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Emotional Cues and the Demand for Televised Sports: Evidence from the UEFA Champions League

Travis Richardson[1], **Georgios Nalbantis**[1], **and Tim Pawlowski**[1]

Abstract

This study provides first evidence on how belief dynamics are driving entertainment utility and consequently the demand for sports *across* markets by analyzing minute-by-minute audience data of UEFA Champions League (UCL) games televised in the UK and the Spanish market during a full (pre-COVID) cycle of broadcasting rights. Overall, we find that *suspense* and *surprise* are the main drivers of demand in both markets while *shock* only has marginal effects in the Spanish market. Interestingly, we find a combined impact of *suspense* and *surprise* in the UK market that is of similar magnitude as reported in a previous study for English Premier League matches in the UK. In the Spanish market, however, the combined impact is considerably larger.

Keywords

suspense, surprise, shock, emotional cue, TV demand, UEFA Champions League
JEL Classification Codes: C23, D12, L82, L83, Z20

[1] Faculty of Economics and Social Sciences, Institute of Sports Science, University of Tübingen, Tübingen, Germany

Corresponding Author:
Travis Richardson, Faculty of Economics and Social Sciences, Institute of Sports Science, University of Tübingen, Wilhelmstraße 124, 72074 Tübingen, Germany.
Email: travis-william.richardson@uni-tuebingen.de

Introduction

The preference to understand and be aware of future events is seen as an influential motivator for survival (Bromberg-Martin & Hikosaka, 2009). Yet, in the realm of music, film, books, and sports, where information is non-vital, consumers seem to prefer disruptions to their expectations (Gold et al., 2019). In their seminal work, Ely et al. (2015) developed a comprehensive theoretical model on the demand for such non-instrumental information by focusing on entertainment utility from *suspense* and *surprise*.

Suspense is an ex-ante emotion; it is the feeling of anxious uncertainty and is experienced when the consumer is forward looking as to what could happen next. As such, *suspense* is greater when the upcoming events have a greater significance on the overall outcome. *Suspense* is most appropriately described as the juxtaposition of hope and fear (Madrigal et al., 2022). For instance, *suspense* can be experienced during the moments leading up to a penalty kick that would win the match, i.e., the hope to see a game-winning goal and the fear of a miss.[1] This is in distinction to *surprise*, which is an ex-post emotion that is present when an event occurs suddenly or unexpectedly and causes a shift in what the consumer previously thought the outcome would be. Ely et al. (2015) define a period to be more surprising when the current belief is further from the last period's belief, i.e., if the current events are vastly different from the previous events, the period is more surprising. For instance, *surprise* can be generated in a soccer match when a team opens the score against all odds.

Quite recently, Buraimo et al. (2020) have introduced a further entertainment utility factor: *shock*. *Shock* is similar to *surprise*. However, while the reference point for *surprise* is the (average) expectation over the outcome in the *minute before*, the reference point for *shock* is the (average) expectation over the outcome prior to *kick-off.* As such, *shock* is experienced when the current outcome probabilities are drastically different from those considered *prior* to the start of the match; For instance, when a heavily favored team is facing a high probability of losing to the pre-match underdog.

Despite the managerial relevance for broadcasters, sponsors, leagues, and clubs, empirical evidence on whether entertainment seeking sport consumers prefer *suspense*, *surprise* and/or *shock* elements in sports competitions is sparse. In a first application of these concepts to sports, Bizzozero et al. (2016) utilized minute-by-minute television audience data from international men's tennis matches played in Wimbledon (UK) broadcast in Switzerland on free-to-air networks. Overall, they find that both *surprise* and *suspense* are important drivers of demand. *Surprise*, however, tends to be more important than *suspense*. In a second application, Buraimo et al. (2020) modeled minute-by-minute television audience data from the English Premier League broadcast in UK on pay-TV networks. Similar to Bizzozero et al. (2016) they found that both *surprise* and *suspense* matter for viewership. However, in contrast to Bizzozero et al. (2016), the authors report a proportionally smaller combined impact of both cues. Simonov et al. (2023) focus on eSports and analyze streaming viewers of the game Counter-Strike: Global Offense (CS:GO). The authors find evidence that *suspense* is a significant indicator for viewership. On the contrary, however, *surprise* has little to no effect on streaming viewers' preference.[2] Similarly, Kaplan (2021), suggests that heightened *suspense* leads to a considerably higher viewership of a National Basketball Association (NBA) game; however, this is only found to have significant impact on viewership when the skill of the performers on the court is lower.

We contribute to this literature by implementing the seminal framework of Ely et al. (2015) in their construction and understanding of *suspense* and *surprise*. Following that framework, we replicate and extend its applications by Bizzozero et al. (2016) and Buraimo et al. (2020). Next to the growing consensus regarding the importance of replication studies in economics and business research (see Hamermesh, 2017; Krumer et al., 2022), we offer insights on a particularly relevant and surprisingly understudied supranational competition, i.e., the UEFA Champions League (UCL).[3] Moreover, we explore two different markets at the same time, i.e., UK and Spain, and thus deliver some first evidence on the salience of emotional cues across markets. By analyzing minute-by-minute audience data of all UCL games televised in the UK and the Spanish market during a full (pre-COVID) cycle of broadcasting rights, we find that *suspense* and *surprise* are the main drivers of demand in both markets while *shock* only has marginal effects in the Spanish market. Interestingly, we find a combined impact of *suspense* and *surprise* in the UK market that is of similar magnitude as previously reported for English Premier League matches in the UK (see Buraimo et al., 2020). In the Spanish market, however, the combined impact is larger and closely resembles that reported for international tennis matches in Wimbledon (see Bizzozero et al., 2016).

Data and Measures

UEFA Champions League

We first begin with a brief description of our setting. The UCL, second only to the FIFA World Cup in worldwide football importance, is the most prestigious club football event in the world. Although the name might say otherwise, the UCL is not a league, rather, a pan-European tournament. This yearly, pre-eminent tournament was first held in the 1955–1956 season and has been played every year since. Its global audience, at about 1.7 billion viewers across all matches of a season, makes the UCL the second most viewed yearly sporting competition, only behind the Tour de France (Shazi, 2018). The Lisbon Final between Real Madrid and Atlético Madrid saw 380 million people tune from over 200 different countries around the globe (Ashby, 2014).

Since 1992, 32 teams qualify for the tournament and are drawn into eight groups of four. The number of qualifying teams varies by country/domestic league. For example, in England and Spain the teams finishing top four in their respective domestic leagues are allowed to join the tournament the following year. While smaller countries, like Croatia or Cyprus, are only allotted one team in the qualification rounds of the tournament. Teams are divided into four pots based on their UEFA club coefficient ranking. Pot 1 consists of the highest-ranked teams, while Pot 4 consists of the lowest-ranked teams. The draw begins with Pot 1, with the eight teams drawn one at a time and placed into groups A to H. Once all teams in Pot 1 have been placed, the draw proceeds to Pot 2, and so on until all four pots have been emptied. Note that restrictions are placed to ensure clubs from the same nation are not drawn into the same group. The winners and runners-up from each of the eight groups then qualify for the round of 16 – which initiates the two-legged knock-out phases for the round of 16, quarter-finals, and semi-final. The final is a single match in a neutral, pre-selected location, with the winner ultimately becoming the UCL champion of the year. Between 1997/98 and 2017/18, the finals have only consisted of clubs from England, Spain, Germany, or Italy (with the exception of the season 2003/04 where AS Monaco [France] and FC Porto [Portugal] met in the Final).

Television Viewership

The viewership data was kindly provided by the Union of European Football Associations (UEFA) and contains a total of 296 (172) UCL games televised in the UK (Spanish) market during four seasons, i.e., from 2014/15 to 2017/18. During this period, Spain and the UK (specifically, England) were among the most relevant markets both with regard to the UEFA association club coefficients as well as to the overall distribution of the UCL's market pool money (see Table A1 in Appendix A). To purge the data from any inconsistencies that might have been caused by the shift of broadcasting rights between 2014/2015 and 2015/2016, we focus in our main estimations on seasons 2015/2016–2017/2018.[4] This period corresponds to a full (pre-COVID) UCL broadcasting rights cycle, leaving us with a total of 180 (131) UCL games televised in the UK (Spanish) market.[5]

For both markets we use aggregate minute-by-minute viewership, due to instances of games being televised by two or more channels (e.g., on regional and national channels in Spain, see Table A3 in Appendix A). To obtain a balanced panel, we drop all observations that go beyond the regular time, thus we are left with 90 min-by-minute observations per game. Table 1 provides an overview of the televised games by season, stage, and market. On average (excluding extra time), between seasons 2015/2016 and 2017/2018 UCL telecasts in the UK attracted around 0.560 million viewers per minute, while in Spain the telecasts had an average minute-by-minute audience of around 2.607 million viewers. This difference in the audience figures may be partly explained by the fact that during the period of study UCL telecasts were available only on paid TV in the UK, whilst in Spain games were televised either on free-to-air channels or on paid TV with the share of free-to-air games being around 34% (see Table 2).[6]

Moreover, Spanish teams were more successful than UK teams in the competition during our observation window. Table 3 shows, by year and round, each team from the UK and Spain that competed in the UCL KO stages.

Table 1. Overview of UEFA Champions League Telecasts by Season, Stage, and Market.

United Kingdom										
	2014/15		2015/16		2016/17		2017/18		Total	
Stage	N	Av. Aud.	N	Av. Aud.	N	Av. Aud.	N	Av. Aud.	N	Av. Aud.
Group	87	0.463	27	0.478	33	0.359	36	0.379	183	0.430
Round of 16	16 (8)	1.454 (1.567)	15 (8)	0.505 (0.522)	16	0.444 (0.447)	15 (8)	0.690 (0.669)	62 (32)	0.779 (0.801)
Quarter-finals	8 (4)	1.023 (1.059)	8 (4)	0.522 (0.496)	7 (3)	0.618 (0.678)	8 (4)	0.760 (0.759)	31 (15)	0.734 (0.753)
Semi-finals	4 (2)	2.735 (2.800)	4 (2)	1.105 (1.111)	4	0.621 (0.688)	4 (2)	1.582 (1.594)	16 (8)	1.511 (1.548)
Final	1	6.367	1	2.323	1	2.891	1	4.369	4	3.987
Total	116	0.768	55	0.571	61	0.470	64	0.637	296	0.641
Spain										
	2014/15		2015/16		2016/17		2017/18		Total	
Stage	N	Av. Aud.	N	Av. Aud.	N	Av. Aud.	N	Av. Aud.	N	Av. Aud.
Group	18	2.188	6	5.858	30	1.501	30	1.183	84	1.918
Round of 16	12 (6)	2.245 (2.154)	4 (2)	5.885 (5.568)	16 (8)	1.911 (1.903)	15 (8)	1.967 (1.648)	47 (24)	2.352 (2.186)
Quarter-finals	6 (3)	3.113 (3.559)	2 (1)	9.579 (10.010)	7 (3)	2.697 (2.763)	8 (4)	2.283 (2.340)	23 (11)	3.26 (3.490)
Semi-finals	4 (2)	4.952 (5.154)	2 (1)	8.742 (8.659)	4 (2)	4.342 (5.211)	4 (2)	4.121 (3.167)	14 (7)	5.082 (5.103)
Final	1	8.654	1	10.040	1	9.247	1	8.861	4	9.291
Total	41	2.767	15	7.049	58	2.089	58	1.976	172	2.645

Notes: In each UCL season (from group stage onwards) a total of 125 UCL games are staged. Numbers indicate the televised games in each market. In parenthesis are displayed the number of first leg games in the corresponding knock-out stage. Season 2014/15 is eliminated from our main estimations due to the shift of broadcasting rights. AV. Aud. is average audience in that round (in millions), while in parenthesis is the average audience figures for first leg games.

Emotional Cues

For modeling the effects of emotional cues on audience size, the exact timing of significant match events such as the beginning and ending of the first and second half, goals scored or red cards received is needed. This exact time stamp information was acquired through the British sports analytics firm, Opta/Stats Perform, allowing for the nontrivial task of synchronizing the audience dataset with the football dataset to be compatible and accurate with the expressed times and events during the games.

To define *suspense* and *surprise*, we closely follow the work of Ely et al. (2015) and shadow Buraimo et al. (2020) for the additional definition of *shock*. While *surprise* is about what just happened in the match and how outcome probabilities changed from minute t-1 to minute t, *shock* refers to the difference between outcome probabilities in minute t and the pre-match outcome probabilities $t = 0$. Accordingly, p_t refers to the match's final outcome probabilities at minute t and H, D, and A identify a home win, draw, and away win, respectively. As such, we define *surprise* and *shock* as:

$$Surprise_t = \sqrt{(p_t^H - p_{t-1}^H)^2 + (p_t^D - p_{t-1}^D)^2 + (p_t^A - p_{t-1}^A)^2} \quad (1)$$

$$Shock_t = \sqrt{(p_t^H - p_0^H)^2 + (p_t^D - p_0^D)^2 + (p_t^A - p_0^A)^2} \quad (2)$$

Since *suspense* is a forward-looking emotion, additional measures are required. The changes in outcome probability are now hypothetical, in which they refer to what would happen if a team were to score a goal in the following minute. Further, the changes in probability must be weighted by the complementary probabilities of either team scoring so that *suspense* is subject to the significance and the likelihood of an event actually occurring. Due to this, we introduce p_{t+1}^{HS} and p_{t+1}^{AS} to specify the respective probabilities of either the home team or away team scoring in the next minute from t. As such, we define *suspense* as:

$$Suspense_t = \sqrt{\sum_{i \in H,\, D,\, A} p_{t+1}^{HS}[(p_{t+1}^i \mid p_{t+1}^{HS}) - p_t^i]^2 + p_{t+1}^{AS}[(p_{t+1}^i \mid p_{t+1}^{AS}) - p_t^i]^2} \quad (3)$$

Here, the terms $(p_{t+1}^i | p_{t+1}^{HS}) - p_t^i$ and $(p_{t+1}^i | p_{t+1}^{AS}) - p_t^i$ are the hypothetical change in outcome probabilities from minute t to $t + 1$ if either team, home or away, were to score in the next minute.

In order to calculate *suspense*, *surprise* and *shock*, in-play outcome probabilities are required. Since available in-play betting odds might suffer from behavioral biases (see, for instance, Angelini et al., 2022), we mimic the approach proposed by Buraimo et al. (2020) and use in-play outcome probabilities calculated with the following model. Assuming independent Poisson distributions for goals scored by the

Table 2. Number of Games Shown on Television by Broadcaster.

			2015/16			2016/17			2017/18			Total		
	Operator	Type	GRP	KO	All	GRP	KO	All	GRP	KO	All	GRP	KO	All
UK	BT Group													
	BT	PAY	27	28	55	33	28	61	36	28	64	96	84	180
Spain	Atresmedia													
	Antena 3	FTA	6	9	15	6	9	15	6	8	14	18	26	44
	LaSexta	FTA	0	0	0	0	0	0	0	1	1	0	1	1
	Radiotelevisión Española													
	Teledeporte	FTA	0	0	0	0	0	0	0	0	0	0	0	0
	Televisió de Catalunya													
	TV3	FTV	6	9	15	6	9	15	5	9	14	17	27	44
	Esport3	FTV	0	0	0	0	0	0	1	0	1	1	0	1
	beIN Media Group & Mediapro													
	beIN	PAY	0	0	0	24	20	44	24	20	44	48	40	88

Notes: In the Spanish market 88 games were televised on pay TV. Since Atresmedia and Televisio de Catalunya televised the same games, the total number of games televised on free TV is 45. Note that two games were available on both pay and free TV. As such, the Spanish data cover overall 131 different games [88 (pay TV) + 45 (free TV) - 2 (overlapping)]. BT includes the channels: BT Sport 1-3, BT Sport ESPN, BT Sport Europe, BT Sport Showcase. beIN includes the channels: beIN Max 1, beIN Max 2, beIN Sports. GRP: Group stage games. KO: Games of knock-out stages and final. PAY: pay-TV platform. FTA: free-to-air; FTV: free-to-view, only available in certain regions of the country.

Table 3. UK and Spanish Teams' Participation in the Knock-Out Stages During the Study Period.

Stage	2015/16		2016/17		2017/18		Total	
	UK	Spain	UK	Spain	UK	Spain	UK	Spain
Round of 16	Arsenal Chelsea Manchester City	Atlético Madrid Barcelona Real Madrid	Leicester City Manchester City	Atlético Madrid Barcelona Real Madrid Sevilla	Chelsea Liverpool Manchester City Manchester United Tottenham Hotspur	Sevilla Real Madrid Barcelona	10	10
Quarter-finals	Manchester City	Atlético Madrid Barcelona Real Madrid	Leicester City	Atlético Madrid Barcelona Real Madrid	Liverpool Manchester City	Barcelona Real Madrid Sevilla	4	9
Semi-finals	Manchester City	Atlético Madrid Real Madrid	.	Atlético Madrid Real Madrid	Liverpool	Real Madrid	2	5
Final	.	Atlético Madrid Real Madrid	.	Real Madrid	Liverpool	Real Madrid	1	4

Notes: Typically, Spanish and English teams have four teams in the group stage. There is, however, an additional berth for UEFA Europa League title holders. In the estimation period, besides for the Round of 16, Spanish teams were more successful in the UCL than English teams, i.e., 42% of Round of 16 teams were from either the UK or Spain. However, in the quarter-finals, UK teams made up 17% of all teams, while Spain consisted of 38% of all teams. Moreover, the semi-finals in this period consisted of 17% UK teams and 31% Spanish teams. Likewise, the teams competing in the finals consisted of 17% English teams and 67% Spanish teams.

home team (X) and the away team (Y), i.e.,

$$X \sim \text{Poisson}\,(\lambda_H), \qquad Y \sim \text{Poisson}\,(\lambda_A) \tag{4}$$

we can estimate the two scoring rates λ_H and λ_A by minimizing the squared difference between the outcome probabilities o_i and m_i, i.e.,

$$\sum_{i \in H,\, D,\, A} (o_i - m_i)^2 \tag{5}$$

using an optimization function in Python. In this regard, H, D, and A refer to the possible outcomes of a home win, a draw, or an away win respectively. Moreover, while o_i are the bookmaker implicit outcome probabilities based on pre-match closing odds on the three outcomes as well as over-under totals,[7] m_i are outcome probabilities calculated from our Poisson model by simply summing the different scoreline probabilities for a given match.

After the scoring rates for each team have been estimated, the next step is to distribute these across the minutes of the match. A rudimentary way to achieve this would be to assume uniform distribution so that each minute was equal to λ/90. However, scoring rates are not evenly distributed throughout a match; for instance, more goals typically occur in the latter moments of a match rather than the opening minutes. To execute a more accurate method, we split the scoring rates in proportion to the empirical distribution of goals per minute, as suggested by Buraimo et al. (2020). The empirical goal distribution for the UCL between the tournament years of 1998/99 and 2020/21 can be seen in Figure 1. It is important to note that goals occurring in stoppage time of their respective half are included in the goal tally for the 45th and the 90th minutes, partially explaining the higher goal totals in those minutes. We use this approach in order to keep all games at exactly 90-min length. As such, any goal occurring in extra-time (i.e., when a knock-out match is tied after the original 90 min) was not included in the goal total.

Using these scoring rates per minute, we simulate the number of goals being scored in each minute of a specific match, then total the score and record the final result. This match-level simulation was repeated 100,000 times per minute, leading to 9 million simulations per match. In other words, each individual match of 90 min was simulated 100,000 times leading to 100,000 "matches" being played.

These simulations are also used to evaluate the probabilities of a home win, a draw, and an away win for calculating *suspense* by using "what if" scenarios: "*What are the probabilities of a home win, draw, or away win if the home team scored in the next minute? What are the probabilities of a home win, draw, or away win if the away team scored in the next minute?*". Red cards are accounted for by following the methods of Vecer et al. (2009) – if a team received a red card, their goal scoring rate, for the rest of the game, was diminished to 2/3 of the original, while the opposition's scoring rate was multiplied by 1.2.

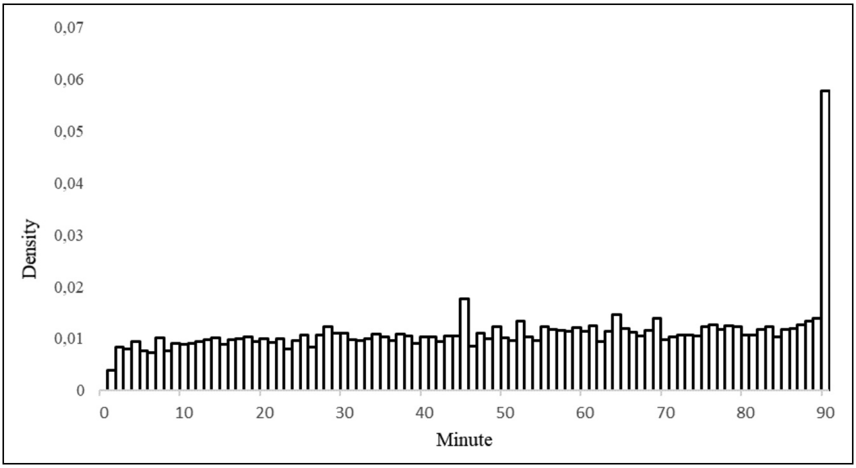

Figure 1. Empirical goal distribution in the UCL between 1998/99 and 2020/21.
Notes: Minute averages are based on all UCL games (n = 2,957) played between 1998/99 and 2020/21. In those games, 8,207 goals were scored. Historical goals data stemmed from fbref.com.

Example Games

For a better grasp and understanding of the data, we illustrate the evolution or our key measures during the course of an "exciting" match (Figure 2) and a kind of "routine" match (Figure 3) that were both televised in the UK and Spanish market. The criteria used to select the example games were as follows: First, the respective game needed to be broadcast in both the UK and Spanish market. Second, the respective game needed to follow the timeline of "routine" or "exciting" (based on the authors' footballing opinion). Third, the respective game needed to be a group stage game to prevent any additional audience views caused by match relevance.

In the first example (Figure 2), a match played between Chelsea vs Roma (played on October 18, 2017) was selected as example of an "exciting" match due to the many goals (six in total) and the back-and-forth nature of the match (2-0; 2-3; 3-3). Chelsea (61% winning probability according to closing odds) opened the scoring with two early goals. *Suspense* remained at low levels due to the initial one-sided win probability for Chelsea. However, Roma managed to take the lead in the second half causing an increase in *suspense*. When Chelsea equalized shortly after, *suspense* in the game reached high levels nearing the final whistle - as a goal for either team would be decisive. Toward the latter minutes of the match when *surprise* and *shock* both saw increased yields due to major shifts in game events, both the UK and Spanish viewing audience follow suite and increase until the final moments.

The second example match (Figure 3) between Manchester City and Borussia Monchengladbach (played on September 14, 2016) was selected as an example of "routine" match. Manchester City (69% winning probability according to closing

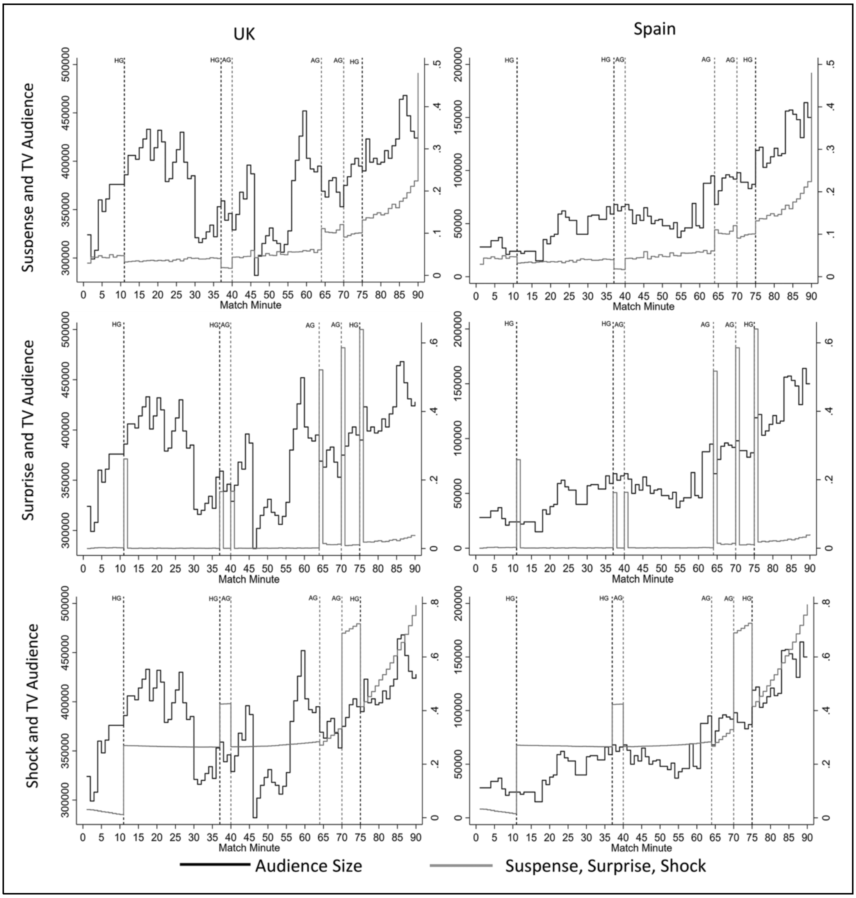

Figure 2. Audience size and emotional cues in an "exciting" match (Chelsea vs Roma, October 18, 2017).

Notes: Indicators HG and AG specify the minute of a home goal or away goal, respectively. The audience data was provided by the UEFA. Data on the exact timings of relevant game events and game halves stemmed from Opta / Stats Perform. Pre-match betting odds data used to estimate suspense, surprise and shock stemmed from oddsportal.com.

odds) routinely produced a 4-0 win, scoring twice in each half. For both *suspense* and *surprise*, the generated yields decreased after each goal was scored and practically disappeared after goal three and as full-time approached. Comparatively speaking, the *shock* levels were still low compared to our "exciting" example, however *shock*, rose until the very end, as the pre-match expectation of such a drastically one-side game was lower than the actual outcome. Interestingly, after halftime the UK viewership gradually decreased, while Spanish viewers were variable throughout the entire match with multiple spikes of audience interest.

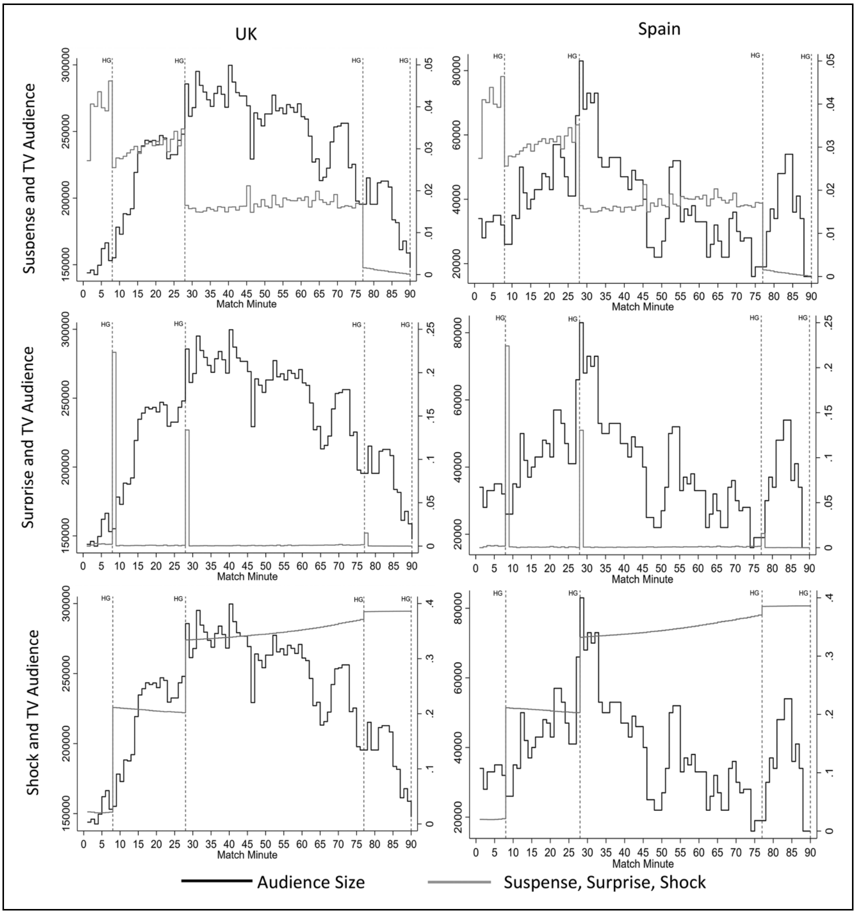

Figure 3. Audience size and emotional cues in a "routine" match (Manchester City vs Borussia Monchengladbach, September 14, 2016).

Notes: Indicators HG and AG specify the minute of a home goal or away goal, respectively. The audience data was provided by the UEFA. Data on the exact timings of relevant game events and game halves stemmed from Opta / Stats Perform. Pre-match betting odds data used to estimate suspense, surprise and shock stemmed from oddsportal.com.

Model Specification

In our main specification, we regress audience size of game *i* in minute *t* on all three emotional cue variables of game *i* in minute *t* as well as lagged audience size, a series of minute-of-match dummies and match fixed-effects. In this regard, we include minute-of-match dummies to account for common temporal patterns, such as the decreased viewership right after halftime due to the viewers switching back to the game after ignoring the halftime show or commercials. Match fixed-effects account for all factors identifying individual matches, including the quality and appeal of teams, the relevance of the game, the location of the match, and the television station. Finally, lagged audience size proxies the inertia when viewing live football on television due to the assumption that our forecasts of audience figures depend on the events occurring in the same game.

In order to avoid spurious correlations, we need to check whether our audience measure is I(1) or stationary. We test this using the full sample as well as different subsamples (e.g., all minute-by-minute observations vs first half only and second half only). Overall, Im–Pesaran–Shin Unit Root tests (2003) strongly reject the null hypothesis that all panels contain unit roots. Moreover, Maddala and Wu (1999) Panel Unit Root tests also strongly reject the null that the series is I(1). Since these "first generation" tests are frequently criticized for assuming cross-sectional independence, we further implemented the Pesaran (2007) Panel Unit Root test which relaxes this assumption. Again, non-stationarity is strongly rejected.

For estimating the model, we must consider the distribution of our dependent variable is right-skewed and includes zero observations.[8] As such, we opt for the Pseudo-Poisson Maximum Likelihood estimator (see Silva & Tenreyro, 2006) which is robust to any distribution (Wooldridge, 2010). Moreover, controlling for lagged audience – which is important in order to avoid any omitted variable bias (see Bizzozero et al., 2016; Buraimo et al., 2020) – might cause problems. While residual autocorrelation may cause a downward bias in models including a lagged dependent variable (Keele & Kelly, 2006), the inclusion of both fixed effects and a lagged dependent variable may raise concerns with regard to Nickell bias (Nickell, 1981). Since, however, the time dimension of our panel is comparably large ($T = 90$ min), we argue that the bias (if any) is small (see Baltagi, 2008; Nickell, 1981).[9]

Findings

In our analysis we focus on two main panels. Panel A contains just group stage games. Panel B contains all group stage games (i.e., Panel A) plus all first leg games of the knock-out stage and the Final match. We do not consider second leg games since emotional cues are expected to be triggered by the probability of qualifying to the next stage rather than the actual outcome of the individual game. Table 4 displays the descriptive statistics for the UK (Spanish) market of the overall 96 (66) matches in Panel A and 140 (100) matches in Panel B.[10]

Table 5 displays our main results. Overall, our findings suggest that particularly *suspense* and *surprise* are driving the demand for UCL games in both markets. *Shock*, however, has a marginal impact on the demand for UCL games in both markets being statistically significant just for the Spanish one (Panel B).[11] Importantly, when estimating all models excluding *shock* the coefficients of *surprise* and *suspense* hardly change (see Table A7 in Appendix A). As such, we conclude, like Buraimo et al. (2020), that *shock* does not absorb any effects of *surprise* or *suspense* and appears to be an additional – though in our setting less relevant – cue.[12]

In order to explore potential effect heterogeneity, we repeat our analysis using different specifications. To start with, we interact the variables of interest with stage of the competition, i.e., group stage or knock-out stages (see Table 6). Overall, our findings suggest that *suspense* and *surprise* seem to matter more for group stages than knock-out games in both markets while only the UK audience seems to value *shock* more when watching group stage games.

We further explore effect heterogeneity with regard to the halves of the match (see Table 7). In line with Bizzozero et al. (2016) we find audience, in both markets, to have a preference for *suspense* particularly in the second half. Interestingly, however, in the Spanish Panel B the interaction effect between first half and *suspense* is negative and statically significant. Additional subsample estimations suggest that this negative effect is primarily driven by knockout games televised on free-to-air channels (see Table A8 in Appendix A). Concerning *surprise,* in UK it seems that this cue is only a precise predictor of demand in the second half. In Spain, however, no differences arise with regard to the impact of *surprise* in both halves.

Finally, we return to the concept of uncertainty of outcome that dominated the empirical research during the last decades (see, for instance, Nalbantis & Pawlowski, 2019; Pawlowski et al., 2018), and estimate our main specification with additional variables directly measuring uncertainty of outcome. Theoretically, uncertainty of outcome as well as *suspense*, *surprise*, and *shock* are closely connected. While *suspense* is increasing with increasing uncertainty of outcome, both *surprise* and *shock* are increasing with decreasing (lagged) uncertainty of outcome. Moreover, an event with high levels of uncertainty will cater to the *suspense* that pleases TV viewers. This is due to *suspense* existing along a continuum in which the audience is aware of the endpoint that will produce an outcome; for each minute that occurs, that potential outcome becomes closer making the audience feel more *suspense* (Madrigal et al., 2023). Madrigal et al. (2023), also, find that uncertainty of outcome only creates *suspense* to the extent that there is an established and known endpoint.[13]

We measure outcome uncertainty by taking the absolute difference between the home and away win probability at minute t and further consider the probability to draw (e.g., Alavy et al., 2010). Moreover, we control for the number of goals at minute t as well as the goal difference between the contestants at minute t (e.g., Buraimo et al., 2020). Overall, while the effects of all three cues partly reduce, controlling for these measures does not change our main findings about *suspense* and *surprise*. Interestingly, however, *shock* becomes even significant for some specifications (see Table 8).[14]

Overall, our models support the notion that *suspense*, *surprise*, and *shock* are viable factors with respect to UCL football television audience demand. But are they also economically significant? For answering this question, we quantify the impact of the emotional cues based on our main results in Table 5 (Panel A). For

Table 4. Descriptive Statistics.

	UK								Spain							
	Panel A (N = 96 games)				Panel B (N = 140 games)				Panel A (N = 66 games)				Panel B (N = 100 games)			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Suspense	0.058	0.048	0	0.521	0.058	0.046	0	0.521	0.055	0.046	0	0.521	0.056	0.045	0	0.521
Surprise	0.015	0.074	0	1.168	0.015	0.073	0	1.170	0.013	0.068	0	1.166	0.014	0.069	0	1.166
Shock	0.295	0.227	0	1.116	0.306	0.243	0	1.116	0.255	0.211	0.001	1.060	0.282	0.236	0	1.060
Audience	0.399	0.254	0	1.648	0.535	0.572	0	4.901	1.844	2.462	0	8.715	2.429	3.065	0	12.100

Notes: Panel A consists of group stage games. Panel B consists of group stage games and first leg games of the round of 16, quarter-finals, semi-finals as well as the finals. UK: United Kingdom; ESP: Spain. *Audience* is in millions. See Appendix A Table A4 for descriptive statistics of the UK and Spain markets including the 2014/15 season.

Table 5. Main Results.

	UK		ESP	
	Panel A	Panel B	Panel A	Panel B
$Audience_{t-1}$	1.215***	0.313**	0.067***	0.053***
	(0.142)	(0.122)	(0.014)	(0.011)
Suspense	0.294***	0.481***	0.613***	0.378***
	(0.096)	(0.076)	(0.116)	(0.114)
Surprise	0.023***	0.021**	0.020*	0.023***
	(0.009)	(0.008)	(0.011)	(0.006)
Shock	0.030	0.035	0.029	0.040*
	(0.019)	(0.023)	(0.026)	(0.021)
Observations	8,448	12,320	5,808	8,800
Number of game IDs	96	140	66	100
Log Pseudolikelihood	−4,850.58	−7,600.21	−4,816.79	−8,259.28

Notes: All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6. Effect Heterogeneity: Group Stage Games vs Knock-Out Games.

	UK	ESP
	Panel B	Panel B
$Audience_{t-1}$	0.361***	0.055***
	(0.133)	(0.01)
Suspense × Group Stage	0.510***	0.593***
	(0.098)	(0.111)
Suspense × Knock-out	0.296***	0.154
	(0.092)	(0.158)
Surprise × Group Stage	0.028**	0.023**
	(0.011)	(0.011)
Surprise × Knock-out	0.008	0.016*
	(0.011)	(0.008)
Shock × Group Stage	0.074***	0.029
	(0.022)	(0.027)
Shock × Knock-out	−0.019	0.032
	(0.035)	(0.033)
Observations	12,320	8,800
Number of game IDs	140	100
Log Pseudolikelihood	−7,599.87	−8,258.61

Notes: All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7. Effect Heterogeneity: First vs Second Half.

	UK		ESP	
	Panel A	Panel B	Panel A	Panel B
Audience_{t-1}	1.208***	0.308**	0.062***	0.048***
	(0.142)	(0.123)	(0.015)	(0.011)
Suspense × 1st half	−0.096	−0.115	−0.074	−0.585***
	(0.279)	(0.321)	(0.273)	(0.192)
Suspense × 2nd half	0.286***	0.469***	0.613***	0.365***
	(0.095)	(0.074)	(0.117)	(0.115)
Surprise × 1st half	0.017	0.011	0.022	0.024*
	(0.019)	(0.017)	(0.017)	(0.012)
Surprise × 2nd half	0.024***	0.024***	0.018	0.021***
	(0.009)	(0.009)	(0.013)	(0.008)
Shock × 1st half	0.024	0.008	0.009	0.012
	(0.029)	(0.032)	(0.034)	(0.025)
Shock × 2nd half	0.015	0.024	0.007	0.01
	(0.027)	(0.028)	(0.028)	(0.023)
Observations	8,448	12,320	5,808	8,800
Number of game IDs	96	140	66	100
Log Pseudolikelihood	−4,850.56	−7,600.15	−4,816.57	−8,258.65

Notes: All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the UK market, an increase of one standard deviation in *suspense* (*surprise*) [*shock*] is predicted to increase audience by 1.4% (0.2%) [0.7%]. In the Spanish market, an increase of one standard deviation in *suspense* (*surprise*) [*shock*] would increase audience size by 2.9% (0.1%) [0.6%]. For both markets, the effects of *suspense* are larger compared to Wimbledon tennis (which was estimated at about 1.2%, see Bizzozero et al., 2016) while the effect of *surprise* is considerably lower (which was estimated at about 2.5%, see Bizzozero et al., 2016). If we take into account the joint effect of *surprise* and *suspense*, our estimates for the Spanish market are close to that reported for Wimbledon tennis. For the UK market, however, the joint effect is similar to that reported for the English Premier League (about 1.2%, see Buraimo et al., 2020).

To better apprehend the economic importance of the emotional cues, we also quantify the impact of *suspense*, *surprise*, and *shock* (based on UK Panel A coefficients, see Table 5) with the help of hypothetical (yet arguably realistic) scenarios. We start the simulations by considering two main scenarios (see Table 9). In scenario A, we closely follow Buraimo et al. (2020) and predict the audience of a group game where both contestants are fairly equally matched, yet the home team has a slight home advantage (outcome probabilities: 38% home win; 25% draw; 37% away

Table 8. Controlling for Game Uncertainty and Current State of Game.

	UK				ESP			
	Panel A		Panel B		Panel A		Panel B	
Audience$_{t-1}$	1.217***	1.210***	0.322***	0.316***	0.066***	0.057***	0.053***	0.047***
	(0.142)	(0.145)	(0.119)	(0.118)	(0.014)	(0.014)	(0.011)	(0.012)
Suspense	0.303***	0.250***	0.501***	0.353***	0.527***	0.299**	0.373***	0.222**
	(0.095)	(0.088)	(0.101)	(0.096)	(0.146)	(0.123)	(0.123)	(0.111)
Surprise	0.023***	0.022**	0.022***	0.021**	0.018	0.014	0.024***	0.016*
	(0.009)	(0.01)	(0.008)	(0.009)	(0.012)	(0.013)	(0.007)	(0.009)
Shock	0.035*	0.045*	0.065**	0.097***	0.026	0.038	0.043**	0.072***
	(0.02)	(0.025)	(0.031)	(0.033)	(0.03)	(0.029)	(0.022)	(0.027)
Abs(hwin-awin)	−0.014	−0.02	−0.059**	−0.071***	0.018	−0.012	−0.006	−0.031
	(0.025)	(0.024)	(0.027)	(0.027)	(0.039)	(0.032)	(0.029)	(0.026)
Draw prob	−0.021	−0.036	−0.081	−0.122**	0.055	−0.016	−0.005	−0.063
	(0.049)	(0.049)	(0.053)	(0.057)	(0.075)	(0.068)	(0.064)	(0.063)
Total goals		0.002		0.002		0.004		0.011
		(0.005)		(0.005)		(0.009)		(0.007)
Goal difference		−0.006		−0.017**		−0.023***		−0.023***
		(0.008)		(0.008)		(0.008)		(0.007)
Observations	8,448	8,448	12,320	12,320	5,808	5,808	8,800	8,800
Number of game IDs	96	96	140	140	66	66	100	100
Log Pseudolikelihood	−4,850.57	−7,600.13	−4,850.57	−7,599.99	−4,816.76	−8,259.28	−4,815.78	−8,258.11

Notes: All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

win). Both teams have a scoring probability of 1.8 and the game starts with 500,000 viewers. We simulate this game with two different outcomes, i.e., the game ends in a goalless tie (A1) and both teams score a total of six goals and end up in a tie (A2). In A2, the home team scores in the 20th, 40th and 60th minute. The away team comes back after each home goal, scoring in the 30th, 50th and 70th minute. In scenario B, we consider a group game where the home team is a strong favorite (outcome probabilities: 80% home win; 13% draw; 7% away win). The home team has a score probability of 2.9 and the away team has a score probability of 0.8. As before, we simulate this game with two different outcomes and a starting audience of 500,000 viewers. In subscenario B1, it is a one-side game with the favorite scoring six times, on the 10th, 20th, 30th, 40th, 60th and 70th minute. In subscenario B2, the away team wins against all odds scoring twice in the 20th and 70th minute. Figure 4 provides the predicted audience based on the aforementioned scenarios.

First, both A1 and A2 are characterized by similar levels of *suspense*, yet A2 is characterized by higher amounts of *surprise* and *shock* around the time of goals. Figure 4 provides the predicted audience for these subscenarios. In the first 20 min both games have exactly the same viewership. After the first goal and up to the 70th minute, the A2 game attracts on average higher viewership than the A1 game. Comparing both subscenarios for the full game, the A2 game attracts extra 611,000 viewer-minutes in comparison to the A1 game. This equates to roughly an extra 6,865 viewers per minute.

Second, the B2 game is characterized by higher amounts of *suspense*, *surprise* and *shock* than the B1 game. In the first 20 min both games have exactly the same viewership. When the underdog scores, the B2 game starts to attract higher viewership

Table 9. Description of the Hypothetical Game Scenarios.

	Score probabilities		Pre-match outcome probabilities					
	Home	Away	Home	Draw	Away	Result	Min. of home [away] goals	Type of game
Scenario A								
A1	1.8	1.8	0.38	0.25	0.37	0-0		Evenly matched teams, no goals
A2	1.8	1.8	0.38	0.25	0.37	3-3	20, [30], 40, [50], 60, [70]	Evenly matched teams, many goals
Scenario B								
B1	2.9	0.8	0.80	0.13	0.07	6-0	10, 20, 30, 40, 60, 70	One-side game for the favorite
B2	2.9	0.8	0.80	0.13	0.07	0-2	[20], [70]	Underdog win

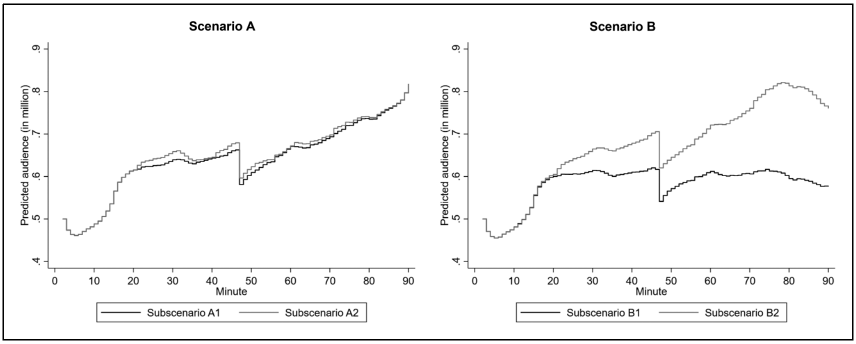

Figure 4. Predicted audience (in millions) based on four hypothetical group stage games.
Notes: For a description of the (sub)scenarios see Table 9. All games start with 500,000 viewers. The predictions are based on the coefficients of the UK Panel A model (Table 5).

than the B1 game with the difference between both becoming substantially higher in the second half of the game. Comparing both subscenarios for the full game, the B2 game attracts extra 7.969 million viewer-minutes in comparison to the B1 game. This equates to roughly an extra 89,540 viewers per minute.

Finally, comparing scenarios A and B, both games A1 and A2 attract larger audiences than game B1, that is extra 5.185 and 5.796 million viewer-minutes respectively.[15] However, game B2 has higher aggregate viewership than games A1 and A2, attracting extra 2.784 and 2.173 million viewer-minutes respectively. These simulations are suggestive that games between equally matched teams attract higher viewership than games in which the favorite win. At the same time, however, games where the underdog wins the match generate even higher audience levels. This is in line with notion that fans seem to have a preference for upsets which is frequently reported in the literature examining the impact of outcome uncertainty on viewership using aggregated audience data (Humphreys & Pérez, 2019) or survey data (Pawlowski et al., 2018). This result is also in line with Antony et al. (2021) who modeled belief-consistent against belief-inconsistent scenarios. The authors concluded that belief-inconsistent results of a game that contradicted the pre-match belief were better predictors of subjective event boundaries (or what the subject *thought* would happen).

Conclusion

We implemented the seminal framework of Ely et al. (2015) by replicating and extending its applications by Bizzozero et al. (2016) and Buraimo et al. (2020). In particular, we explored for the first time whether and how belief dynamics during the course of the *same* events are driving entertainment utility and, consequently, the demand for televised sports in *different* markets.

Overall, we find that *suspense* and *surprise* are statistically and economically significant drivers of demand for UCL matches in both the UK and Spanish market. These effects are not absorbed when controlling for traditional uncertainty of outcome measures. Moreover, our findings suggest that *suspense* and *surprise* matter more for group stage (rather than knock-out-stage) matche*s* as well as in the second (rather than the first) half of a match.

Interestingly, we find the combined effects of *suspense* and *surprise* in UK to be fairly similar to those reported for the English Premier League (see Buraimo et al., 2020), while in the Spanish market the combined effects are fairly similar to those reported for Wimbledon tennis (Bizzozero et al., 2016). Buraimo et al. (2020) argued that any differences in effect sizes between their study and the study by Bizzozero et al. (2016) may be attributed to the fact that Wimbledon matches were shown on free-to-air television, while Premier League games are only accessible on pay-TV platforms. At first sight, our findings could be considered as suggestive evidence that this argument may hold. However, our sample size prohibits running sub-sample estimations focusing *just* on free-to-air games in the Spanish market to further support this argument. As such, we are cautious with any such conclusions.

Moreover, differences regarding the salience of emotional cues in the two markets could be also ascribed to distinct social/cultural contexts. For instance, Liddell and Williams (2019) find that response to emotional cues (or "emotional regulation strategies", in their words) may depend on various contextual factors, including cultural differences. As such, future research focusing on cross-cultural differences could deliver some meaningful insights in this regard.

A further highly relevant line of future research is exploring effect heterogeneity with regard to fandom. Even though Madrigal et al. (2023) find that enjoyment differences are independent of "favorable" outcomes (see also Hall, 2015), behavioral responses to emotional cues could differ across the different types of viewers. Initially, we thought about exploring this in our setting by simply comparing the effects for UCL games involving (or not) domestic teams. Doing so, however, is problematic already from a theoretical perspective, since viewing figures probably consist of fans of a team hoping for a favorable outcome as well as "haters" that tune in to watch hoping for a poor outcome for a rival team. As such, individual level data is required. Such data would also allow delving into how emotional cues are related to a viewer's tuning and switching behavior as well as their attention level (see Liu et al., 2020).

Overall, these results offer some implications for broadcasters, advertisers/sponsors, and league organizers/governing bodies.

In this regard, our findings could inform advertisers and sponsors on the proper timing of ads placement and sponsor messages during live sports content. More precisely, our findings suggest that advertisers and sponsors may benefit from increased visibility due to higher viewership after surprising moments (e.g., a goal of an underdog), when an upset seems very likely to happen, or when a game is very suspenseful. At first glance, this implication seems to be in line with the consumer psychology literature. For instance, Bee and Madrigal (2012) find that fans react more favorably to ads shown after suspenseful games. Since, however, viewers are less attentive to sponsor messages in suspenseful situations (Breuer et al., 2020), the overall effectiveness of placing an ad or sponsor message when a game is suspenseful remains unclear.

Our findings also suggest that broadcasters should not be afraid to show a game with a clear favorite as long as there is still a chance for an upset to happen. Although it is difficult to predict which games may result in an upset, it may be possible to stimulate fan engagement by promoting one-sided games in a way that invokes a "David and Goliath" narrative.

Finally, wins of underdogs are rare in football and depend – amongst others – also on referee decisions. Hereto, there is an abundance of empirical findings showing that referees tend to favor the favorite team (e.g., Erikstad & Johansen, 2020; Lago-Peñas & Gómez-López, 2016). Such implicit biases can pose a barrier to the prospect of upsets. Consequently, any endeavors aimed at mitigating such bias could potentially yield a positive impact on viewership. Numerous leagues including the UCL have introduced video-assistant-referee systems to promote impartial and accurate decision making with notable success (see Holder et al., 2022). Increasing the level of impartiality even further and standardizing referee decision-making by revising rules that are open to subjective interpretation (e.g., stoppage time estimation) could be a step in the right direction.

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Authors' Note

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ORCID iDs

Travis Richardson https://orcid.org/0000-0003-2988-7672
Georgios Nalbantis https://orcid.org/0000-0003-3748-9295
Tim Pawlowski https://orcid.org/0000-0001-5829-963X

Notes

1. To expand upon Ely et al. (2015), Li et al. (2021) empirically test the power to this *suspense* reward theory by designing a task-based casino game to experimentally induce *suspense* and to test if greater *suspense* (higher reward) motivates playing the game more. They find preliminary evidence that a more suspenseful experience enhances the patron's willingness to engage longer.
2. Next to these studies exploring the demand for sports *directly* there are some recent efforts in exploring behavioral responses to emotional cues from sports in other areas like Twitter activity (see Pawlowski et al., 2023) and alcohol use (see Fischer et al., 2023).
3. As of writing the paper, only two studies exist which have analyzed TV demand of UCL matches (Budzinski et al., 2022; Wills et al., 2022). However, both studies use match-level data and do not explore any effects of belief dynamics during the course of a match.
4. As a robustness check we run the main estimations using also the 2014/15 season (see Table A2 in Appendix A). Overall, our findings remain. *Surprise*, however, remains statistically significant just for the Spanish market.
5. In the UK, ITV broadcasting coverage of the UCL ended in 2015, because the broadcaster lost its 23-season agreement as the only provider. For the 2015/16 season, SKY became the UCL broadcaster, starting a new cycle of broadcasting rights in the country. Within the same timeframe, CanalTV+ lost their agreement to broadcast the tournament in Spain, with beIN Sport taking over as a sole provider. Note that for the 2015/16 season, Mediapro (operator of beIN) showed UCL games strictly on the agency's TotalChannel OTT platform. Indicating the lack of televised games in the data for the corresponding year. During this cycle, a total of 375 games were staged, of which 180 (131) games were televised in the UK (Spain).
6. Note that in the 2015/16 season, the average Spanish viewing audience was considerably larger when compared to other seasons in our dataset. This may rely on the fact that beIN showed exclusively most games on over-the-top (OTT) television while only a limited number of games were available on linear TV (and as such included in our data). Within the already limited number of games shown on linear TV, all but one game involved a Spanish team. Remarkably, in 2015/2016 three Spanish teams competed in the quarter-finals (see Table 3) with Barcelona being eliminated by Atlético Madrid in two tight games (aggregate score: 2–3), while similarly tight was also the final between Real Madrid and Atlético Madrid (1–1 draw at the end of extra time, 5–3 on penalties). This could potentially explain the high average television audience. As a robustness check for Spain, we run models excluding season 15/16 (due to the few game broadcasts and the extraordinarily large audiences). Our main findings largely remain. Results are available upon request.

7. Pre-match betting odds come from oddportal.com. We use average betting odds across multiple betting odds providers (up to ten different companies). All odds were transformed by taking the inverse of the betting odd to obtain implied probabilities. Over-round is removed by scaling the bookmaker implicit probabilities to one. Overall, these pre-match odds can be expected to reflect factors such as current form and match results, strength of the opposition, and other relevant factors that influence the outcome.
8. 0.45% (0.90%) of the game-minute observations in the UK Panel A (B) and 5.8% (4.3%) of the game-minute observations in the Spanish Panel A (B) contain zeros. Since games with zero audience at a given minute in our data are commonly games between relatively low-quality clubs, we posit that these zeros display "true" zero demand.
9. As a robustness check, we run models excluding lagged audience. Our main findings largely remain. Results available upon request.
10. In general, one could also think of exploring lagged effects in our setting. Theoretically, this seems relevant since, for instance, fans could watch their beloved team get scored on and angrily watch the replay and the next couple of minutes before switching off the TV. Econometrically, however, this raises concerns since the number of T would reduce substantially, thus eventually causing the Nickell bias as discussed before. As such, we refrain from exploring any lagged effects in our study.
11. As a robustness check we analyzed the data from UK and Spain all together (see Table A5 in Appendix A) and we further checked market specific heterogeneity with regard to the impact of emotional cues (see Table A6 in Appendix A). The results are in line with our original market specific models. There are no market specific differences concerning the impact of emotional cues for Panel A games. In Panel B games, however, *shock* seems to matter more in Spain.
12. Upon comparing the average cues reported by Buraimo et al. (2020; Table 1) for the EPL with those of our study (see Table 4), it appears that UCL group stage games exhibit on average lower cues. This is in line with the notion that – while featuring the best clubs in Europe – the level of predictability (in the UCL group stage) has increased over time (Schokkaert & Swinnen, 2014). However, given the data at hand it remains unclear whether this – or other issues such as design differences between both competitions – are driving the differences regarding the relevance of *shock* between both studies.
13. An attempt to test the interplay between uncertainty of outcome and the emotional cues is provided on Table A9 in Appendix A. As expected, we find that game uncertainty increases with increasing levels of *suspense*, while game uncertainty reduces with increasing levels of *shock*. While the sign for *surprise* is as expected (positive) suggesting that game uncertainty and *surprise* are negatively correlated, these estimates are not precise enough to be significant.
14. We further estimated models excluding the emotional cue variables (see Table A10 in Appendix A). Our findings suggest that only draw probability is statistically significant while the estimate for the absolute difference between home and away win probability at minute t still lacks in precision. These findings are suggestive of the cue measures "better" picking up the viewers' preferences for UCL matches.
15. Due to the fact that our simulations include lagged audience, to derive the additional viewers per minute from the additional viewer-minutes, we use 89 instead of 90 minutes. That is, our predictions start from minute two, as we need minute one audience to predict minute two audience.

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Author Biographies

Travis Richardson is a PhD student at the Research Group on Sport Economics, Sport Management and Media Research at the University of Tübingen, Germany. His research interests include sports consumer demand and sports consumer behavior.

Georgios Nalbantis is a Postdoctoral Researcher at the Research Group on Sport Economics, Sport Management and Media Research at the University of Tübingen, Germany. His research interests include the economics of league competitions as well as the econometric analysis of (international) sports demand.

Tim Pawlowski is a Professor and Head of the Research Group on Sport Economics, Sport Management and Media Research at the University of Tübingen, Germany. His empirical work follows three broader lines, i.e., 'leagues and competitions', 'society and public policy' and 'media and management'.

Appendix A

Table A1. Top 5 Market Pools, UEFA Association Club Coefficients and Number of Participating Clubs by Country.

	2014/15			2015/16			2016/17			2017/18		
	Market Pool	Rank	# Clubs	Market Pool	Rank	# Clubs	Market Pool	Rank	# Clubs	Market Pool	Rank	# Clubs
England	€ 93,560,000	2	4	€ 142,676,000	2	4	€ 138,214,000	3	4	€ 147,663,000	3	5
France	€ 68,052,000	6	2 (3)	€ 68,141,000	6	2 (3)	€ 75,195,000	6	3	€ 68,077,000	5	2 (3)
Germany	€ 65,600,000	3	4	€ 68,334,000	3	4	€ 65,986,000	2	4	€ 61,335,000	2	3 (4)
Italy	€ 93,518,000	4	2 (3)	€ 100,785,000	4	2 (3)	€ 99,954,000	4	2 (3)	€ 115,178,000	4	3
Spain	€ 83,756,000	1	4	€ 89,124,000	1	5	€ 79,461,000	1	4 (5)	€ 90,013,000	1	4

Notes: The market pool is the share of TV money each participating club receives based on how relevant their market is. Data comes from UEFA yearly reports on revenue distribution, provided on uefa.com. The association club coefficients are based on the results of each association's clubs in the five previous UEFA Champions League and UEFA Europa League seasons. We present the number of teams participating in the UCL group stage by country. In parenthesis is the total number of teams including the clubs eliminated in the UCL play-off round (i.e., the last qualification round before the UCL group stage). For season 2014/15, the market pool data as reported by UEFA do not consider teams that fail to qualify to the group stage via the play-off round.

Table A2. Estimations Including All Four Seasons.

	UK		ESP	
	Panel A	Panel B	Panel A	Panel B
Audience_{t-1}	0.113***	0.095***	0.073***	0.054***
	(0.029)	(0.018)	(0.011)	(0.008)
Suspense	0.623***	0.426***	0.603***	0.351***
	(0.144)	(0.097)	(0.102)	(0.096)
Surprise	0.014	0.022	0.030**	0.026***
	(0.022)	(0.014)	(0.012)	(0.006)
Shock	0.080***	0.083***	0.03	0.045**
	(0.029)	(0.021)	(0.023)	(0.018)
Observations	14,872	20,064	7,392	11,440
Number of game IDs	169	228	84	130
Log Pseudolikelihood	−7,137.22	−11,024.85	−6,357.56	−11,010.76

Notes: All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3. Number of Channels a Game is Televised Simultaneously.

	UK				Spain			
	Panel A		Panel B		Panel A		Panel B	
Channels	N	Share	N	Share	N	Share	N	Share
1	82	85.4%	118	84.3%	.	.	.	.
2	14	14.6%	33	15.7%	48	72.7%	67	67%
3	.	.	.	.	18	27.3%	31	31%
4	.	.	.	.	.	.	2	2%

Notes: Panel A consists of group stage games. Panel B consists of group stage games and first leg games of the round of 16, quarter-finals, semi-finals as well as the finals. UK: United Kingdom; ESP: Spain. *Channels* is the number of channels that a game is televised. *N* is the number of games that are shown on the respective number of channels.

Table A4. Descriptive Statistics Including Season 2014/15.

	UK								Spain							
	Panel A (N = 169 Games)				Panel B (N = 228 Games)				Panel A (N = 84 Games)				Panel B (N = 130 Games)			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Suspense	0.056	0.046	0.000	0.521	0.058	0.045	0.000	0.521	0.054	0.045	0.000	0.521	0.056	0.044	0.000	0.521
Surprise	0.014	0.074	0.000	1.185	0.015	0.073	0.000	1.170	0.013	0.065	0.000	1.166	0.013	0.066	0.000	1.166
Shock	0.298	0.232	0.000	1.116	0.307	0.243	0.000	1.116	0.254	0.213	0.000	1.060	0.278	0.233	0.000	1.060
Audience	0.466	0.834	0.000	5.985	0.631	1.072	0.000	7.233	1.918	2.496	0.000	8.715	2.499	3.101	0.000	12.100

Notes: Panel A consists of group stage games. Panel B consists of group stage games and first leg games of the round of 16, quarter-finals, semi-finals as well as the finals. UK: United Kingdom; ESP: Spain. *Audience* is in millions. The sample includes all four seasons, and excludes N = 14 games of season 2014/15 in UK that have zero audience across all 90 min.

Table A5. Regression Estimates – Combined UK and Spain Games.

	UK & Spain	
	Panel A	Panel B
Audience_{t-1}	0.077***	0.060***
	(0.080)	(0.007)
Suspense	0.600***	0.381***
	(0.089)	(0.086)
Surprise	0.023***	0.024***
	(0.009)	(0.005)
Shock	0.038*	0.041***
	(0.019)	(0.016)
Observations	14,256	21,120
Number of game IDs	162	240
Log Pseudolikelihood	−9,673.83	−15,863.44

Notes: All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6. Effect Heterogeneity – Combined UK and Spain Games.

	UK & Spain	
	Panel A	Panel B
Audience_{t-1}	0.077***	0.058***
	(0.010)	(0.009)
Suspense × UK	0.551***	0.408***
	(0.103)	(0.082)
Suspense × Spain	0.614***	0.382***
	(0.112)	(0.109)
Surprise × UK	0.032***	0.033***
	(0.012)	(0.009)
Surprise × Spain	0.020*	0.021***
	(0.011)	(0.007)
Shock × UK	0.040	0.023
	(0.029)	(0.023)
Shock × Spain	0.037	0.048**
	(0.027)	(0.021)
Observations	14,256	21,120
Number of game IDs	162	240
Log Pseudolikelihood	−9,673.84	−15,863.39

Notes: All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7. Regression Estimates – Excluding Shock.

	UK		ESP	
	Panel A	Panel B	Panel A	Panel B
$Audience_{t-1}$	1.224***	0.320**	0.069***	0.054***
	(0.142)	(0.120)	(0.014)	(0.011)
Suspense	0.307***	0.470***	0.627***	0.367***
	(0.096)	(0.074)	(0.120)	(0.115)
Surprise	0.025***	0.024***	0.020*	0.025***
	(0.009)	(0.007)	(0.011)	(0.017)
Observations	8,448	12,320	5,808	8,800
Number of game IDs	96	140	66	100
Log Pseudolikelihood	−4,850.59	−7,600.26	−4,816.85	−8,259.53

Notes: All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8. Effect Heterogeneity: First vs Second Half – Pay TV Audience.

	ESP	
	Panel A	Panel B
$Audience_{t-1}$	0.555***	0.303***
	(0.074)	(0.097)
Suspense × 1st half	−0.093	0.738
	(0.702)	(0.498)
Suspense × 2nd half	0.764***	0.676***
	(0.247)	(0.187)
Surprise × 1st half	0.050	0.016
	(0.046)	(0.030)
Surprise × 2nd half	−0.014	0.017
	(0.020)	(0.017)
Shock × 1st half	−0.022	−0.047
	(0.097)	(0.069)
Shock × 2nd half	−0.078	−0.005
	(0.058)	(0.062)
Observations	4,224	6,072
Number of game IDs	48	69
Log Pseudolikelihood	−2,043.29	−3,133.95

Notes: All models include game fixed effects and minute-of-game dummies. Dependent variable is audience of pay TV telecasts in Spain. Given the limited sample sizes with regard to free TV games we refrain from reporting free TV audience estimates. In parenthesis are displayed robust standard errors clustered at game level. ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9. Outcome Uncertainty Regressed on Emotional Cues.

	UK		ESP	
	Panel A	Panel B	Panel A	Panel B
Suspense	−5.295***	−5.179***	−5.497***	−5.267***
	(0.704)	(0.608)	(0.808)	(0.098)
Surprise	0.027	0.077	0.178	0.179*
	(0.103)	(0.083)	(0.126)	(0.098)
Shock	1.567***	1.747***	0.989***	1.450***
	(0.244)	(0.189)	(0.311)	(0.257)
Observations	8,640	12,600	5,940	9,000
Number of game IDs	96	140	66	100
Log Pseudolikelihood	−6,135.39	−8,811.05	−4,407.42	−6,489.21

Notes: Outcome variable: Absolute difference between the home and away win probability at minute *t.* All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A10. Regression Estimates on the Impact of Outcome Uncertainty – Excluding Emotional Cues.

	UK		ESP	
	Panel A	Panel B	Panel A	Panel B
Audience_{t-1}	1.246***	0.320***	0.071***	0.055***
	(0.141)	(0121)	(0.015)	(0.011)
Abs(hwin-awin)	0.027	0.016	0.067*	0.043
	(0.026)	(0.025)	(0.037)	(0.026)
Draw prob	0.089	0.113**	0.243***	0.135**
	(0.050)	(0.048)	(0.067)	(0.059)
Observations	8,448	12,320	5,808	8,800
Number of game IDs	96	140	66	100
Log Pseudolikelihood	−4,850.68	−7,600.63	−4,817.37	−8,260.09

Notes: All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.