Entertainment Demand from Expectations*

Scott Kaplan[†]

Oskar Zorrilla[‡]

December 31, 2022

Abstract

This paper uses revealed preference methods to estimate demand for non-instrumental information in entertainment. We apply and extend the theory presented in Ely et al. (2015) to conduct an empirical analysis that examines the effect of suspense and surprise on consumer demand. We first introduce alternative definitions of suspense and surprise using the theory of mutual information, and prove that suspense is in fact expected surprise. We then estimate the impact of suspense and surprise on television viewership using play-by-play and high-temporal frequency television ratings data from the National Basketball Association (NBA). Our primary results suggest that a one standard deviation increase in suspense increases viewership by 2.53% - 2.91%, while surprise has no impact. We also estimate within-game impacts of (i) absolute score differential and (ii) absolute score differential with respect to the point spread on viewership. These findings have important implications for entertainment media companies, including leagues and television broadcasters, and advertisers.

Keywords: non-instrumental information, suspense, surprise, television viewership, NBA

[†]Assistant Professor, Department of Economics, United States Naval Academy. email: skaplan@usna.edu.

[‡]Assistant Professor, Department of Economics, United States Naval Academy. email: zorrilla@usna.edu.

*We would like to thank the Naval Academy Research Council and the Naval Academy Volgenau Fund for generous financial support. We thank Cheenar Gupte for excellent research assistance. Special thanks to Ben Handel, Jim Sallee, Sofia Villas-Boas, and David Zilberman for comments and inspiration. We'd also like to thank Nola Agha, Anocha Aribarg, Max Auffhammer, Giovanni Compiani, Kwabena Donkor, Karl Dunkle-Werner, Claire Duquennois, Gabe Englander, Alexander Frankel, Hal Gordon, Andy Hultgren, Benjamin Krause, Megan Lang, Brian Mills, Kate Pennington, Jeff Perloff, Dan Putler, Gordon Rausser, Leo Simon, Avner Strulov Shlain, Steve Tadelis, Dmitry Taubinsky, and Miguel Villas-Boas for thoughtful comments on this research. We'd also like to thank participants in the United States Naval Academy Economics Seminar, UC Berkeley IO Seminar Series, the North American Association of Sports Economics Annual Meeting, the Marketing Summer Research Series in the Haas School of Business, the ERE Seminar Series at UC Berkeley, the NYU Stern Marketing Seminar Series, and participants at the 2022 Southern Economic Association Annual Meeting. Finally, special thanks to Ryan Davis for help in acquiring the play-by-play data, and Todd Whitehead for useful feedback. All remaining errors are our own.

I Introduction

Access to information is a crucial component of an economic agent's decision-making process. Information leading to such contingent actions is defined as instrumental. Instrumental information applies to the entire spectrum of economic decisions, for instance how gas prices influence which type of car to buy, how a sugar-sweetened beverage tax impacts soda consumption, or how wages in a certain industry impact whether or not to change jobs. In particular, this information provides additional certainty about a subsequent decision, which leads to welfare-improving actions, and it is often the case that agents are willing to pay a premium for such information because of the additional certainty it offers. In contrast, non-instrumental information does not have direct consequences for economic decision-making under constraints, but provides utility nonetheless. For instance, individuals may be attentive to the performance of candidates in a political debate, how a television series will play out, or which team will prevail in a sporting event. In situations featuring non-instrumental information, uncertainty over an outcome is itself a source of pleasure for individuals.

Most sources of non-instrumental information are found in entertainment settings, since the uncertainty associated with the information is not associated with a financial stake. The global entertainment media industry exceeds $2 trillion, and has grown 60% over the last 10 years (PWC 2019). Entertainment in its current form does not exist without well-crafted and targeted information updating that attracts and keeps consumers' attention. Additionally, provision of non-instrumental information in certain entertainment settings has important social implications. The ability to retain consumers through media outlets allows them to remain informed about important, economically consequential issues.

One can think of the outlay of non-instrumental information as the "thrill" associated with an event. Thrill refers to adjustments in a spectator's belief state as a result of new information about an outcome. Ely et al. (2015) define two primary characteristics of thrill: suspense and surprise. Higher suspense is defined as higher variance in future beliefs over an outcome, and higher surprise is defined as a larger difference in current beliefs about an outcome compared to previous beliefs. For instance, suppose a golfer is entering the final nine holes of a tournament in second place. There is clear suspense over whether or not the golfer will prevail—beliefs are going to update relatively soon given the approaching finality of the event. But on the 13th hole, the golfer drives the tee shot into the water! This constitutes a significant change in the belief state about the golfer's chances to win.

This paper uses revealed preference methods to explore and quantify demand for non-instrumental information in entertainment, examining the "thrill" associated with the trajectory of an event. We take as our starting point the definitions of suspense and surprise from Ely et al. (2015). We propose alternative definitions based on information theory and show that suspense and surprise are —both according to the Ely et al. (2015) and our own definitions— the same concept: suspense corresponds to the *ex ante* flow of information while surprise corresponds to the *ex post*. We then take both of our definitions as well as the theory presented in Ely et al. (2015) to conduct an empirical analysis that examines the effect of thrill on consumer demand. We do so by leveraging national 15-minute level viewership with play-by-play data for all games during the 2017-18 and 2018-19 seasons. Future work will rely on richer household-level second-by-second television viewership data for all National Basketball Association (NBA) games during the 2021-22 season. While there are many different avenues of entertainment to study non-instrumental information, live sports is a natural application since (i) the suspense and surprise at any given moment of the game is directly observed and publicly available, (ii) outcomes are plausibly random conditional on an initial information state, unlike a book or movie, and (iii) because of the size of and value generated by the industry.

Our empirical strategy employs conventional panel data methods to estimate a reduced form model to determine the impact of suspense and surprise on total viewership, taking advantage of the temporal granularity of our viewership and play-by-play data. Future work will estimate heterogeneous effects using household-level data that features demographic and geographic information. We also plan to estimate a structural model of demand using each household's viewership timeline during the course of a game. That is, we observe the outside option faced by each household as long as they tuned into a given game at some particular point (e.g. turning on a different game, watching the news, turning the TV off, etc.), and use these switching events to infer a household's willingness-to-pay for thrill.

The reduced form findings suggest that thrill is a large and significant factor affecting viewership demand. Using the absolute score differential at different points in a game as a coarse measure of thrill, we find that a one-point decrease in the absolute score differential does not impact viewership in the first or second quarters, but increases viewership by 0.6% and 1.2% in the third and fourth quarters, respectively, strongly supporting the hypothesis that viewers relish thrilling games, not just games that are close. Contextualizing these results further, second half viewership is 8.2-20.5% lower on average for games with a 14+ score differential compared to a 0-8 differential, while these differences are 12.0-29.6% when only examining the fourth quarter.

We extend this analysis to look at absolute score differential during a game *in reference to the closing point spread*, similarly finding that viewership declines are starker towards the end of games. I find that for every one-point increase in the score differential from the closing spread, viewership declines by 0.1-0.9%, with larger decreases found in later stages of a game. This suggests that a one-standard deviation change in score differential in reference to the spread during the final quarter segment (9.3 points) exhibits an economically meaningful impact on viewership (6.4-7.3%

reduction), which amounts to roughly half the size of the impact of thrill over the absolute score differential.

Finally, we estimate the viewership response to the structural definitions of suspense and surprise. Using the definitions of suspense and surprise from Ely et al. (2015), we find that a one standard deviation increase in suspense increases viewership by 2.53%, while surprise has no statistically significant impact on viewership. The results are quite similar using our proposed alternative definitions of suspense and surprise: a one standard deviation increase in suspense increases viewership by 2.91%, while surprise again has no statistically significant impact. While these magnitudes are seemingly small, suspense and surprise can take on an extremely large range of values. For instance, in the last segment of the fourth quarter, a 0-2 point game experiences between 5.57-5.60 standard deviations more suspense than a 14+ point game. In this case, viewership would be approximately 15.34-17.08% higher through suspense alone.

The remainder of this paper proceeds as follows. First, we review the bodies of literature this work is motivated by and contributes to in section II. Next, section III develops a conceptual framework that introduces our alternate definitions of suspense and surprise and compares them with the definitions provided in Ely et al. (2015). Section IV overviews the structure of the viewership and play-by-play data and presents relevant summary statistics, including estimates of suspense and surprise from the play-by-play data. Section V develops the set of reduced form empirical strategies used in estimating viewership responses thrill. We present the results of the reduced form analysis in section VI. Section VII proposes several additions we plan to implement in future work.

II Literature Review

This research contributes to several notable bodies of literature. First and foremost, there is a growing existing literature on suspense and surprise. Ely et al. (2015) is the seminal study that provides the original definitions of suspense and surprise. They determine the optimal suspense and surprise information policies that maximize expected utility. Their study incorporates practical examples from entertainment and socially-relevant settings, including novels, political races, and live sports. Preceding studies have also examined modified versions of suspense and surprise in a theoretical manner and in various settings, including live sports (Bryant et al. 1994, Su-lin et al. 1997), game shows (Chan et al. 2009), and in the context of the Hangman's Paradox (Geanakoplos et al. 1989, Geanakoplos et al. 1996; Borwein et al. 2000). An adjacent literature uses laboratory experiments to measure physiological responses to suspense and surprise, emphasizing that animals are genetically driven to respond to such occurrences (Itti and Baldi 2009; Ranganath and Rainer 2003; Fairhall et al. 2001; Ebstein et al. 1996).

To the best of our knowledge, there have been two peer-reviewed, empirically-oriented studies to date using the suspense and surprise framework developed in Ely et al. (2015), and several other working papers. Bizzozero et al. (2016) examine television viewership responses to suspense and surprise over the course of tennis matches, finding that surprise, and to a lesser extent, suspense, generate positive but relatively small viewership impacts. In particular, they find that a one standard deviation increase in suspense (surprise) raises audience viewership by 1,260 (2,630) viewers per minute, which combine to cause a 3.65% viewership increase. They implement two separate, but similar, methodologies to measure impacts of suspense and surprise: a Markov method and a "betting odds" method, which uses live betting odds between each point during a match to dictate outcome probabilities. Buraimo et al. (2020) examine television viewership in response to suspense and surprise using the European professional football market. They also introduce "shock," at each portion of a match, which is defined as the difference between current outcome probabilities and expected probabilities prior to the start of a match. Their findings also suggest relatively small impacts of suspense and surprise on viewership; a one standard deviation in both suspense and surprise increase audience viewership by 1.2%. Two recent working papers have assessed viewership responses to suspense and surprise in esport tournament streams (Simonov et al. 2020) and professional baseball (Liu et al. 2020).

This paper aims to extend the suspense and surprise literature in several key ways. First, we introduce alternate definitions of suspense and surprise using the theory of mutual information, which we apply in our empirical approach. Second, we examine an entirely different sport and geographic market: professional basketball in the United States. There are notable differences between the structure of basketball games and the settings studied in other related work, as well as differences in the types of spectators watching games, which may lead to additional insights. Next, we aim to take advantage of rich viewership and game play-by-play data to (i) estimate both reduced form and structural models of viewership demand that account for household-level demographic and geographic heterogeneity, and (ii) examine viewership responses to thrill over alternative game outcomes (e.g. the point spread of a game), which may be unrelated to the final outcome of who wins or loses. Finally, in future work we plan to use our empirical estimates of viewership responses to thrill to assess the impact of a counterfactual game structures that can be achieved through league rule changes.

The second body of literature focuses on information preferences, which includes the theory of addictive goods, and outcome resolution, formalizing the notion that individual taste preferences are consistent with utility-maximizing behavior and may change over time (Stigler and Becker 1977; Becker and Murphy 1988; Kreps and Porteus 1978; Caplin and Leahy 2001). We aim to expand on this work by discussing and evaluating preferences for non-instrumental information, especially in the context of outcome resolution. In particular, evaluating the psychological and emotional attributes of entertainment is important in understanding the types of information individuals desire (Fowdur et al. 2009). For instance, studies have shown that story "spoilers" have large impacts on demand for entertainment goods, even suggesting that they have the potential to increase consumer enjoyment (Leavitt and Christenfeld 2011; Johnson and Rosenbaum 2015; Levine et al. 2016; Ryoo et al. 2020). Naturally, there has also been significant research assessing the impact of outcome uncertainty on demand for live sports (Rottenberg 1956; Knowles et al. 1992; Humphreys and Miceli 2019; Alavy et al. 2010; Forrest et al. 2005).[1] We extend this research by more closely examining the evolution of beliefs over the course of an event, using random variation in event trajectories to assess attention-based responses. This is particularly important as audiences increasingly explore real-time gambling in live sports, which is likely to depend heavily on information relayed throughout the course of an event (Kaplan and Garstka 2001; Haugh and Singal 2020; Salaga and Tainsky 2015).

The third relevant body of literature is in hedonic pricing. Rosen (1974) provides a theoretical framework that describes the total value of a good as a combination of the values of its attributes, which has led to a rich body of literature applying the concept to a wide range of products (Busse et al. 2013; Sallee et al. 2016; Currie and Walker 2011; Chay and Greenstone 2005; Luttik 2000). This work focuses on an important attribute of entertainment goods - thrill. Television ratings data is a natural avenue to explore impacts of these characteristics on consumer demand, as there has been other work examining viewership responses to well-defined programming characteristics (Fournier and Martin 1983; Anstine 2001; Livingston et al. 2013). Furthermore, there is existing

[1]It is important to note that while thrill and outcome uncertainty are related, they characterize different processes. Outcome uncertainty examines probabilities of different outcomes happening at different times, while thrill looks more fundamentally at the variance in the evolution of beliefs over the course of an event.

work using hedonic pricing methods in entertainment to understand the value of star performers, which is highly related to the entertainment value generated by suspense and surprise (Scully 1974; Kahn 2000; Rosen 1981; Hausman and Leonard 1997; Krueger 2005; Chung et al. 2013, Grimshaw and Larson 2020; Kaplan 2020).

The fourth and final body of literature is on the economics of advertising and consumer attention. Many forms of entertainment rely on advertising as a large source of revenue, and advertisers themselves pay for the quantity and types of consumers the entertainment attracts (Becker and Murphy 1993; Wilbur 2008; Bertrand et al. 2010; Hartmann and Klapper 2018). The stakes for advertisers are quite high – analyzing time-use survey data, Aguiar et al. (2013) finds that the average American spends about 20% of their time consuming some form of entertainment. The evolution of thrill during the course of an event is paramount in generating spectator attention, and this work aims to assess the extent to which each contributes to recruitment and retention of viewers. Furthermore, the type of information content used by advertisers in entertainment settings is important for generating meaningful engagement with potential customers (Resnik and Stern 1977; Bagwell 2005). In particular, there is a clear differentiation between informative content, which corresponds characteristics like prices and deals, and emotional content, which corresponds to characteristics like humor, slang, and emojis. Studies have shown that provision of emotional content leads to higher levels of consumer engagement (Aaker 1997; Lee et al. 2018). In fact, Madrigal and Bee (2005) find that the use of suspense as an advertising tactic is an important driver of consumer attention. Using revealed preference methods to understand how consumers respond to thrill is important in understanding how to better engage audiences with different advertising strategies.

III Conceptual Framework

Two opponents face each other in a match that is decided by the points scored — basketball, tennis, football, among others — and a spectator watches in order to satisfy her desire to consume the information flow that arises from the match. From the spectator's vantage point the match can be described as a stochastic process of beliefs. She approaches the match with an initial belief about the eventual winner; as the clock ticks and the score differential changes so do her beliefs. In this paper we will consider matches of this type with Bayesian spectators. While our framework applies to any such match, our empirical focus will be on basketball.

A Beliefs

The state space in a match is binary, $\Omega \equiv \{0, 1\}$, where, by convention, we let $\omega = 0$ denote a loss by the side initially favored to win. A belief at time t, b_t, is a probability distribution over outcomes $b_t \in \Delta(\Omega)$. Since Ω is binary, b_t lies in the unit interval and is the probability at time t that the initially favored side wins. A match of length T is a stochastic process $\gamma \equiv \{b_t\}_{t=0}^{T}$.

Definition 1. *A match, γ, is a stochastic process, $\{b_t\}_{t=0}^{T}$, that satisfies the following conditions:*

$$b_t = \mathrm{E}_t[b_{t+1}] \qquad \textit{(Dynamic Consistency)} \qquad \text{(III.1)}$$

$$b_t \in [0\ 1] \qquad \textit{(Full Support)} \qquad \text{(III.2)}$$

$$b_0 < 1 \qquad \textit{(Interesting)} \qquad \text{(III.3)}$$

$$b_T \in \{0, 1\} \qquad \textit{(Resolution of Uncertainty)} \qquad \text{(III.4)}$$

Condition III.3 makes the match worth watching to begin with; if the match is a foregone conclusion, our spectator won't watch it. Condition III.1 is the only requirement that Bayesian updating imposes on beliefs: it requires that γ is a random walk. Conditions III.2 and III.4 constrain the distributions, $\tilde{\mu}_t$, from which each innovation is drawn. It immediately follows that the innovations to the random walk will not be drawn from identical distributions.

A Bayesian spectator's beliefs will evolve according to the following law of motion:

$$b_{t+1} = b_t + \varepsilon_{t+1}, \quad \varepsilon_{t+1} \sim \tilde{\mu}_t \tag{III.5}$$

where $\tilde{\mu}_t$ is a time-varying, mean zero, conditional distribution whose support is *at most* the unit interval.

The two most crucial pieces of information are the margin and the time remaining: the point differential and the time left to overturn that differential are the most straightforward determinants of the outcome. Let δ_t denote the score advantage of the initially favored team at time t. Then b_t is the probability that the initially favored team ($b_0 > 1/2$) wins conditional on δ_t while $\tilde{\mu}_t$ is the probability distribution over δ_{t+1} conditional on δ_t.

B *Preferences and Information*

How does our Bayesian spectator evaluate the flow of information generated by the match? We begin with the two concepts —suspense and surprise— developed by Ely et al. (2015). We offer alternative definitions of these concepts and show that suspense is, in fact, expected surprise.

Definition 2. Surprise *is the Euclidean distance squared between the current belief vector* $[b_t \;\; 1-b_t]$ *and the prior belief vector* $[b_{t-1} \;\; 1-b_{t-1}]$.

$$(b_t - b_{t-1})^2 + ((1-b_t) - (1-b_{t-1}))^2 \tag{III.6}$$

Surprise is a measure of how far current beliefs are from previous ones. Importantly, it is a *realization*. For any current beliefs, there are many possible future beliefs, surprise is the distance between two consecutive belief realizations. Since beliefs are functions and we are interested in measuring the distance between them, we instead propose the Kullback-Leiber distance between two functions. We propose this distance because it is the standard used to measure distances between probability distributions. In information theory it is also known as Relative Entropy. This is also the definition of surprise used by Itti and Baldi (2009).

Definition 3. Surprise *is the Relative Entropy between current beliefs* b_t *and prior beliefs* b_{t-1}*.*

$$b_t \log\left(\frac{b_t}{b_{t-1}}\right) + (1 - b_t)\log\left(\frac{1 - b_t}{1 - b_{t-1}}\right) \tag{III.7}$$

While the two definitions imply differences in marginal surprise, they share some similarities. For a given prior belief, b_{t-1}, both are convex functions of the posterior belief, b_t, that reach the same minimum of zero at the prior. When beliefs do not change there are no surprises, regardless of how we define surprise.

Figure 1 plots both surprise functions for three different priors. At the point of maximum uncertainty, when the prior is 1/2, changes in beliefs in either direction are equally surprising under both definitions. Both functions are symmetric around 1/2. As the prior moves closer to one of the edges further movement of beliefs towards that edge becomes less surprising. In other words, the more likely a state is, the less surprising confirmatory evidence becomes. Movement of beliefs in the opposite direction, by contrast, become more and more surprising. Surprise is the *ex post* revelation of information: at any moment in time it is a single point on one of the curves, given the prior belief. The curves themselves represent the *ex ante* surprises that are possible for a given prior belief.

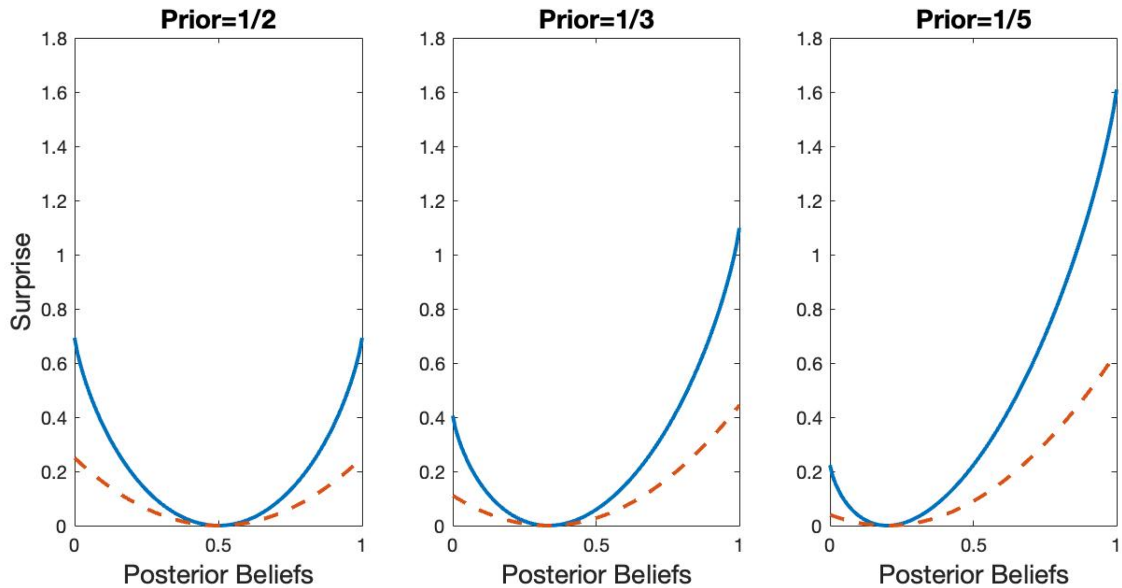


Figure 1: Surprise as function of belief realizations for three given priors: 1/2 (far left), 1/3 (center), and 1/5 (far right). Solid, blue curve is Relative Entropy. Dashed, red curve is Euclidean distance squared.

The *ex ante* counterpart of surprise is suspense. Ely et al. (2015) define suspense as follows:

Definition 4. Suspense *is the sum of the conditional variance of* b_{t+1}*, where the sum is taken over states of the world. In the binary case of basketball we have:*

$$\sum \tilde{\mu}_t \left[((b_{t+1} - b_t)^2 + ((1 - b_{t+1}) - (1 - b_t))^2\right] \tag{III.8}$$

We can rewrite suspense only in terms of the innovations of the belief process.

Proposition 1. *Suspense is twice the variance of* ε_{t+1}*.*

Proof.

$$
\begin{aligned}
&= \sum \tilde{\mu}_t \left(\varepsilon_{t+1}^2 + (-\varepsilon_{t+1})^2\right) \\
&= 2\sum \tilde{\mu}\varepsilon_{t+1}^2 \\
&= 2\sigma_t^2
\end{aligned}
$$

□

Broadly, suspense is an expectation of how much beliefs will change. But since beliefs are bounded, the higher ε_{t+1} is, the closer b_{t+1} must be to the edges of the simplex– the less uncertain the spectator becomes. To be more precise, suspense is measuring how much *information* the agent expects to receive. We therefore propose an alternative definition of suspense as the expected amount of information flow between two consecutive periods.

As we have discussed above, the relevant information in a match is time remaining and score differential. Let x and y be two random variables with joint pdf $f(x, y)$ and $f(x)$, $f(y)$, denote the marginal pdfs. The mutual information measures how much information you learn about x if you know y, *on average* and vice versa.

$$
\sum_{x,y} f(x, y) \log \left(\frac{f(x, y)}{f(x)f(y)} \right) \tag{III.9}
$$

In our case, let x denote the state and y the score differential. The mutual information tells us, on average, how much we find out about the outcome of the game, ω, upon observing a score differential δ_{t+1}. We can rewrite (III.9) in terms of conditional, rather than joint probabilities:

$$\sum_{\omega,\delta_{t+1}} f(\omega, \delta_{t+1}) \log\left(\frac{f(\omega, \delta_{t+1})}{f(\omega)f(\delta_{t+1})}\right)$$
$$\sum_{\omega,\delta_{t+1}} f(\omega|\delta_{t+1})f(\delta_{t+1}) \log\left(\frac{f(\omega|\delta_{t+1})f(\delta_{t+1})}{f(\omega)f(\delta_{t+1})}\right)$$
$$\sum_{\delta_{t+1}}\sum_{\omega} f(\omega|\delta_{t+1})f(\delta_{t+1}) \log\left(\frac{f(\omega|\delta_{t+1})}{f(\omega)}\right)$$
$$\sum_{\delta_{t+1}} f(\delta_{t+1})\sum_{\omega} f(\omega|\delta_{t+1}) \log\left(\frac{f(\omega|\delta_{t+1})}{f(\omega)}\right)$$

$f(\omega|\delta_{t+1})$ is the posterior probability of winning/losing upon observing the score differential in period $t + 1$, which we have denoted b_{t+1} for winning and $1 - b_{t+1}$ for losing. $f(\omega)$ is the prior probability of winning/losing, which is b_t for winning and $1-b_t$ for losing. Technically b_t conditions on the entire history of score differentials up to time, t, $\{\delta_j\}_{j=0}^{t}$. Under Markovicity, however, the current score differential is a sufficient statistic. And finally, $f(\delta_{t+1})$ is the probability of each possible future score differential. But each possible score differential must be associated with a unique posterior. So $f(\delta_{t+1})$ is the probability of each posterior, which we have denoted $\tilde{\mu}_t$. If we expand the inner sum over the two outcomes of winning and losing and replace each $f(\cdot)$ with the terminology we have defined so far we end up with the following definition for Suspense:

Definition 5. Suspense *is the Mutual Information between* ω *and* δ_{t+1}.

$$\sum \tilde{\mu}_t \left[b_{t+1} \log\left(\frac{b_{t+1}}{b_t}\right) + (1 - b_{t+1}) \log\left(\frac{1 - b_{t+1}}{1 - b_t}\right)\right] \tag{III.10}$$

While our information theoretic definitions of suspense and surprise are well-behaved in the interior of the simplex, we have to take some care at the edge when uncertainty is fully resolved. We have required the uncertainty is resolved by the end of the match, but have not ruled out that uncertainty might be resolved *before*; physical limitations make it so that certain score differentials simply cannot be overturned in the remaining time. Bayesian updating implies the edge of the simplex is an absorbing state. If $b_\tau = 0$ then $\forall j > 0$, $b_{\tau+j} = 0$, and similarly if $b_\tau = 1$. After uncertainty has been resolved, there cannot be any further information flow. Both suspense and surprise going forward must be zero. This leads us to adopt the following two conventions based on continuity: $\lim_{x\to 0} \log\left(\frac{x}{x}\right) = 0$ and $\lim_{x\to 0} x\log(x) = 0$.

There is a close information-theoretic connection between suspense and surprise. Suspense is the expected information flow between the current and next period. Surprise is the realized information flow between the previous and current period. We formalize this connection in the following theorem:

Proposition 2. *Suspense is expected Surprise.*

The proof is fairly straightforward, so we include here.

Proof. We will prove it using both types of definitions. We begin with our definition. Iterate expression (III.7) forward one period:

$$b_{t+1}\log\left(\frac{b_{t+1}}{b_t}\right) + (1-b_{t+1})\log\left(\frac{1-b_{t+1}}{1-b_t}\right) \tag{III.11}$$

This expression is the surprise at time $t+1$. Of course, *ex ante* at time t there are many values that (III.11) may take. Each value corresponds to a particular value of b_{t+1} and the probability of each is given by $\tilde{\mu}_t$. Therefore, the expected surprise is

$$\sum \tilde{\mu}_t \left[b_{t+1} \log \left(\frac{b_{t+1}}{b_t} \right) + (1 - b_{t+1}) \log \left(\frac{1 - b_{t+1}}{1 - b_t} \right) \right] \tag{III.12}$$

But this is simply the mutual information between ω and δ_{t+1}. The proof using the Ely et al definitions is identical. □

Since the expectations operator is linear, the relationship between suspense and surprise can be depicted geometrically. Consider figure 1. The future beliefs are on the horizontal axis. Whatever the distribution of these possible future beliefs, its first moment must fall on the prior: 1/2, 1/3 or 1/5. We follow Kamenica and Gentzkow (2011) and depict this relationship geometrically in figure 2 for our alternative definitions of surprise and suspense.

While there are many possible values of suspense consistent with a prior belief, we are able to bound those values. The minimum amount of suspense between two consecutive periods occurs when the spectator knows, with probability one, that no new information will be revealed in the following period. In that case, both the suspense and the surprise are zero. Notice that the surprise functions in each of the three panels of figure 2 reaches its minimum value at the prior, or in this case, the current belief. Zero information flow is equivalent to saying that beliefs do not change and so this is the minimum amount of suspense possible.

The maximum amount of suspense between two consecutive periods occurs when the spectator knows, with probability one, that the state will be fully revealed in the following period; once the spectator knows the state of the world, she is fully informed. This means that only two posterior beliefs are possible, zero or one. What is the distribution of these beliefs? Bayesian updating pins down this distribution since it requires that its expected value is the prior. Since surprise is a convex function, linearity of expectations implies that the suspense associated with this case lies

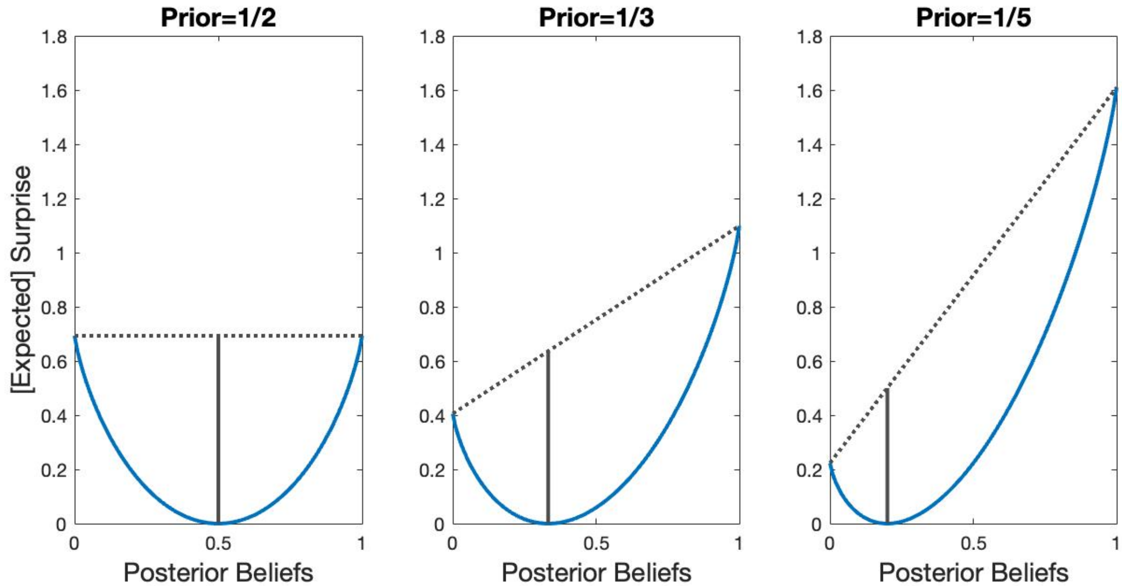


Figure 2: Suspense for three given priors: 1/2 (far left), 1/3 (center), and 1/5 (far right). Solid, blue curve is Relative Entropy. Dotted line is its convex closure. Vertical line segment represents the suspense loci.

on the convex closure of the surprise function. Specifically, it is the point on the convex closure that intersects with the prior belief. In figure 2 we depict the convex closure with a dotted line. The resulting vertical line segment in each of the panels between zero and the convex closure is the suspense locus for each of the three priors.

This result implies a type of observational equivalence between suspense and surprise in the following sense: more suspenseful matches will, *on average*, yield more surprises. This means that an econometrician might incorrectly conclude that a spectator likes surprise when in fact, she likes suspense. We test this possibility in section V and report the results in Table 4. When we regress viewership of basketball games on both suspense and surprise, only suspense is statistically significant.

C Alternative Outcomes

According to our definition of a match, γ, suspense and surprise occur with respect to the binary outcome of winning/losing. Who wins need not be the only outcome of interest. Here we consider two possible enrichments of the state space.

Within a match there are many intermediate outcomes that can elicit suspense, *ex ante*, and surprise, *ex post* yet only marginally affect beliefs about which side will ultimately win. A player who decides to take a shot from half-court can generate suspense among spectators as the ball flies through the air.[2] If the ball goes in, then spectators experience surprise: the *ex post* realization of an *ex ante* low probability event has, by definition, a high information content (See the right-most panel in figure 1).

It is also possible that the outcome of the match itself is not binary. Beyond the obvious fact that in some matches draws are possible, the state space can be more general; just look at all of the types of bets that can be placed around a given match. For a spectator who has placed a bet, the relevant state space might, in fact, be the margin of victory. As Ely et al. (2015) show, it is straightforward to generalize the state space from 2 to N dimensions. This applies to our definitions as well. Both mutual information and relative entropy are well-defined for a an arbitrarily large, discrete, state space.

Suspense and surprise over alternative outcomes is relevant for our empirical analysis, while the case of most intermediate outcomes (e.g. the outcome of a single shot) are less so. The reason is that moments within a game that generate suspense and surprise are too fleeting. It is not clear why, on the margin, people might decide to tune in to a match — in our case, basketball — because of the expectation that a rare play might be made, unless of course it is associated with a specific

[2] This is actually one of the most tired tropes in sports films. When such a shot is taken, filmmakers underscore the suspense by following the trajectory of the ball in slow motion.

alternative outcome of interest (e.g. a bet over how many points a player may score in a game). It is therefore unlikely that such moments would affect the consumption of information flow as measured by TV ratings. The second enrichment, however, is less fleeting. If a consummate fan has placed a bet on the score differential, suspense for her is not a function of who wins or loses, rather, it is a function of the margin of victory.

IV Data and Summary Statistics

This section presents an overview of the data used in the analysis and the reduced form empirical strategy. In the reduced form approach, we first estimate a coarse specification of the relationship between suspense and surprise with viewership, relying on level changes in the absolute score differential over the course of a game. We then estimate the viewership response to suspense and surprise using the parameters defined in III, and separately repeat this estimation using the suspense and surprise parameters defined in Ely et al. (2015).

A Overview of Data

There are two primary sets of data used in the analysis: (i) second-of-game play-by-play data providing time-invariant information about each analyzed game as well as detailed information about each moment of the game, and (ii) national 15-minute television viewership data for each game from The Nielsen Company.[3] Future work will leverage richer household-level data at the second-by-second level, provided by FourthWall Media.

[3]Data granted from The Nielsen Company (US), LLC. The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

A.1 Play-by-Play Data

The play-by-play data spans the 2013-22 seasons, and includes both time invariant and time variant information about each game. Relevant time invariant characteristics include the home and away teams, time-of-day, network (local or the specific nationally-televised network), the initial point spread, and an extensive list of team- and player-specific characteristics associated with each game. the time variant data characterizes every "meaningful" action within a game, and is provided at a second-of-play level.[4] Most importantly, this data characterizes the real-time score at each second of play a game, as well as a "wall clock" variable representing the time-of-day associated with each observation. The last component is crucial, since it allows for accurate and precise merging of the play-by-play data with the TV ratings data, which are denoted in time-of-day units.

A.2 Television Ratings Data

The second primary dataset used in this analysis is TV ratings data acquired from The Nielsen Company.[5] The data includes 15-minute interval ratings for every nationally televised NBA game from the 2017-18 and 2018-19 seasons (including playoffs). The relevant metric for this analysis is the projected total number of individuals watching during any given 15-minute interval.

B Summary Statistics

Table 1 presents a simple set of summary statistics spanning the two primary datasets. The table is decomposed into Fixed-Game Characteristics and Within-Game Characteristics. The Fixed-Game

[4] A non-exhaustive list of common occurrences warranting an observation include a made or missed basket, turnover, foul, out-of-bounds stoppage, or timeout.

[5] Data granted from The Nielsen Company (US), LLC. The conclusions drawn from the Nielsen data are those of the researcher and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

Characteristics provides information spanning 2013-22 coming from the play-by-play data, and depicts the distribution of the absolute value of initial point spreads, total points scored in a game, and the number of unique scoring events in a game. There are 12,765 games found in this sample. We use this information to construct measures of suspense and surprise within games, which are presented below.

Table 1: Summary Statistics

		Mean	SD	Min	Max	N
Fixed-Game Characteristics (2013-22)						
	Point Spread	5.89	3.64	0	21.5	12,765
	Total Points Scored	209.85	21.65	134	374	12,765
	# of Scoring Events	145.79	11.84	103	198	12,765
Within-Game Characteristics (2017-19)						
	Total Viewership (1,000s)	2,683.29	2,460.62	265	20,956	4,771
	Score Differential	8.14	7.02	0	53	58,771
	Underdog Margin	-2.79	10.38	-53	38	58,771
	Consecutive Points	3.34	2.17	0	30	58,771
	Real-Time Win Prob. Diff.	49.86	31.65	0	100	58,771

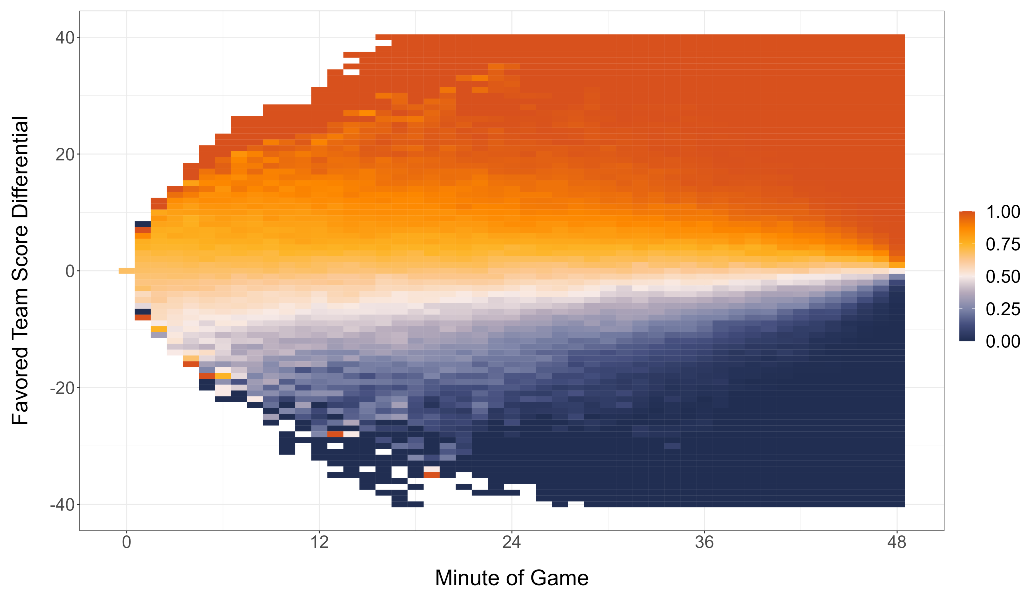
Note: The Fixed-Game Characteristics data is taken from play-by-play data across the 2013-22 seasons (both regular season and playoffs). The 2013-22 data is used to calculate measures of suspense and surprise that are used in the empirical analyses. The Within-Game Characteristics data includes only a subset of the play-by-play data, taken across the 2017-19 seasons. The TV viewership data spans the 2017-19 seasons. Thus, the final column represents the number of unique games from 2013-22 (12,765), the number of 15-minute viewership observations during the 2017-19 seasons (4,771), and the total number of play-by-play events during the 2017-19 seasons (58,776).

The Within-Game Characteristics depicts information about events occurring *within* each game, and only consists of play-by-play observations during the 2017-19 seasons. The first row represents Total Viewership, which is observed at the 15-minute level within each game, amounting to 4,771 total observations. For these two seasons of data, we also provide distributions for score differential, underdog margin (defined as the average score differential between the favored team and the underdog), consecutive points scored, and the real-time difference in win probability.

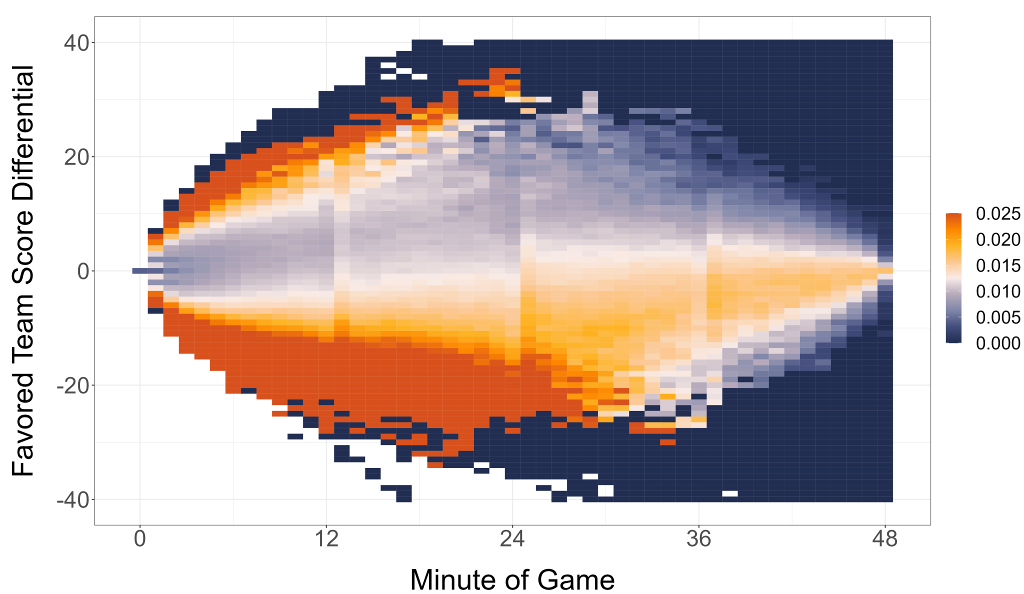
Figure 3 provides a heat map by favored team score differential and minute of game for a) the

Figure 3: Win Probabilities and Standard Errors by Time and Score

a) Average Win Probabilities for Favored Team



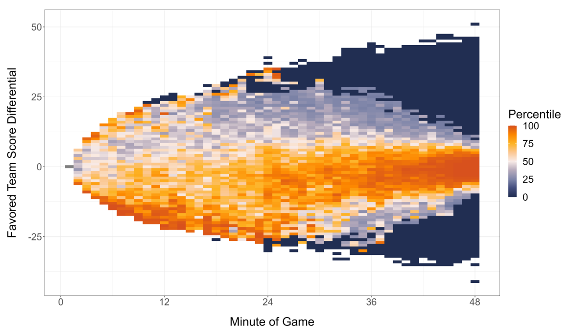
b) Standard Errors of Outcome Probabilities for Favored Team



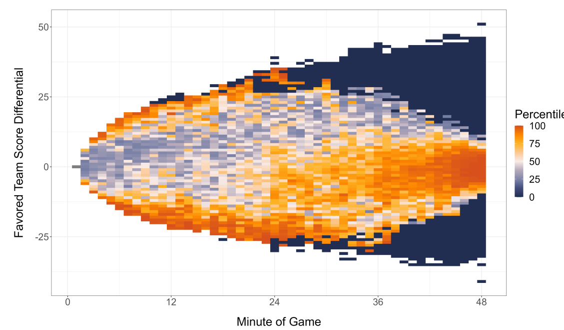
average win probabilities for the favored team, and b) the standard errors of these win probabilities. A high standard error suggests that there is relatively high variance in the win probability estimate for that favored team score differential in that minute of the game. One can see that the highest standard errors occur earlier in the game and for larger magnitudes in favored team score differential.

Figure 4: Suspense and Surprise by Time and Score

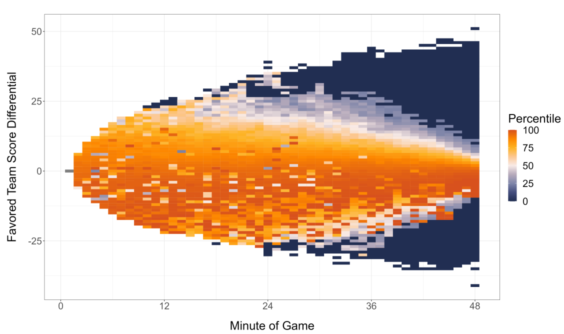
a) Ely, Frankel, and Kamenica Suspense



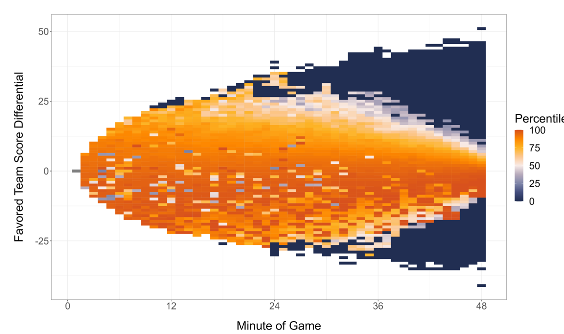
b) Kaplan and Zorrilla Suspense



c) Ely, Frankel, and Kamenica Surprise



d) Kaplan and Zorrilla Surprise



Finally, Figure 4 presents heat maps of the estimates of suspense and surprise by favored team score differential and minute of game. We present estimates of suspense following the Ely et al. (2015) definitions, which are presented in equations III.6 and III.8, as well as estimates corresponding to our alternative definitions, depicted in equations III.7 and III.10. The heat maps show single percentiles of the suspense and surprise estimates. First, one can see in both the EFK and KZ definitions there is a smoother gradient for adjustments in surprise compared to adjustments in suspense. Intuitively, both suspense and surprise tend to be much higher in later stages of a game when the score is relatively close. However, later stages of a game can also exhibit the lowest levels of suspense and surprise when games feature scores that are not close. In earlier stages of the game, suspense is significantly higher when the favored team trails the underdog, which is also intuitive. Another important insight is that EFK surprise and KZ surprise appear almost perfectly consistent with one another, in terms of percentiles. On the other hand, the heat maps appear to differ more substantially in terms of suspense. This is a feature of the additional convexity introduced by using the log-specification in the KZ definition of suspense, which results in a distribution with higher variance. The standard deviation of EFK suspense is 0.0255 (mean: 0.0133), while the standard deviation of KZ suspense is 0.0345 (mean: 0.0199).

V Empirical Strategy

The empirical analysis in this section attempts to identify the impact of suspense and surprise on television viewership. We first estimate a coarse specification of the relationship between suspense, surprise, and viewership, examining heterogeneous impacts of level changes in the absolute score differential by time remaining in the game. We expand on this by considering an alternative game outcome: winning team with respect to the initial point spread. Finally, we estimate the viewership response to suspense and surprise using the parameters defined in III, and separately repeat this estimation using the suspense and surprise parameters defined in Ely et al. (2015).

A Viewership Responses to Score Differential

We first analyze viewership responses using a directly observable game characteristic: absolute score differential at each point during a game. Absolute score differential is the primary metric by which a viewer internalizes suspense and surprise with respect to the final outcome of a game. While it is inherently difficult to separate the notions of suspense and surprise using this metric (since score differential at a given point can reflect both forward- and backward-looking beliefs), it provides an intuitive understanding of how viewership responds to thrill over the course of a game.

As implied by the definitions in Section III, suspense and surprise are heavily dependent on time remaining in an event, since this impacts the extent to which beliefs can change across periods. Equation V.1 provides a general empirical model to measure viewership impacts in response to observed absolute score differential and time remaining in an event.

$$V_{jt} = (C_{jt} * \mathbf{Q_{jt}})\boldsymbol{\Lambda} + \alpha_j + \eta_t + \epsilon_{jt} \tag{V.1}$$

V_{jt} represents total viewership for game j at time-of-game t. C_{jt} denotes the specific game characteristic impacting thrill (e.g. absolute score differential), and Q_{jt} is a time-of-game indicator (e.g. a minute of a game). $\boldsymbol{\Lambda}$ represents a vector of time-varying coefficients that reflect the impact of C_{jt} on viewership. α_j and η_t represent game and quarter-segment fixed effects, respectively.

One important distinction to make is the difference between a close game and a thrilling game. A game featuring a low score differential in the first quarter would be characterized as close, but not thrilling, since the variance in beliefs about the outcome probabilities in the next period is low (suspense), and there was likely low variance in the evolution of beliefs prior to this point (surprise).[6] On the other hand, a low score differential in the fourth quarter would be considered

[6] See Figure 4 for a visual depiction of this.

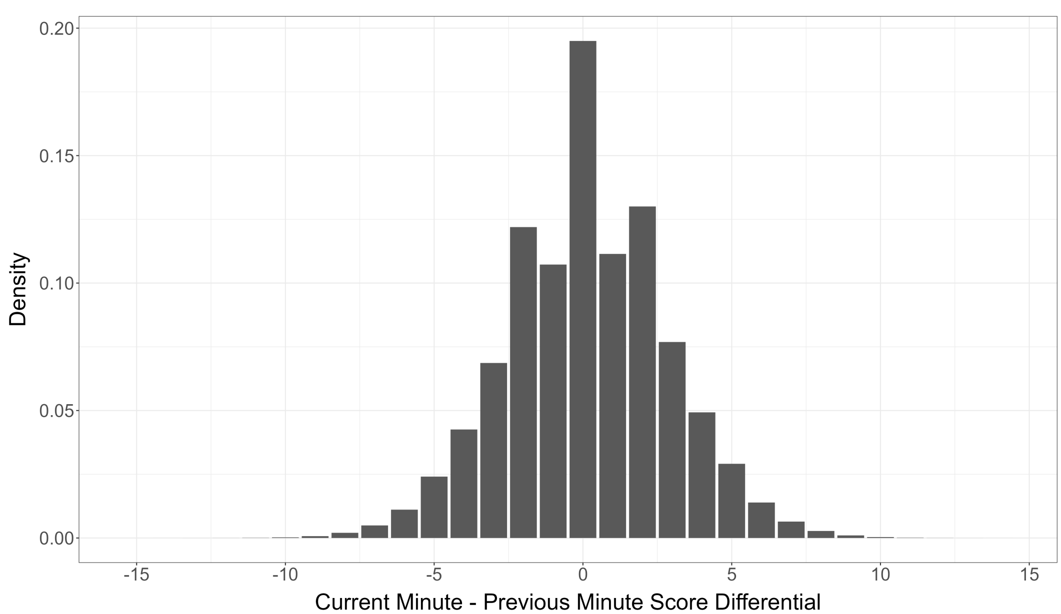
both close and thrilling. Intuitively, the differential viewership impacts across the horizon of a game for similar score differentials is the variation used to separate the impact of thrill on viewership versus the impact of a close game.

We rely on Definition III.5 to interpret these estimates as plausibly causal, which stipulates that beliefs over the final outcome update according to a first-order Markov process. Applying this to the score differential itself, the realized absolute score differential in period $t+1$, $|D_{t+1}|$, is random conditional on the score differential at time, $|D_t|$, and fixed information known prior to a game, b_0. We believe a live sporting event to be an ideal setting in support this process.

$$|D_{t+1}| \sim \mathcal{N}(|D_t|, \sigma^2 \mid b_0) \tag{V.2}$$

Figure 5 provides visual evidence in support of this assumption. It depicts the distribution of the difference in the score differential at minute t versus minute $t-1$. Thus, a difference of 0 implies that the score differential did not change between minute $t-1$ and t. This figure suggests

Figure 5: Distribution of Difference in Score Differential at minute t and $t-1$



the evolution of the score differential from $t-1$ to t follows a normal distribution centered around 0, which has important implications for spectator beliefs. From minute to minute, there is more likely to be relatively small updating in beliefs than larger updating.

B *Viewership Responses to Alternative Outcomes*

Individuals may also experience suspense or surprise with respect to an outcome unrelated to which team wins the game. Examples include which team covers the point spread, total points scored over/unders, and other within-game propositions. The alternative outcome we examine empirically is with respect to the point spread set before a game begins, which is one of the most common measures gambled on by bettors. In this case, it is not the absolute score differential that determines thrill, rather the absolute score differential *in reference to the point spread*.

The point spread is defined as the number of points P_{jT} such that $V_{jA} + F(P_{jT}) = V_{jB}$, where $F(\cdot)$ is a one-to-one function mapping points to strength.[7] We index by T since point spreads typically refer to $\mathbb{E}[D_T]$. Using this setup, the absolute score differential in reference to the closing point spread can be defined:

$$|D_{jt}^{'}| = |D_{jt} + P_{jT}| \tag{V.3}$$

where both D_{jt} and P_{jT} use the same team as the reference point for scoring. For instance, if the home team is always used as the reference point, $D_{jt} > 0$ implies the home team is leading, and $P_{jT} > 0$ implies the home team is an underdog. To understand this further, take the following concrete example. Suppose there is a game featuring the Cleveland Cavaliers and Boston Celtics, where the Cavaliers are the home team. If the closing point spread was -7, and the score at the end of the third quarter was 85 - 82 favoring Cleveland, then the absolute score differential from the

[7]Note that we index strength here at the game level, allowing for strength for a specific team to differ across games.

spread would be equal to four. However, if the score was 85 - 82 in favor of Boston, the absolute score differential from the spread would be equal to ten.

To measure thrill from this outcome, we rely on the methodology used in Salaga and Tainsky (2015), who study television viewership for all PAC-12 football games from 2009-15. They examine the impact of score differential during a game in reference to the closing point spread on average television viewership for a game (they do not measure viewership changes over time within games). The authors note that it is important to de-confound estimates from viewership corresponding to the actual game outcome, represented by the raw score differential. To try and account for this, the authors subset their analysis sample to i) the second half of games, ii) games with the absolute score differential above some threshold level $G_{t=0.5T}$ at halftime, and iii) games whose absolute score differential does not fall below some threshold $G_{t>0.5T}$ during the second half of a game.

One important difference in my approach is that we use real-time win probability estimates for each game instead of absolute score differential to determine the subsample to study. This is because a uniform score differential threshold may correspond to significantly different win probabilities in different games. We set $G_{t=0.5T} = 0.6$ and $G_{t>0.5T} = 0.4$. Games must meet the criteria where at halftime, the difference in win probabilities of each team winning is ≥ 0.6, and over the course of the second half, that difference does not fall below 0.4. The results are not sensitive to restrictions reasonably close to these bounds.

Applying this approach, we estimate a model of viewership in response to suspense over the absolute score differential in reference to point spread as follows:

$$V_{jt} = (|D'_{jt}| * \mathbf{Q_{jt}})\mathbf{\Lambda} + (|D_{jt}| * \mathbf{Q_{jt}})\mathbf{\Gamma} + \alpha_j + \eta_t + \epsilon_{jt} \tag{V.4}$$

$$\text{s.t.} \quad |P_{t=halftime}(A) - P_{t=halftime}(B)| > G_{t=0.5T} \quad \& \quad |P_{t>halftime}(A) - P_{t>halftime}(B)| > G_{t>0.5T}$$

where all the terms maintain their previous definitions.

C Viewership Responses to Suspense and Surprise

Finally, we develop a reduced form model to jointly estimate the impacts of suspense and surprise on viewership, as defined in section III. We perform two separate estimations: one using the definitions of suspense and surprise provided in Ely et al. (2015) (definitions III.8 and III.6), and one using the alternative definitions we propose (definitions III.10 and III.7). The general form of the estimating equation is as follows:

$$V_{jt} = \mu X_{jt} + \rho Y_{jt} + \alpha_j + \eta_t + \epsilon_{jt} \tag{V.5}$$

V_{jt} represents total viewership for game j at time-of-game t. X_{jt} denotes the structurally defined suspense parameter and Y_{jt} the structurally defined surprise parameter. Game and time-of-game fixed effects are denoted as α_j and η_t, respectively. Therefore, μ and ρ represent the impacts of suspense and surprise on viewership, respectively. As opposed to the previous estimations using raw score differential, we can treat suspense and surprise as two different characteristics in this estimation. The following section will present the results from each of the estimation approaches discussed here.

VI Results

In this section we present three sets of results: (i) viewership responses during a game to the absolute score differential, (ii) viewership responses during a game to the absolute score differential with respect to the point spread, and (iii) viewership responses during a game to suspense and surprise.

A Viewership Responses to Score Differential

Table 2 shows two separate estimations. Column (1) presents a "naive" estimation, namely the average impact of absolute score differential on log viewership. This specification is meant to capture the average viewership response to score differential measured uniformly over a game (i.e. a 2-point game in the first quarter is just as close as a 2-point game in the fourth quarter).[8] Column (2) differs from column (1) in that it presents the time-varying impacts of absolute score differential on viewership, which corresponds to equation V.1.

Table 2: Impact of Absolute Score Differential on TV Ratings

	Dependent Variable: log(Total Proj. Viewers Watching)	
Absolute Score Diff.	-0.0054^{*}	0.0014
	(0.0013)	(0.0018)
Absolute Score Diff. * Q2		-0.0011
		(0.0018)
Absolute Score Diff. * Q3		-0.0055^{+}
		(0.0023)
Absolute Score Diff. * Q4		-0.0118^{**}
		(0.0027)
Game FE	X	X
Quarter Segment FE	X	X
Game + Quarter Segment Clusters	X	X
Observations	60,208	60,208
R^2	0.9453	0.9471
Adjusted R^2	0.9449	0.9466
Note:	$^{+}$p<0.05; *p<0.01; **p<0.001; ***p<0.0001	

One can see that on average across an entire game, a one point increase in the absolute score

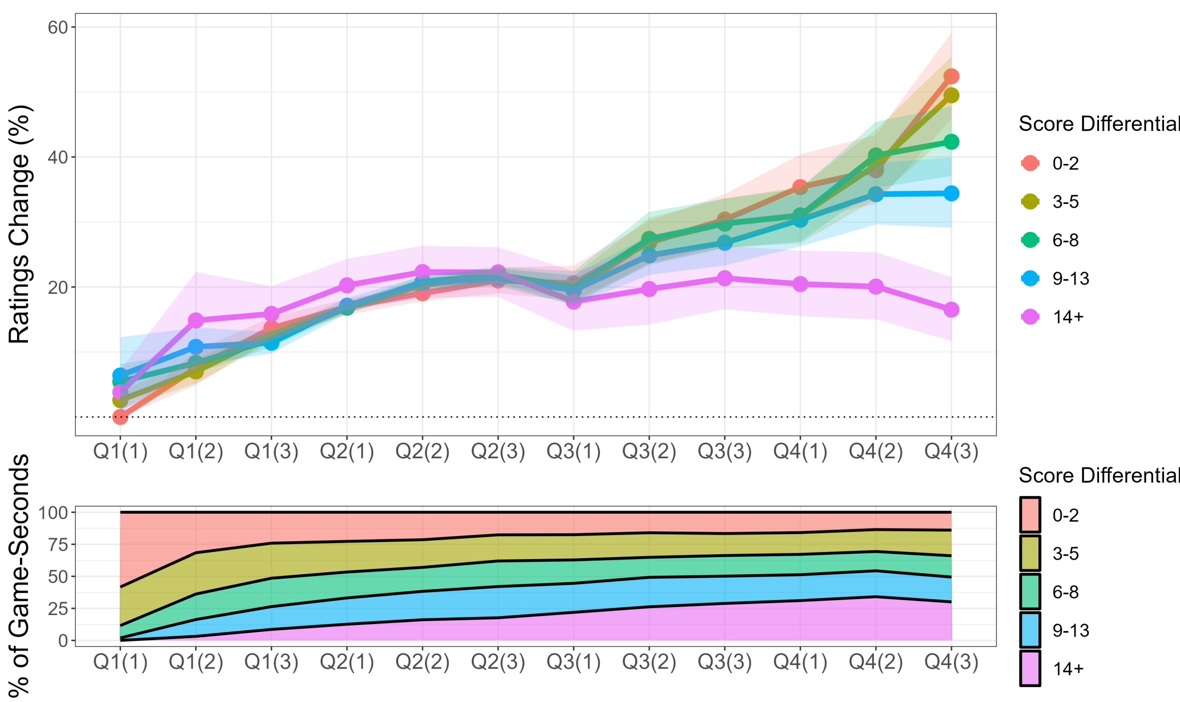
[8] As mentioned previously, it is important not to conflate the definition of a close game versus a thrilling game.

differential reduces television viewership by 0.54%, and so close games are important in raising viewership. Columns (2) shows a clear relationship between time remaining in the game and the impact of score differential on viewership – a one point increase in absolute score differential in the third and fourth quarters leads to an approximately 0.55% and 1.2% drop in viewership, compared to a drop in the first two quarters that is not significantly different from zero. This is strong evidence in support of the impact of thrill on viewership – marginal score differential changes lead to higher viewership impacts when they lead to a larger variance in beliefs, either forward- or backward-looking. As shown in Table 1, which depicts summary statistics of the play-by-play data, the mean and standard deviation of absolute score differential are 8.14 and 7.02, respectively, suggesting that viewership changes in response to changes in absolute score differential are quite sensitive. Specifications are robust to clustering only at the game or quarter segment levels.

Figure 6 expands on Table 2 by examining the impacts of absolute score differential on viewership at a more granular level. We split each game into twelve equally long quarter segments, and absolute score differential is divided into five bins using the quintiles of the distribution of score differential in the data. All points in Figure 6 represent coefficients from an estimation taking the form of equation V.1, and can be interpreted as relative to the omitted score differential bin-by-quarter segment (the 0-2 bin in the first quarter segment, Q1(1)).

First, this graph shows that average viewership over the course of a game is generally increasing.Similar to Table 2, there are heterogeneous impacts of absolute score differential on viewership as a game progresses to its later stages. While in the first half there are no significant differences between each of the score differential bins and viewership changes, in the second half viewership flattens out for the higher score differential bins compared to the lower bins. In particular, a game in the closest absolute score differential quintile (0-2 points) features 8.2-20.5% lower viewership in

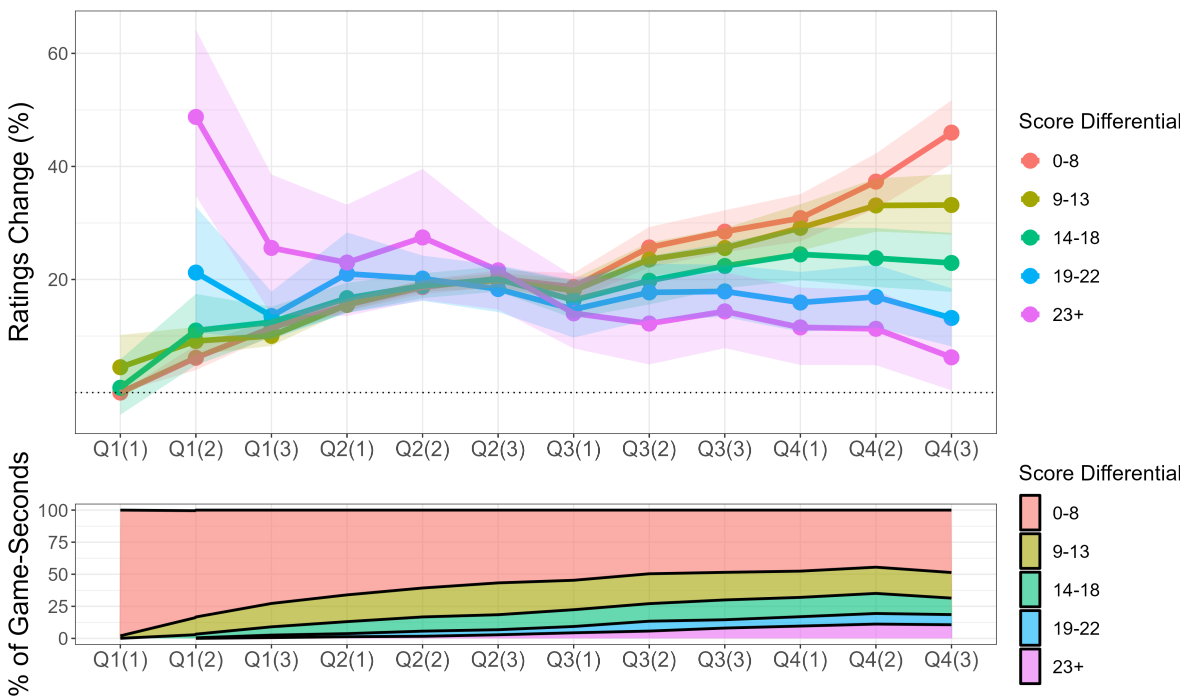
Figure 6: Household Viewership Results by Score Differential Bin by Quarter Segment (% Change)



the second half compared to a game in the largest absolute score differential quintile (14 + points), with the difference increasing monotonically as a game approaches the end.

It is clear that the 14+ absolute score differential bin exhibits the most stark impacts on viewership. Figure 7 examines these effects more closely, looking at the tails of the distribution of absolute score differential. Here, impacts appear to be much more sensitive than those in the primary support of the score differential distribution, where marginal increases in absolute score differential when the differential is already quite high are much more impactful on viewership than marginal increases when the differential is quite low. This effect is not only apparent towards the end of games, but also for uncommonly large score differentials in the very early stages of games, which would indicate heightened surprise. Estimations are robust to alternative clustering

Figure 7: Household Viewership Results by Score Differential Bin by Quarter Segment (Tails)



structures, which are presented in the Appendix.

To assess estimated revenues from thrill, I use changes in advertising revenues associated with differences in thrill across games. Assuming a cost-per-thousand (CPT) viewership minutes estimate of $25 (Fou 2014; Friedman 2017), 20% of programming time during a game spent on advertisements (Statista 2014), and a 15-minute average length of each of the 12 quarter segments, the difference in advertising revenue between a 0-2 point game versus a 14+ point game in the final quarter segment is approximately $50,000.[9] Aggregating this difference over the course of an entire second-half, I find that advertising revenues are $130,000 higher for 0-2 point games compared to 14+ point games. While these revenue differences are economically sizeable, they are likely to underestimate

[9]The five absolute score differential bins in Figure 6 represent the quintiles of the distribution within the data. Thus, approximately 20% of game-seconds within a game experience a 0-2 point score differential, and 20% of game-seconds experience a 14+ point score differential.

the true welfare associated with thrill since they do not account for increases in consumer surplus of inframarginal viewers due to enhanced thrill.

B Viewership Responses to Score Differential in Reference to the Point Spread

Table 3 presents results depicting the effect of absolute score differential in reference to the closing point spread on viewership. Columns (1) and (2) present results of the naive estimation, which measures average viewership impacts associated with games close-to versus far-from the initial point spread, while columns (3) and (4) show thrill-driven impacts. Additionally, columns (2) and (3) control for the average impact of the raw absolute score differential on viewership, while column (4) controls for differential impacts of the raw absolute score differential on viewership by time of game.

In the naive model, the hypothesized sign of the coefficient on absolute score differential from the spread is negative, namely the further the absolute score differential gets from the point spread, the lower viewership becomes. One can see from columns (1) and (2) that controlling for absolute score differential is important, since it is likely correlated with absolute score differential from the point spread and also has negative impacts on viewership. Column (2) suggests there are no statistically significant viewership impacts associated with a close game in reference to the spread in a national audience.

Columns (3) and (4) provide the thrill-driven impacts of score differential from the spread on viewership. While there does not appear to be significantly different effects from zero until the end of the third quarter, it is clear that as the game progresses, a higher absolute score differential from the spread leads to larger decreases in viewership. This is result has an identical explanation to the results found in Table 2 and Figures 6 and 7. Since the omitted period is Q3(1), the true effect of the score differential in reference to the point spread on viewership in the final quarter

Table 3: Impact of Absolute Score Differential in Reference to Point Spread on Viewership

	Dependent Variable: log(Total Proj. Viewers Watching)			
Absolute Score Diff. From Spread	−0.0035	−0.0041	0.0021	0.0025
	(0.0016)	(0.0024)	(0.0021)	(0.0020)
Absolute Score Diff. From Spread * Q3(2)			−0.0003	-0.0010^{+}
			(0.0002)	(0.0004)
Absolute Score Diff. From Spread * Q3(3)			-0.0022^{+}	-0.0023^{+}
			(0.0006)	(0.0007)
Absolute Score Diff. From Spread * Q4(1)			-0.0031^{+}	−0.0021
			(0.0010)	(0.0014)
Absolute Score Diff. From Spread * Q4(2)			-0.0061^{*}	-0.0055^{+}
			(0.0012)	(0.0015)
Absolute Score Diff. From Spread * Q4(3)			-0.0100^{**}	-0.0094^{*}
			(0.0013)	(0.0018)
Score Differential Control		X	X	X
Score Differential x Quarter Segment Control				X
Game FE	X	X	X	X
Quarter Segment FE	X	X	X	X
Game + Quarter Segment Clusters	X	X	X	X
Observations	40,588	40,588	40,588	40,588
R^2	0.9821	0.9821	0.9857	0.9859
Adjusted R^2	0.9821	0.9821	0.9857	0.9859

Note: $^{+}p<0.05$; $^{*}p<0.01$; $^{**}p<0.001$; $^{***}p<0.0001$

segment is -0.0079 in specification (3) and -0.0069 in specification (4), suggesting that for every one-point increase in the score differential from the spread, viewership declines by approximately 0.79% and 0.69%, respectively. As expected, these results are approximately half the magnitude of the impact of raw absolute score differential on viewership. However, given these estimates, a one-standard deviation change in score differential in reference to the initial point spread during the final quarter segment (9.3 points) can still have an economically meaningful impact on viewership (6.4-7.3% reduction).

C Viewership Responses to Suspense and Surprise

Table 4 presents results of the estimation identifying the impacts of suspense and surprise on viewership. Columns (1) and (2) use the definitions of suspense and surprise provided in Ely et al. (2015) (definitions III.8 and III.6), and columns (3) and (4) use the alternative definitions we propose (definitions III.10 and III.7). Columns (1) and (3) include only suspense in the estimation, while equations (2) and (4) include both suspense and surprise. All specifications include game and quarter segment fixed effects, and are two-way clustered at the game + quarter segment level.

We interpret the coefficients considering a one standard deviation change in either suspense or surprise. In column (1), a one standard deviation increase in EFK suspense corresponds to a 0.0255 unit increase in suspense, which leads to an approximately 2.53% increase in viewership. In column (1), a one standard deviation in KZ suspense leads to an approximately 2.91% increase in viewership. One can see in columns (2) and (4) that increases in surprise does not affect viewership. This is intuitive based on (i) suspense is simply expected surprise, and (ii) it is difficult for viewers to proactively respond to surprise based on the mechanism by which it occurs. The slight increase in the coefficient on suspense in columns (2) and (4) combined with the negative coefficient on surprise suggests a positive correlation between the two (EFK: 0.66 and KZ: 0.67), which is intuitive. A one standard deviation increase in suspense in specifications (2) and (4) corresponds to a 2.74% and 3.07% increase in viewership, respectively. Tables 6 and 7 present results from the same estimation using percentiles for suspense and surprise and estimations only including surprise, respectively.

To better compare these results to viewership responses associated with the absolute score differential, we compute average suspense in games with a score differential between 0-2 points vs.

Table 4: Impact of Suspense and Surprise on TV Ratings

	Dependent Variable: log(1000's of Total Viewers)			
	Ely, Frankel, and Kamenica		Kaplan and Zorrilla	
Suspense (EFK)	0.9925^{**} (0.1871)	1.0735^{***} (0.1686)		
Surprise (EFK)		$-0.1511^{\cdot}$ (0.0637)		
Suspense (KZ)			0.8440^{**} (0.1448)	0.8889^{***} (0.1310)
Surprise (KZ)				-0.0857 (0.0479)
Game FE	X	X	X	X
Quarter Segment FE	X	X	X	X
Game + Quarter Segment Clusters	X	X	X	X
Mean Suspense	0.0133	0.0133	0.0199	0.0199
Mean Surprise	0.0068	0.0068	0.0103	0.0103
SD Suspense	0.0255	0.0255	0.0345	0.0345
SD Surprise	0.0202	0.0202	0.0265	0.0265
Observations	58,776	58,771	58,776	58,771
R^2	0.9487	0.9487	0.9490	0.9490
Adjusted R^2	0.9483	0.9483	0.9486	0.9486
Note:	$^{+}p<0.05$; $^{*}p<0.01$; $^{**}p<0.001$; $^{***}p<0.0001$			

14+ points in the final quarter segment (less than four minutes left in the fourth quarter), and determine the viewership effect.[10] Table 5 suggests that the viewership response estimates across the two specifications are similar - the viewership impacts from EFK and KZ suspense are 15.34% and 17.08%, respectively, while the viewership impact in the absolute score differential specification

[10] We do not compute surprise since it is not statistically different from 0 in Table 4.

was 20.5%.[11]

Table 5: Comparison of Viewership Responses in Last Four Minutes of the Fourth Quarter

	0 - 2	14+	Difference (in SDs)	Viewership Impact	Viewership Impact (Absolute Score Differential)
EFK Suspense	0.143	0.00011	5.60	15.34%	20.5%
KZ Suspense	0.193	0.00089	5.57	17.08%	20.5%

Future work will replicate the suspense and surprise estimation with respect to the outcome over the initial point spread, as opposed to the final outcome of the game.

VII Future Work

References

Aaker, J. L. (1997). Dimensions of brand personality. *Journal of marketing research 34*(3), 347–356.

Aguiar, M., E. Hurst, and L. Karabarbounis (2013). Time use during the great recession. *American Economic Review 103*(5), 1664–96.

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

Anstine, D. B. (2001). How much will consumers pay? a hedonic analysis of the cable television industry. *Review of Industrial Organization 19*(2), 129–147.

[11] 20.5% is determined from comparing the 0-2 point and 14+ point quintiles in the final quarter segment in Figure 6.

Bagwell, K. (2005). The economic analysis of advertising. columbia university department of economics. Technical report, Discussion Paper Series.

Becker, G. S. and K. M. Murphy (1988). A theory of rational addiction. *Journal of political Economy 96*(4), 675–700.

Becker, G. S. and K. M. Murphy (1993). A simple theory of advertising as a good or bad. *The Quarterly Journal of Economics 108*(4), 941–964.

Bertrand, M., D. Karlan, S. Mullainathan, E. Shafir, and J. Zinman (2010). What's advertising content worth? evidence from a consumer credit marketing field experiment. *The Quarterly Journal of Economics 125*(1), 263–306.

Bizzozero, P., R. Flepp, and E. Franck (2016). The importance of suspense and surprise in entertainment demand: Evidence from wimbledon. *Journal of Economic Behavior & Organization 130*, 47–63.

Borwein, D., J. M. Borwein, and P. Marechal (2000). Surprise maximization. *The American Mathematical Monthly 107*(6), 517–527.

Bryant, J., S. C. Rockwell, and J. W. Owens (1994). Buzzer beaters" and "barn burners": The effects on enjoyment of watching the game go "down to the wire. *Journal of Sport and Social Issues 18*(4), 326–339.

Buraimo, B., D. Forrest, I. G. McHale, and J. Tena (2020). Unscripted drama: soccer audience response to suspense, surprise, and shock. *Economic Inquiry 58*(2), 881–896.

Busse, M. R., C. R. Knittel, and F. Zettelmeyer (2013). Are consumers myopic? Evidence from new and used car purchases. *American Economic Review 103*(1), 220–56.

Caplin, A. and J. Leahy (2001). Psychological expected utility theory and anticipatory feelings. *The Quarterly Journal of Economics 116*(1), 55–79.

Chan, W., P. Courty, and L. Hao (2009). Suspense: Dynamic incentives in sports contests. *The Economic Journal 119*(534), 24–46.

Chay, K. Y. and M. Greenstone (2005). Does air quality matter? Evidence from the housing market. *Journal of political Economy 113*(2), 376–424.

Chung, K. Y., T. P. Derdenger, and K. Srinivasan (2013). Economic value of celebrity endorsements: Tiger woods' impact on sales of nike golf balls. *Marketing Science 32*(2), 271–293.

Currie, J. and R. Walker (2011). Traffic congestion and infant health: Evidence from e-zpass. *American Economic Journal: Applied Economics 3*(1), 65–90.

Ebstein, R. P., O. Novick, R. Umansky, B. Priel, Y. Osher, D. Blaine, E. R. Bennett, L. Nemanov, M. Katz, and R. H. Belmaker (1996). Dopamine d4 receptor (d4dr) exon iii polymorphism associated with the human personality trait of novelty seeking. *Nature genetics 12*(1), 78–80.

Ely, J., A. Frankel, and E. Kamenica (2015). Suspense and surprise. *Journal of Political Economy 123*(1), 215–260.

Fairhall, A. L., G. D. Lewen, W. Bialek, and R. R. d. R. van Steveninck (2001). Efficiency and ambiguity in an adaptive neural code. *Nature 412*(6849), 787–792.

Forrest, D., R. Simmons, and B. Buraimo (2005). Outcome uncertainty and the couch potato audience. *Scottish Journal of Political Economy 52*(4), 641–661.

Fou, A. (2014). Comparative media costs: Cost to reach 1,000 users or impressions. *Marketing Science Consulting Group, Inc.*. , (last accessed 2020-09-25).

Fournier, G. M. and D. L. Martin (1983). Does government-restricted entry produce market power?: New evidence from the market for television advertising. *The Bell Journal of Economics*, 44–56.

Fowdur, L., V. Kadiyali, and V. Narayan (2009). The impact of emotional product attributes on consumer demand: An application to the us motion picture industry. *Johnson School Research Paper Series* (22-09).

Friedman, W. (2017). Nfl tv networks see generally higher cpms. *Television News Daily*. , (last accessed 2020-09-25).

Geanakoplos, J. et al. (1996). The hangman's paradox and newcomb's paradox as psychological games. *COWLES FOUNDATION DISCUSSION PAPER*.

Geanakoplos, J., D. Pearce, and E. Stacchetti (1989). Psychological games and sequential rationality. *Games and economic Behavior 1*(1), 60–79.

Grimshaw, S. D. and J. S. Larson (2020). Effect of star power on nba all-star game tv audience. *Journal of Sports Economics 22*(2), 139–163.

Hartmann, W. R. and D. Klapper (2018). Super bowl ads. *Marketing Science 37*(1), 78–96.

Haugh, M. B. and R. Singal (2020). How to play fantasy sports strategically (and win). *Management Science*.

Hausman, J. A. and G. K. Leonard (1997). Superstars in the National Basketball Association: Economic value and policy. *Journal of Labor Economics 15*(4), 586–624.

Humphreys, B. R. and T. J. Miceli (2019). The peculiar preferences of sports fans: Toward a preference-based motivation for the uncertainty of outcome hypothesis. *Journal of Sports Economics 20*(6), 782–796.

Itti, L. and P. Baldi (2009). Bayesian surprise attracts human attention. *Vision research 49*(10), 1295–1306.

Johnson, B. K. and J. E. Rosenbaum (2015). Spoiler alert: Consequences of narrative spoilers for dimensions of enjoyment, appreciation, and transportation. *Communication Research 42*(8), 1068–1088.

Kahn, L. M. (2000). The sports business as a labor market laboratory. *Journal of Economic Perspectives 14*(3), 75–94.

Kamenica, E. and M. Gentzkow (2011). Bayesian persuasion. *American Economic Review 101*(6), 2590–2615.

Kaplan, E. H. and S. J. Garstka (2001). March madness and the office pool. *Management Science 47*(3), 369–382.

Kaplan, S. (2020). The economic value of popularity: Evidence from superstars in the national basketball association. *Available at SSRN*.

Knowles, G., K. Sherony, and M. Haupert (1992). The demand for major league baseball: A test of the uncertainty of outcome hypothesis. *The American Economist 36*(2), 72–80.

Kreps, D. M. and E. L. Porteus (1978). Temporal resolution of uncertainty and dynamic choice theory. *Econometrica: journal of the Econometric Society*, 185–200.

Krueger, A. B. (2005). The economics of real superstars: The market for rock concerts in the material world. *Journal of Labor Economics 23*(1), 1–30.

Leavitt, J. D. and N. J. Christenfeld (2011). Story spoilers don't spoil stories. *Psychological science 22*(9), 1152–1154.

Lee, D., K. Hosanagar, and H. S. Nair (2018). Advertising content and consumer engagement on social media: Evidence from facebook. *Management Science 64*(11), 5105–5131.

Levine, W. H., M. Betzner, and K. S. Autry (2016). The effect of spoilers on the enjoyment of short stories. *Discourse processes 53*(7), 513–531.

Liu, X., M. Shum, and K. Uetake (2020). Attentive and inattentive tv viewing: Evidence from baseball telecasts. *Available at SSRN*.

Livingston, J. A., D. L. Ortmeyer, P. A. Scholten, and W. Wong (2013). A hedonic approach to testing for indirect network effects in the lcd television market. *Applied Economics Letters 20*(1), 76–79.

Luttik, J. (2000). The value of trees, water and open space as reflected by house prices in the Netherlands. *Landscape and urban planning 48*(3-4), 161–167.

Madrigal, R. and C. Bee (2005). Suspense as an experience of mixed emotions: Feelings of hope and fear while watching suspenseful commercials. *ACR North American Advances*.

PWC (2019). Perspectives from the global entertainment & media outlook 2019-2023. *Price Waterhouse Cooper Reports*. link here, (last accessed 2020-06-01).

Ranganath, C. and G. Rainer (2003). Neural mechanisms for detecting and remembering novel events. *Nature Reviews Neuroscience 4*(3), 193–202.

Resnik, A. and B. L. Stern (1977). An analysis of information content in television advertising. *Journal of marketing 41*(1), 50–53.

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of political economy 82*(1), 34–55.

Rosen, S. (1981). The economics of superstars. *The American economic review 71*(5), 845–858.

Rottenberg, S. (1956). The baseball players' labor market. *Journal of political economy 64*(3), 242–258.

Ryoo, J. H., X. Wang, and S. Lu (2020). Do spoilers really spoil? using topic modeling to measure teh effect of spoiler reviews on box office revenue. *Journal of Marketing Forthcoming*.

Salaga, S. and S. Tainsky (2015). Betting lines and college football television ratings. *Economics Letters 132*, 112–116.

Sallee, J. M., S. E. West, and W. Fan (2016). Do consumers recognize the value of fuel economy? Evidence from used car prices and gasoline price fluctuations. *Journal of Public Economics 135*, 61–73.

Scully, G. W. (1974). Pay and performance in major league baseball. *The American Economic Review 64*(6), 915–930.

Simonov, A., R. Ursu, and C. Zheng (2020). Do suspense and surprise drive entertainment demand? evidence from twitch. tv. *Evidence from Twitch. tv (October 14, 2020)*.

Statista (2014). Length of tv ad time in 120 minutes of selected sporting events in united states in 2013 and 2014. *Statista.* , (last accessed 2020-09-25).

Stigler, G. J. and G. S. Becker (1977). De gustibus non est disputandum. *The american economic review 67*(2), 76–90.

Su-lin, G., C. A. Tuggle, M. A. Mitrook, S. H. Coussement, and D. Zillmann (1997). The thrill of a close game: Who enjoys it and who doesn't? *Journal of Sport and Social Issues 21*(1), 53–64.

Wilbur, K. C. (2008). A two-sided, empirical model of television advertising and viewing markets. *Marketing science 27*(3), 356–378.

A Appendix

Figure 8: Household Viewership Results by Score Differential Bin by Quarter Segment (% Change): Game Clustering

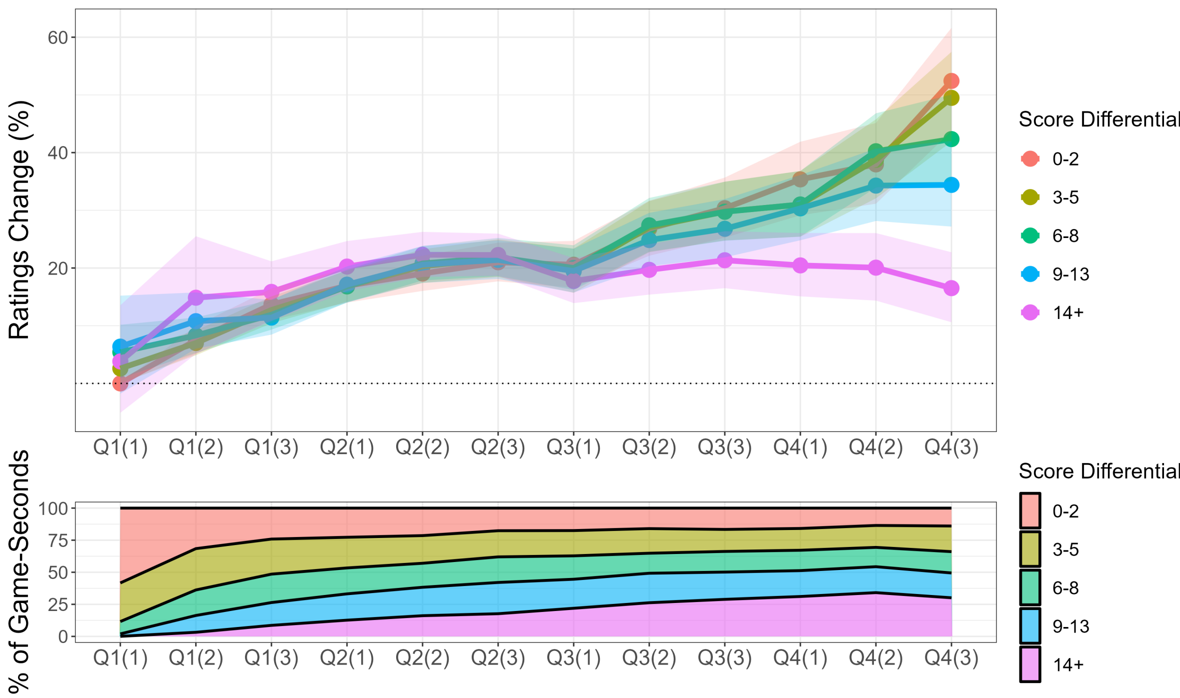


Figure 9: Household Viewership Results by Score Differential Bin by Quarter Segment (% Change): Quarter Segment Clustering

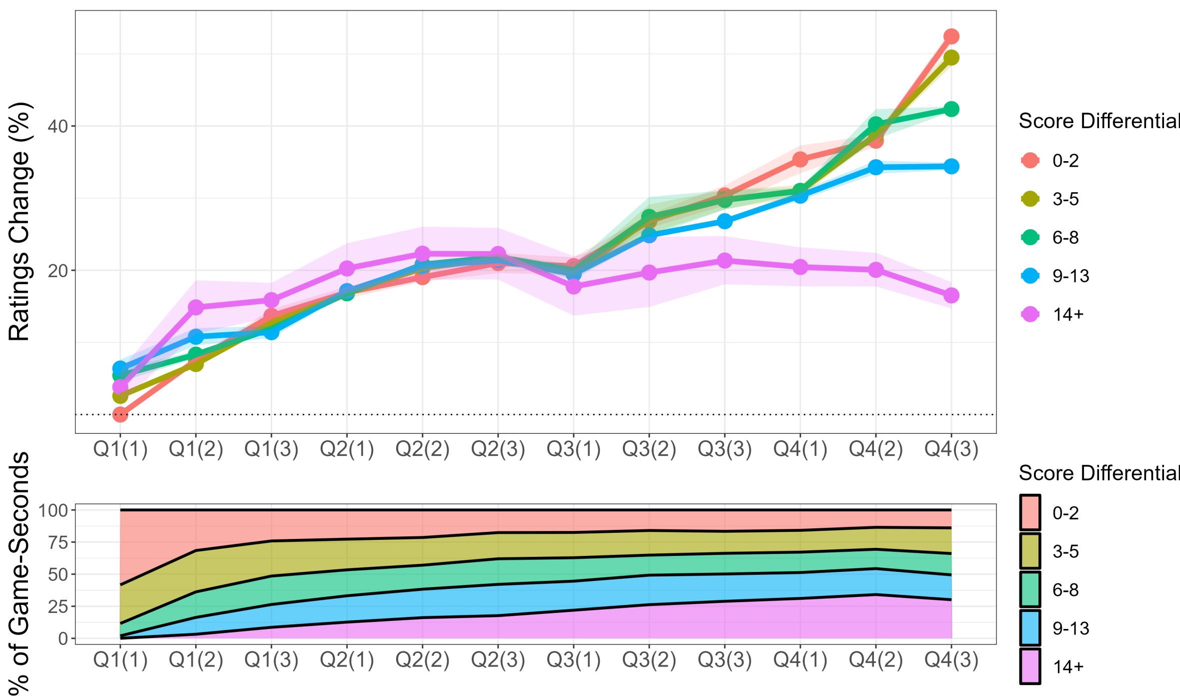


Table 6: Impact of Suspense and Surprise Percentiles on TV Ratings

	Dependent Variable: log(1000's of Total Viewers)			
	Ely, Frankel, and Kamenica		Kaplan and Zorrilla	
Suspense Percentile (EFK)	0.0015^{***}	0.0013^{***}		
	(0.0002)	(0.0002)		
Surprise Percentile (EFK)		$0.0004^{\cdot}$		
		(0.0001)		
Suspense Percentile (KZ)			0.0015^{**}	0.0013^{***}
			(0.0003)	(0.0002)
Surprise Percentile (KZ)				$0.0005^{\cdot}$
				(0.0002)
Game FE	X	X	X	X
Quarter Segment FE	X	X	X	X
Game + Quarter Clusters	X	X	X	X
Observations	58,776	58,771	58,776	58,771
R^2	0.9497	0.9497	0.9497	0.9498
Adjusted R^2	0.9492	0.9493	0.9493	0.9494
Note:	$^{+}p<0.05$; $^{*}p<0.01$; $^{**}p<0.001$; $^{***}p<0.0001$			

Table 7: Impact of Surprise on TV Ratings

	Dependent Variable: log(1000's of Total Viewers)	
	Ely, Frankel, and Kamenica	Kaplan and Zorrilla
Surprise (EFK)	0.6306**	
	(0.1166)	
Surprise (KZ)		0.5709***
		(0.0687)
Game FE	X	X
Quarter Segment FE	X	X
Game + Quarter Clusters	X	X
Mean Surprise	0.0068	0.0103
SD Surprise	0.0202	0.0265
Observations	58,771	58,771
R^2	0.9479	0.9481
Adjusted R^2	0.9475	0.9476
Note:	$^{+}p<0.05$; $^{*}p<0.01$; $^{**}p<0.001$; $^{***}p<0.0001$	