The impact of uncertainty on fan interest surrounding multiple outcomes in open European football leagues

Received: 5 June 2023 | Accepted: 4 September 2025

DOI: 10.1111/ecin.70024

ORIGINAL ARTICLE

Economic Inquiry

The impact of uncertainty on fan interest surrounding multiple outcomes in open European football leagues

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Abstract

This paper uses searches via Google to evaluate the importance of uncertainty in driving demand for entertainment events. We consider various dimensions of uncertainty of outcome in European football to examine whether the removal of uncertainty surrounding the winner of a competition before its conclusion reduces interest. We find a significant decrease in interest, although this appears mitigated by the existence of multiple objectives, such as qualifying for European competitions and avoiding relegation. We conclude that such a diversified and open structure (including promotion and relegation) is desirable in leagues that do not have a final play-off system.

KEYWORDS

competitions' multiple prizes, event analysis, global sports, Google Trends, open leagues, outcome certainty

JEL CLASSIFICATION

Z20, Z21, Z28

1 | INTRODUCTION AND OBJECTIVES

The demand for any product depends on the willingness to pay of consumers, which is a function of the characteristics of the product, holding other factors like price and income constant. In the entertainment industry, one such characteristic is how "interesting" an event is expected to be. In sport this idea has long been expressed as the *uncertainty of outcome hypothesis* (UOH)—the demand for a sporting event is a function of the level of uncertainty surrounding the outcome. It is understood that preserving such uncertainty is essential to the financial sustainability of sporting leagues, because it determines the ability of a sport competition to attract attention of the fans and to generate revenues.

In our analysis we exploit a particular feature common to many sporting events to understand the impact of the *uncertainty of outcome* (UO). Due to their round-robin structure, the champion is often known some weeks before the end of the competition in European football leagues. We consider the effect of this *removal of UO* on interest in European football leagues using internet search volumes, a novel source of information in this context. We measure the

Abbreviations: AISD, actual to idealized standard deviation; GTN, Google Trends News; GTW, Google Trends Web; UO, uncertainty of outcome; UOH, uncertainty of outcome hypothesis.

Managing Editor: Rob Simmons

level of interest of fans (potential consumers) based on the searching behavior of Google users. Specifically, we quantify the impact of the *removal of UO* on internet search volumes. We construct an empirical model that seeks to explain variation in search volumes for five top European football leagues over almost 20 years, paying attention to a range of phenomena previously noted in the literature on UO, and also considering the emerging literature on competitive intensity (CI). The literature on CI emphasizes the importance of other prizes in a league competition—qualification for continental competitions, and avoiding relegation—on spectator interest. As such, with our model we are able to consider the extent to which the uncertainty surrounding the champion and only the champion (often felt to be the "ultimate prize at stake" in a league competition) is the main driving force behind interest, or whether other dimensions like the intrinsic interest of the matches played each week, or CI, matter more.

Hence in our analysis we pay particular attention to unique aspects of these competitions, namely their open structure of promotion and relegation, and the qualification for continental competitions. We develop a model that explains a number of characteristics of weekly search volumes for Europe's top football leagues in order to identify more clearly the impact of the winner of the championship becoming known. Such information is important for the administrators of football leagues, since much advertising revenue is a function of online level of interest, and hence the documentation of such trends will be crucial for the sport business. Football leagues may seek to restructure in order to better protect their revenue sources if the effect is particularly stark.

In examining the previous literature, we look at different areas that may help accomplishing our objectives: (i) studying to what extent outcome uncertainty (more specifically, uncertainty on the championship winner) affects the fans interest on European football; (ii) identifying other significant driving factors of the fans' engagement over the season; and (iii) exploring alternative goals that football teams aim to achieve. The last feature naturally leads to diversifying the financial risk of professional football leagues, since the existence of multiple targets ensures for longer time the attachment of fans to follow certain sport competition.

The rest of the paper will proceed as follows; Section 2 reviews the relevant literature. In Section 4, after describing the data and sources, the adopted modeling methodology is set out. Then, Section 5 presents the main results from the econometric estimations; and, finally, Section 6 concludes.

2 | RELATED LITERATURE

There is abundant literature claiming that *UO* is a major source of interest in sport competitions. The idea that the demand for sporting events is driven by the level of UO was initially conjectured by (Rottenberg, 1956). Then, Neale (1964) made an explicit mention of the UOH, claiming that it is a main factor commanding the attention of fans. Economists also call attention to the role of what Neale (1964) named as the *pennant race*: the competition for the ultimate prize, finishing a season in first position in the league standings. This final position may be known before all the matches in the competition have been completed. The name given to it varies; it is often referred to as the "title race," or the "championship race." We will call it the championship, and refer to the champion becoming known, in this paper. Neale (1964) also referred to the league standing effect, pointing toward interest in other aspects of a league competition that are position-based. Andreff and Scelles (2015) more explicitly emphasized that this could be applied in particular to prizes other than the championship.

In this context, Késenne (2014b)—inspired by earlier papers (Cairns et al., 1986; Humphreys, 2002; Jennett, 1984; Kringstad & Gerrard, 2007; Szymanski, 2003)—distinguished various levels of UO in sports: (i) match uncertainty, (ii) "within-season" or seasonal uncertainty, and (iii) "between-season" or championship uncertainty. The relationship of outcome uncertainty with *Competitive Balance* (CB) has motivated other papers (Fort and Quirk (1995); Owen (2014); Késenne (2014a)). Zimbalist (2002) and Owen (2014) stressed that there is general acknowledgment on the fact that sport competitions must enjoy a certain level of CB, even though it is difficult to know how much. Manasis et al. (2013) argued that conventional indices used to measure the degree of competitive (un)balance typically fail to account for the multiplicity of objectives and prizes established in open European football leagues. This emphasis on the range of different outcomes in a league is often referred to as *CI* (Kringstad & Gerrard, 2007).

A number of studies address the UOH by examining stadium attendances—Peel and Thomas (1992), Czarnitzki and Stadtmann (2002), Garcia and Rodríguez (2002), Borland and MacDonald (2003), Fort and Lee (2007), Coates and Humphreys (2012), Manasis et al. (2013); while others focus on TV audiences—Pérez Carcedo et al. (2017), Buraimo and Simmons (2015) or even on both attendances and TV audiences Buraimo and Simmons (2009). From Buraimo and Simmons (2009) TV spectators are more affected by unpredictable matches than stadium spectators. The difficulty of verifying if UO is relevant in European football prompted Pawlowski and Anders (2012), to also examine the relationship between UO and stadium attendance. More recently, Pawlowski et al. (2018) adopts a new approach to overcome the usual shortcomings associated with the appraisal of CB by means of subjective measurements of fans' perceptions of balance. Besides, the issue was examined in the context of individual and team-sport leagues, like –respectively– European football (Késenne, 2000; Szymanski, 2010) and Formula One (Judde et al., 2013; Mastromarco & Runkel, 2009).

Papers examining the role of CB on the degree of interest that fans show for sport competitions yield contrasting outcomes. The difficulty in determining the importance of the UOH in the demand for sporting events is essentially twofold: a measurement issue, and an identification problem. Considering firstly the measurement issue, studies need to both measure uncertainty, and the demand for sport. Historically, attendance numbers at sporting events, which are generally made available publicly, have been used to evaluate the demand for sport and hence the impact of uncertainty on it (Coates & Humphreys, 2010, 2012; Cox, 2018; Garcia & Rodríguez, 2002; Peel & Thomas, 1988, 1992; Schreyer & Ansari, 2022). More recently, motivated by the limitations of attendance numbers (measurement error, censoring above and below) a number of innovative studies have used television viewership figures (Buraimo & Simmons, 2009, 2015; Forrest et al., 2005). These are still likely measured with some error, but avoid issues of stadium capacity censoring data above.

Even if demand can be measured, it is not necessarily clear how outcome uncertainty should be measured; while a standard set of measures now exist for measuring CB (see e.g., Owen, 2014), these remain the construction of a statistician or econometrician, and need not necessarily conform to fan perceptions of CB or intensity (Pawlowski et al., 2018).

Turning to the identification problem, partisan fans of a team (or individual player) may prefer to watch events where their favorite is more likely to win, and may be loss averse when it comes to uncertainty. Coates et al. (2014) and Humphreys and Zhou (2015) have developed models of reference-dependent preferences that allow the identification of different factors associated with the demand for sporting events.

Our paper uses internet search frequencies to measure demand, and captures the impact of uncertainty on the demand for a competition by the impact of its complete removal once the winner of an event becomes known. This *removal of uncertainty* is hence our identification strategy. We follow Garcia-del-Barrio and Reade (2022), who addressed the case of Formula One, in two main aspects. First, we adopt a similar approach, based on Google Trends records applied to team-sports. Second, we investigate the impact of this removal of a significant source of uncertainty to identify its impact on interest in an event. We consider the biggest five football leagues in Europe: England's Premier League, Spain's La Liga, Germany's Bundesliga, Italy's Serie A and France's Ligue 1. By most conventional accounts, these are the top five competitions.[1] They dominate financially, in terms of attendances, and in terms of success, providing all but two of the winners of Europe's top competition, the UEFA Champions League, since 1991, and at least one finalist in every season since 1988. We examine whether knowledge of the winner of each of these "big five" competitions, which is often known a number of weeks before the season has completed, is consistent with a fall in Internet searches—measured through search activity on Google—associated with that competition. The mentioned paper found such a fall in the context of Formula One motor racing and, hence, we anticipate documenting a similar type fall in team-sport leagues. We develop the method of Garcia-del-Barrio and Reade (2022) for the multi-prize context of football leagues building on the CI literature, as European competition qualification and relegation ensure that the overall winner of the competition is not the only seasonal outcome of interest. In addition to Pawlowski et al. (2018) the impact of CI, the range of prizes on offer for teams in European football, on fan demand in European men's football has been tested by an array of papers: Scelles et al. (2013, 2016), Andreff and Scelles (2015), Scelles (2017), Schreyer and Däuper (2018), Bond and Addesa (2019), Bond and Addesa (2020), Addesa and Bond (2021), Hautbois et al. (2022), Wills et al. (2022), and Wills et al. (2023). The previous literature lends support to the claim that accounting for CI is a better approach than assuming that outcome uncertainty regarding the winner is all what matters. We also attempt to understand search activity within a broader event-study type framework.

The scope of the current paper involves accounting for the global interest that European football arises, as professional football leagues seem to attract increasing amounts of investments thus encouraging business development. Actually, new consumption patterns through new technologies seem to have permitted (primarily European) football clubs and leagues to expand the market in Asian and American countries (Aguiar-Noury & Garcia-del-Barrio, 2019; Fleischmann & Fleischmann, 2019).[2] Over recent decades new technologies have arguably developed the emotional link between consumers and sport events. The role of social media, not least in the context of sport, is a growing area of interest. A variety of papers examine issues related to social networks and the analysis of content, brand reputation, fan feelings, etc. (Araújo et al., 2014; Corthouts et al., 2019; Maderer et al., 2018).

There is, naturally, no single measure of social media interest in sporting events; rather, a range of varying social media platforms exist, offering the potential to understand more about the UOH; to date, only Pawlowski et al. (2022) have explored this, building on Buraimo et al. (2020) and using messages (Tweets) sent on the Twitter platform during football matches in England.[3] They find that shock, surprise and suspense are all drivers of Twitter activity during football matches.

Finally, in the attempt to measure the global interest on professional football events, we use here the searching intensity with which Internet users look for specific contents or news referring to each of the considered domestic football leagues. We use the Google search volumes as reported by "Google Trends," normalized with respect to the maximum number of searches in the searching period (Choi & Varian, 2012), for comparing the degree of attention that is paid to the different leagues. For the sake of robustness we used both data obtained from "Google Trends Web" (GTW) and from "Google Trends News" (GTN).[4] Garcia-del-Barrio et al. (2020) also consider Google search intensity to understand the impact of uncertainty. Our paper builds on this by incorporating ideas related to CI, allowing for the hypothesis that uncertainty on the winner may encompass other plausible targets, such as teams aspiring to avoid relegation or to qualify for participating in the UEFA competitions in the following season.

3 | DATA

Our data is collected from Google Trends (trends.google.com) for the so-called "big five" European football leagues: England's Premier League, Spain's La Liga, Germany's Bundesliga, Italy's Serie A and France's Ligue 1. Each of these "big five" league seasons run from the late summer (late July or early August) through to the Spring of the following year (May), and each competition has between 18 and 20 teams which, with a double-round robin structure, means between 306 and 380 matches.

Our data from Google Trends is worldwide searches for these leagues, making use of Google's categorization of them as sports leagues to avoid falsely capturing searches for closely related terms (such as, e.g., leagues in other countries with similar names). We collect from the start of the time period that Google Trends makes data available, namely 2004, and we finish collection at the end of the most recent season at the time of writing, 2022/2023. We collect worldwide searches rather than restricting our interest to any particular geographical area.

Google Trends data provides a measure of search volume for user requested search terms on the Google search engine. As per Garcia-del-Barrio and Reade (2022), we argue that this provides a measure of interest in a sporting competition. If interesting events are taking place in a competition, then it is reasonable to assume that people will search for that event in order to find out more. This is the rationale behind a number of the academic uses of Google Trends over recent years (e.g., Choi & Varian, 2012). Google Trends has for some time provided two types of search data; simple *Google Trends Web* (GTW), and *Google Trends News* (GTN).[5] GTW searches are all searches made for any particular search term, whereas if the user, having searched, then selects to look at only news items related to the search item, it is recorded as a GTN search. We consider both as informative data series and present results on both.

We download data on the number of searches, both in GTW and in GTN, for each of the "big five" of domestic football leagues in Europe. The number of searches is normalized to lie between 0 and 100, where 100 represents the time period where the most searches took place for the particular search term. We extract search volume for each league for each season. This means that in each competition and each season, the value 100 is achieved in the week(s) when the maximum search volume for that league and that season was achieved. Because Google Trends only ever returns relative search volumes, there is little to be gained from allowing only one season for a league, or one league for a season, to be the maximum that achieves 100, and the others be scaled down.[6] If we do this, then we will under-estimate the relative effect *within season* of the champion becoming known in the leagues or seasons that do not achieve 100. The argument that we might *over*-estimate the impact via this method is somewhat negated by the scaling of the dependent variable to lie between 0 and 100. It means that any interpretation can be in terms of percentage points. Furthermore, by downloading season-by-season we also are able to collect weekly data, a much more useful frequency for our purposes.[7]

It is worth noting additionally that any particular search request on Google Trends will only use a proportion of its search database, meaning that the same request could yield slightly different numbers of search frequencies if made at a different point in time. We have collected search volumes from a number of different time points, and compared the results, and we have found no meaningful difference in our results from doing so. We have included Figure A4 on page 25 to graphically display the discrepancies between two separate downloads from Google Trends of our dataset.[8]

Even if searches in Internet engines like Google only reflect part of the overall interest, there is no reason to expect that the data will be biased for or against any particular league or season in which the empirical study is conducted.

Moreover, the outstanding development of new media and technological devices facilitating global access to the Internet suggest we can consider these figures to be worldwide measurements of interest.

Figure 1 plots the data for illustrative purposes, week by week, for each of the years in our dataset for the five leagues we consider. The first week is always the first week in August, reflecting that most European football seasons are played in the late Summer, Autumn, Winter and Spring in the Northern Hemisphere, hence reach across calendar years.[9] Each year has a colored line, with the thickest colored line corresponding to the 2019/2020 season, which was impacted by the Covid-19 Pandemic.

The plots show a general increase in search activity in the weeks that the season is on, and also an increase as the season draws to a close, with variation from season to season in the exact levels of search. In the Covid-19 seasons, all leagues closed down in the immediate lockdown response to the Pandemic in March 2020 (Tovar, 2021). Four of the five leagues we cover (Germany, followed by England, Spain and Italy) resumed play in May, June and July, months in which league football is not usually extensively played. The French league was abandoned, and these patterns are all reflected in Figure 1, with flat periods of almost no search from week 33 until week 41 when the Bundesliga resumed, week 45 when La Liga resumed, week 46 when the Premier League restarted and week 47 when Serie A resumed.

This highly unusual pattern of searches might prompt us to consider dropping this period from our analysis. From the plots, however, it is clear that search activity during the weeks without football during the Pandemic was at a similar level to that during the summer when no football is taking place. As we seek to explain search volumes by footballing activity and events, we thus retain the Covid-19 affected season, and indeed the subsequent season when almost all football took place in front of empty stadiums. As we include season fixed effects, then if fans being unable to attend football in the stands simply increased search activity across the season, this will be absorbed into these terms.

We additionally plot the distributions for searches for each league over the entire sample period from 2004/2005 through to 2022/2023 in Figure 2, alongside kernel density plots. In each case there are values at zero and 100, as these are the extreme values the search index can take. However, these constitute just 2% of our sample and hence we do not use any censored regression methods.

4 | METHODOLOGY

We employ an event-study approach to consider the impact on search volume of a relevant treatment event, namely the revelation of the winner of the competition. In European leagues, which are all simple round robins, it is not uncommon for the winner to be known several weeks in advance of the end of the season. In our dataset, which considers

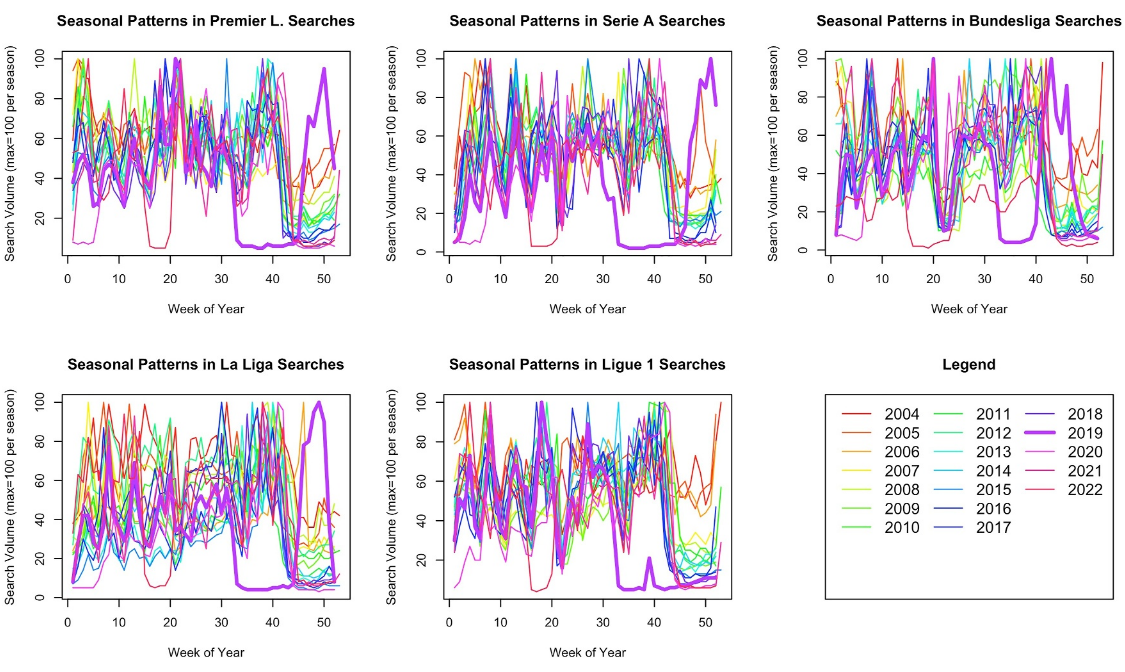

FIGURE 1 Search frequencies by week for all five competitions between 2004/2005 and 2022/2023 seasons.

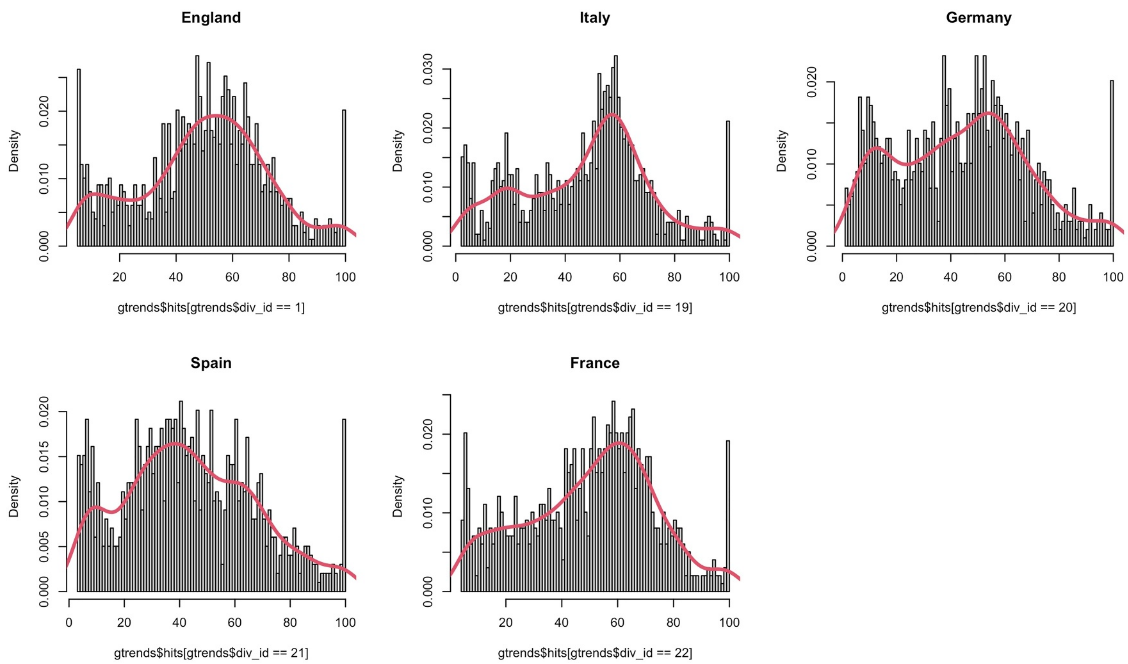

FIGURE 2 Distribution (with kernel density plot superimposed) of the Google Trends searches across all five leagues.

19 seasons since 2004/2005 across five major leagues, on average the champion is known 3 weeks in advance. As such, the point at which the champion is known varies in each season and each competition, and can be thought of in the context of an event-study model. In such models dummy variables are introduced to consider the impact of some exogenous event on another metric of interest. Dummy variables are added for time periods both before and after the exogenous event, which in our case is the knowledge of the champion of a football league competition.

Our dependent variable is search volume for a given league competition in particular season, and we have collected this data at a weekly frequency. We initially estimate models of the following form, for league i, season s, and time t:

$$G_{it} = \sum_{j=-5}^{3} \alpha_j X_{i,t=t^*_{is}+j} + \xi(i,t,s) + \varepsilon_{it}, \tag{1}$$

where G_{it} is Google search volume (web or news), and $X_{i,t=t^*_{is}+j}$ are dummy variables for the weeks centered around when the champion is determined, where t^*_{is} is the week that the champion becomes known for league i in seaason s. Hence $X_{i,t=t^*_{is}}$ is one for the week that the champion becomes known for league i in a given season, and zero otherwise. The term $\phi(i,t,s)$ represents fixed effects for the competition (i), season (s), and week of the season (t). Hence we consider each league's search volume to be treated by the revelation of the identity of the champion. This methodology was first introduced by Fama et al. (1969) to consider the impact of a stock split on share prices of companies, and in the time since has been applied in many contexts, not least in sport. To give a small number of relevant examples, Gannon et al. (2006) considered the impact of the announcement of deals for the televising of the English Premier League on share prices of football clubs and broadcasters, Kent et al. (2013) considered the impact of rule changes in football on CB in top European football leagues, Lertwachara and Cochran (2007) considered the impact of professional sport franchises on local US economies, Scholtens and Peenstra (2009) looked at the impact of football match results on club share prices, and Fischer et al. (2022) considered the impact of a Covid-19 infection on various measures of footballer productivity.

Our aim in constructing an empirical model to capture the observed trends in search activity is thus to quantify the build up and subsequent drop off in interest, so as the identify the impact of the removal of uncertainty regarding the champion. To do this we must separate that from other causes of searches for competitions at different points during their seasons. This will enable us to more clearly identify the impact of the removal of UOs on search interest. This is a distinctly different approach to the event study estimations in Equation (1), which seek only to consider the size of the impact rather than necessarily explain it. Furthermore, we seek to document the impact of the champion being known, and hence would rather pool the post-revelation weeks into a single dummy variable. In pooling and hence reducing the number of regressors in our model, we allow ourselves to better consider each league in isolation, too, which we do in case there is clear variation.

We thus consider regression models of the form:

$$G_{it} = \alpha_1 winnerweek_{it} + \alpha_2 winnerknown_{it} + \alpha_3 C_{it} + \xi(i,t,s) + \varepsilon_{it}, \tag{2}$$

where $winnerweek_{it}$ is a dummy variable taking the value one in the week that a champion is determined in a competition, and $winnerknown_{it}$ is one for all of the following weeks until the season is finished. We split out the effect of the champion becoming known since it is likely that in the week that the champion is determined much interest is focused on that competition, but in the subsequent weeks that interest would fall away—as shown graphically in Figure 3.[10]

We allow some systematic (and unobserved) variation by including fixed effects as in Equation (1), denoted $\xi(i,t,s)$, for the season and competition, as well as the week of the year.

In Equation (2), C_{it} is a set of other football-related explanatory variables, or control variables. We introduce this set of variables to help explain search levels at any given point in a football season. These variables are summarized in Table 1. Adding these variables will allow us to better qualify, and quantify, the extent of the impact of the removal of UO in football leagues. More broadly, Table 1 presents summary statistics of the variables we include in our regression models.[11]

We include a number of dummy variables to capture important explanations for variation in search activity. For example, we include a dummy for whether the season is on-going. The football season accounts for around 40 of the 52 weeks of the year over our sample (or 79% of the time). It is likely that as the season progresses, interest increases (as indicated in Figure 3), as events and narratives build up for clubs, and so we include a linear trend that increases linearly through the season.

We construct a range of football-related variables by using match results data from www.soccerbase.com. We include league-specific information, as this may be expected to influence interest and hence search volumes. We include the number of matches played in the competition in a given week, and we also include the ratio of the *actual to idealized standard deviation* (AISD), a measure of CB that captures the disparity between teams in the competition at any point that adapts to the different number of teams in different competitions (Zimbalist, 2002).[12] That is, the standard deviation of points shares is divided by the hypothetical value for the standard deviation in the case that all teams are of equal strength ($0.5/\sqrt{N}$, where N is the number of matches in a league season). We calculate AISD for each week of the season, according to the standings at the end of that week. We detrend this, however, since in the course of any season it trends upwards, and hence would mask the impact of other trending variables in our model in its raw form.[13] By including this, we can consider whether CB within season has any impact on interest, as a complementary approach to considering whether the complete removal of uncertainty once the champion is known matters.

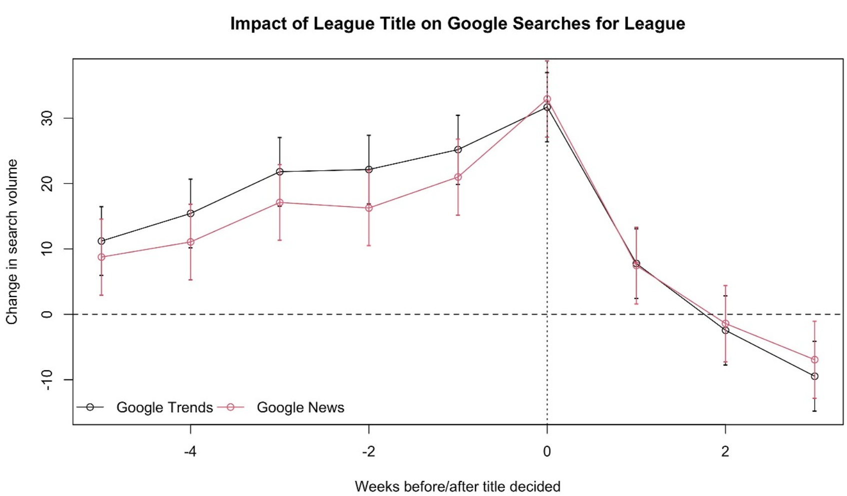

FIGURE 3 The change in search activity on Google around the point that the winner of a football league championship is known.

TABLE 1 Summary statistics of the data used in this study.

Statistic	*N*	Mean	St. dev.	Min	Max
Google Trends Web search index (0–100)	4960	47.263	23.515	1	100
Google Trends News search index (0–100)	3915	43.469	22.317	0	100
Season ongoing (0/1)	4960	0.774	0.418	0	1
Season linear trend	4960	17.443	14.028	0	52
Hiring window (0/1)	4960	0.340	0.474	0	1
Total matches in week (number)	4960	6.974	5.610	0	30
Idealized standard deviation	4960	0.770	0.599	0.000	2.362
Week before season starts (0/1)	4960	0.021	0.144	0	1
Week season starts (0/1)	4960	0.021	0.144	0	1
Week after season ends (0/1)	4960	0.021	0.144	0	1
Second week after season ends (0/1)	4960	0.020	0.140	0	1
Wins needed by leader to be champion (inverse)	4960	0.102	0.264	0.022	3.000
Week champion decided (0/1)	4960	0.016	0.126	0	1
Champion decided (0/1)	4960	0.039	0.192	0	1
Week Champions League decided (0/1)	4960	0.017	0.129	0	1
Champions League decided (0/1)	4960	0.041	0.198	0	1
Week relegation decided (0/1)	4960	0.015	0.122	0	1
Relegation decided (0/1)	4960	0.012	0.108	0	1

In order to try to model the increasing search interest shown in Figure 3 as the championship race culminates, we include the reciprocal of the number of wins that the team in first place needs to secure the championship. This is a common metric used by football commentators and journalists as a season draws toward a close to express how close to becoming champions a team is. We calculate the difference between the total number of seasonal points the second placed team can potentially amass in the remaining games of the season and the current number of points that the first placed team has, and divide this by three.[14] As this number of required wins reduces as a team gets closer to securing the championship, the reciprocal is used to create a metric that is increasing at an increasing rate as a season draws to its climax. Figure A1 on page 22 plots this measure for one season of our data, as a graphic illustration.

Football leagues also have other outcomes of interest, namely European qualification for the top few teams, and relegation for the worst performing teams. It seems likely that these alternative outcomes may also determine interest in the competition above and beyond that of the champion.[15] A range of measures developed to account for these broader aspects of European football competition are usually referred to as measures of *CI*, as opposed to CB (Kringstad & Gerrard, 2004; Manasis et al., 2013). CB can be thought of as weighting all positions in a league competition equally, whereas CI treats positions with importance for multiple prizes with a greater weight. Kringstad and Gerrard (2005) developed the concept of CI further, building upon Jennett (1984). Sloane (1971) (p. 124) already alluded to the idea behind CI by stating that: “a match between two lowly teams fighting to escape relegation will often attract a larger attendance than a match between two middle-of-the-table teams.”

As with the timing of the determination of the champion, we include dummy variables for the week when all the European (Champions League) qualification places are confirmed, and all the relegation places are confirmed. On average, these two outcomes are determined 1 week before the season ends. We also include a measure for how many teams can still win the title, qualify for European competitions, or be relegated. We anticipate that as each number decreases, interest in the competition will increase.

Finally, there are two periods in the year when teams in these competitions can trade players; the summer “transfer window,” or “hiring window,” and a winter one. The summer one lasts for July, August and September, while the winter one lasts for January. We include a variable that is 1 for all weeks where the hiring window is open, as it is likely that there is increased interest in the top leagues during these periods.

5 | RESULTS

To illustrate the impact that we intend to qualify and quantify in this paper, Figure 3 plots our data source, both "Google Trends Web" (GTW) and "Google Trends News" (GTN), for the weeks surrounding the revelation of the winner of the championship. Week zero, with the vertical dotted line, is the week in which the winner of a league championship is decided. As with any points-based league system, the leading team can amass a sufficiently large number of points that they cannot be reached by any other team given the number of matches that remain in the competition.[16] We plot the search volumes, and the associated volumes reported on Google, in the five previous weeks, which is building steadily. The units are the scaling that Google reports its data in, such that 100 is the maximum weekly search volume in our dataset for a given competition and season. As such, searches are between 10 and 20 points higher in the last few weeks before the winner is known, and then once the winner is known, in the three subsequent weeks interest falls away quite dramatically.

Uncertainty exists at different levels for any sports league; there is the individual event level (a match, or race), the seasonal level (the pennant race), and the cross-seasonal level (long term domination). Given this multi-dimensional nature to UO, it may thus be possible to consider the impact of removing one aspect of uncertainty on interest levels.

We plot the coefficients from the estimated model Equation (1) in Figure 4. These coefficients represent deviations from mean search activity for a given week in and around the time that the champion becomes known in a football league. The black lines represent the estimates from Equation (1) for GTW searches (left) and GTN searches (right). The observation at zero (marked with a vertical dotted line) is the week in which the champion is determined, and we plot 5 weeks beforehand, and 3 weeks afterward (recalling that, on average, the season ends 3 weeks after the champion is known). Conventionally, it might be anticipated that in advance of the event being studied, there is no noticeable trend of any sort, but in this case, the opposite is true; there appears to be an anticipation effect, as search activity builds up week by week until the champion is determined. Once the champion has been decided, search activity then drops off markedly. This is a pattern that might be anticipated given the UOH, and given our purpose in writing this paper; however, it is important to consider alternative explanations for search volume variation, in order to determine more precisely what the impact is of the champion becoming known.

We present a graphical summary of those more in depth results in Figure 4. The red lines refer to the model when we include all of the control variables listed in Section 4, though removing the week fixed effects due to the number of week-specific explanatory variables in our main specification. These lines suggest that our in-depth modeling is able to explain much of the variation in and around the revelation of the title winner. The coefficient estimates for the explanatory variables added to the Full Model are presented in Table 2 for Google trends web, and Table 3 for Google trends news. The only difference between the model estimated for Figure 4 (see Equation 1) and those in Tables 2 and 3 (see Equation 2) are that the five pre-title dummies, and three post-title dummies are replaced with a dummy variable for the week that the champion is decided, and another for the subsequent weeks until the end of the season.

In Tables 2 and 3 we present each of the five leagues as a separate column (with season fixed effects), before presenting a pooled model (with competition fixed effects) in the final column. All six regressions have season fixed effects included. We present the pooled model, despite tests for poolability of coefficients failing, for information purposes. In Figure A5 on page 26 we present plots of the residuals from each estimated model against the actual values. These plots all indicate that for search volumes across the full range of possible values, our model seems reasonable able to explain that variation given residuals are generally relatively small.

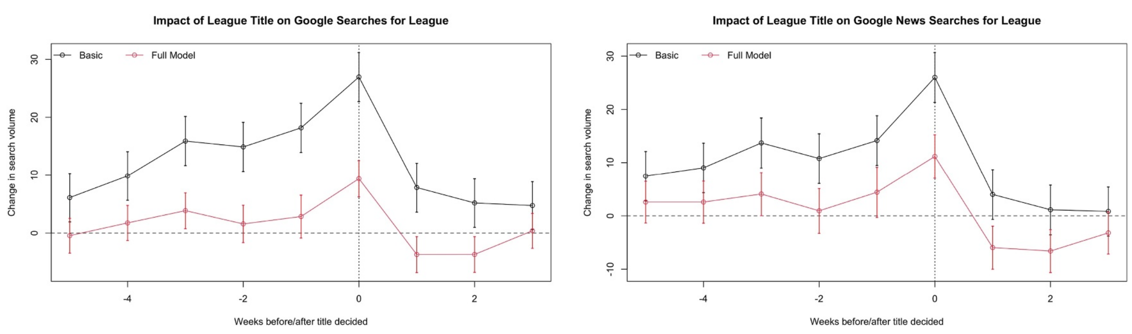

FIGURE 4 Event study plots looking at Google search volume (left) and Google news volume (right) around the time that the league champion is decided.

TABLE 2 Regression results with Google Trends Web (number of searches in Google Web) as the dependent variable.

	Dependent variable					
	Google Trends Web					
	(1) ENG	(2) FRA	(3) DEU	(4) ESP	(5) ITA	(6) All
Season ongoing	12.270	25.698***	15.334***	17.626**	−4.217	18.233**
	(7.498)	(7.146)	(5.093)	(6.526)	(6.225)	(5.451)
Hiring window	3.550***	2.705***	2.383***	0.690	4.879***	2.893**
	(0.768)	(0.700)	(0.742)	(0.768)	(0.682)	(0.796)
Total matches in week	2.506***	2.957***	4.056***	3.004***	3.174***	3.013***
	(0.198)	(0.166)	(0.219)	(0.182)	(0.139)	(0.237)
Position mean	−0.456**	−0.412	−1.360***	−0.999***	−0.686***	−0.581*
	(0.171)	(0.269)	(0.234)	(0.266)	(0.210)	(0.243)
Idealized standard deviation (detrended)	10.763	−6.190	12.908*	3.561	1.977	−2.029
	(9.569)	(7.652)	(6.928)	(5.654)	(8.897)	(3.756)
Week before season starts	35.389***	22.824***	37.195***	17.881***	22.702***	27.472***
	(3.678)	(2.562)	(3.337)	(2.236)	(2.332)	(4.228)
Week season starts	12.686***	−0.449	6.684**	4.354*	12.392**	6.292*
	(3.071)	(2.322)	(2.584)	(2.183)	(4.594)	(2.686)
Week after season ends	0.256	4.987***	3.650	1.580	1.627	2.720*
	(0.940)	(0.869)	(2.177)	(1.709)	(1.127)	(0.993)
Second week after season ends	−1.994*	2.712**	−0.799	−1.233	0.377	0.018
	(0.953)	(1.098)	(1.525)	(0.750)	(1.063)	(0.908)
Wins needed by leader to be champion (inverse)	1.140	−2.285	1.305	−3.253	2.982	2.587
	(3.318)	(2.292)	(1.989)	(2.355)	(2.144)	(1.339)
No. teams can be champion	0.668***	0.143	−0.519**	−0.134	0.259	−0.095
	(0.155)	(0.305)	(0.205)	(0.140)	(0.263)	(0.281)
Week champion decided	3.375	6.358	0.785	−6.109	6.417	8.089**
	(4.832)	(4.960)	(4.574)	(4.063)	(5.615)	(2.620)
Champion decided	−5.668	−10.137*	−9.115	−29.049***	−3.411	−4.039
	(6.493)	(5.783)	(5.981)	(4.751)	(6.613)	(3.272)
No. teams can qualify Champ. Lge	−0.489	−0.836	0.304	−0.130	0.633	−0.173
	(0.372)	(0.503)	(0.313)	(0.351)	(0.388)	(0.346)
Week Champions League decided	−0.584	−0.108	2.130	8.817**	4.973	2.162
	(3.388)	(3.094)	(4.227)	(3.697)	(3.523)	(1.230)
Champions League decided	−10.933*	2.649	1.114	8.350	−5.355	−2.750
	(5.644)	(3.972)	(6.397)	(5.985)	(5.600)	(2.840)
No. teams can be relegated	1.314*	0.865	1.047**	1.048***	1.593***	0.460
	(0.655)	(0.589)	(0.464)	(0.315)	(0.506)	(0.333)
Week relegation decided	−5.910	−8.087**	3.784	−3.878	−11.124***	−1.865
	(4.097)	(3.611)	(5.175)	(4.642)	(3.813)	(2.618)

TABLE 2 (Continued)

	Dependent variable					
	Google Trends Web					
	(1) ENG	(2) FRA	(3) DEU	(4) ESP	(5) ITA	(6) All
Relegation decided	−9.502	−30.791***	−19.684***	−9.495	−15.806***	−15.498**
	(5.622)	(5.705)	(5.192)	(5.547)	(3.563)	(3.693)
Google Trends Policy 2016	8.020***	9.506***	−1.320	7.277***	2.652***	4.626*
	(1.059)	(2.006)	(0.965)	(1.117)	(0.823)	(1.832)
Google Trends Policy 2022	−2.617**	−10.020***	−8.274***	1.174	4.956***	−3.059
	(1.237)	(1.160)	(0.812)	(1.073)	(0.951)	(2.547)
Observations	992	992	992	992	992	4960
R^2	.789	.779	.762	.837	.821	.721
Adjusted R^2	.781	.770	.753	.831	.814	.718
Residual std. error	10.493 (df = 952)	11.037 (df = 952)	12.131 (df = 952)	9.748 (df = 952)	10.074 (df = 952)	12.480 (df = 4916)

Note: Fixed effects are included for seasons, and standard errors are clustered at the seasonal level.
**p* < .1, ***p* < .05, ****p* < .01.

Our variables of interest are thus the dummy for the week that the champion is determined, and the dummy for the subsequent weeks. In the final column of Table 2 the week the champion is determined, search volume is eight points higher, while in subsequent weeks it is four points lower. This is the effect we would anticipate from the UOH, namely that once the news regarding the champion's identity has been processed, there is significantly less interest in the competition. Across the leagues this negative effect once the champion is known varies in magnitude and significance, but it is always negative and of an economically meaningful magnitude. These magnitudes are slightly larger for Google trends news from Table 3, where in the week the champion is decided there is 11 points more news searching, but in the following weeks four points less, than the usual amount of news searching.

The variable constructed to explain the anticipation clear in the black line in Figure 4 is the inverse of the number of wins required for the leading team to become champion. The rationale is that in many countries, the media narrative as a team is ahead in the championship relates to the number of wins that are required for that team to be mathematically certain to win the championship (i.e., such that no other team can amass enough points to go ahead of them). We calculate for each week how many wins away the leading side is in each competition, and then take the inverse. This is so that as that number of wins decreases and the team is closer to securing the championship, the measure increases. Once the team has secured enough wins, the number of wins is reset to 34 or 38, depending on how many matches a team has to play per season, since whoever will win the next championship immediately becomes that many wins away once the current championship has been decided.

This variable is positive for three of the five leagues, the Premier League, Bundesliga and Serie A, but also in the pooled model, suggesting an increasing impact on search volume as a team gets close to the championship, which in turn suggests that there is increasing interest as the time when the suspense on the sport outcome is resolved gets closer. It is, however, generally insignificant, suggesting that other variables are able to explain much of the variation in search activity. We can see from the red line in Figure 4 that taken together these variable have the desired effect of reducing the magnitude of the pre-champion-decided weeks. As such, our model says that once the UO has been removed from the championship, that search volumes for the league do fall, and hence that, taken alone, the early determination of the champion is bad for the interest in a competition, as would be predicted by the UOH. It is worth noting that this effect ranges from about a quarter to a half of the positive impact of the season being ongoing, and hence suggests that the size of the impact of the removal of uncertainty is substantial. As noted in Section 2, stadium attendances have commonly been used to evaluate the impact of the UOH; we can apply our method to stadium attendances, despite their widely documented drawbacks for such analyses. In Figure A3 in page 24, we plot an equivalent event-study plot as in

TABLE 3 Regression results with Google Trends News (number of searches in Google News) as the dependent variable.

	Dependent variable					
	Google Trends News					
	(1) ENG	(2) FRA	(3) DEU	(4) ESP	(5) ITA	(6) All
Season ongoing	−10.369	8.910	18.896**	23.086**	−15.151**	13.815*
	(9.732)	(11.980)	(6.915)	(9.708)	(5.713)	(5.931)
Hiring window	7.120***	6.490***	3.405***	2.284**	6.938***	5.272**
	(0.915)	(1.461)	(1.090)	(0.819)	(0.894)	(1.281)
Total matches in week	2.310***	2.548***	3.157***	2.438***	2.601***	2.587***
	(0.109)	(0.260)	(0.295)	(0.138)	(0.276)	(0.190)
Position mean	−0.401**	−0.066	−1.217***	−0.575**	−0.354	−0.461*
	(0.162)	(0.225)	(0.251)	(0.206)	(0.281)	(0.168)
Idealized standard deviation (detrended)	10.500	−15.759**	10.197	11.177**	−11.853*	0.948
	(7.379)	(7.328)	(8.529)	(4.833)	(6.703)	(4.915)
Week before season starts	33.125***	28.742***	39.233***	19.976***	21.337***	28.627***
	(3.528)	(5.100)	(5.948)	(3.876)	(4.817)	(4.430)
Week season starts	19.736***	17.316***	12.107***	15.546***	17.026***	15.810***
	(3.862)	(4.890)	(3.894)	(3.424)	(4.104)	(2.201)
Week after season ends	6.228***	6.790**	13.057***	4.731***	6.767**	7.447***
	(1.411)	(3.116)	(4.196)	(1.444)	(2.371)	(1.359)
Second week after season ends	4.853**	9.257**	7.293*	1.896	4.142*	5.283**
	(1.828)	(3.222)	(3.924)	(1.931)	(1.998)	(1.295)
Wins needed by leader to be champion (inverse)	2.905	−5.327	−1.295	−6.710**	−1.296	0.891
	(4.182)	(3.374)	(3.562)	(2.711)	(1.710)	(2.596)
No. teams can be champion	0.750***	0.199	−0.319	−0.188	0.362	−0.136
	(0.232)	(0.180)	(0.215)	(0.243)	(0.385)	(0.290)
Week champion decided	8.820	8.645	−0.349	−0.524	3.283	11.116**
	(6.198)	(7.202)	(5.682)	(6.116)	(5.393)	(3.535)
Champion decided	−11.583	−6.859	−3.199	−30.504***	−5.336	−3.883
	(7.433)	(7.886)	(5.869)	(8.673)	(4.695)	(6.513)
No. teams can qualify Champ. Lge	0.257	−0.360	−0.227	−0.623	0.810**	−0.169
	(0.480)	(0.617)	(0.516)	(0.522)	(0.346)	(0.252)
Week Champions League decided	−4.322	−3.506	7.262	6.743	4.869	2.603
	(6.041)	(4.201)	(7.315)	(5.710)	(5.229)	(2.323)
Champions League decided	−4.802	1.363	−1.921	14.060	7.232	4.357
	(10.524)	(6.946)	(8.230)	(8.391)	(7.056)	(2.577)
No. teams can be relegated	2.218***	1.270	0.576	0.360	2.032***	0.245
	(0.684)	(0.956)	(0.502)	(0.694)	(0.552)	(0.499)
Week relegation decided	2.210	−1.019	16.685*	0.900	−18.873***	2.928
	(5.224)	(6.160)	(8.316)	(7.543)	(3.681)	(4.103)

TABLE 3 (Continued)

	Dependent variable					
	Google Trends News					
	(1) ENG	(2) FRA	(3) DEU	(4) ESP	(5) ITA	(6) All
Relegation decided	−3.835	−21.335***	−4.025	−7.377	−22.210***	−11.269**
	(7.417)	(6.364)	(7.108)	(6.837)	(4.732)	(3.622)
Google Trends Policy 2016	−2.412	−6.235***	−3.379*	2.830	−2.710*	−2.531
	(1.560)	(1.905)	(1.866)	(1.727)	(1.496)	(1.780)
Google Trends Policy 2022	−3.716	−12.246***	−4.946***	−0.941	8.442***	−1.864
	(2.440)	(2.195)	(1.624)	(1.659)	(1.807)	(2.687)
Observations	783	783	783	783	783	3915
R^2	.708	.642	.692	.752	.736	.596
Adjusted R^2	.694	.625	.678	.740	.724	.592
Residual std. error	11.704 (df = 747)	13.505 (df = 747)	13.214 (df = 747)	11.320 (df = 747)	11.532 (df = 747)	14.253 (df = 3875)

Note: Fixed effects are included for seasons, and standard errors are clustered at the seasonal level.

*$p < .1$, **$p < .05$, ***$p < .01$.

Figure 4, but instead using weekly average stadium attendances. The removal of uncertainty associated with the league winner can be seen to reduce average attendances as well as Google search volumes.

Considering the various control variables added in to identify the impact of the champion, from the final column of Table 2 we see that the season being on adds substantially to search interest; Italy is the only exception but that small negative coefficient is insignificant, with the remainder being 12 points or larger. The hiring window, where teams in a competition can recruit players, increases search activity by about three points, and each match in a competition in a given week increases search by about three points.

While our main focus in this paper is on the end-of-season removal of uncertainty, we also include a mesaure of CB measured each week throughout the season, to see whether search activity and hence interest is related to how competitive a league is. The coefficients on the ratio of AISD are generally positive although insignificant. This is perhaps contrary to what might be anticipated based on the UOH, as it suggests that a greater spread of points amongst teams in the league given the stage of the season results in greater interest. Finally, in terms of control variables, the week that the season starts sees an increase in search activity (six or more points), and the preceding week shows a much larger increase in anticipatory searching (between 20 and 30 points), while the week after the season ends also shows a significant increase in search activity of up to three points, perhaps as fans look forward to the next season.

It is to be noted that the championship is not the only prize at stake, or outcome of significant interest, in any of these five competitions. As such, we include variables for the week that all the Champions League teams are known for the following season (plus subsequent weeks), and when all the teams to be relegated are known. On average, this occurs around a week before the season is completed. In the case of the Champions League positions, there is a small positive impact, while for relegation, once this is fully determined the effect is small (around two points), negative, and generally insignificant statistically. This could be explained potentially by fans of these teams now searching on Google for a *different* league; the effect, though, is insignificant. The weeks after the Champions League positions are confirmed see a negative impact on search volumes only in England and Italy, while for relegation the effect is generally quite large and significant, around 10 points. It may also reflect that this is often known in the last week of the season, and hence it shares the general impact of the season being over of lower search interest. This negative impact of relegation need not be an argument against its presence in European football; more broadly, Noll (2002) note that promotion and relegation has a positive impact on remuneration in leagues, as well as on attendances, and Speer (2022) note that promotions are more valuable, and their effects more persistent, than relegations, again providing suggestive evidence in favor of the system. In the case of the Champions League, the few subsequent weeks before the season ends have a positive increment to search activity in Spain, France and Germany, and this could be rationalized by the idea that

Champions League qualification is forward looking, with fans speculating on how will these teams will fare next season when they enter European competition.

These results emphasize the value of a diversified competition structure like these football leagues have. The champion may be known 3 weeks before the season ends, but one of the later weeks will see the Champions League positions determined, and relegation, both of which affect search activity and hence interest, for the competitions.

6 | CONCLUSIONS

In this paper we utilize a hitherto unused source of information for evaluating the UOH. We use web searches via Google for the five top football leagues globally, a measure that avoids the capacity constraints of stadium ticket demand, and represents interested observers from around the world. To examine the extent to which certainty on the league winner may diminish the interest of fans on European Football leagues, our empirical analysis relies on *Google Trends* records. For the sake of robustness, we use as dependent variables two measures: *Google Trends News* (GTN) and *Google Trends Web* (GTW). In line with the results reached by Garcia-del-Barrio and Reade (2022), we hypothesize that the degree of attention that fans pay to sport events will diminish once the Championship winner team is known.

We ask whether the removal of all uncertainty surrounding the league winner in advance of the competition concluding reduces search volume, as would be predicted by the UOH. We find that across the five competitions, this removal of interest is at least half of the size of the impact on search of the season being ongoing—as such, the impact is non-trivial. However, that effect is mitigated by the presence of multiple outcomes of interest in these competitions, namely, the potential for qualification into European competitions for the following season, and the risk of relegation out of the competition. We find that, in particular, European qualification and the battle against relegation drive significant search interest and thus indicates the value of such a diversified structure of outcomes in elite footballing competitions in Europe.

ACKNOWLEDGMENTS

We are grateful to Nicolás Becerra for supporting us to collect the data. Helpful comments on earlier versions of the paper are acknowledged to Carl Singleton and to participants at the XI ESEA European Conference on Sport Economics (August 2019. Gijón, Spain). We also thank the editor, associate editor, data editor, and anonymous referees for their contributions to improving this paper. Any remaining errors are our own.

DATA AVAILABILITY STATEMENT

Data openly available in a public repository that issues data sets with DOIs: The data that support the findings of this study are openly available in Garcia-del-Barrio and Reade (2025): and in openICPSR at https://doi.org/10.3886/E201302V7.

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ENDNOTES

[1] See for example, the Deloitte Annual Review of Football Finance 2022, www2.deloitte.com/uk/en/pages/sports-business-group/articles/annual-review-of-football-finance.html.

[2] According to Garcia-del-Barrio and Medina (2022), European football has an increasing capacity to attract the interest of fans, as reflected by the intensity with which Internet users search for the most popular sport disciplines worldwide.

[3] In mid-2023, Twitter rebranded itself as X.

[4] Earlier papers proved that the data obtained from this source is helpful to anticipate customer tendencies (Choi & Varian, 2012; Vosen & Schmidt, 2011).

[5] At the time of writing Google had recently expanded this to allow users to look at searches for videos, shopping and other subcategories. We restrict our attention to general web searches and news searches as these have always been offered on Google Trends.

[6] Or, indeed, only one season and one league to acheive the maximum. In addition, when searching for the whole Google Trends search data for 2004 to the present date, it only allows a download of monthly data, which is too aggregated a time frequency for our purposes.

[7] Depending on the time period requested on the Google Trends website, a different frequency of data will be presented. When looking over many years, monthly frequencies will be presented, when looking over a year, weekly frequencies, and over shorter intervals like a month,

a daily frequency will be reported. When looking at a particular day, the data is provided at 8-min intervals. It may be that the weekly frequency discards relevant information, not least given that the champion in a competition will become known on a particular day (or indeed a particular time on a particular day). At the same time, however, such a high frequency will also introduce significant noise. We relegate consideration of the advantages and disadvantages of different time frequencies for future research.

[8] The difference between the downloaded search frequencies for two different datasets collected at different times on the same day (September 21, 2023). The mean of the differences are zero, and across all five leagues, 73% of the downloaded weekly search frequencies are identical between downloads, and 98% of frequencies are within four points of each other.

[9] A small number of leagues, usually in very northern parts of Europe, play only in the summer.

[10] There is a subtle point worth raising here, namely that at the beginning of the week that the champion becomes known, it is not known that the champion will become known that week. As our dependent variable is the number of searches in a week, some proportion of searches in that week will be before the champion is known, and some afterward. This is another reason for splitting out the impact on search volume in that week the champion becomes known, and the impact in the following weeks.

[11] Note that the Google News data has fewer observations as this information is only available back to 2008 (14 years, 5 leagues, 52 weeks = 3640 observations), whereas Google search data is available back to 2004 (18 years, 5 leagues, 52 weeks = 4680 observations).

[12] There is a range of different measures of competitive balane, and each has its advantages and disadvantages (see e.g., Depken, 1999; Owen et al., 2007; Lee et al., 2019; Owen & King, 2015). We choose the ratio of actual to idealized standard deviation not out of any particular preference, or belief regarding its superiority.

[13] See Figure A2 on page 23 for how the AISD looks for all seasons in Italy, both in its raw form, and detrended. Our detrending method is to regress each league-season's AISD on a constant and time trend, and then use the residuals from that regression.

[14] The points system awards three points to the team that wins a match, and one to each side in case of a drawn, or tied, outcome.

[15] For some competitions, namely the German Bundesliga and French Ligue 1, the bottom two are automatically relegated and the third bottom team enters a play-off with a team from the division below. We take this into account in our regressions; in seasons when any such system is in place, there are only two relegation places and calculations are made based on that.

[16] All top European leagues operate as double round robins, but have no play-off system to determine the overall winner; instead, the team that finishes at the top of the table is the champion. Hence the identity of this champion can be known in advance of all games being completed. In our dataset, it happens on average 3 weeks before the season has completed.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Garcia-del-Barrio, P. & Reade, J.J. (2025) The impact of uncertainty on fan interest surrounding multiple outcomes in open European football leagues. *Economic Inquiry*, 1–20. Available from: https://doi.org/10.1111/ecin.70024

APPENDIX A: GOOGLE TRENDS

A.1 | Figures

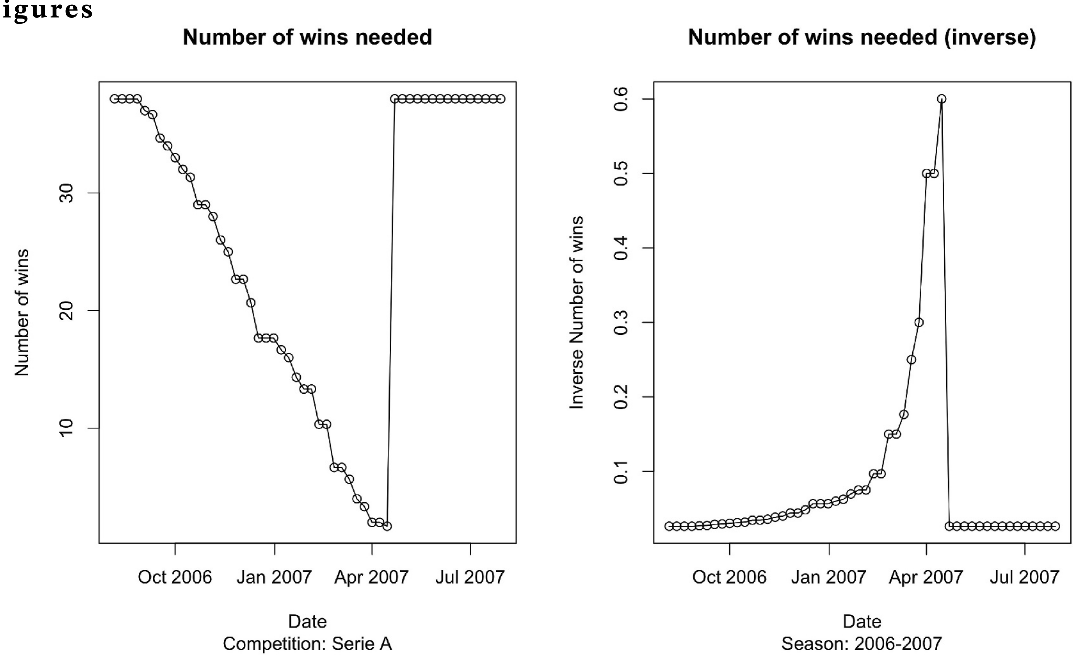

FIGURE A1 Plots illustrating the measure of the inverse number of wins required by a team to become champion. The particular season in question in the plots is the Serie A season from 2006/2007.

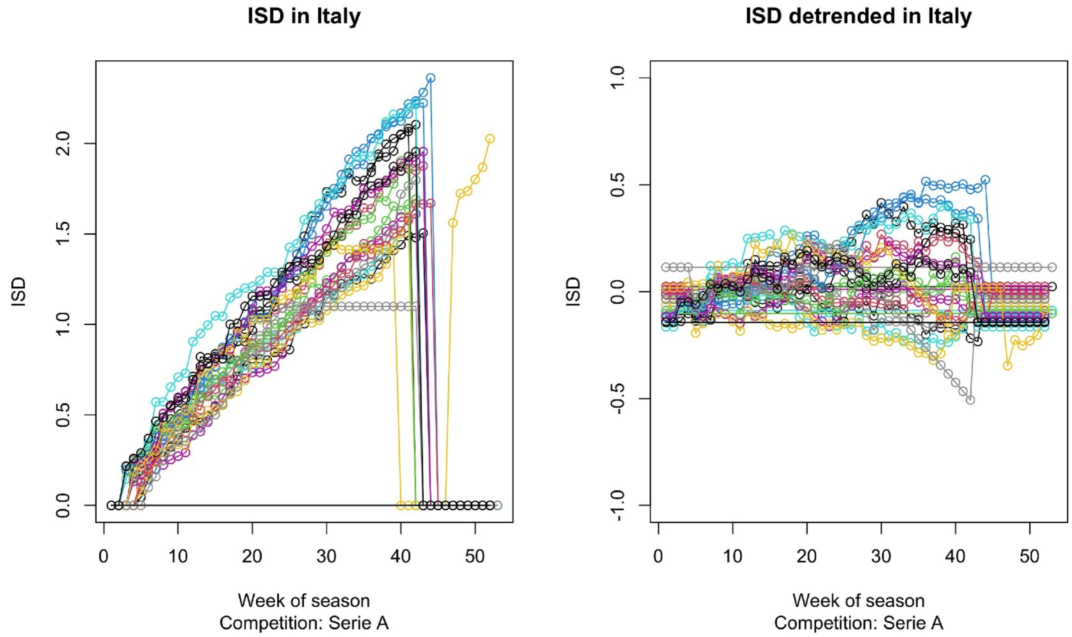

FIGURE A2 Plots illustrating the Idealized Standard Deviation (ISD) measure (left) and its detrended variant (right hand plot). Each line is from a Serie A season between 2004/2005 and 2021/2022.

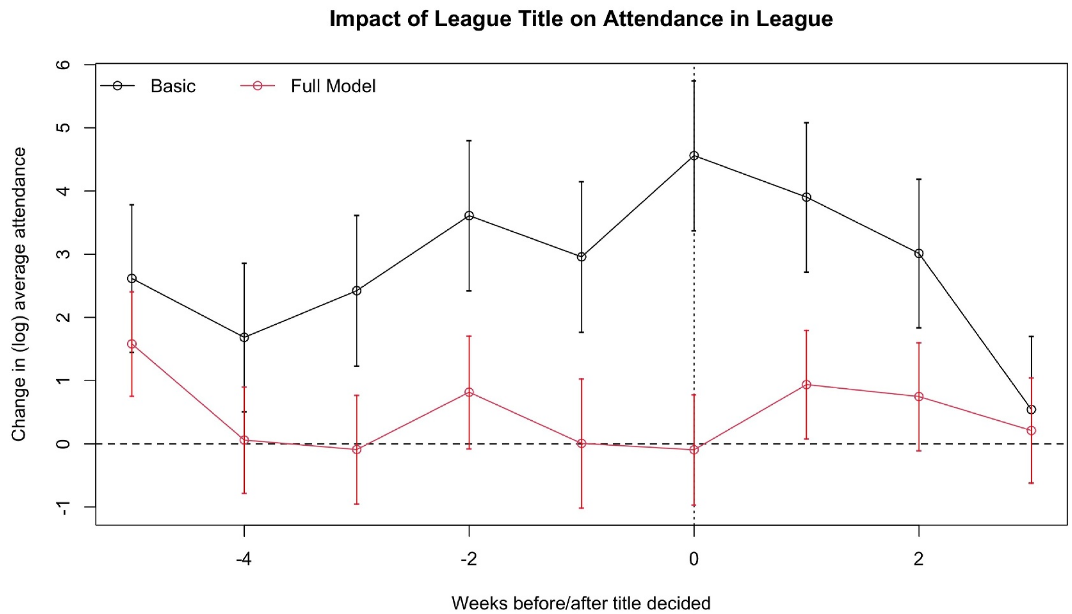

FIGURE A3 The change in stadium attendances around the point that the winner of a football league championship is known.

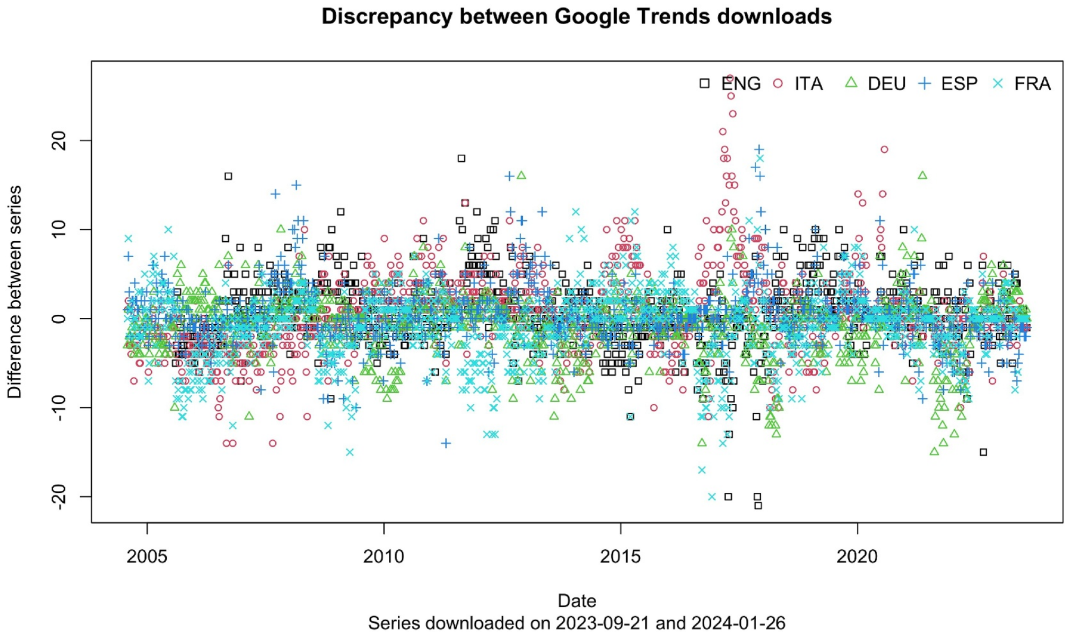

FIGURE A4 The difference between the downloaded search frequencies for two different datasets collected at different times on the same day (September 21, 2023). The mean of the differences are zero, and across all five leagues, 73% of the downloaded weekly search frequencies are identical between downloads, and 98% of frequencies are within four points of each other.

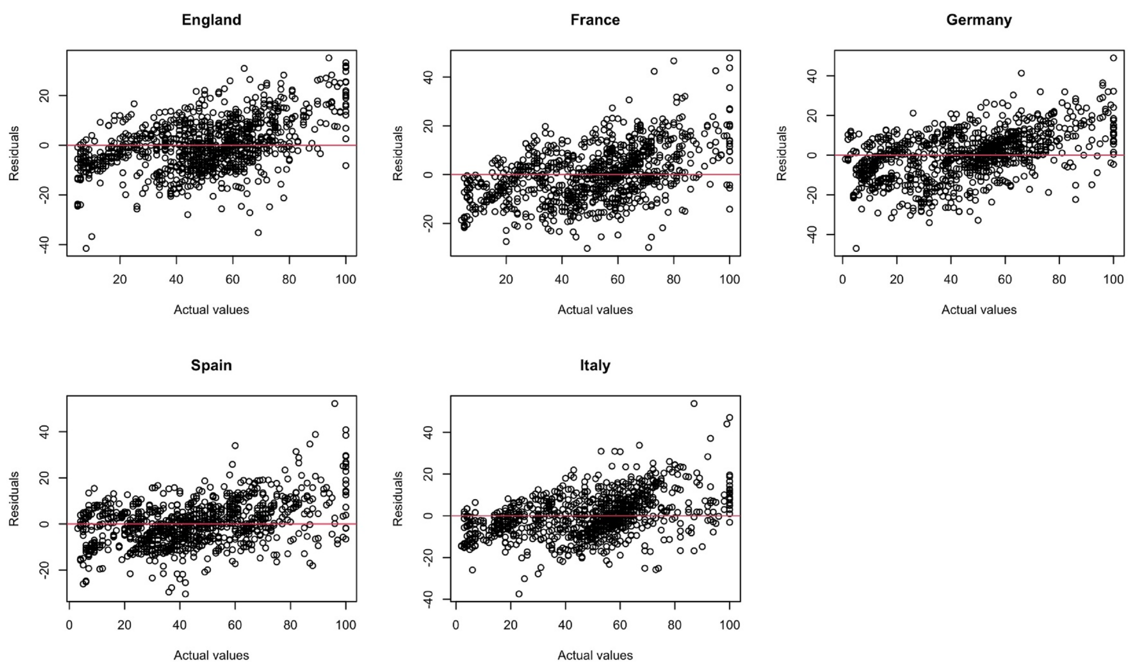

FIGURE A5 Plots of model residuals against actual values for all five country regressions.