home team winning was calculated using bets. Bets represents the winning amount per one ruble from the bet on a particular team winning. In order to calculate the home team winning probabilities, bets were converted through the following formula:

$$home\ team\ win\ probability = 1/bet\ on\ home\ team \quad (2)$$

derived from the betting model prevalent in Russian betting offices. Sauer (2005) adjusts the winning probabilities, taking into account bettor margins. However, in our case, due to lack of information on the markups used in betting offices and bets on a draw, the home team winning probabilities may be partially biased, although this fact does not influence the nature of the connection between attendances and probabilities therefore we have confidence in our results. However, it should be taken into account that the real probabilities of a home team win are slightly lower than the ones observable here. Figure 1 shows the density of the probabilities of the home team winning. Since it is clearly bimodal, we can conclude that there are both favourites and underdogs in the RPFL.

Table 2. Descriptive statistics

	N	Mean	St. Dev.	Min	Max
temperature	470	13.130	9.282	-12	33
precipitation	470	0.300	0.459	0	1
attendance	470	12,444.400	6,992.483	1,950	67,740
stadium capacity	470	27,245.900	14,588.070	3,000	84,745
betting coefficient	465	2.807	1.822	1.130	16.000
distance between cities	470	1,388.338	844.562	0	4,207
not home stadium	470	0.060	0.237	0	1
home team goals per previous game	470	1.270	0.520	0.000	3.000
visiting team goals per previous game	470	1.301	0.522	0.000	3.000
goals allowed visiting team per previous game	470	1.312	0.477	0.000	2.556
goals allowed home team per previous game	470	1.277	0.484	0.000	3.000
the home team winning probability	465	0.462	0.197	0.062	0.885
derby	470	0.060	0.237	0	1

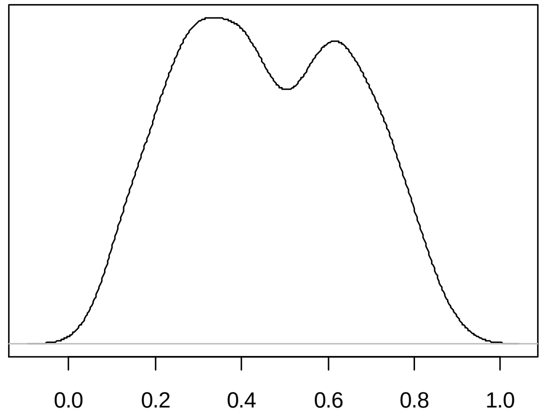

Fig. 1. Distribution of the home team winning probability.

Table 2 contains the basic descriptive statistics of our indicators. The mean value of the precipitation variable of 0.3 means that in 30% of matches rain or snow occurred. The correlation between goals scored per game by a home team and its winning probability is 0.43. In terms of attendance and stadium capacity, there were only four matches played in full stadiums, and only three matches where attendance was close to stadium capacity (with the difference between them less than 100). This quantity is so low in comparison with our sample that a special variable controlling sellouts was not included. The variation in attendance is wide; it varies from 2,000 to 68,000. The mean value of attendance was relatively low compared with European leagues; thus, the RFPL represents opportunities for potential growth.

Another significant difference between Russian and European leagues is that Russian fans generally have to travel long distances in order to watch matches in other cities. As a rule, only very loyal supporters do this, and this restricts the potential demand from other sectors of the market. Demand can also be diminished by match postponements; however, these take place only rarely (only 6% of matches).

Empirical Results

The presentation of results begins with an initial model that includes all games in the sample. These results are presented in Model (1) in Table 3. The results for the control variables are as expected. Temperature positively affects attendance, while the influence of precipitation is negative. Goals scored are positively significant for both home and visiting teams, whereas goals allowed are negatively significant. Hence, the attendance is higher in cases when fans anticipate more spectacular games. Derbies generate an increase in attendance of 6,100. Playing a “home” game not at the home stadium is insignificant, as is distance between cities. This is unusual for Russia, since the variation in distances is high (up to 4,200 kilometres). It is genuinely insignificant because most fans are travelling by plane. Distance and prices for tickets are not perfectly correlated and the timings of flights do not vary widely for cities of teams participating in the RFPL.

Since we use a squared indicator for home team win probability it is necessary to test the joint significance of these coefficients. The last row of Table 3 contains the results of the joint significance test of the *htwp* and $htwp^2$ coefficients. For convenience of presentation, Figure 2 reflects the effect of uncertainty on attendance. The plot numbers in the figure correspond to the model numbers in Table 3.

According to the first plot of Figure 2, the effect of uncertainty is mostly negative. This means that the higher the probability of the home team winning, the lower the attendance. This result contradicts the UOH. This can be explained by the fact that a lower probability of the home team winning means that the visiting team is supposed to be stronger in a particular game. Fans may be interested in coming to see superior teams playing against their home team.

Table 3. Estimation results

	(1) Initial model	(2) Top visiting team	(3) Top visiting team and low home team	(4) Low home team	(5) Initial model with home team dummies	(6) Initial model with visiting team dummies	(7) Initial model with all teams' dummies
the home team winning probability	-22,861.990***	-77,261.570**	-173,877.300**	-35,577.900***	-19,822.580***	-4,882.176	2,767.718
	(6,843.895)	(29,363.970)	(64,866.330)	(10,026.810)	(6,048.558)	(7,374.770)	(6,538.019)
squared the home team winning probability	18,038.330**	102,292.500**	504,925.000**	42,424.680***	12,437.000**	8,493.772	1,731.222
	(7,097.340)	(44,152.820)	(167,243.200)	(13,230.440)	(6,256.256)	(7,192.409)	(6,130.970)
stadium capacity	0.119***	0.207***	0.150	0.345***	0.100***	0.120***	0.105***
	(0.019)	(0.066)	(0.097)	(0.041)	(0.021)	(0.018)	(0.020)
temperature	178.044***	131.998	124.745	141.526***	143.645***	159.779***	125.918***
	(29.614)	(97.878)	(81.882)	(34.339)	(26.073)	(28.633)	(24.287)
precipitation	-1,291.798**	-1,002.715	104.193	-932.434	-1,028.145**	-1,128.911**	-779.176*
	(586.324)	(2,107.229)	(1,548.557)	(678.766)	(499.444)	(566.015)	(465.587)
distance between cities	0.073	0.538	-2.061**	-0.511	-0.430	0.270	-0.446
	(0.341)	(1.351)	(0.925)	(0.359)	(0.322)	(0.378)	(0.370)
not home stadium	-299.592	5,862.090		3,761.536	1,468.864	-855.934	1,038.463
	(1,130.115)	(4,533.237)		(2,484.985)	(1,029.497)	(1,087.951)	(952.135)
home team goals per previous game	2,640.937***	899.355	-2,396.909	3,115.598***	2,723.493***	1,709.878**	1,970.104***
	(643.847)	(2,081.813)	(2,397.539)	(965.454)	(635.760)	(677.106)	(632.483)
visiting team goals	1,722.712***	991.332	676.137	1,156.074	1,183.477**	264.139	227.603

	(1) Initial model	(2) Top visiting team	(3) Top visiting team and low home team	(4) Low home team	(5) Initial model with home team dummies	(6) Initial model with visiting team dummies	(7) Initial model with all teams' dummies
per previous game							
	(603.021)	(1,852.330)	(1,834.324)	(785.869)	(553.692)	(688.738)	(593.366)
goals allowed visiting team per previous game	-1,140.179*	5,351.890**	-3,912.120	-1,233.982	-1,091.348*	-449.045	-679.318
	(663.916)	(2,535.573)	(2,997.509)	(945.618)	(599.562)	(780.533)	(666.767)
goals allowed home team per previous game	-3,714.711***	-9,046.228***	-3,513.773	-3,194.397***	-2,898.143***	-2,183.225***	-1,786.814***
	(663.730)	(2,456.075)	(2,290.222)	(730.525)	(658.962)	(706.204)	(648.224)
derby	6,109.348***	11,465.420***			7,390.917***	4,652.735***	6,768.299***
	(1,264.399)	(3,243.818)			(1,141.788)	(1,286.803)	(1,117.028)
team dummies					home	visiting	both
Constant	13,547.41*** (2,105.692)	23,044.47*** (6,757.613)	36,631.64*** (7,842.845)	10,540.86*** (2,548.919)	12,165.72*** (2,352.546)	2,814.82 (1,934.74)	2,311.086 (2,979.631)
Observations	465	56	22	175	465	465	465
R^2	0.374	0.637	0.835	0.556	0.588	0.454	0.667
Adjusted R^2	0.358	0.535	0.685	0.526	0.561	0.417	0.631
F Statistic	22.551*** (df = 12; 452)	6.278*** (df = 12; 43)	5.558*** (df = 10; 11)	18.582*** (df = 11; 163)	21.431*** (df = 29; 435)	12.465*** (df = 29; 435)	18.236*** (df = 46; 418)
F test (the home team winning probability = the home team winning probability ^{2}=0)	8.02***	3.56*	5.13*	6.39**	9.82***	1.48	1.15

Notes: ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

To test this proposition, we estimate Models (2), (3) and (4). Model (2) is estimated on the restricted sample of games with top visiting teams. We define these as the two highest-ranking teams because they participate in the Champion's League. Model (3) is estimated on a sample of a top visiting team and a low home team, defined here as a team with a rank lower than 10. The choice of threshold is optional; hence, several robustness checks were made, and these are available upon request. Model (4) is estimated for the games of low home teams, without any restrictions for visiting teams.

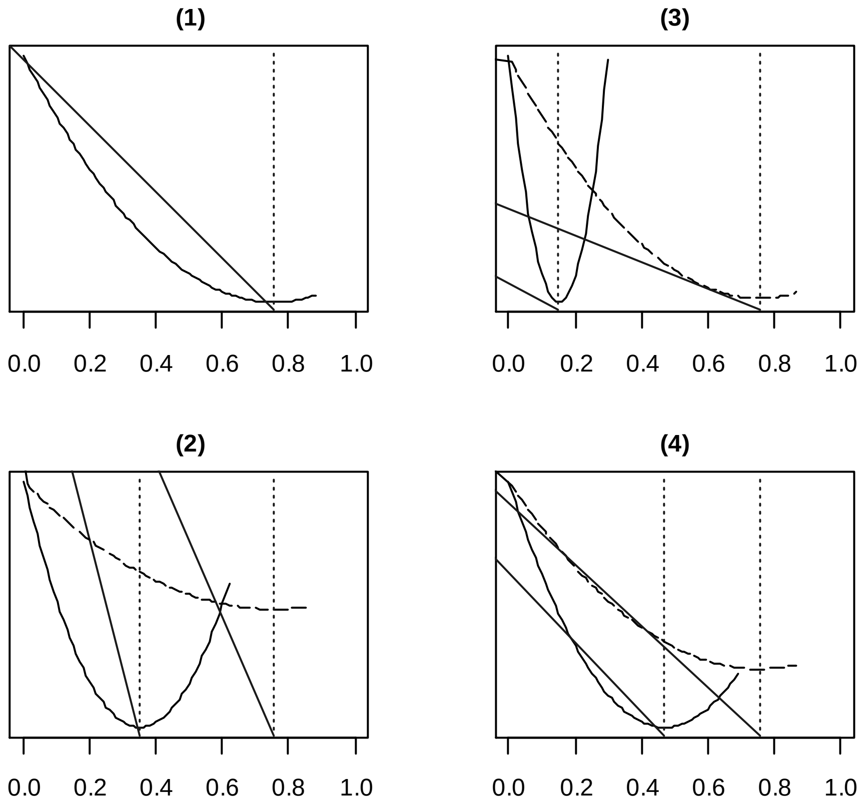

Fig. 2. Effects of uncertainty (the home team winning probability). The X-axis is the probability of home team winning. The Y-axis reflects attendance according to the estimated model. The graph numbers correspond to Table 1 models (1 – initial model, 2 - top visiting team, 3 – top visiting team and low home team, 4 – low home team). The vertical dashed lines indicate the threshold for each line ($\frac{\partial attendance}{\partial bet} = 0$). Plots (2), (3) and (4) also include the curve from plot (1) in order to make it possible to compare the uncertainty effects of different models with the initial model.

According to plots (2) and (3) of Figure 2, the dependence between uncertainty and attendance is U-shaped. This contradicts the UOH, but conforms to the model of Coates et al. (2014). However, we explain this not by a reference-dependent preferences model, but with the attendee's utility derived from watching the top visiting team. The threshold probability of the U-curve for plot (2) is higher than for (3). This means that for games between a low home team and a top visiting team, the attendance starts to rise even faster than for the games between top teams. Plots (3) and (4) appear similar; one can conclude that, for a low team, almost every visiting team is attractive for attendance. It can be concluded that for Russian fans, the brand of the visiting team is much more important than the probability of the home team winning. In other words, the key driver of attendance is the brand of the visiting team. This is in line with the findings of Coates et al. (2015) on the significant brands of some Russian teams.

Models were estimated with fixed effects for the teams as a further test of this hypothesis. Model (5) contains dummies for home teams, Model (6) for the visiting team and Model (7) for both the home and visiting teams. According to the joint test, the home team winning probability is significant only in the model with home team dummies. Therefore, one can conclude that the visiting team effect captures the effect of uncertainty. The visiting team is more important to the attendees than the chances of the home team.

Robustness Checks

In order to test the robustness of the model to alternative specifications we included other measures of uncertainty and *derby*. In line with Buraimo and Simmons (2015) we use the difference between home team and visiting team winning probabilities to measure the level of uncertainty. In Buraimo and Simmons (2015) found that the difference between probabilities is almost perfectly correlated with the Theil index (94.4%), which also takes into account draw probabilities. Table 4 contains descriptive statistics for the new variables. The estimation results are presented in Model (8) in Table 5. They are consistent with the results of the previous models, in which the home team winning probability was a dependent variable. The threshold difference between probabilities is 57.22%, which also indicates that spectators prefer attending matches of powerful visiting teams.

Table 4. Descriptive statistics for new variables

	N	Mean	St. Dev.	Min	Max
difference between home team and visiting team winning probabilities	470	0.141	0.372	-0.738	0.846
top visiting team	470	0.120	0.326	0	1
top visiting team* the home team winning probability	470	0.031	0.095	0	0.625
derby for traditional rivals	470	0.045	0.208	0	1
round	465	15.417	8.715	1	30
difference in points of home team and visiting team	470	-0.118	12.457	-38	38

Model (9) includes an alternative measure of *derby*, which equals one if teams are perceived as traditional rivals (CSKA, Spartak, Lokomotiv, Zenit). Matches between these teams are often described as “derbies” in media. Clearly, the inclusion of a new *derby* does not change values of other variables.

At the same time, our understanding of derby allows us to evaluate how the necessity of travelling to another city affects attendance.

Model (10) tests the hypothesis that attendance increases toward the end of a season when matches are becoming more important for teams. However, this variable is not statistically significant: we can assume that the demand for football matches is spread evenly through a season. Model (11) assesses the importance of matches from the perspective of competition for league positions. When teams' standings are close, games can be more important for fans because the match outcome changes the distribution of places between competitors. However, this hypothesis is not confirmed. At the same time, our estimations are robust to the inclusion of new variables.

In order to test interaction effects between the power of teams and the importance of uncertainty we included the product of the home team winning probability and a dummy variable for top teams. The threshold probability of the home team winning probability for top teams is 22% while the threshold probability in Model (2) is 38%. We explain this difference by the fact that Model (12) includes the home team winning probability variable, which partially contains data for matches with top visiting teams. Because of that, the threshold probability for top teams can be biased, and, in this sense, Model (2) seems to be more flexible and reliable. However, the probability of 22% derived from Model (12) does not contradict our results and explanations.

Table 5. Estimation results for alternative specifications

	(8) Model with difference between probabilities	(9) Model with derby for traditional rivals	(10) Model with round	(11) Model with difference in points	(12) Interaction model
difference between home team and visiting team winning probabilities	-4,036.691***				
	(1,100.182)				
squared difference between home team and visiting team winning probabilities	3,527.002*				
	(1,959.123)				
the home team winning probability		-23,485.040***	-22,782.690***	-22,766.880***	-20,007.350*
		(6,812.681)	(6,849.214)	(6,861.525)	(7,871.041)
squared the home team winning probability		18,233.890**	18,073.970**	18,160.780**	16,759.910**
		(7,049.051)	(7,101.970)	(7,121.524)	(7,898.610)

	(8) Model with difference between probabilities	(9) Model with derby for traditional rivals	(10) Model with round	(11) Model with difference in points	(12) Interaction model
top visiting team					5,206.927
					(3,726.369)
top visiting team* the home team winning probability					-33,358.750
					(24,621.810)
squared top visiting team* the home team winning probability					77,519.570**
					(37,380.020)
stadium capacity	0.119***	0.111***	0.118***	0.119***	0.118***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.018)
temperature	175.607***	175.220***	183.773***	178.271***	178.208***
	(29.652)	(29.412)	(30.874)	(29.659)	(29.088)
precipitation	-1,298.036**	-1,556.237***	-1,251.326**	-1,287.106**	-1,330.863**
	(587.420)	(579.521)	(589.877)	(587.232)	(575.502)
distance between cities	0.094	-0.190	0.071	0.072	-0.043
	(0.342)	(0.323)	(0.341)	(0.341)	(0.336)
not home stadium	-249.688	-449.191	-328.837	-255.454	-551.941
	(1,131.857)	(1,125.544)	(1,131.685)	(1,144.942)	(1,110.552)
home team goals per previous game	2,637.989***	2,501.999***	2,605.409***	2,699.426***	2,287.958***
	(643.014)	(643.168)	(646.487)	(685.546)	(635.515)
visiting team goals per previous game	1,721.306***	1,325.324**	1,722.731***	1,656.644**	1,307.479**
	(606.252)	(605.776)	(603.397)	(658.805)	(602.081)
goals allowed visiting team per previous game	-1,124.760*	-855.404	-1,201.126*	-1,090.888	-1,142.329*
	(666.133)	(663.249)	(670.699)	(693.151)	(650.405)
goals allowed home team per previous game	-3,753.420***	-3,542.485***	-3,686.808***	-3,762.002***	-3,173.046***
	(666.148)	(662.701)	(665.485)	(690.747)	(664.17410
derby for the same cities	6,083.837***		6,142.864***	6,119.535***	5,747.371***
	(1,266.110)		(1,266.203)	(1,266.366)	(1,241.371)
derby for traditional rivals		7,419.997***			
		(1,391.457)			
round			21.040		
			(31.834)		
difference in points of home team and visiting team				-9.377	
				(37.452)	

	(8) Model with difference between probabilities	(9) Model with derby for traditional rivals	(10) Model with round	(11) Model with difference in points	(12) Interaction model
Constant	7,590.305***	14,612.130***	13,186.650***	13,470.710***	12,588.680***
	(1,546.075)	(2,096.310)	(2,176.555)	(2,130.025)	(12.282.602)
Observations	465	465	465	465	465
R^2	0.372	0.381	0.375	0.375	0.404
Adjusted R^2	0.355	0.365	0.357	0.357	0.384
F Statistic	22.318*** (df = 12; 452)	23.196*** (df = 12; 452)	20.824*** (df = 13; 451)	20.778*** (df = 13; 451)	20.270*** (df = 15; 449)
F test (the home team winning probability = the home team winning probability ^{2}=0)	7.12***	8.87***	7.83***	7.26***	3.98**
F test (top visiting team*the home team winning probability = top visiting team*the home team winning probability ^{2}=0)					4.87**

Notes: ***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Conclusion

Our results suggest that the UOH does not explain the behavioural pattern of the attendees in the RFPL. We have found that the dependence between attendance and uncertainty is U-shaped or even declining. Our results contradict those of Rascher and Solmes (2007) and Lemke et al. (2010), and are more in line with the results of Coates et al. (2014). However, in contrast to Coates et al. (2014), who use a reference-dependent preferences model, we explain such U-shaped dependence by the visiting team effect. In other words, an attendee's utility in the RFPL depends more on the visiting team's brands than on the uncertainty of outcome.

Our study is subject to several limitations. Firstly, these findings may not be transferable to the other leagues due to the differences between the RFPL and developed leagues. Second, we lack information on the ticket prices in the RFPL. For this reason, we estimate the reduced form model. Thirdly, we lack information about season ticket attendance. However, for most teams in the RFPL, the number of season tickets is low.

References

Alavy, K., Gaskell, A., Leach, S. & Szymanski, S. (2010). On the edge of your seat: Demand for football on television and the uncertainty of outcome hypothesis. *International Journal of Sport Finance*, *5*(2), 75.

Benz, M-A., Brandes, L., Franck, E. (2009). Do soccer associations really spend on a good thing? Empirical evidence on heterogeneity in the consumer response to match uncertainty of outcome. *Contemporary Economic Policy, 27*(2), 216-235.

Borland, J. (1987). The demand for Australian Rules football. *Economic Record*, *63*(3), 220-230.

Borland, J., Lye, J. (1992). Attendance at Australian rules football: a panel study. *Applied Economics, 24*, 1053-1058.

Borland, J., Macdonald., R. (2003). *Demand for sport. Oxford Review of Economic Policy, 19*(4), 478-502.

Buraimo, B., Simmons, R. (2008). Do sports fans really value uncertainty of outcome? Evidence from the English Premier League. *International Journal of Sport Finance, 3,* 146-155.

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

Cairns, J. A. (1987). Evaluating changes in league structure: The reorganization of the Scottish football league. *Applied Economics, 19,* 259–275.

Cairns, J., Jennett, N., Sloane, P. J. (1986). The economics of professional team sports: A survey of theory and evidence. *Journal of Economic Studies, 13,* 3–80.

Coates, D., Humphreys, B. R. (2010). Week to week attendance and competitive balance in the National Football League. *International Journal of Sport Finance*, *5*(4), 239-252.

Coates, D., Humphreys, B. R. (2012). Game attendance and outcome uncertainty in the National Hockey League. *Journal of Sports Economics*, *13*(4), 364-377.

Coates, D., Humphreys, B. R., Zhou, L. (2014). Reference- Dependent Preferences, Loss Aversion, and Live Game Attendance. *Economic Inquiry*, *52*(3), 959-973.

Coates, D., Naidenova, I. and Parshakov, P. (2015). “Determinants of Russian Football Brand”. Presented at *Southern Economic Meetings*, 2015.

Falter, J. M., Pérignon, C., Vercruysse, O. (2008). Impact of Overwhelming Joy on Consumer Demand: The Case of a Soccer World Cup Victory. *Journal of Sports Economics*, *9*(1), 20-42.

Forrest, D., Beaumont, J., Goddard, J., Simmons, R. (2005). Home advantage and the debate about competitive balance in professional sports leagues. *Journal of Sports Sciences*, *23*(4), 439-445.

Forrest, D., Simmons, R. (2002). Outcome uncertainty and attendance demand in sport: the case of English soccer. *The Statistician, 51*(2), 229-241.

Lee, Y., Fort, R. (2008). Attendance and the Uncertainty-of-Outcome Hypothesis in Baseball. *Review of Industrial Organization, 33,* 281-295.

Lemke, R., Leonard, M., Tlhokwane, K. (2010). Estimating attendance at Major League Baseball games for the 2007 season. *Journal of Sports Economics, 11*(3), 316-348.

Meehan, Jr. J. W., Nelson, R. A., Richardson, T. V. (2007). Competitive balance and game attendance in Major League Baseball. *Journal of Sports Economics, 8,* 563-580.

Mills, B., Fort, R. (2014). League- Level Attendance and Outcome Uncertainty in US Pro Sports Leagues. *Economic Inquiry*, *52*(1), 205-218.

Nelson, R. A., Glotfelty, R. (2012). Movie stars and box office revenues: an empirical analysis. *Journal of Cultural Economics, 36*(2), 141-166.

Paul, R. J., Weinbach, A. P. (2007). The uncertainty of outcome and scoring effects on Nielsen ratings for Monday Night Football. *Journal of Economics and Business, 59,* 199-211.

Pawlowski, T. (2013). Testing the uncertainty of outcome hypothesis in European professional football: A stated preference approach. *Journal of Sports Economics*, *14*(4), 341-367.

Pawlowski, T., Anders, C. (2012). Stadium attendance in German professional football - the (un)importance of uncertainty of outcome reconsidered. *Applied Economics Letters*, *19*(16), 1553-1556.

Pawlowski, T., Budzinski, O. (2013). The monetary value of competitive balance for sport consumers: A stated preference approach to European professional football. *International Journal of Sport Finance*, *8*(2), 112.

Pawlowski, T., Nalbantis, G. (2015). Competition format, championship uncertainty and stadium attendance in European football – a small league perspective. *Applied Economics, 47*(38), 4128-4139.

Peel, D. A., Thomas, D. (1992). The demand for football: Some evidence on outcome uncertainty. *Empirical Economics*, *17*(2), 323-331.

Peel, D., Thomas, D. (1997). Handicaps, outcome uncertainty and attendance demand. *Applied Economics Letters*, *4*(9), 567-570.

Rascher, D., Solmes, J. P. (2007). Do Fans Want Close Contests? A Test of the Uncertainty of Outcome Hypothesis in the National Basketball Association. *International Journal of Sport Finance, 2,* 130-141.

Rottenberg, S. (1956). The baseball players' labor market. *The Journal of Political Economy*, 242-258.

Sacheti, A., Gregory-Smith, I., Paton, D. (2014). Uncertainty of outcome or strengths of teams: an economic analysis of attendance demand for international cricket. *Applied Economics*, *46*(17), 2034-2046.

Salaga, S., Tainsky, S. (2015). The effects of outcome uncertainty, scoring, and pregame expectations on Nielsen ratings for bowl championship series games. *Journal of Sports Economics*, *16*(5), 439-459.

Sauer, R. D. (1998). The Economics of Wagering Markets. *Journal of Economic Literature, 36,* 2012–2064.

Sauer, R. D. (2005). The state of research on markets for sports betting and suggested future directions. *Journal of Economics and Finance, 29*(3), 416-426.

Sloane, P. J. (1976). Sporting equality: Labour market versus product market control—A comment. *The Journal of Industrial Relations*, *18*, 79-84.

Soebbing, B. (2008). Competitive Balance and Attendance in Major League Baseball: An Empirical Test of the Uncertainty of Outcome Hypothesis. *International Journal of Sport Finance, 3,* 119-126.

Szymanski., S. (2003). The economic design of sporting contests. *Journal of Economic Literature*, *41*, 1137-1187.

Tainsky, S., Winfree, J. A. (2010). Short-run demand and uncertainty of outcome in Major League Baseball. *Review of Industrial Organization*, *37*(3), 197-214.

Whitney, J. D. (1988). Winning Games Versus Winning Championships: The Economics of Fan Interest and Team Performance. *Economic Inquiry*, *26*(4), 703-724.

Ye, Q., Law, R., Gu, B., Chen, W. (2011). The influence of user-generated content on traveler behavior: An empirical investigation on the effects of e-word-of-mouth to hotel online bookings. *Computers in Human Behavior*, *27*(2), 634-639.

Petr A. Parshakov
National Research University Higher School of Economics (Perm, Russia). International Laboratory of Intangible-driven Economy. Research Fellow;
E-mail: pparshakov@hse.ru

Kseniya O. Baydina
National Research University Higher School of Economics (Perm, Russia). Faculty of Economics, Management, and Business Informatics. Student;
E-mail: baydinaksusha59@yandex.ru