Economic Inquiry

UNSCRIPTED DRAMA: SOCCER AUDIENCE RESPONSE TO SUSPENSE, SURPRISE, AND SHOCK

BABATUNDE BURAIMO, DAVID FORREST, IAN G. MCHALE and J.D. TENA

By modeling minute-by-minute television audience figures from English Premier League soccer matches, with close to 50,000 minute-observations, we show that demand is partly driven by suspense and surprise. We also identify an additional relevant factor of appeal to audiences, namely shock, which refers to the difference between pre-match and current game outcome probabilities. Suspense, surprise, and shock remain significant in the presence of a traditional measure of outcome uncertainty. (*JEL* C23, D12, L82, L83, Z20)

I. INTRODUCTION

The importance of suspense and surprise in creating an engaging narrative has long been recognized in literary and cinematographic criticism (e.g., Lüttiken 2006). But Ely, Frankel, and Kamenica (2015) proposed that these two product attributes are in fact key drivers of demand across a wide swathe of the entertainment industries. Thus, suspense is experienced not only by the reader of a detective novel, turning the pages as the story builds up toward revealing the identity of the killer, but also by the sports fan as a close game reaches its climax, and in the casino as the roulette wheel spins to determine whether the gambler has won or lost.

"Suspense" in each of these different contexts refers to the emotion experienced during the evolution of a narrative when the consumer looks to what will happen next, where what will happen next is expected to play a significant role in determining the final outcome of the story (such as the winner of the basketball match or the identity of the murderer). Suspense is therefore an ex ante concept: the consumer is looking to what will happen next. By contrast, "surprise" is experienced ex post and refers to the interest generated when new information has been revealed which causes a significant reassessment of what the final outcome might be. In a novel, this would be called a "twist in the plot" and in football (soccer) it might be generated by a goal which puts one team ahead in a game which had looked to be heading for a draw.

Casual observation regarding, for example, the success of particular novels and films, suggests that consumer preferences do indeed favor suspense and surprise as product attributes when they are seeking entertainment.[1] In other domains too, public interest may be stimulated by suspense and surprise, for example, interest in an

Buraimo: Senior Lecturer, Centre for Sports Business, University of Liverpool Management School, Liverpool, L69 7ZH, United Kingdom. Phone +44-1517953536, E-mail b.buraimo@liverpool.ac.uk
Forrest: Professor, Centre for Sports Business, University of Liverpool Management School, Liverpool, L69 7ZH, United Kingdom. Phone +44-1517950679, E-mail david.forrest@liverpool.ac.uk
McHale: Professor, Centre for Sports Business, University of Liverpool Management School, Liverpool, L69 7ZH, United Kingdom. Phone +44-1517952178, E-mail ian.mchale@liverpool.ac.uk
Tena: Senior Lecturer, Centre for Sports Business, University of Liverpool Management School, Liverpool, L69 7ZH, United Kingdom. DiSea & CRENOS, Università di Sassari, 07100, Sassari, Italy. Phone +44-1517953616, E-mail jtena@liverpool.ac.uk

1. In other contexts, suspense and surprise may of course be sources of pain rather than pleasure. For example, the suspense felt when about to receive the result of a cancer screening test is unlikely ever to be a positive experience. Even in an entertainment, a surprise, such as the death of Little Nell in a story by Dickens, might be badly received by the audience.

ABBREVIATIONS

AG: Away Goal
AFC: Athletic Football Club
AIC: Akaike Information Criterion
BARB: Broadcasters' Audience Research Board
GMM: Generalized Method of Moments
HG: Home Goal
IPS: Imm, Pesaran and Shin
MLE: Maximum Likelihood Estimation
NFL: National Football League
VIF: Variance Inflation Factor

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election may be heightened if the contest is "too close to call" or if polls show strong changes in opinion, and suspense and surprise may then even impact voter turnout, with real political and social consequences. Again, important groups may recognize the public taste for suspense and surprise and exploit it for their own ends. The behavior of terrorists or hostage takers may be better understood by recognizing that they seek to intimidate a general population rather than just their immediate victims (Enders and Sandler 2012, 4). To maximize their impact on the population, they may seek to stage sequences of events (including such as consecutive explosions across a city or fake executions of hostages) to keep their target audience engaged in the story. These parties will aim to create suspense and surprise as weapons in drawing in an audience for their outrages. More generally, Ely, Frankel, and Kamenica (2015) note that understanding the role and power of suspense and surprise informs many situations where agents must decide on the timing with which information is revealed to audiences, which may be readers, television viewers, voters, etc.

Rather than rely on casual observation, it would clearly be preferable to explore consumer preferences for suspense and surprise more formally. However, in many areas of entertainment, formal analysis faces many obstacles. For example, books and cinema tickets are purchased before consumption and buyers have to take decisions on the basis of expectations about how much suspense and surprise they will experience. This would add a layer of complexity to modeling of demand as a function of suspense and surprise content. In any case, it would be difficult to measure suspense and surprise. For example, a twist in the plot might shift final outcome probabilities but these are subjective and might be different for every reader or viewer. It would be very costly to collect assessments from a sufficient sample of readers to find consensus outcome probabilities at each stage in the story.

At the end of their paper, Ely, Frankel, and Kamenica (2015) note that data on the size of television audiences would be a promising avenue to explore because these are estimated minute-by-minute, enabling researchers to trace the effect of suspense and surprise on viewers who have not precommitted to consume but are free to withdraw from the program if it is insufficiently satisfying. If this idea is to be pursued, estimation of a demand function to model preferences over suspense and surprise appears to be most tractable where the programs show sports matches because advances in sports analytics have yielded rich models which generate probabilities of final outcomes that can be exploited to measure suspense and surprise at any point in the game given what has happened so far.

In this paper, we test the suspense and surprise hypothesis in the realm of sport by analyzing minute-by-minute data on television audience size in Britain for 540 football (soccer) matches played in the English Premier League between 2014 and 2017, allowing regression based on 47,520 minute-observations. Our explanatory variables include suspense and surprise but we also conceptualize another ingredient which might be particularly salient in the sporting context: "shock." This refers to another possible source of interest in a narrative. Shock (as commonly understood in commentary on sport) is experienced when the current outcome probabilities are radically different from those assessed before the start of the event. For example, shock will be high if the match has evolved to the point where a strong favorite now faces a high probability of being defeated by the underdog. Sport is different from many other entertainments in that the dramatis personae will nearly always be well known to the audience before the start and they will therefore have prior views on likely outcomes. Again sport analytics provides the means of estimating pre-match probabilities. We hypothesize that interest will be stimulated as an unexpected result becomes more likely and that the broadcast in such a case will consequently be more successful in retaining and indeed growing its audience.

II. PRIOR LITERATURE

Given that we intend to examine consumer preferences for the content of sports events, it is relevant first to reflect on the relationship between the notions of suspense, surprise, and shock and one of the central concepts in sports economics, the outcome uncertainty hypothesis, first proposed by Rottenberg (1956), which holds that demand for a sports event will be greater, the greater the uncertainty over the outcome of the match. This has often been taken as an article of faith in sports economics; but it begs the question of *why* consumers value prospective uncertainty when they make the decision on whether or not to attend. One obvious line of thought is that a match with high ex ante uncertainty (e.g., one where betting odds for either team winning are the same as each other) has a high potential to be "exciting": relative to a match where there is a strong favorite, there is a better chance of there being multiple changes in the lead (frequent surprise) and a better chance that the outcome will be in doubt until nearly the end (high suspense). Thus, if the outcome uncertainty hypothesis is valid, the underlying explanation may lie in consumers' craving for suspense and surprise.

But a large number of attendance demand studies for sports matches, carried out over several decades and in multiple settings, have in fact failed to establish widespread empirical support for the uncertainty of outcome hypothesis (Borland and Macdonald 2003; Pawlowski 2013; Szymanski 2003). One reason may be that it is hard, when modeling stadium attendance, to disentangle the separate effects of a preference for a close match and the conflicting preference of local fans for a home team win. Another possibility is that the measures used to capture outcome uncertainty in econometric studies prove to be poor predictors of a close match, proxied by final goal difference in the case of football (Buraimo, Forrest, and Simmons 2007).

Both these problems are potentially resolvable by analyzing television audience rather than attendance demand. The national television audience is likely to have a much lower proportion of partisan viewers than the crowd in the stadium. And, during a match, as events unfold, it becomes evident whether the match, which may or may not have had high ex ante uncertainty, is delivering high within-match outcome uncertainty. Effects on audience size may then be observed.

Analyzing data for National Football League (NFL) football and South Korean baseball, respectively, Paul and Weinbach (2007) and Chung, Hoon Lee, and Kang (2016) examined the determinants of both television ratings at the start of a game and changes in audience size during the game. Both papers found some role for ex ante outcome uncertainty in explaining starting audience size and then a role for within-match uncertainty in accounting for the retention of viewers. In the first case, the authors modeled the fall in audience size between the half-way point and the final minutes and found that the points difference at half-time was a positive predictor of the drop in television ratings (if a team were ahead by one additional touch down at half time, the predicted fall in TV rating points implied the loss of half a million households, on average). Chung, Hoon Lee, and Kang (2016) used more granular data, minute-by-minute audience size estimates from 481 baseball matches, and found run difference between the teams to be a significant negative predictor of audience, with the effect more pronounced as the match progressed.

The findings in these papers are consistent with suspense being important to viewers in that, all things being equal, a large current difference in points or runs suggests low uncertainty over the final result, therefore low suspense, and a net loss in audience. A caveat is that points or run difference will be imperfectly correlated with uncertainty and suspense to the extent that it matters which team is leading. For example, a 16-point half-time lead for a strong favorite suggests a game which is almost dead whereas the same lead for a heavy underdog may be associated with high uncertainty of final outcome given that the stronger team will still have a high probability of winning the second half.

Xu et al. (2015) also modeled the falloff in audiences during NFL matches, in their case from peak audience during the game to the final minutes. Their focus explanatory variable was the points difference in the final result. The novelty of their contribution is that they were able to estimate separate models for regional markets which could be regarded as either partisan or neutral according to whether one of the teams was a regional team. In all cases, a larger points difference predicted a greater loss of audience; but the size of the effect was much lower if the points difference was in favor of the local team. This is suggestive that the common failure to find an effect on stadium attendance from ex ante outcome uncertainty is indeed linked to the preference of committed fans to see their team win.

Turning to the sport on which we focus, Alavy et al. (2010) was the first study to model television viewing of football using minute-by-minute audience data. Further, the authors employed a statistical model to estimate final outcome probabilities rather than just rely on the current score difference to proxy uncertainty. Based on figures from 248 English matches, they found that closer games, measured according to the squared difference between the win probabilities of the two teams at given minute t, were more successful in retaining viewers. This was consistent with the idea that uncertainty of outcome is a desired attribute and that "suspense" matters.[2]

Alavy et al. (2010) also included in the model total goals in the match to date and a dummy variable indicative of a goal having been scored in the last minute. Only the latter was statistically significant. Viewed through the lens of the suspense-surprise paradigm developed in later literature, this could be interpreted as suggestive of a role for surprise in driving the evolution of audience size because football is a low scoring game and a recent goal will often have been associated with a radical change in outcome probabilities (i.e., will have created surprise). The study also found a role for a variable similar to what in our paper we call shock: viewer interest indeed seemed to be stimulated if current outcome probabilities were significantly different from expectations at the start of the match.[3] Altogether, then, the insights offered by Alavy et al. (2010) seem consistent with the hypotheses to be tested in the present paper although their results do not constitute a formal test because they were focusing on related but different concepts.

Similarly, findings in Mutz and Wahnschaffe (2016) are strongly suggestive of the relevance of suspense, surprise, and shock to viewers of televised football games, albeit they worked with data from only 33 matches televised in Germany. For example, in the final 15 minutes of a match, each additional goal separating the teams predicted an 8.5% loss of viewers (low *suspense* if the end of the match is near and one side has a clear advantage). And, in the final 30 minutes, the audience size was substantially higher if an odds-on favorite was not in the lead (prospect of a *shock* result).

Although related to a different sport, Bizzozero, Flepp, and Franck (2016) is by far the most relevant empirical paper for our study because these authors did offer formal, explicit testing of the significance of suspense and surprise (in the Ely–Frankel–Kamenica sense) by modeling the size of minute-by-minute television audience for sports matches. Their setting was the Wimbledon tennis championships and they analyzed Swiss audience data for 80 men's singles matches between 2009 and 2014 (which yielded 8,563 minute-observations). They reported that both suspense and surprise were statistically significant determinants of demand (with surprise being the more important) and, while the proportionate effect sizes seemed to be small, they regarded them as economically significant in that they involved changes to the absolute audience size which would matter to broadcasters and advertisers.[4] Comparing our study to that by Bizzozero and colleagues, we add shock to the mix.

III. DEFINITIONS OF SUSPENSE, SURPRISE, AND SHOCK

We follow the definitions of suspense and surprise proposed by Ely, Frankel, and Kamenica (2015)[5] and define the additional concept of shock in analogous fashion. In all cases, probabilities p_t refer to probabilities of final match outcomes as perceived at minute t, with superscripts H, D, and A indicating home win, draw, and away win, respectively. Each of the concepts, suspense, surprise, and shock, focuses on a change in the set of probabilities between two time points. Since these changes in the outcome probabilities must always sum to one, changes in each of p^H, p^D, and p^A are squared and the shift in the set of probabilities captured by taking the square root of the sum of the three terms.

Surprise (Equation 1) is about what has just happened to outcome probabilities and therefore the comparison is between the sets of probabilities at t and $t-1$. Shock (Equation 2) is about the difference between current outcome probabilities and pre-match outcome probabilities and

2. On the other hand, the regression results in Alavy et al. (2010) also found a negative coefficient estimate on the probability at minute t that the game would end in a draw. This seems to be inconsistent with the uncertainty of outcome hypothesis (and with suspense being a positive attribute). The authors speculate on explanations such as some drawn matches, particularly scoreless draws, being characterized by a tendency toward boringly defensive playing styles. It should also be reiterated here that the concept of suspense proposed by Ely, Frankel, and Kamenica (2015) was far from identical with the idea of outcome uncertainty in the literature on sports economics, and in Alavy et al. (2010), because Ely and his colleagues saw suspense as involving consumers looking forward to how outcome probabilities might change in $t+1$ rather than considering only outcome probabilities at t.

3. Readers moved to study Alavy et al. (2010) should take note that the analogue to our "shock" variable is referred to by these authors as measuring "surprise." Their use of the term is therefore not the same as in Ely, Frankel, and Kamenica (2015), who were of course writing several years later. In all the following text, we use the terms suspense and surprise consistently in the same sense as Ely, Frankel and Kamenica.

4. Unlike our data set that is used by these authors included separate estimates of male and female audience size. Suspense and surprise remained significant when each market was analyzed separately though the response of the male audience to both suspense and surprise was estimated to be greater.

5. Who indeed illustrated their definitions of suspense and surprise by showing how these concepts could be operationalized for a football match.

therefore the comparison is between the sets of probabilities at t and at $t = 0$:

(1)

$$\text{Surprise}_t = \sqrt{\begin{array}{l}(p_t^H - p_{t-1}^H)^2 + (p_t^D - p_{t-1}^D)^2 \\ +(p_t^A - p_{t-1}^A)^2\end{array}}$$

(2)

$$\text{Shock}_t = \sqrt{(p_t^H - p_0^H)^2 + (p_t^D - p_0^D)^2 + (p_t^A - p_0^A)^2}.$$

The definition of *suspense* is forward-rather than backward-looking and this requires additional notation. The changes in probability are now hypothetical in that they refer to what would happen were a team to score in the next minute. These changes in probability should be weighted by the respective probabilities of either team scoring such that suspense then depends on both the likelihood and the significance (for match outcome) of possible events actually occurring. Hence, we introduce p_{t+1}^{HS} and p_{t+1}^{AS} to indicate the respective probabilities of the home and away teams scoring a goal in the next minute from now and define suspense as:

(3)

$$\text{Suspense}_t = \left(\sum_{i \in H,D,A} p_{t+1}^{HS} [(p_{t+1}^i | p_{t+1}^{HS}) - p_t^i]^2 + \sum_{i \in H,D,A} p_{t+1}^{AS} [(p_{t+1}^i | p_{t+1}^{AS}) - p_t^i]^2 \right)^{1/2}.$$

IV. DATA

A. Television Audience Data

Data were purchased from the Broadcasters' Audience Research Board (BARB), which is charged with estimating audience sizes for programs on all but the tiniest stations in the British television market. BARB's estimates are derived from monitoring viewing in a panel of more than 5,000 private households, recruited by Ipsos Mori to be representative of all UK households (therefore they do not pick up communal viewing in public spaces such as pubs[6] or in institutional residences such as care homes). Monitoring is from devices, fitted in each home to all televisions (and other equipment capable of receiving programs), which record whether the set is switched on and tuned to a particular channel. In addition, each member of the household over age four is assigned a hand-set and instructed to press buttons to indicate when they enter or leave the room, so that the number of persons present while a program is playing can be inferred from the records. Thus, variation in the number of viewers can be because of any combination of change in the number of households tuned into a program or change in the mean number of persons watching in each household. We envision, for example, that if the match being broadcast becomes more suspenseful, more sets may be switched to the program as potential viewers are alerted by social media or radio commentary and individuals within some households may be called into the television room by those already watching. Changes in audience size from minute to minute will reflect net inflow but we are unable from the data set provided to separate out numbers joining and quitting the program.

Minute-by-minute audience estimates were obtained for all 540 matches shown on television during the data period. All were exclusively on a subscription channel, most commonly Sky Sports but sometimes BT Sport. Most games broadcast took place on Saturday lunchtime, Sunday afternoon, or Monday evening. In 2017, Friday evening football was introduced to provide an additional time slot. Across all match minutes, the mean of estimated audience size was 1.10 million with a range of 52,700–2.94 million.

B. Football Data

To estimate outcome probabilities, data were required on significant match events (timing of goals and issuance of red cards). These data were sourced from optasports.com. OPTA is the official data partner of the English Premier League.

Particular care had to be taken to synchronize the audience data and the football data. Audience data were provided in clock time but official football data in match time. For example, the OPTA data might record that a goal was scored in the first minute of the second half. If the match had started at 8 p.m., this should have been at

6. Watching football in pubs appears to be popular: a marketing survey for the pub industry indicated that nearly one-fifth of respondents engaged in the activity (https://www.morningadvertiser.co.uk/Article/2017/09/05/Quarter-of-consumers-visit-pubs-to-watch-live-sport). However, accurate data on audience size for individual matches would be hard to collect systematically as the number present would not necessarily coincide with the number actively viewing the television.

around 9.02 p.m. but might actually have been a few minutes different from this, for example, if the first period had been unusually long because of an injured player being treated on the field. Sometimes there might even have been a serious delay, for example, because the match had begun late on account of traffic disruption around the stadium. Fortunately, we were able to obtain from OPTA exact clock times for the start of each first and second half and then convert the two data sets to be compatible with each other and expressed in match time. This was a nontrivial task which we note to alert future researchers to the importance of the issue. For example, in our analysis reported below, we include minute (of the match) dummies in our model specification to account for predictable variations in audience size, such as a tendency for depressed viewing figures at the start of the second half, as viewers return to the football from household tasks or from catching up on the news on another channel. The relative timing of this blip in the data will vary if the first half had finished late.

C. Probabilities for Defining Suspense, Surprise, and Shock

In order to calculate suspense, surprise, and shock, as defined above, we required the probabilities of each outcome (home win, draw, away win) for each minute of each match, given the current match situation. The current match situation includes information on the time remaining, the current score, and the number of red cards awarded to each team.

Given past evidence of the broad efficiency of wagering markets, it might seem natural to turn to archives of bookmaker odds from in-play betting to source these probabilities. However, while this would be feasible in the cases of surprise and shock, historic odds could not be used to calculate suspense. Suspense is a forward-looking emotion based, in the present case, on hypothetical changes in probabilities were a team to score in the next minute. Because the scenario is hypothetical, there are no odds quoted from which the probabilities required could be derived. Addressing this problem for tennis, Bizzozero, Flepp, and Franck (2016) forecast future hypothetical probabilities using a Markov chain method, where future probabilities of a player winning an individual point were set according to the server's career record of winning service points. But the method cannot readily be applied to football because it depends on a sports structure where the future will be divided into discrete plays. Football, by contrast, is a continuous sport (and carries the additional complication of there being three rather than two possible outcomes).

To calculate the probabilities required, we constructed an in-play model which exploits the information on team strength which is embedded in the pre-match odds. Such odds would be expected to incorporate such factors as recent match results, implicitly weighted to take account of strength of opposition and other relevant circumstances.

In-play models of football are surprisingly scarce in the academic literature. Dixon and Robinson (1998) presented a birth-process model for estimating scoring rates during a game, and Titman et al. (2015) proposed a multivariate counting process for modeling both goals and cards. Here, we adapt the process used by many in the bookmaking industry to generate in-play match predictions.

To begin, bookmaker odds were collected from the result (home win/draw/away win) and the over–under goals markets.[7] These were then rescaled to remove over-round[8] such that they summed to one. From these "bookmaker implicit probabilities," we backward engineered the scoring rates of the two teams. To do this, we assumed an independent Poisson model for the goals by the two teams such that:

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

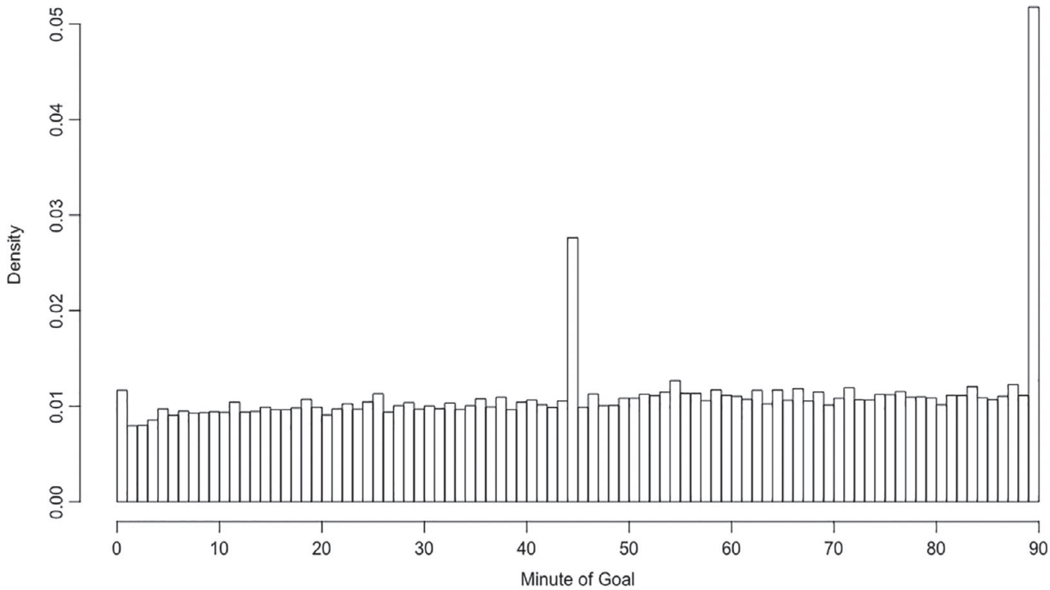
where X is the number of goals scored by the home team, and Y the number of goals scored by the away team. This model can be used to generate the probabilities of every scoreline in a match, and summing these scoreline probabilities can be used to calculate the probabilities of a home win, a draw, and an away win, given the two scoring rates λ_H and λ_A. We used an optimization routine in R to estimate λ_H and λ_A so that we minimized the squared difference between the bookmaker implicit probabilities and the match win probabilities calculated from this simple model. The function we minimized was:

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

7. Specifically, we used odds from Bet365, a leading sports betting operator in both the British and international markets.

8. Over-round is the sum of the bookmaker's probability-odds on each outcome. Absent a technical error, the sum is always greater than one: if it were less than one, bettors could gain a sure profit by betting on all of the possible outcomes. The difference between the over-round and one is often taken as an estimate of bookmaker commission.

FIGURE 1
Relative Frequency of Goal Times by Minute of Match



where m_i is the implied probability of outcome i according to the model, o_i is the bookmaker implicit probability, and the possible outcomes are home win (H), draw (D), and away win (A).

Once the two scoring rates for the teams had been estimated, we distributed the scoring rates across the minutes of a match. One could have assumed a uniform distribution so that the scoring rate in any 1 minute was approximately equal to $\lambda/90$. However, scoring rates are not constant during the match and so we split the scoring rate in proportion to the empirical distribution of goals per minute, shown in Figure 1. Note that the goals in the 45th and 90th minutes include those scored in added time in the respective half. For the simulations, we assumed the match would have the average amount of injury time in each half such that the inflated goal scoring rate in minutes 45 and 90 were shared out evenly in these extra minutes. All matches were assumed to be 93 minutes long.

Using these "per minute scoring rates," we simulated the number of goals occurring in each minute of the match before totaling up the final scoreline and recording the result. This *match level simulation* was repeated 100,000 times. As such, there were $93 \times 100{,}000 = 9.3$ million simulations per match.

We evaluated the required probabilities for calculating suspense using "what if" scenarios: "what is the probability of a home win *if* the home team scores in the next minute?," etc.

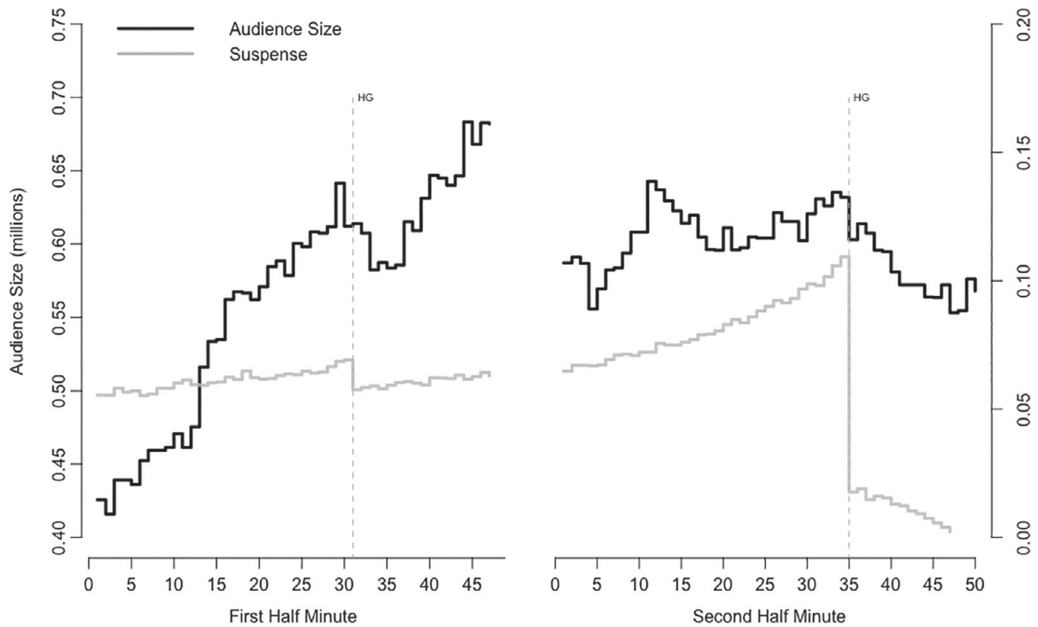
To account for red cards, we followed the results in Vecer, Kopriva, and Ichiba (2009). The team receiving a red card had its scoring rate reduced to two-thirds of the original scoring rate, while the opposition's scoring rate was increased by a factor of 1.2.

D. *Illustrations of the Data*

To enable the reader to get a feel for the look of the data, we focus in this section on two example matches. To avoid the risk of cherry-picking cases from the whole data set that appeared most supportive of our hypotheses, we selected these two cases from the first 12 matches in the audience data file, picking what to us seemed, from the scores, to be one very "routine" match and one "exciting" match. Because the data were stacked in alphabetic order of home club, both games featured here had AFC Bournemouth as the home team.[9]

9. Because AFC Bournemouth is colloquially called "The Cherries," perhaps we could be said to have cherry-picked after all!

FIGURE 2
Audience Size and Suspense in a "Routine" Match (AFC Bournemouth vs. Southampton, March 1, 2016)



Figures 2 and 3 show the evolution of audience sizes and our measure of suspense during the first and second halves of the "routine" match and the "exciting" match, respectively.[10] In both matches, there was added (stoppage) time at the end of each half. We continue to show audience size during stoppage time but the measure of suspense is not observed beyond 3 minutes of added time at the end of the match because, as noted above, our forecasting model is based on assuming each game to last till this point. Pointers labeled HG and AG signify goals scored by the home and away teams, respectively.

The first match (Figure 2), where Southampton was the visiting team, proceeded routinely and produced a common result in this League, a 2–0 win for the club enjoying home advantage. The second goal deflated suspense, which virtually disappeared as full-time approached, and audience figures duly fell. This is an example of a match which failed to keep its audience.

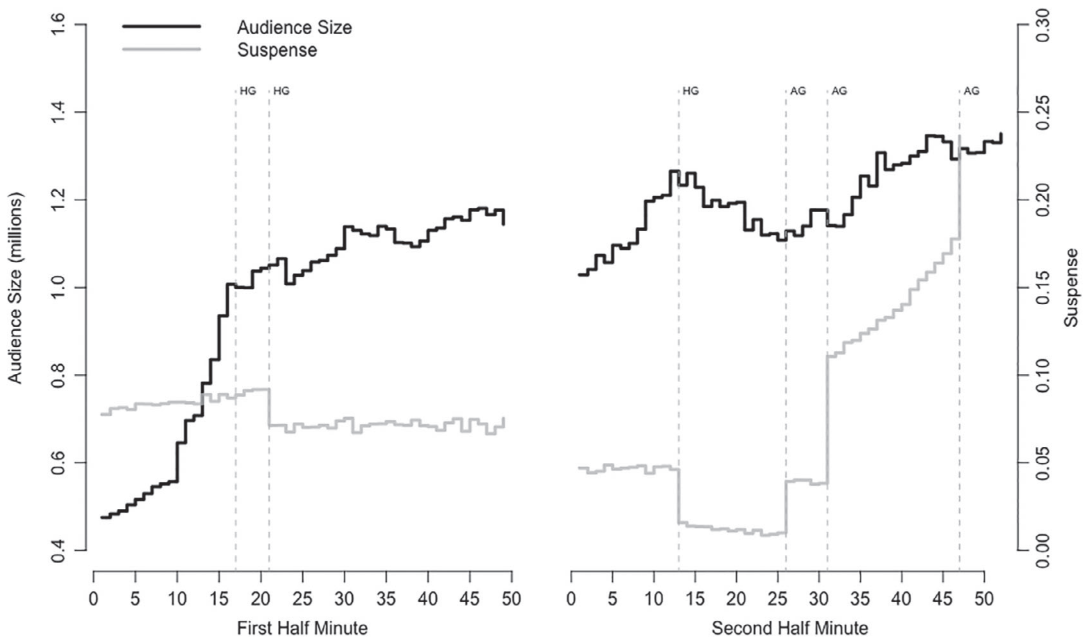
In the second match, against Arsenal, the home team, the underdog on this occasion, took a three goal lead. Now suspense will have been low because even a goal for the visitors would not have put them back very strongly into contention given the limited time remaining. However, they actually did succeed in drawing level, through three goals of their own, and suspense in this game reached a high level as the final whistle came closer (any goal now was likely to be decisive).[11] From Figure 3, some of the audience appears to have quit when the score went to 3–0 but audience recovered as further goals arrived and in fact this match is an example of one which had its peak audience at the end.

These two matches are just examples and, of course, while the evolution of audience size

10. Our data source provided minute-by-minute viewing figures for the interval in-between the halves but this period is suppressed in the diagrams. The half-time programming includes replays of key moments, punditry, and commercials. Invariably audience size dips between the two halves and typically is still lower than before the break for a minute or two after the resumption (e.g., some viewers might catch up on the news on another channel or fit in a household task, returning to the football a little late).

11. It is in fact common in this League for the match outcome (in terms of home win, draw, or away win) still to be capable of being changed by just one goal even very late in the game. From 5 years of data on all Premier League fixtures, Butler and Butler (2017) noted that, in 65% of them, added time after the 90 minutes began with the teams level or separated by a single goal.

FIGURE 3
Audience Size and Suspense in an "Exciting" Match (AFC Bournemouth vs. Arsenal, January 3, 2017)



seems to be linked in a way that suggests suspense as playing a role, the relationship would not necessarily hold generally and formal testing of the hypothesis required modeling over the whole data set. The illustrations here are provided primarily to help readers appreciate how the suspense measure is driven by events on the field.

For completeness, we show in Figure 4 how our measures of surprise and shock varied during the "exciting" match. It should be noted first that the time pattern of surprise typically looks very different from that of suspense, as surprise occurs at an instant whereas suspense may be sustained and indeed build up over several minutes. Note that the third Bournemouth goal in this sample match generates much less surprise than earlier goals because, with two-thirds of the game played, a two-goal lead had already made it strong favorite and one more goal then made relatively little difference. Similarly, Arsenal's first score raised the chances of anything other than a home win by relatively little. In contrast, the very late, final goal (recorded as 2 minutes into added time) yielded a major shift in probabilities with a draw now extremely likely compared with the situation when the score was 3–2.

Regarding the concept of shock, the home team was the pre-match underdog in this sample match. Figure 4 illustrates that, at first, the lack of goals leads to a slow upward drift in the difference between current and pre-match outcome probabilities. But then two goals, scored close together for the underdog, create a sharp increase in the value of shock, increased subsequently by a third goal and by the clock running down. The value of the variable depreciates somewhat as Arsenal score twice but recovers as time runs out for Arsenal to equalize (but which then happens at the very end of the game).

V. MODEL SPECIFICATION AND ECONOMETRIC ISSUES

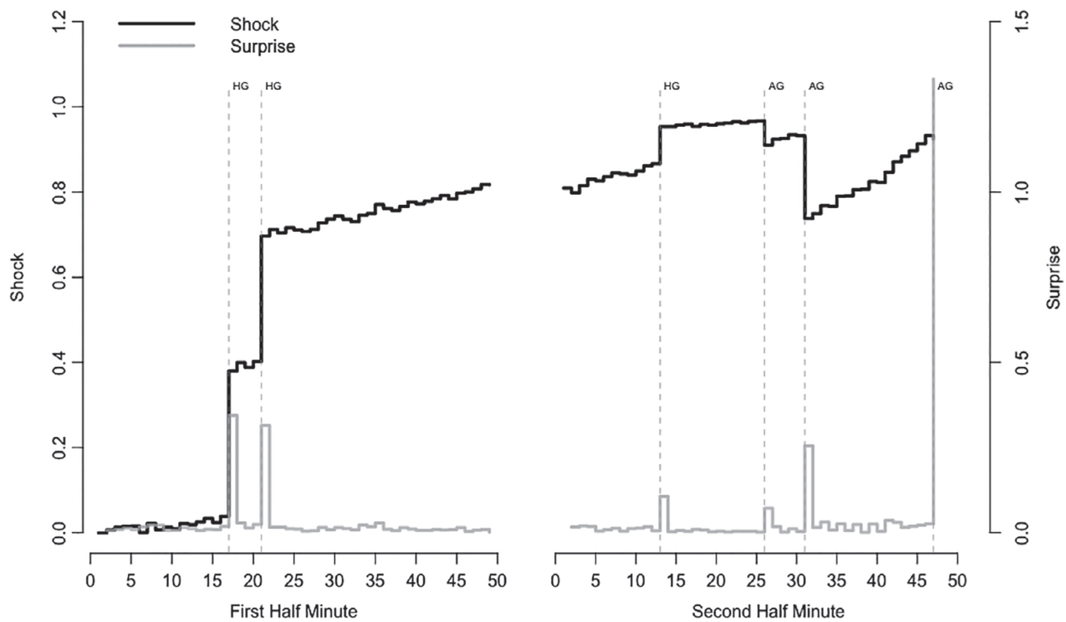
Our model is:

$$\text{(6)} \quad \mathrm{Ln}(\text{audience})_{i,t} = \alpha_0 + \beta_1(\mathrm{Ln}(\text{audience})_{i,t-1}) + \beta_2(\text{suspense}_{i,t}) + \beta_3(\text{surprise}_{i,t}) + \beta_4(\text{shock}_{i,t}) + \gamma_t + \upsilon_i + u_{i,t}$$

Subscripts i and t refer to the match and the minute, respectively; the γ are a series of

FIGURE 4

Surprise and Shock in an "Exciting" Match (AFC Bournemouth vs. Arsenal, January 3, 2017)



minute-of-match dummies; and the υ_i are match fixed effects. Match fixed effects account for factors affecting the overall appeal of the match, such as the popularity of the teams, the relevance of the fixture for the Championship, the time of day, the broadcasting platform (Sky Sports or BT Sport), and the weather outside. A lagged dependent variable captures inertia when viewing football on television (the inclusion of further lags was ruled out by experimentation and testing for significance). The closer β_1 is to one, the greater the extent to which changes in suspense, surprise, and shock will have an ongoing rather than an instantaneous effect on audience size.

Our results are based on applying maximum likelihood estimation (MLE) with fixed effects. The employment of least squares could be argued to be problematic given the presence of a lagged dependent variable alongside fixed effects because the set-up introduces Nickell bias (Nickell 1981), affecting coefficient estimates, primarily on the lagged dependent but also on other variables. Dynamic panel estimation, and in particular the Arrellano-Bond Generalized Method of Moments (GMM) technique, provides a way to deal with the problem, based on removing the fixed effects by means of the first difference transformation of the model together with the use of a complete set of lagged dependent variables as instruments, albeit there is a cost in terms of loss of efficiency. Indeed Bizzozero, Flepp, and Franck (2016) favor GMM in their minute-by-minute modeling of audiences for Wimbledon tennis.

On the other hand, GMM was designed for use in "short" panels and the degree of Nickell bias falls as the number of time points (T) in the panel increases. Using Monte Carlo simulations, Beck and Katz (2004) found that the Nickell bias is already low (2% or less) at moderate values of T and advocated the use of a least-squares estimator with a lagged dependent variable included if $T \geq 20$. Because the cross-sectional units in our panel are football matches, we observe about 90 time points in each match. Hence, with a long panel, we choose not to correct for endogeneity of the lagged dependent variable. Doing so would increase root-mean-square-error while bias from using our preferred MLE will be minimal.

Although our specification also allows for time effects, which makes the problem of a spurious regression less pressing, we consider whether our dependent variable is $I(1)$ or stationary. Under the former case, a regression with ln(audience) as dependent variable would be spurious unless we could identify a covariate (or a set of covariates) that works in a cointegration relationship with the audience. We tested the null hypothesis that all the 540 audience panels contain a unit root using the Im, Pesaran, and Shin (2003) (IPS) test and this was rejected at conventional levels of significance. Given that there tends to be a substantial drop in the audience series at half-time and this structural break could affect the power of the test, we also ran separate IPS tests for the first and second halves; the null hypothesis was rejected in each case. Further, when we tested the unit root hypothesis in each of the 540 individual panels using an augmented Dickey–Fuller test, the null hypothesis was rejected at the 5% significance level in more than 90% of the cases. In the light of all this evidence, we concluded that a regression with (natural log of) audience in levels was a sound approach and the estimated parameters were able to be interpreted in the standard way.

VI. RESULTS

Table 1 presents summary statistics from the 47,520 minute-observations[12] and Table 2 displays our regression results.

The first column in Table 2 has results from a specification with only the variables proposed by Ely, Frankel, and Kamenica (2015), suspense and surprise. In model (2), we add shock as an additional covariate. The stability of coefficient estimates in moving to the second model suggests that there is little reason to be concerned about the addition of shock introducing multicollinearity problems. Nor did we detect multicollinearity issues when calculating variance inflation factors (VIF). The highest VIF for any variable was 2.19 (for shock).

In both models, the coefficient estimate on audience lagged by 1 minute exceeds 0.9, indicating short-term inertia in viewing. The coefficient estimates on suspense, surprise, and shock are positive and highly significant, consistent with our hypothesis that these are desired attributes which contribute to demand for the broadcast.[13]

TABLE 1
Summary Statistics

	Mean	*SD*	Minimum	Maximum
Suspense	0.0631	0.0389	0	0.2364
Surprise	0.0227	0.0726	0	1.2859
Shock	0.3319	0.2481	0	1.1816
Audience	1,102,947	492,468	52,700	2,937,000
ln(audience)	13.807	0.4822	10.872	14.893

TABLE 2
Regression Results: Dependent Variable Is ln(audience)

	(1)		(2)	
	Coeff	*p*	Coeff	*p*
$\ln(\text{audience})_{t-1}$	0.9378	<.0001	0.9376	<.0001
Suspense	0.0746	<.0001	0.0741	<.0001
Surprise	0.0042	.002	0.0039	.004
Shock	—	—	0.0033	.008
Constant	0.8880	<.0001	0.8911	<.0001
Adj-R^2	0.964	—	0.964	—
AIC	−209,892.8	—	−209,901.4	—
Obs	47,520	—	47,520	—

Notes: All models were estimated with match fixed effects and minute-of-match dummies. *p* values were calculated from standard errors adjusted for clustering at the match level.

In an extension, we repeated the analysis but with each of the three focus variables interacted with first- and second-half dummies. Results are exhibited in Table 3. In similar experimentation, Bizzozero, Flepp, and Franck (2016) found that the slopes of suspense and surprise increased in the later sets of a tennis match but we do not have analogous results here. A possible reason is that football viewers may make a firmer commitment of time to watching the entire event. Football schedules are known several weeks in advance, take place in most people's leisure time and have a definite duration. In tennis tournaments, it is typically known only 1–3 days before which players will meet each other, the matches are often on weekday afternoons, the start time of the match is uncertain (unless it is the first on-court and only then if the weather permits), and the length of the match can be extremely variable.

Disaggregation by halves of the match does, however, reveal additional information about

12. The first minute of each half was excluded from the estimation sample because of the presence of a lagged dependent variable in the specification. We also included only minutes up to the end of "normal time." Most matches will feature a little added time but the number of extra minutes varies. Including added time would increase the sample size only marginally, so we exclude them to avoid introducing the complication of an unbalanced panel. Hence, we have 88 time points and 540 cross-sectional units in the sample used for estimation.

13. When we repeated the estimation using GMM, results were very similar except that surprise lost significance.

TABLE 3
Regression Results with First and Second Half Interactions: Dependent Variable Is ln(audience)

	(1)		(2)	
	Coeff	***p***	**Coeff**	***p***
ln(audience)$_{t-1}$	0.9378	<.0001	0.9376	<.0001
Suspense*first-half	0.0563	.016	0.0716	.005
Suspense*second-half	0.0748	<.0001	0.0742	<.0001
Surprise*first-half	0.0070	.028	0.0068	.034
Surprise*second-half	0.0032	.026	0.0031	.032
Shock*first-half	—	—	0.0018	.382
Shock*second-half	—	—	0.0040	.006
Constant	0.8895	<.0001	0.8917	<.0001
Adj-R^2	0.964	—	0.964	—
AIC	−209,891.2	—	−209,897.7	—
Obs	47,520	—	47,520	—

Notes: Both models were estimated with match fixed effects and minute-of-match dummies. *p* values were calculated from standard errors adjusted for clustering at the match level. AIC, Akaike Information Criterion.

shock (from results in Table 3, model 2). Shock appears to play a role in determining demand only in the second-half of a football game. We speculate that some viewers' interest is aroused by the prospect of seeing an upset but this does not become evident until the estimated probability of an upset passes a threshold. There will be few cases in the first-half where there is yet a high probability of a win by a much weaker team. And if the attraction of seeing an upset derives from *schadenfreude*, the pleasure of witnessing the mighty laid low will be the greater when their end is in sight.[14]

VII. MAGNITUDE OF EFFECTS

As in the study of Swiss television audiences for tennis (Bizzozero, Flepp, and Franck 2016), our modeling provides strong support for the hypothesis in Ely, Frankel, and Kamenica (2015) that suspense and surprise are ingredients in driving entertainment demand. And shock also seems to matter in the case of football. However, at first glance, the economic importance of these product attributes seems rather limited. For example, at the mean of audience size, an on-field event which triggers an increase of one standard deviation in both suspense and surprise is (from model 2, Table 2) predicted to increase audience size by only 1.2%.[15] On the other hand, such a calculation does not tell the full-story. It neglects the ongoing influence of the on-field event first through the lagged dependent variable and second from influences on the values of suspense and shock in the following minutes. Football is a low-scoring game. Often a single goal will either create or deflate suspense and, absent further goals, suspense will remain at a higher or lower level than it would have been during the rest of the game.

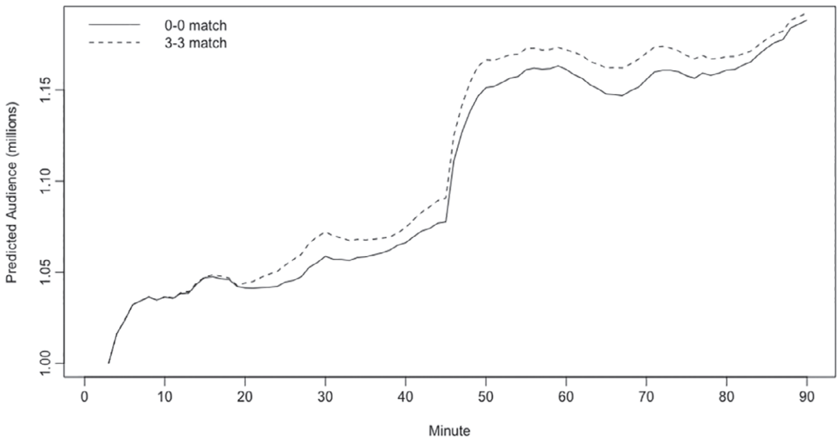
Consequently effect sizes would be better evaluated through simulation of matches and comparing predicted audiences between the several cases. Here, space limitations restrict us to offering just one illustrative comparison between a pair of hypothetical matches. Both match A and match B are between two teams which are equally matched once home advantage is taken into account: each has a scoring rate (the λ in Equation 4) of 1.8. We assume each match to have a starting audience of 1 million viewers. At minute 70, each match is currently a draw and goes on to the end without a further goal, giving identical values of suspense, surprise, and shock throughout the final 20 minutes. However, the matches had reached that final phase through different routes. Match A had no goals and the score was still 0–0 at minute 70. But in match B, the score was 3–3 at minute 70 and there had been goals for the home team at $t = 20$, 40, and 60 and for the away team at $t = 30$, 50, and 70. One might say that the second match had been littered with surprise.

Figure 5 shows the predicted evolution of audience size (from estimates in Table 2, model 2). Although suspense, surprise, and shock are identical in the final phase of the two matches, the "exciting" match continues to attract a higher audience throughout this period, amounting to 258,003 extra viewer-minutes or 12,904 viewers per minute of play. This may be an economically meaningful increase in demand but it is nevertheless proportionately small. Although audience

14. We note one other experiment. We estimated the two models with "cumulative surprise" substituted for "surprise," where cumulative surprise was the aggregation of the surprise measure over the whole match up to the current minute *t*. This alternative measure was always highly significant and results across the board were similar in terms of coefficient estimates and significance levels of the other focus variables.

15. Bizzozero, Flepp, and Franck (2016) report the result of a similar calculation where the impact is of the order of 3%, again proportionately small, perhaps bigger than in the football case because the tennis in Switzerland is shown on free-to-air television. Compared with football in Britain, particularly interesting matches may then draw in casual fans whereas British viewers are likely all to be hard-core football followers given that they have chosen to subscribe to the sports channel.

FIGURE 5
Evolution of Predicted Audience Size in Two Hypothetical Matches



size varies systematically with variation in suspense, surprise, and shock, it is plausible that there is a sizeable section of the audience which persists in watching the whole game regardless of the degree of excitement it generates. This should not necessarily lead one to discount the degree of importance to be attached to suspense, surprise, and shock. As noted above, time may already have been allotted to watching the game and that decision may have been based on an expectation concerning how exciting an experience it would be. A sports league where suspense, surprise, and shock are not regularly supplied may lose audience over a much longer period of time, months and years (not least through a fall in the number of subscribers to the broadcasting platform).

VIII. OUTCOME UNCERTAINTY

We return finally to the concept of outcome uncertainty, which has long been a principal focus in attempts by sports economists to understand consumer demand. It is legitimate to ask whether the effects of suspense, surprise, and shock on audience size are in fact just alternative representations of the influence of outcome uncertainty. On the other hand, audiences may have independent preferences over the level of uncertainty and over how this uncertainty comes to be resolved (the latter captured by suspense and surprise).

Certainly outcome uncertainty and suspense/surprise are related. For example, high uncertainty will help create the suspense which appears to appeal to the audience. Nevertheless, suspense and uncertainty are not the same either in the ways in which they could be quantified[16] or conceptually.[17] Further, Pawlowski, Nalbantis, and Coates (2018), in a stated preference study where football fans were asked about their intention to watch a particular future match on television, the respondents' perceptions' of how "suspenseful" the match was likely to be and how uncertain the outcome was were each significant when both were included in the modeling. Thus, prospective football viewers appeared to understand suspense and outcome uncertainty as distinct concepts. Therefore, in this section, we reestimate our lead model (model 2, Table 2) with additional covariates which directly measure outcome uncertainty. We wish to establish whether results on suspense, surprise, and shock are robust to the presence of outcome uncertainty in the model

16. For example, outcome uncertainty relates to differences in probabilities concerning the different *final* results of the match whereas suspense focuses on how these probabilities might change *in the next minute*.

17. Delatorre et al. (2018) report an experiment where participants were shown a simple story displayed as a sequence of slides on a computer screen. The plot was whether a replacement organ would arrive in time to save the life of a dying child. Subjects self-rated their level of suspense before/during two viewings of the story. Although diminished, they still reported experiencing suspense on second viewing even though they themselves now knew the ending. Uncertainty appears therefore not to be a necessary condition for suspense to be present. A possible explanation of this paradoxical finding is that interest is sustained when the protagonists in the drama do not know what will happen next even if the viewer does.

and also whether there is any independent role for outcome uncertainty beyond any effects mediated through the suspense, surprise, and shock variables.

Following Alavy et al. (2010), we used, as our measure of uncertainty at minute t, the squared difference between the probabilities of a home win and an away win at that point in the match. Ceteris paribus, the greater the value of this measure, the less uncertainty surrounds which team will win. However, this on its own is an inadequate measure of within-match outcome uncertainty. In contrast to American sports, there is a third possible (and indeed common) outcome, the draw. For example, if the two teams have equal probabilities of winning, the draw might sometimes but not always be the strong favorite, such as very late in the game when there is little time for either side to score and break the deadlock. We therefore again follow Alavy et al. (2010) in also including the draw probability (at minute t) in the empirical model. Alavy et al. (2010) reported a negative coefficient on the squared difference between the two win probabilities (consistent with the outcome uncertainty hypothesis) but also a negative coefficient on the draw probability (which they attributed to the presence in the data set of "boring draws" where teams were content to defend and take the draw, driving viewers away). Of course, a principal difference between our model and theirs is that we include suspense and surprise in the specification.

Our results are presented in Table 4. The outcome uncertainty measure takes the expected sign but the estimate is only very marginally significant ($p = .116$). The draw probability is strongly statistically significant and, as in Alavy et al. (2010), takes a negative sign. It should be borne in mind that these additional variables reflect only direct impacts on audience size as there will also be indirect impacts through suspense, surprise, and shock. The coefficient estimates on suspense, surprise, and shock themselves remain highly significant in the presence of the outcome uncertainty measures and, compared to our main results in Table 2, coefficient estimates on surprise and shock are virtually unchanged while that on suspense is rather higher than before. We conclude from the pattern of results that suspense, surprise, and shock are robust to the presence of outcome uncertainty in the model, validating that these measures capture characteristics of a match which are relevant to the audience. This is not to dismiss the notion that outcome uncertainty matters because uncertainty to an extent drives the values of the focus variables and may play some independent role as well.

TABLE 4
Regression Results: Dependent Variable Is ln(audience)

	Coeff	***p***
ln(audience)$_{t-1}$	0.9375	<.0001
Suspense	0.0904	<.0001
Surprise	0.0039	.004
Shock	0.0039	.005
Sq. diff. in win probs	−0.0030	.116
Draw prob	−0.0087	.004
Constant	0.8656	<.0001
Adj-R^2	0.964	—
AIC	−209,910.6	—
Obs	47,520	—

Notes: All models were estimated with match fixed effects and minute-of-match dummies. p values were calculated from standard errors adjusted for clustering at the match level. AIC, Akaike Information Criterion.

Another issue is whether the effect of our focus variables is affected by the context, by which we mean the current state of the match. Of course the focus variables themselves already capture the current score; but the measures of suspense, surprise, and shock may fail to proxy the underlying consumer experience of these emotions sufficiently fully so as to rule out additional insights to be obtained by including additional information in the model.

We tested the robustness of the results on suspense, surprise, and shock to the inclusion of additional variables representing key statistics about the state of the game, such as total goals to date and current goal difference; these sorts of measures are customarily employed by authors modeling the evolution of the television audience during a sports event (e.g., Tainsky et al. 2014 use score total and score difference when modeling audiences for American college football).

Results are displayed in Table 5. Current goal difference takes the expected negative sign and is statistically significant. Total goals to date prove to have a direct, positive effect on predicted audience size (there will also be an indirect effect through the lagged dependent variable). One possible interpretation of this latter finding is that viewers may be more likely to be retained if earlier in the match there have been lots to interest them in terms of surprise (shifts in outcome probabilities induced by goals). Indeed when we ran an alternative regression with cumulative surprise (the sum of surprise across all minutes up to $t-1$) included instead of goals, we obtained

TABLE 5
Regression Results: Dependent Variable Is ln(audience)

	Coeff	p
ln(audience)$_{t-1}$	0.9369	<.0001
Suspense	0.0773	<.0001
Surprise	0.0032	.020
Shock	0.0058	.002
Sq. diff. in win probs	−0.0027	.177
Draw prob	−0.0092	.002
Total goals	0.0009	.001
Goal difference	−0.0015	.045
Constant	0.8724	<.0001
Adj-R^2	0.964	—
AIC	−209,929.4	—
Obs	47,520	—

Notes: All models were estimated with match fixed effects and minute-of-match dummies. p values were calculated from standard errors adjusted for clustering at the match level.

very similar results. It may be noted that the results on suspense, surprise, and shock are once again robust to the inclusion of (still relevant) additional variables more familiar from prior literature in sports economics, strengthening our conclusion that suspense, surprise, and shock are generally key, attractive ingredients in drama.

IX. DIRECTION OF FUTURE RESEARCH

The principal contributions of this paper have been: to test and offer support for the role of suspense and surprise in entertainment demand; to identify and test for another conceptual attribute, shock, with the finding that the emergence of a story line that is far from what would have been anticipated at the start of the match is interesting for the audience and affects demand; and to construct and demonstrate the utility of an in-play model that could be used in future sports studies.

And yet the relatively small effect sizes for suspense, surprise, and shock imply that there is much more to be learned about preferences of football viewers. One possibility is that interest in the final outcome is insufficiently weak in some matches for variations in outcome probabilities to draw a strong response. One way of exploring this would to seek out data for sports leagues where it was possible to identify sub-markets where the audience could be assumed to be partisan in favor of a particular team.

Again, as in literature and cinema, suspense and surprise would not seem likely to attract consumers if the aesthetic experience is poor (e.g., poor writing, bad acting, defensive football). To that extent, models such as we present may suffer from omitted variable bias. At the top level, football now generates numerous metrics from which it would be possible to construct indicators of styles of play, technical aspects of performance, and incidence of violent conduct. The role of such factors could be explored using minute-by-minute audience data, potentially valuable in itself for industry leaders in showing what consumers want, but also valuable from the perspective of isolating the independent influences of suspense, surprise, and shock.

It would also be worthwhile, in our view, to repeat the exercise reported here for other sports. Results could not be presumed to be the same. Fundamental questions in sport include not only why do consumers demand sport but also why they have heterogeneous preferences over which sports they follow. Sports differ in many dimensions including aesthetics, duration of events, degree of physical contact, etc. But they may also differ in the packages of suspense, surprise, and shock they deliver. It would be interesting just to measure these factors for different sports. For example, football is the most popular spectator sport (globally). Is it because its unusually low-scoring nature throws up more stimulation as captured by measures of suspense, surprise, and shock? Such fundamental and challenging questions remain to be explored in the academic literature.

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