Entertainment Utility from Skill and Thrill*

Scott Kaplan†

December 20, 2020

(Current Version Here)

Abstract

This paper uses revealed preference methods to estimate demand for non-instrumental information in entertainment. I do this by examining the "thrill" associated with the trajectory of an event, which includes both suspense and surprise, and the "skill" of performers in an event. I apply the theory presented in Ely et al. (2015) to conduct an empirical analysis that examines the effect of thrill on consumer attention. I extend the Ely et al. (2015) framework by examining spectator preferences for characteristics of the performers themselves, which I call "skill." I use game-specific, high-temporal frequency television ratings data from the National Basketball Association (NBA) to measure spectator responses to skill and thrill. First, I find that a doubling of skill present in a game leads to an approximately 11% increase in initial viewer turnout, while the expected thrill of a game has no statistically significant impact. Next, I show that thrill during a game increases viewership by 7-30%, while a doubling of skill on the court during a specific portion of a game leads to a 1.9-2.4% increase in viewership, depending on specification. Interestingly, I find a negative interactive effect between suspense and skill, suggesting that heightened suspense leads to differentially higher viewership with lower skill on the court. The findings suggest that skill of information-conveying agents primarily impacts viewership on the extensive margin (across games), while thrill is highly time-dependent and primarily impacts viewership on the intensive margin (within games). These findings have important implications for entertainment media companies, including leagues and television broadcasters, and advertisers.

Keywords: non-instrumental information, suspense, surprise, consumer attention, difference-in-differences

†PhD Candidate, Department of Agricultural and Resource Economics, UC Berkeley. email: scottkaplan@berkeley.edu.

*Thanks to Cheenar Gupte for excellent research assistance. Special thanks to my core advising team: Ben Handel, Jim Sallee, Sofia Villas-Boas, and David Zilberman. I'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. I'd also like to thank participants in the 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, and the NYU Stern Marketing Seminar Series. Finally, special thanks to Ryan Davis for help in acquisition of the play-by-play data, and Todd Whitehead for useful feedback. All remaining errors are my 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 constrast, 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.

There is an important piece missing from these events, though: the performers themselves. The extent to which thrill is meaningful may depend on which golfer, tennis player, or political candidate is conveying the information. A political debate between Joe Biden and Donald Trump likely garners much higher overall attention than a debate between candidates for a local election. I define "skill" using characteristics of the performers themselves, which includes measures of productivity and popularity.

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, and the "skill" associated with the performers involved. I take the theory presented in Ely et al. (2015) to conduct an empirical analysis that examines the effect of thrill on consumer attention. I extend the Ely et al. (2015) framework by examining spectator preferences for skill. I employ game-specific, minute-by-minute television ratings data from the National Basketball Association (NBA) during the 2017-18 and 2018-19 seasons to measure viewership responses to skill and thrill. Thrill is the suspense and surprise experienced during the course of a game, as defined in Ely et al. (2015). I define the skill of a specific player as the total number of fan All-Star votes they receive in a given season. While there are many different interesting domains to study non-instrumental information, live sports is a natural application since (i) the skill of players 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.

I rely on two primary empirical strategies to measure these impacts. First, I estimate initial viewership turnout in response to the presence of total skill and the expected thrill of a game. Next, I utilize within-game play-by-play data at the second-of-game level, where I observe the level of skill on the court, score differential, and real-time win probabilities for each team, to assess television viewership responses to skill and thrill as they evolve during a game. I then use these estimates to understand the viewership impact of counterfactual game structures.

The findings suggest that skill and thrill play important, but different, roles in generating consumer attention. First, I find that a doubling of skill present in a game leads to an approximately 11% increase in initial viewer turnout, while expected thrill has no statistically significant impact. For context, LeBron James' All-Star vote total in the 2018-19 season corresponds to approximately 120% of the average aggregate number of All-Star fan votes of all players in a game. Thus, the presence of LeBron alone results in an approximately 13.5% increase in initial TV viewership. These results are remarkably similar to those found in Kaplan (2020), which uses secondary ticket marketplace data to assesses the impact of a superstar absence announcement for a specific game on listed prices, finding that the absence of LeBron James leads to a 13% ($42/ticket) average reduction in ticket prices.

Next, I use the evolution of absolute score differential over the course of a game to measure viewership responses to thrill. This analysis uses a more observable measure of thrill than the structural definitions from Ely et al. (2015). I 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 idea that viewers relish thrilling games, not just games that are close. Contextualizing these results further, second half ratings are 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. I 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 0.10-0.94%, with larger decreases found in later stages of a game. For context, 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).

Finally, I jointly assess within-game viewership impacts from suspense, surprise, and skill, directly implementing the structural definitions of suspense and surprise from Ely et al. (2015). I find that a doubling of suspense during a game increases viewership by 0.4-0.6%, and a doubling of surprise by 0.6-1.0%, not accounting for additional or differential impacts associated with skill. 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 averages 18 times more suspense than a 14+ point game. In this case, viewership would be approximately 6.8-10.8% higher through suspense alone. On the other hand, the range of surprise exhibited over the course of a game is slightly lower than that of suspense. Specifically, in the fourth quarter a 0-2 point game features 14 times more surprise on average than a 14+ point game, which would translate into a viewership increase of 9.0-13.4%.

In the fully interacted model accounting for within-game variation in skill, I find that a doubling of skill on the court at a given time during the game leads to a 1.9-2.4% increase in viewership. The comparison of responses to skill and thrill using initial versus within-game viewership suggest that viewers respond to skill primarily on the extensive margin (across games), while responses to thrill take place primarily on the intensive margin (within games).

In other words, viewers are much more likely to be interested in a game prior to it starting because of the skill of the players involved, but are more likely to respond within a game as thrill evolves. Interestingly, I also find a negative interactive effect between suspense and skill, suggesting that heightened suspense leads to differentially higher viewership with lower skill on the court, supporting the traditional notion that spectators may only turn on games featuring lesser-known players (or teams) if they're nearing the end and exhibiting sufficiently high suspense. I find no evidence for an interactive effect between skill and surprise, and in fact when conducting the joint estimation featuring both thrill and skill, I find little evidence to suggest surprise impacts viewership in this entertainment setting.

This research contributes to several notable bodies of literature. First and foremost, there is a small existing literature on suspense and surprise. Ely et al. (2015) provide the definitions of suspense and surprise used in this analysis and is the primary existing study on this topic. Their study incorporates examples from practical entertainment and socially-relevant settings, including novels, political races, and live sports. I expand on their work by examining the quality of the performers themselves, and how the presence of these agents can affect responses to suspense and surprise in an event. 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 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 occurances (Itti and Baldi 2009; Ranganath and Rainer 2003; Fairhall et al. 2001; Ebstein et al. 1996).

To the best of my knowledge, there have been two peer-reviewed, empirically-oriented studies to date using the suspense and surprise framework from Ely et al. (2015). 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% minute-level 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 extends the suspense and surprise literature in several key ways. First, I explore a broader question that includes how the quality of agents performing in these events affects viewership, providing evidence of the relative magnitude impact of "skill" and "thrill." Second, I examine viewership responses to thrill over alternative game outcomes, which may be unrelated to the final outcome of who wins or loses. In particular, I explore suspense and surprise with respect to the closing point spread of a game, finding statistically significant and economically meaningful impacts. Third, I use my estimates of viewership responses to thrill to assess the impact of a counterfactual game structure that leads to higher levels of thrill by construction. Finally, I examine an entirely different sport and geographic market: spectators of professional basketball in the United States. There are notable differences between the structure of the event and the types of spectators attending and watching games, which may partially explain magnitude differences in television viewership responses in this paper compared to previous work.

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). I 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] I 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

[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.

products (Busse et al. 2013; Sallee et al. 2016; Currie and Walker 2011; Chay and Greenstone 2005; Luttik 2000). This work focuses on two primary attributes of entertainment goods–the skill of the performers and the thrill of the event itself. Television ratings data is a natural avenue to explore impacts of these characteristics on consumer attention, 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 work using hedonic pricing methods in entertainment to understand the value of star performers (Scully 1974; Kahn 2000; Rosen 1981; Hausman and Leonard 1997; Krueger 2005; Chung et al. 2013, Kaplan (2020)). To the best of my knowledge, there is no existing research jointly measuring the impact of skill and thrill on demand.

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 skill of performers and 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. Measuring in a revealed preference manner how consumer attention responds to skill and thrill is important in understanding how to better engage audiences with different advertising strategies.

The remainder of this paper proceeds as follows. First, I develop a model of spectator utility from entertainment in section II. I then overview the data, develop the set of empirical strategies used in estimating viewership responses to skill and thrill, and present the results of the analysis in section III. Section IV contextualizes and provides an economic interpretation of the results, while also presenting a counterfacutal analysis assessing viewership responses to an alternative game structure. Finally, section V concludes.

II Model of Utility from Entertainment

This section presents a conceptual framework to understand consumer demand for skill and thrill. While the definition of player skill is straightforward (the number of fan All-Star votes received), thrill requires a more structured definition of the specific characteristics that lead to excitement transpiring during a game. Specifically, I separate thrill into two distinct components: suspense and surprise. I rely on structure from Ely et al. (2015) to formally develop a mathematical interpretation of suspense and surprise that can be used in conjunction with skill to assess spectator preferences.

A Defining Suspense and Surprise

Suppose there are two teams, A and B. Teams can be thought of as sports teams, political candidates, or characters in a movie, book, or play. Suppose each team i is defined by their "strength," $V_i \in \mathbb{R}^+$, which corresponds to their ability compared to other teams. Denote Team A's strength as V_A and Team B's strength as V_B. Team A and B compete in an event lasting T periods, where the outcome is fully resolved in period T when a winner is declared. Let

$P_t(A)$ denote the probability at time t that Team A wins, and $1 - P_t(A)$ the probability at time t that Team A does not win, where the set $P_t = \{P_t(A), 1 - P_t(A)\}$ represents an outcome probability pair at time t. For the specific case of $t = 0$, $P_0(A) = \frac{V_A}{V_A + V_B}$ and $P_0(B) = 1 - P_0(A)$, representing the prior belief that each respective team will emerge victorious at $t = T$.

Let beliefs about future outcome probabilities take the following structure. At time t there is a belief martingale $\tilde{\mu} = (\tilde{\mu}_t)_{t=0}^{T}$, which is a sequence of beliefs about future outcome probability pairs believed at time t. Assume now that $\tilde{\mu}$ evolves as a first-order Markov process over $t = 1, ..., T$. Namely, $\mathbb{E}[\tilde{\mu}_{t+1} | \mu_0, ..., \mu_t] = \mu_t$ for all $t \in \{1, ..., T\}$. It is important to note that with this structure, there must be a sequence representing realized outcome probability pairs observed at each t, P_t. Denote this sequence $\mu = (P_t)_{t=0}^{T}$. Additionally, beliefs about some period $t + n$ while based at time t are written as $\mathbb{E}[\tilde{\mu}_{t+n} | \mu_0, ..., \mu_t] = \mu_t$ where $n \in [1, T - t]$. With this setup, I define suspense at time t, X_t, as follows:

$$X_t = \mathbb{E}_t \left[(\tilde{\mu}_{t+1} - \mu_t)^2 \right] \tag{1}$$

Thus, suspense at time t is higher when there is higher variance in beliefs about the difference in the probability pair at time $t + 1$ and the realized probability pair at time t. In words, the larger the potential swings in the probability pair between period t and $t + 1$, the higher the suspense. Due to the Markovian nature of the setup, $\mathbb{E}_t[P_{t+1}] = P_t$.

Surprise, on the other hand, is a backward-looking (*ex-post*) belief. An agent only experiences surprise in response to something that has already transpired. Using the framework above, surprise Y_t is defined as follows:

$$Y_t = (\mu_t - \mu_{t-1})^2 \tag{2}$$

Thus, there is higher surprise at time t the larger the variance in the realized probability pair between time t and time $t-1$. In words, the larger the "swing" in realized outcome probabilities between $t-1$ and t, the higher the surprise in t. It should be noted that surprise is tightly interlinked with suspense—an event with a large amount of surprise may lead to a more or less suspenseful state at time t.

B *Model of Entertainment Utility*

In this section, I introduce a novel model of spectator utility derived from entertainment, which includes suspense, surprise, and skill. I begin by developing a framework that generates utility for individual i from an entertainment event j. Denote the total skill of all players in a game as S_j, which I assume to be time invariant and continuous, and the thrill during a specific portion of a game as $H_j(r) = X_j(r) + Y_j(r)$, where r is a continuous measure of time remaining in an event. Thus, the expected thrill of an entire event can be written $\int_{r=R}^{0} \mathbb{E}[H_j(r)]$ where R represents the length of an entire event.[2]

Additionally, assume the cost of watching $C(t, X_j)$ to be a function of time spent watching t and all time-invariant, event-specific costs X_j. I assume $\frac{\partial C(t,X_j)}{\partial t} > 0$ and $\frac{\partial^2 C(t,X_j)}{\partial t^2} > 0$, and $t = T$ denotes the maximum time that can be spent watching an event. Thus, the utility for individual i from game j can be written as follows:

$$(3)\quad U_{ij} = B_j - C(t, X_j) + \psi\left[S_j * t\right] + \int_0^t \phi\mathbb{E}[H_j(r)]dr + \theta\left[(S_j * t) * \int_0^t \mathbb{E}[H_j(r)]dr\right] + \xi_i + \epsilon_{ij}$$

where ψ and ϕ are average marginal utilities from skill and thrill, respectively. I also allow for an interactive effect of skill and thrill on utility, where θ represents the average marginal

[2] In contrast to the definitions of suspense and surprise, I rely on continuous time notation in the development of the model in order to derive solutions analytically. However, the implications are analagous for a setup using discrete time.

utility associated with this interaction. For example, an event with large levels of skill and thrill may exhibit differentially higher (or lower) utility than the additive components of skill and thrill alone. I assume here that an individual experiences the skill in an event linearly with time spent watching, although this assumption will be relaxed.[3] B_j represents some baseline average utility from event j, ξ_i an individual utility shifter, and ϵ_{ij} an i.i.d. residual term.

There are two choices an individual must make in their decision to watch an event: a choice of the amount of time to spend watching, t^*, and how to allocate t^* across a game. Here, I rely on the assumption that $\frac{\partial \mathbb{E}_{r=R}[H_j(r)]}{\partial r} < 0$, which suggests that expected thrill (at time remaining R) is monotonically increasing over the course of an event. With this assumption in place, an individual making an *ex-ante* decision about how much time to spend watching a game should choose to allocate their time beginning with the end of an event, working backwards.[4] With this structure, t^* is the solution to the following:

$$(4) \quad \arg\max_t U_{ij}(t) = -C(t, X_j) + \psi(S_j * t) + \int_0^t \phi \mathbb{E}[H_j(r)]dr + \theta \left[(S_j * t) * \int_0^t \mathbb{E}[H_j(r)]dr \right]$$

$$(5) \qquad \frac{\partial C(t, X_j)}{\partial t} = \psi S_j + \phi \mathbb{E}[H_j(t^*)] + \theta \left[S_j * \int_0^{t^*} \mathbb{E}[H_j(r)]dr + (S_j * t^*) * \mathbb{E}[H_j(t^*)] \right]$$

This result suggests that the optimal time spent watching is determined by setting the marginal opportunity cost of time spent watching equal to the marginal benefit from watching. The marginal benefit from watching is the sum of the marginal benefit from additional skill,

[3]This assumption will be relaxed in different ways. For instance, skill in an event can actually be measured as "skill-minutes," which accounts for the length of time players of different skill spend actually playing in a game, and how that overlaps with time spent watching.

[4]In reality, an individual may not make an *ex-ante* decision about how much time to spend watching an event. However, they may have a well-formed prior about how much time they plan to watch given expected thrill, and then adjust using some stochastic process depending on the progression of an event. Thus, it may be the case that the expression is not monotonic for $r < R$. Section III A presents evidence of the validity of this assumption.

additional thrill, and the interaction of skill and thrill.[5] The empirical analysis will directly estimate the marginal utilities from skill, thrill, and their interaction.

C *Linking Theory to the Empirical Application*

The theoretical framework presented in subsections A and B of section II provides structural definitions of suspense and surprise, and a general utility function for spectators of entertainment that incorporates skill. Now, I apply the theoretical framework to examine viewership responses to both skill and thrill (1) before a game begins and (2) as a game evolves.

To measure thrill, I use real-time outcome probabilities computed and observed at the second-of-game level to calculate suspense and surprise at each second of a game. In particular, I use a pre-defined forward (backward) looking window W, which is measured in seconds-of-play within a game, to compute suspense (surprise). I compute the variance of observations found within W to obtain a second-of-play measure of suspense and surprise. To measure skill, I use the total number of fan All-Star votes received by each player playing within a specific game.

I take a three-fold approach to measuring viewership responses to skill and thrill. First, I measure how *initial* viewership (i.e., the number of individuals tuning in for the start of a game) responds to total skill present in a game, and *ex-ante* thrill expected in a game. I measure *ex-ante* expected thrill using variation from the initial point spread given for a specific matchup.[6] Next, I estimate viewership responses over the course of a game to "observable" thrill. Observable thrill is defined as the absolute point differential at different points of a game. Although observable thrill does not directly implement the definitions of suspense and surprise presented in Ely et al. (2015), it provides a proxy for thrill that is more directly observed by the viewer (since the viewer is not likely to observe second-by-second real-time

[5] Note that with the assumption $\frac{\partial \mathbb{E}_{r=R}[H_j(r)]}{\partial r} < 0$, time spent watching t and time remaining r are identical.

[6] In other words, I measure initial viewership in response to *ex-ante* expected thrill *only* through variation in the initial point spread.

outcome probabilities). Finally, I jointly implement the structural definitions of suspense and surprise, as well as skill, to estimate viewership responses within a game. In particular, I use variation in skill present on the court *at specific times of a game*.[7] With this framework, I am also able to determine the interactive effect of skill and thrill on viewership.

C.1 A Note on Alternative Outcomes and Viewership Response Mechanisms

As constructed, the model assumes that thrill manifests itself with respect to beliefs about the final outcome of an event, which takes place at time T. However, suspense and surprise can be generalized to refer to beliefs about a state *within* an event. For instance, instead of $P_t(A)$ referring to the probability at time t that Team A will emerge victorious, $P_t(A)$ could refer to the probability that Team A makes a highly improbable shot (i.e. a half-court buzzer beater) at time t. Specifically, suppose that such a shot takes place at time $t-1$ and the outcome of the shot at time t. The same definitions of suspense and surprise would apply: an agent would experience suspense during $t = \{0, ..., t-1\}$ as to whether or not such a shot will go in, which may be more suspenseful if Team A has a player known for taking and making these types of shots. An agent would experience some amount of surprise at time t depending on whether or not the shot goes in at t. This stylistic example is important in explaining why agents may experience suspense and surprise with respect to moments during an event that have little to no bearing on the event's final outcome. In the context of the empirical analysis, this generalization will be useful in examining viewership responses to suspense and surprise over alternative outcomes.

It is also important to expand upon mechanisms for within-game viewership responses to suspense, surprise, and skill. There are two primary ways viewership may respond: through *viewer addition* and *viewer retention*. In the case of suspense, both viewer addition and viewer

[7] For instance, skill changes within a game when a player is playing versus off the court.

retention are likely to occur. For example, a potential viewer who is not currently watching may be alerted in some way about a game reaching some level of suspense, and decide to tune in. A more naive viewer may be channel surfing and determine a game has a necessary threshold of suspense to stop and tune in. A game that becomes more suspenseful is also more likely to retain viewers who were already tuned in before suspense increased. In the case of surprise and skill, viewer retention is a more likely mechanism for increased viewership than viewer addition. To be surprised, a viewer must have been watching at both $t-1$ and t, and so a viewer may not be inclined to enter an event because something surprising took place. On the other hand, surprise witnessed by viewers already watching is likely to lead to significant viewership retention. Additionally, a viewer is not likely to respond to a superstar getting put back in the game, rather is more likely to turn off the game when a superstar is taken out. While the viewership data I have access to does not allow me to separately identify these mechanisms, empirical estimates can be interpreted under this general framework. Future work could directly assess the relevance of each of these mechanisms using complementary data from information-providing applications (e.g. Twitter).

III Television Viewership Responses to Skill and Thrill

This section presents analysis of television viewership responses to skill and thrill. First, I examine initial viewership responses to skill and expected thrill, where expected thrill is measured via the relationship between cumulative observed thrill and the initial point spread of a game. Next, I estimate viewership responses within a game to "observable" thrill, as measured by changes in the absolute score differential over the course of a game. Finally, I jointly estimate the viewership response to skill and thrill using the structurally defined parameters laid out in Section II.

A Overview of Data

There are three primary sets of data used in the analysis: (i) fixed game characteristics data providing time-invariant information about each analyzed game, (ii) second-of-game play-by-play data indicating detailed information about each moment of the game, including the real-time outcome probability for each team, and (iii) high temporal frequency television viewership data from The Nielsen Company©.[8]

A.1 Game Characteristic Data

Game characteristics data, which includes time-invariant information about each game in the sample, was collected from `NBA.com`, `fivethirtyeight.com`, and `Basketball Reference` for all NBA games (regular season and playoffs) during the 2017-18 and 2018-19 NBA seasons. Most important of these characteristics include the home and away teams, time-of-day, network (local or the specific nationally-televised network), the closing point spread, and an extensive list of team- and player-specific characteristics associated with each matchup.

A.2 Play-by-Play Data

Play-by-play data characterizes every meaningful action *within* a game, and is provided at a second-of-play level. A non-exhaustive list of common occurrences warranting an observation include a made or missed basket, turnover, foul, out-of-bounds stoppage, or timeout. Most importantly, this data characterizes the real-time score and win probability at each second of play a game, as well as a wall clock variable representing the time-of-day associated with each

[8]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.

observation.[9] 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.3 Television Ratings Data

The final dataset used in this analysis was TV ratings data acquired from The Nielsen Company©.[10] 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

B.1 Television Viewership and Game Characteristics

Table 1 presents conventional summary statistics for the data used in the viewership analysis. The table is broken down into two separate parts: (i) characteristics that are static and do not adjust over the course of a matchup (fixed-game characteristics) and (ii) characteristics that dynamically change during a matchup (within-game characteristics). One can see that there are 477 different games analyzed in this study, and nearly 1.4 million unique "plays," as given by the play-by-play data. In the fixed-game characteristics, there is good observed variation in the expected competitiveness of matchups, as given by the distribution of the "Point Spread" variable. The within-game data includes the primary characteristics used in the analysis of suspense, surprise, and stardom. There is substantial variation in "Total Viewership," where

[9] According to Inpredictable, the real-time win probability is a function of game time, point differential, possession, and the closing point spread. A locally-weighted logistic regression is performed at each second of the game, where the smoothing window shrinks as the game progresses. For the final few seconds of the game, regression is abandoned in favor of a decision tree approach. There are additional complexities associated with "non-possession states," which account for times during the game when neither team discretely possesses the ball. The `locfit` package in `R` was used to perform the analysis.

[10] 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.

the least-viewed games attract hundreds of thousands of viewers, and the most-viewed games receive tens of millions of viewers.

Table 1: Summary Statistics

		Mean	SD	Min	Max	# of Obs.
Fixed-Game Characteristics						
	Cum. All-Star Votes (1,000s)	6,710.16	3,893.84	372.69	17,035.61	477
	Point Spread	4.88	3.56	0	18	477
	Cum. PER	313.85	34.74	226.80	430.60	477
	Total Points Scored	218.32	21.29	158	301	477
	Number of Scoring Events	111.98	11.83	85	153	477
Within-Game Characteristics						
	Total Viewership Each 15 Mins. (1,000s)	2,683.29	2,460.62	265	20,956	1,383,209
	Score Differential	8.14	7.02	0	53	1,383,209
	Underdog Margin	-2.79	10.38	-53	38	1,383,209
	Consecutive Points	3.34	2.17	0	30	1,383,209
	Real-Time Difference in Win Prob.	49.86	31.65	0	100	1,383,209

Figures 1 and 2 show the average viewership trajectories by absolute score differential quintile and inital point spread, respectively. Interestingly, there is a nearly monotonic upward trend in viewership during a game. This may reflect several possible dynamics, including individual time constraints preventing the viewing of a full game, or that the end of games typically feature more thrill. Another important insight from Figure 2 is that initial point spread appears to predict viewership, at least in the final stages of a game, suggesting that games expected to end with a close margin are, on average, more suspenseful and surprising in later stages of a game.

Figure 3 presents the correlation between the difference in real-time win probabilities of two competing teams and the absolute score differential, computed at the quarter segment level. While the definitions of suspense and surprise map real-time outcome probabilities to beliefs, there are a couple of key reasons score differential can also be useful in understanding viewership impacts from these characteristics. First, score differential is immediately observable to the viewer (unlike real-time win probability), and so it is likely the case that transparency of score differential is driving thrill-induced viewership responses. Second, because the television viewership data is observed over 15-minute intervals, it is difficult to pick up specific "spikes" in

Figure 1: Average Television Viewership Over Time by Score Differential Quintile

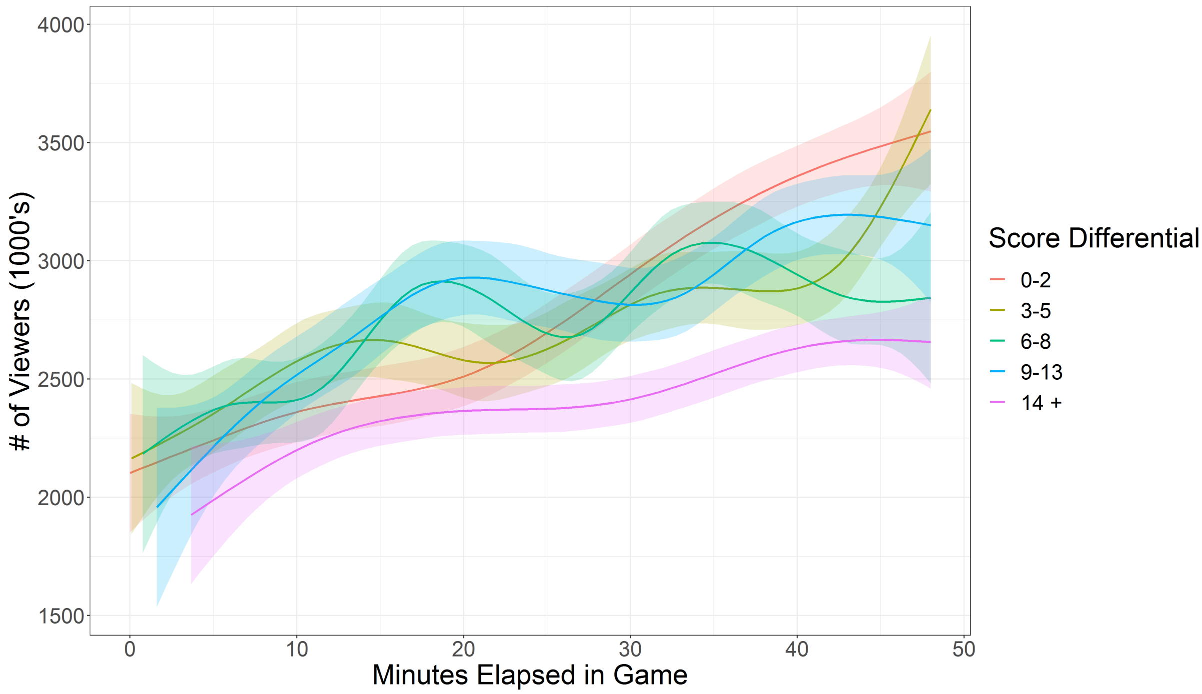
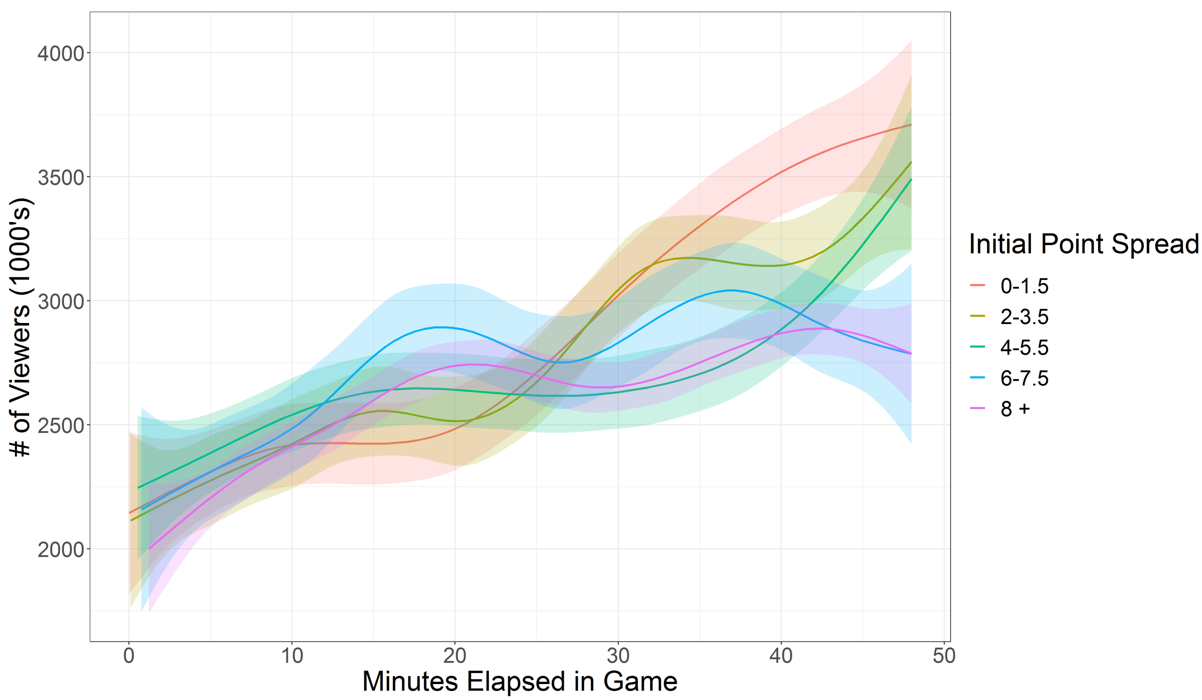
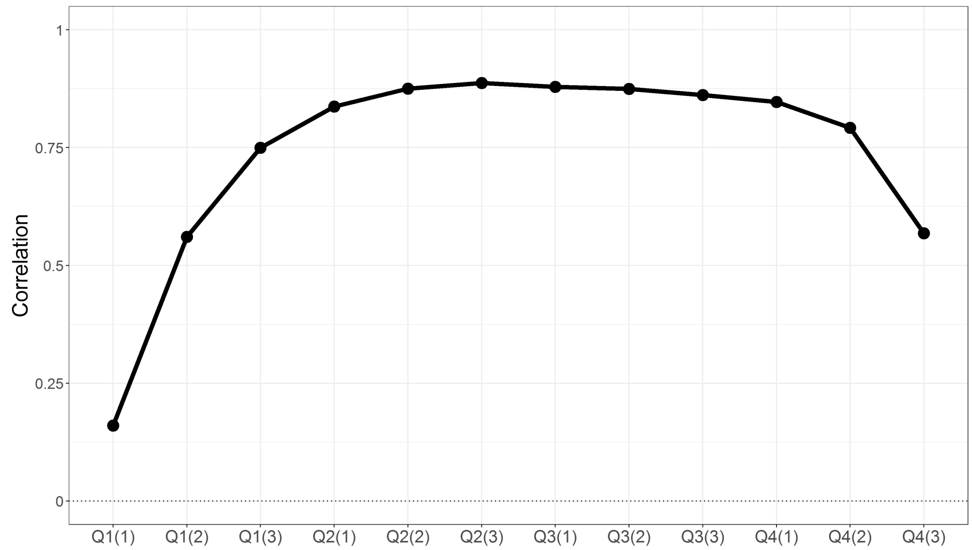


Figure 2: Average Television Viewership Over Time by Initial Point Spread Quintile



real-time win probability changes that are likely to occur in a thrilling game. Score differential is a smooth metric that still enables the capture of changes in suspense and surprise.

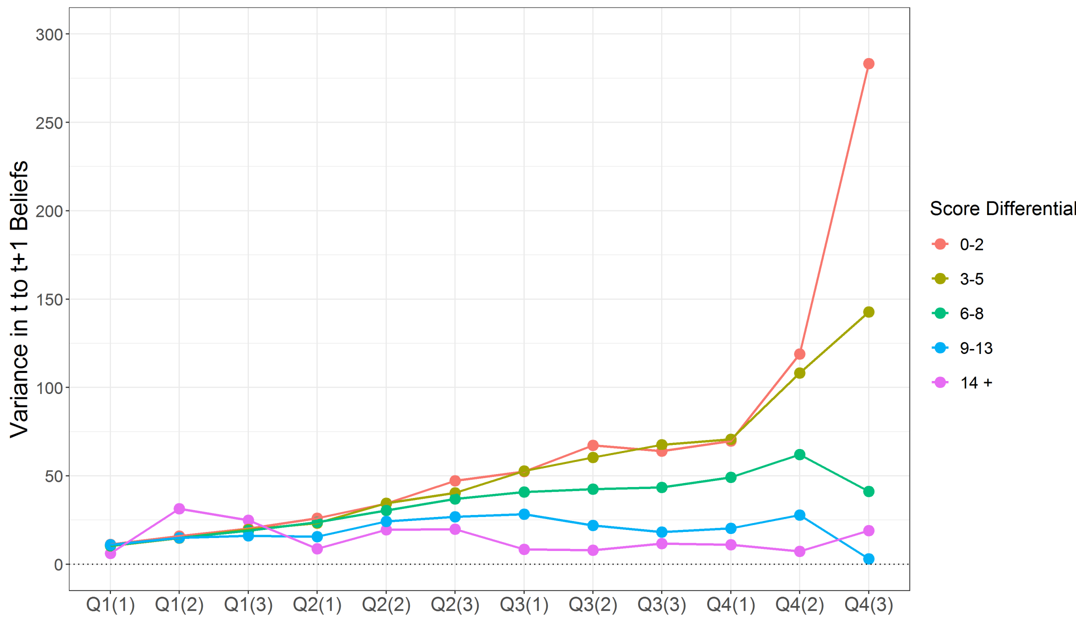
Figure 3: Correlation between Difference in Real-Time Win Probability and Absolute Score Differential



While the correlation is generally quite high (> 0.85), it is lower at the start and end of a game. This is intuitive—at the beginning of a game, absolute score differential is likely to be relatively low, yet real-time win probabilities remain heavily dependent on the initial expectation state over which team is likely to emerge victorious. On the other hand, at the end of a game win probabilities can fluctuate dramatically, even for small changes in the absolute score differential. This is precisely the effect I set out to measure–higher suspense (surprise) is associated with higher variance in future (past) beliefs about an outcome period-to-period.

Finally, Figures 4 and 5 visually depict the nature of suspense and surprise over the course of a game. Each of the figures relies on the real-time win probability data provided at the second-of-game level, although these figures present the average suspense and surprise at the quarter segment level. Figure 4 examines the one-period forward-looking variance in real-time win probability differences between the two competing teams, which corresponds to suspense, while Figure 5 examines the one-period backward looking variance, corresponding to surprise. Figures 4 and 5 use a forward-(backward-)looking window of three minutes of game time (180 seconds). In subsection D, I examine viewership impacts for one and three minute windows, but the results are generally robust to different window sizes.

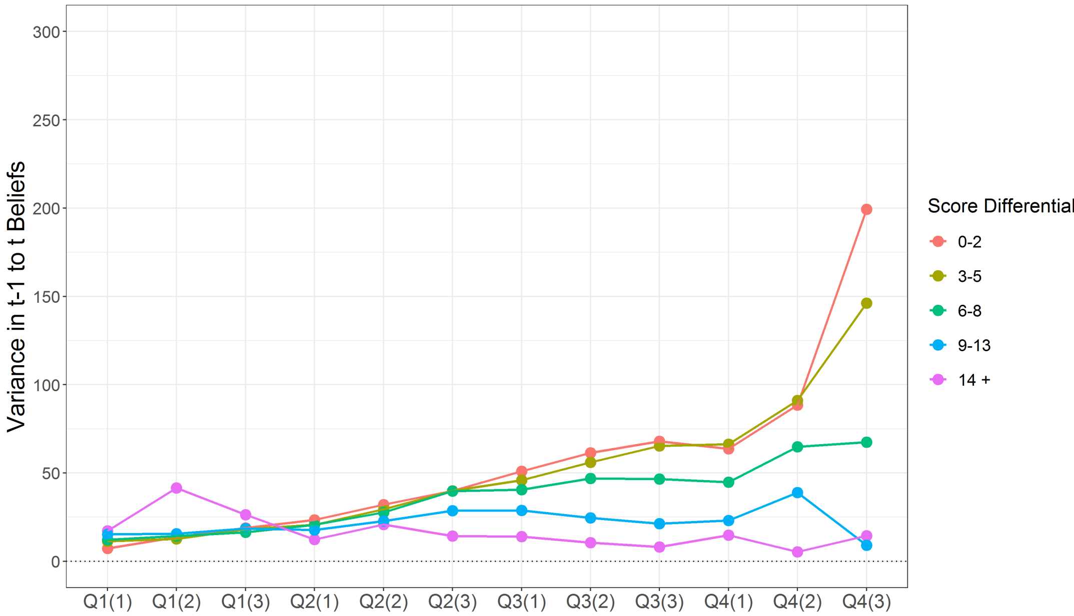
Figure 4: Variance in One-Period Forward-Looking Real-Time Win Probability Differential by Score Differential (Suspense)



In Figure 4, we see that games generally become more suspenseful as they progress, and then trail off slightly at the very end when outcome resolution begins to take place. Additionally, suspense is increasing at a faster rate and earlier on for close games. In terms of magnitude, a 0-2 point game experiences anywhere from 0-18 times more suspense than a 14 + point game, depending on the stage of the game.

Figure 5 depicts the trend associated with surprise. Games generally become more surprising as they progress, as is the case with suspense, but high score differential games exhibit greater surprise earlier in games. This is also intuitive—for there to be high variance in backward-looking win probability differential, there must be large leads occuring. Furthermore, while close games may not be surprising initially, they tend to feature more surprise in later stages, since even marginal score differential changes lead to relatively large swings in real-time win

Figure 5: Variance in One-Period Backward-Looking Real-Time Win Probability Differential by Score Differential (Surprise)



probability differences.[11] Section D will present the viewership implications associated with suspense and surprise using both the observed absolute score differential and the structural variance parameters visualized in Figures 4 and 5.

C Empirical Strategy

The empirical analysis in this section attempts to understand the impact of skill and thrill on television viewership. First, I develop a model to estimate *initial* viewership responses to skill and expected thrill. Second, I construct a model to estimate television viewership responses to "observable" thrill as it evolves within a game. Finally, I provide a framework to jointly estimate viewership responses to suspense, surprise, and skill within a game.

[11] While Figures 4 and 5 appear quite similar, the correlation between suspense and surprise at the second-of-game level is 0.26.

C.1 Initial Viewership Responses to Skill and Expected Thrill

The first component of the viewership analysis is to examine initial television viewership in response to skill and *expected* thrill. While there is full information before a game starts about the amount of skill that will be present (i.e. which players will be playing and their associated skill, measured by the number of All-Star fan votes they receive), thrill evolves quasi-randomly during a game and so is not known beforehand. However, thrill may be correlated with the expected competitiveness of a game, where one may believe a more competitive game induces greater levels of thrill. The expected competitiveness of a game is measured by the initial point spread, and is directly observable prior to a game starting.

To measure expected thrill, I perform the following estimation, which resembles a two-stage least squares procedure.

$$\text{CumulativeThrill}_j = \delta \text{APS}_j + \lambda \text{Skill}_j + \mathbf{X}_j \boldsymbol{\Delta} + \epsilon_{j,t=0} \tag{6}$$

$$\text{Viewership}_{j,t=0} = \gamma \widehat{\text{CumulativeThrill}}_j + \beta \text{Skill}_j + \mathbf{X}_j \boldsymbol{\Gamma} + \epsilon_{j,t=0} \tag{7}$$

Where $\text{CumulativeThrill}_j$ is the summation of all instantaneous suspense and surprise that occurs during game j, $\widehat{\text{CumulativeThrill}}_j$ are the fitted values from the first-stage, and APS_j is the closing absolute point spread observed prior to a game. Note that the estimates are not meant to be interpreted as causal, rather as a descriptive relationship between initial point spread and cumulative thrill in the first stage, and the relationship between skill and expected thrill (as predicted by the initial point spread) on initial viewership in the second stage.

C.2 *Observable Thrill*

Measuring viewership responses to instantaneous suspense and surprise, which evolve during the course of a game, requires richer data and a different modeling strategy. Section II characterizes suspense and surprise in a structural way using the definitions from Ely et al. (2015), relying on outcome probabilities at a granular level that are not directly observed by spectators. However, I first analyze viewership responses to thrill 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 thrill 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 II, 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 8 provides a general empirical model to measure viewership impacts in response to observed absolute score differential and time remaining in an event.

$$V_{jt} = (C_{jt} * \mathbf{Q_{jt}})\mathbf{\Lambda} + \gamma S_{jt} + \alpha_j + \eta_t + \epsilon_{it} \tag{8}$$

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). $\mathbf{\Lambda}$ represents a vector of time-varying coefficients that reflect the impact of C_{jt} on viewership. S_{jt} represents the cumulative number of fan All-Star votes of all players on the court in game i at time t of the game (i.e. a measure of cumulative skill). It is critical to control for time-varying skill, since it is likely to be correlated with thrill during certain portions of a game. 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.[12] On the other hand, a low score differential in the fourth quarter would be considered both close and thrilling. Intuitively, the differential viewership impacts across the horizon of a game for similar score differentials is the variation necessary to separate the impact of thrill on viewership versus the impact of a close game.

An important assumption to make to interpret these estimates as plausibly causal, and the reason a live sporting event is a desirable setting to examine suspense and surprise, is *path-independence* of outcomes.

Assumption 1: Path-Independence. 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, μ_0.

$$|D_{t+1}| \sim \mathcal{N}(|D_t|, \sigma^2 \mid \mu_0) \tag{9}$$

This assumption states that the absolute score differential evolves randomly, conditional on the score differential in the previous time period and fixed information known prior to a game that may impact the evolution of the score differential (e.g. the closing absolute point spread). Essentially, the evolution of the absolute score differential is a first-order Markov process, accounting for dependence on the initial state of the game μ_0.

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

C.3 Observable Thrill over 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-matchup propositions. To make the analogy to absolute score differential, I assume that an agent who cares about these outcomes maintains the same utility function from thrill as seen in equation 3.[13] Here, the alternative outcome I examine is the closing 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 closing 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.[14] I 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:

$$|D'_{jt}| = |D_{jt} + P_{jT}| \tag{10}$$

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 the application of this outcome empirically, take the following concrete example. Suppose there is a matchup 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

[13] This may be a strong assumption if individuals that care about these outcomes have an explicit financial stake, and thus suspense is endogenously chosen.

[14] Note that I index strength here at the matchup level, allowing for strength for a specific team to differ across matchups.

favoring Cleveland, then the absolute score differential from the 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, I 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 I 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. I 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, I estimate a model of viewership in response to suspense over the absolute score differential in reference to point spread as follows:

$$V_{jt} = (|D'_{jt}| * \mathbf{Q_{jt}})\mathbf{\Lambda} + (|D_{jt}| * \mathbf{Q_{jt}})\mathbf{\Gamma} + \alpha_j + \eta_t + \epsilon_{jt} \tag{11}$$

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

where all the terms maintain their previous definitions.

C.4 Joint Model of Suspense, Surprise, and Starpower

This section presents an empirical model to jointly estimate the impacts of skill and thrill on viewership. I rely on the structural definitions of suspense and surprise given in Section II. The general form of the estimating equation is as follows:

$$V_{jt} = \mu X_{jt} + \rho Y_{jt} + \psi S_{jt} + \lambda(X_{jt} * S_{jt}) + \nu(Y_{jt} * S_{jt}) + \mathbf{Z_{jt}\Gamma} + \alpha_j + \eta_t + \epsilon_{jt} \tag{12}$$

V_{jt} represents total viewership for game j at time-of-game t. X_{jt} denotes the structurally defined suspense parameter, Y_{jt} the structurally defined surprise parameter, and S_{jt} a cumulative measure of skill.[15] $\mathbf{Z_{jt}}$ includes a set of controls that evolve within-game, and matchup and time-of-game fixed effects are denoted as α_j and η_t, respectively.

There are several advantages of this estimation approach. First, it allows for suspense and surprise to be included as separate terms in a single estimation so their impacts on viewership can be separately identified. Second, it allows for the inclusion of a time-variant measure of observable skill, since it relies on within-game variation in the cumulative skill of all players playing at a given point in a game. Finally, it allows for the inclusion of interaction terms

[15]Using the definitions of suspense and surprise presented in section II, it is necessary to define the length of the period-to-period interval in which they can occur. I use several different bandwidths in the estimations presented in section D, including a 1-minute of play time window (i.e. 60 seconds of game clock time, not real time), 3-minute, and 5-minute window.

between skill and suspense, and skill and surprise, which are useful in understanding differential viewership impacts to thrill depending on the presence of skill. The following section will present the results from each of the empirical models discussed here.

D Results

This section presents estimation results from the empirical models of skill and thrill posed in the previous section.

D.1 Initial Television Viewership

Table 2 presents the impact of skill, as measured by cumulative All-Star fan votes for all players playing in a game, and expected cumulative thrill on initial TV ratings for nationally-televised games. Cumulative thrill is the sum of instantaneous suspense and surprise, as defined in Section II, over the course of an entire game. Column (1) presents the first-stage estimation examining the relationship between initial point spread and cumulative thrill. Column (2) presents the second-stage estimation, examining initial viewership in response to skill and expected thrill, where expected thrill only relies on variation from the initial point spread. Each of these specifications controls for "combined current win percentage" to account for the average quality of the two teams playing in a game, as well as an "aggregate team value" continuous control variable to account for the number of people that may be expected to watch a specific team independent of other important factors.[16] These team values are calculated each year by Forbes, and are a good indicator of the total size of each team's fanbase (Badenhausen and Ozanian 2019). Other important controls are listed at the bottom of the table, which include month-of-

[16]Since these are nationally televised games, a home team fixed effect does not make as much sense in these specifications as it does in the context of the ticket price analysis (since there are geographic preferences). Including a dummy for each team present in a matchup leads to insignificant point estimates for all variables, likely because of the insufficient power associated due to the relatively low number of nationally-televised games.

year, day-of-week, and time-of-day fixed effects.

Table 2: Impact of Skill and Expected Thrill on Initial TV Ratings

	Dep. Var: log(Cumulative Thrill)	Dep. Var: log(1000's of Initial Viewers)
Abs. Point Spread	-0.0218^{***}	
	(0.0082)	
$\log(\widehat{\text{Cum. Thrill}})$		0.0580
		(0.2416)
log(Ag. All-Star Votes)	0.0835^{*}	0.1124^{***}
	(0.0462)	(0.0362)
log(Avg. Current Win PCT)	-0.4468^{*}	0.2822^{*}
	(0.2677)	(0.1607)
log(Ag. Team Value)	-0.1354^{**}	0.1830^{**}
	(0.0644)	(0.0891)
Month FE	Yes	Yes
Day-of-Week FE	Yes	Yes
Time-of-Day FE	Yes	Yes
Streak FE	Yes	Yes
TV Network FE	Yes	Yes
Dbl Header FE	Yes	Yes
Holiday FE	Yes	Yes
Playoff Gm FE	Yes	Yes
Clustered Robust SEs (Home + Away)	Yes	Yes
Observations	477	477
R^2	0.1386	0.7441
Adjusted R^2	0.0420	0.7154
Note:	*p<0.1; **p<0.05; ***p<0.01	

Intuitively, column (1) shows there is a negative and statistically significant relationship between the initial point spread and cumulative thrill, suggesting that for games featuring higher initial absolute point spreads (i.e. games that are expected to be less competitive), we observe less total thrill. The effect is sizable – for every one point increase in the absolute point spread, cumulative thrill falls by approximately 2.18%.[17] However, column (2) suggests that initial viewership is not affected by the expected thrill of a game (or the initial point spread), suggesting that individuals are no more likely to tune in for the start of a game that features

[17]The distribution of absolute point spreads within the sample of data is presented in Table 1.

a higher expected level of thrill. On the other hand, the skill present in a game significantly impacts initial viewership. For a 100% increase in the skill of players present, initial viewership increases by approximately 11.2%. One can also see that "combined current win percentage" and "aggregate team value" have larger impacts on initial viewership than skill and expected thrill. This is not surprising considering that the quality of the two competing teams and their market sizes are likely to be primary determinants of initial viewership.

It is clear that skill is a significant driver causing individuals to tune into games. For context, LeBron James obtained over 4.6 million fan votes during the 2018-19 season, which corresponds to approximately 120% of the average aggregate number of All-Star fan votes of all players in a matchup (3.8 million). In other words, LeBron's average fan All-Star vote total is just above the total number of All-Star votes of all players in an average game. Using the results from analysis in Table 2, the presence of LeBron alone results in an approximately 13.5% increase in initial TV ratings. These results are remarkably similar to those found in Kaplan (2020), which uses secondary ticket marketplace data to assesses the impact of a superstar absence announcement for a specific game on listed prices. The analysis finds that the absence of LeBron James leads to a 13% average reduction in ticket prices.

D.2 Observable Thrill

The primary observable characteristic of thrill in these matchups is the absolute score differential in matchup i at time t, D_{it}. Table 3 shows four separate estimations. Columns (1) and (3) present the "naive" estimations, namely the average impact of absolute score differential on log viewership. This specification is meant to capture viewership in response to the close game effect, which can be 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).[18] Column (3) differs from column (1)

[18] As mentioned previously, it is important not to conflate the effect of a close game versus suspense and surprise on viewership.

only in that it controls for time-varying skill. Columns (2) and (4) present the time-varying impacts of absolute score differential on viewership, which corresponds to equation 8. Again, column (4) differs from column (2) in that it controls for time-varying skill.

Table 3: Impact of Absolute Score Differential on TV Ratings

	Dependent Variable: log(Total Proj. Viewers Watching)			
Absolute Score Diff.	-0.0056^{***}	0.0014	-0.0047^{***}	0.0017
	(0.0013)	(0.0018)	(0.0009)	(0.0018)
Absolute Score Diff. * Q2		-0.0012		-0.0015
		(0.0018)		(0.0018)
Absolute Score Diff. * Q3		-0.0059^{**}		-0.0060^{**}
		(0.0024)		(0.0024)
Absolute Score Diff. * Q4		-0.0115^{***}		-0.0105^{***}
		(0.0025)		(0.0023)
log(Ag. All-Star Votes)			0.0324^{***}	0.0210^{**}
			(0.0093)	(0.0072)
Game FE	Yes	Yes	Yes	Yes
Quarter Segment FE	Yes	Yes	Yes	Yes
Observations	1,384,623	1,384,623	1,382,923	1,382,923
R^2	0.9450	0.9466	0.9464	0.9476
Adjusted R^2	0.9450	0.9466	0.9464	0.9475
Note:	*p<0.1; **p<0.05; ***p<0.01			

One can see that on average across an entire game, a one point increase in the absolute score differential reduces television viewership by 0.47-0.55%, and so close games are important in raising viewership. Columns (2) and (4) break out the impacts of absolute score differential by quarter of the game. There is 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 fourth quarter leads to an approximately 1.1-1.2% 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. Examining both columns (3) and (4), it is clear that skill impacts viewership within a game, albeit to a lesser extent than thrill. A doubling (one SD) increase in skill on the court during a game increases viewership by approximately 2.1-3.2% (1.2-1.9%).

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

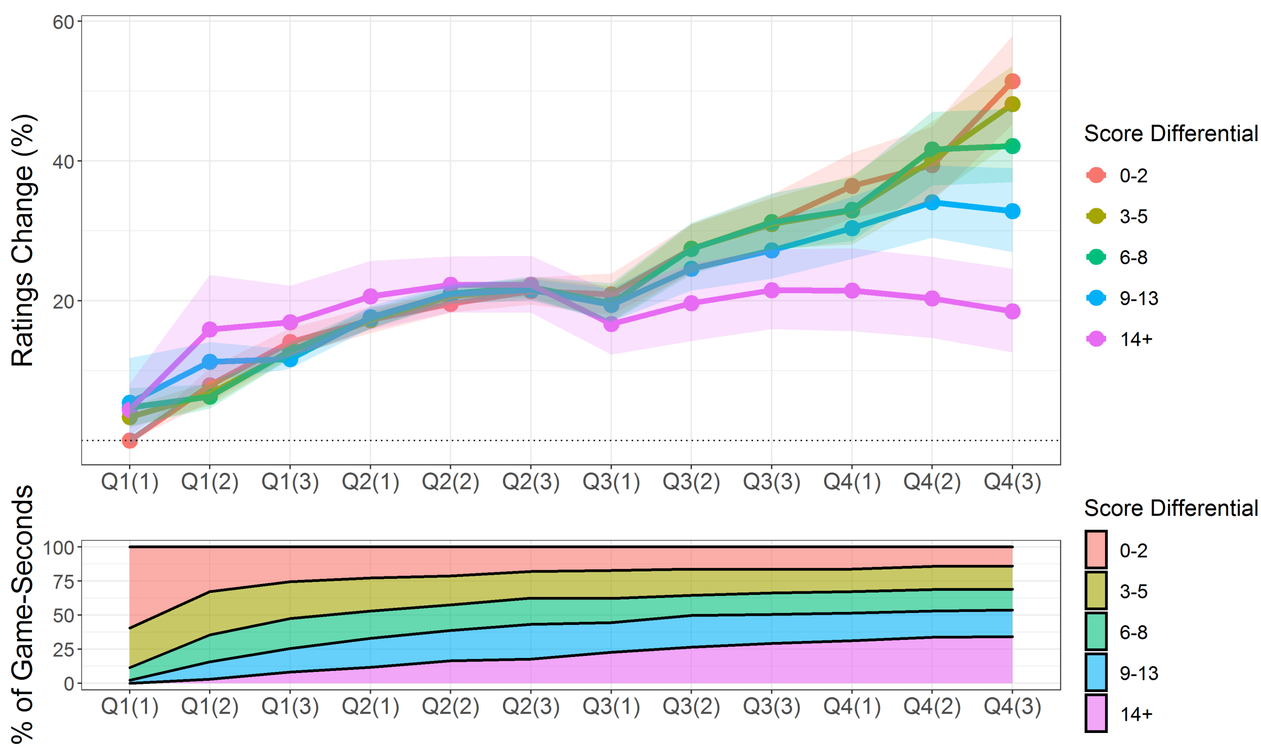


Figure 6 depicts thrill impacts using absolute score differential at an even more granular level. I split each game into twelve equally long quarter segments, and absolute score differential is divided into five bins using the quintiles of the distribution of score differential in the data. All points in Figure 6 represent coefficients from an estimation taking the form of equation 8, and can be interepreted as relative to the omitted score differential bin-by-quarter segment (the

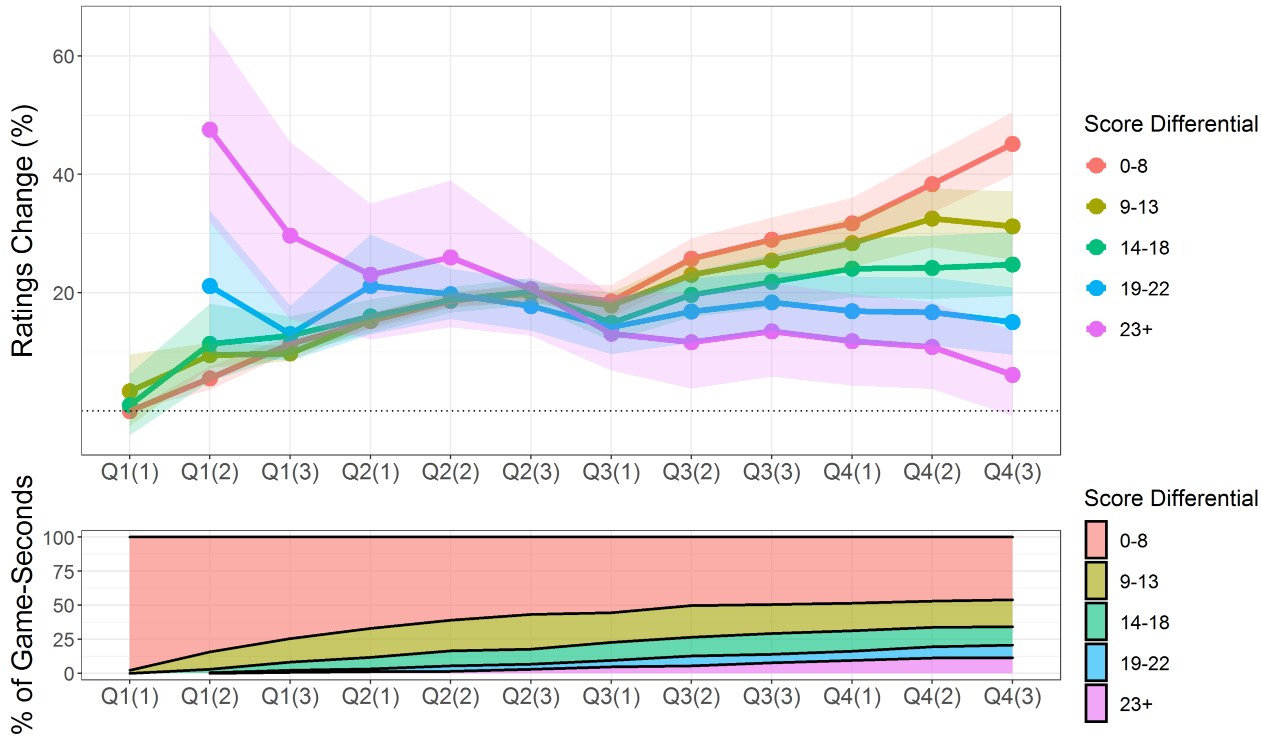
0-2 bin in the first quarter segment, Q1(1)). First, this graph confirms that average viewership over the course of a game is generally increasing, as shown in Figures 1 and 2. It is also clear that there are heterogeneous impacts of absolute score differential on viewership as a game progresses to its 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 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 its finality.

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 may suggest a non-linear response to thrill during a game. Estimations using alternative binning structures as well as level (instead of log) changes in viewership on are presented in the Appendix.

D.3 Observable Thrill in Reference to the Point Spread

Table 4 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

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



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 4: Impact of Thrill with Respect to Point Spread on TV Ratings

	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	No	Yes	Yes	Yes
Score Differential x Quarter Segment Control	No	No	No	Yes
Game FE	Yes	Yes	Yes	Yes
Quarter Segment FE	Yes	Yes	Yes	Yes
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<0.1; **p<0.05; ***p<0.01

Table 3 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 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).

D.4 Joint Estimation of Suspense, Surprise, and Starpower

The next set of estimations assesses the joint impact of suspense, surprise, and skill on television viewership. This analysis relies on the structurally defined suspense and surprise parameters, as well as within-game variation in the level of skill on the court, providing high-temporal frequency changes that can be separated from time invariant, game-specific factors and general viewership trends over the course of a game. Table 5 presents the results of six separate estimations: columns (1) - (3) use a one-minute forward-(backward-)looking window to calculate suspense (surprise) at each second-of-play during a matchup, while columns (4) - (6) use a three-minute window.[19] Columns (2) - (3) and (5) - (6) also control for the average impact of absolute score differential during a game on viewership, so as to account for potential correlation between a suspenseful or surprising game and a "close" game. Finally, columns (3) and (6) include the interactive effect of suspense and surprise with skill with the goal of measuring differential viewership responses to thrill under varying levels of skill.

There are several notable takeaways from Table 5. First, the estimates suggest that a doubling of instantaneous suspense increases viewership by 0.38-0.6%. However, as exhibited in Figure 4, suspense can take on an extremely large range of values. For instance, in the last segment of the fourth quarter, a 0-2 point game averages 18 times more suspense than a 14+ point game. In this case, viewership would be approximately 6.84-10.8% higher through suspense alone. On the other hand, the magnitude of the surprise effect depends greatly on the specification, particularly when comparing the fully interacted estimations (columns 3 and 6) with the other specifications. In the non-fully interacted estimations, a doubling of instantaneous surprise increases viewership 0.64-0.96%. In the fourth quarter, a 0-2 point game features 14 times more surprise on average than a 14+ point game, which would translate into a

[19] The results are not sensitive to reasonable window size adjustments.

Table 5: Impact of Suspense, Surprise, and Starpower on TV Ratings

	Dependent Variable: log(1000's of Total Viewers)					
	1 Minute Window			3 Minute Window		
log(Surprise)	0.0075***	0.0064***	0.0074	0.0096***	0.0086***	−0.0178
	(0.0011)	(0.0010)	(0.0146)	(0.0020)	(0.0019)	(0.0224)
log(Suspense)	0.0056***	0.0038**	0.0424**	0.0060***	0.0039***	0.0462**
	(0.0015)	(0.0013)	(0.0153)	(0.0012)	(0.0011)	(0.0184)
log(All-Star Votes)	0.0236**	0.0237**	0.0203***	0.0200**	0.0202**	0.0187***
	(0.0082)	(0.0078)	(0.0052)	(0.0073)	(0.0070)	(0.0051)
Absolute Score Diff.		−0.0021**	−0.0023**		−0.0022**	−0.0024**
		(0.0010)	(0.0010)		(0.0010)	(0.0010)
log(Surprise) * log(All-Star Votes)			−0.0002			0.0017
			(0.0010)			(0.0014)
log(Suspense) * log(All-Star Votes)			−0.0026**			−0.0029**
			(0.0010)			(0.0012)
Game FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Segment FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,381,973	1,381,973	1,381,973	1,381,973	1,381,973	1,381,973
R^2	0.9470	0.9471	0.9474	0.9471	0.9473	0.9474
Adjusted R^2	0.9470	0.9471	0.9473	0.9471	0.9473	0.9474
Note:	*p<0.1; **p<0.05; ***p<0.01					

viewership increase of 8.96-13.44%. However, specifications (3) and (6) exhibit largely different impacts of surprise on viewership. In particular, when interacting suspense and surprise with skill, the impact of surprise on viewership is no longer statistically significant. It is intuitive that for a sport like basketball, which features frequent scoring and smooth updating in outcome probabilities, surprise would have a lower impact on viewer attention.

There are a couple of interesting and intuitive takeaways regarding the impact of skill on viewership. First, examining the average impact of skill while holding suspense and surprise constant, all specifications suggest that a doubling in the number of All-Star fan votes on the court at a given time during the game leads to a 1.87-2.37% increase in viewership. While these estimates are substantially lower than those found in the initial TV viewership analysis, the source of variation, and therefore interpretation of the coefficient magnitudes, is different. While the afformentioned analyses look at the time invariant impact of skill on viewership, this estimation relies on within-game changes in the level of skill on the court at any given time, and thus they complement one another in interpreting the impact of skill on spectator demand. One can think of the skill-induced viewership changes estimated in Table 5 as occuring on the intensive margin (within games), while the larger estimates found in the initial TV viewership analysis as occuring on the extensive margin (across games). It may be the case that spectators face two different decisions with respect to skill: the likelihood of watching a game *at all* because of the aggregate skill of all players playing, and whether to continue watching a game when it features changes in skill on the court at a given time.

Table 6: Within-Game Superstar Viewership Impacts

Player	All-Star Fan Votes	Avg. Total Votes when Off Court	Viewership Impact (%)
LeBron James	4,620,809	3,310,401	2.83
Giannis Antetokounmpo	4,375,747	2,652,937	3.35
Luka Doncic	4,242,980	1,286,935	6.94
Kyrie Irving	3,881,766	2,711,703	2.91
Stephen Curry	3,861,038	4,680,438	1.67
Kawhi Leonard	3,580,531	3,388,249	2.15
Derrick Rose	3,376,277	2,742,202	2.50
Paul George	3,122,346	3,505,377	1.81
Kevin Durant	3,150,648	5,280,465	1.21
James Harden	2,905,488	2,578,477	2.29
Joel Embiid	2,783,833	3,155,921	1.79
Anthony Davis	2,520,728	1,893,613	2.70
Dwyane Wade	2,208,598	1,833,541	2.45
Kemba Walker	1,395,330	1,190,191	2.38
Dirk Nowitzki	394,622	2,463,873	0.33

Table 6 translates the coefficient on skill from specification (3) to the corresponding within-game viewership impact for some of the most skilled players. I compare each individual superstar's total All-Star fan vote tally to the average cumulative number of All-Star fan votes when each player is *off* the court. For instance, LeBron James received 4.6 million All-Star fan votes in the 2018-19 season. The total average number of All-Star fan votes on the court in games where he is playing but not on the court is 3.3 million. Thus, LeBron's average skill impact translates to a 140% increase in on-court popularity, increasing within-game viewership by 2.83% when he is on the court playing.

The second important takeaway from Table 5 related to skill are the results from the fully interacted estimations in columns (3) and (6). Most interesting is the relationship between skill and suspense. While suspense (holding skill constant) continues to have a significant and meaningful impact on viewership, the interactive effect between skill and suspense is negative and of smaller magnitude importance than the individual coefficients on suspense and All-Star votes. In words, suspense leads to differentially *higher* viewership with *lower* skill on the court. While an individual may watch a game featuring LeBron James no matter the level of suspense, they may exhibit a more sensitive and heightened response to suspense in games featuring less skill. This supports and quantifies the traditional idea that spectators only turn on games featuring lesser-known players if they're nearing the end and exhibiting sufficiently high suspense.

IV Discussion

This section discusses important implications of the empirical findings. First, I contextualize the results from the television viewership analyses by comparing their effects with other important drivers of demand for NBA games. In doing this, I also provide revenue implications for the NBA associated with demand for skill and thrill. Next, I propose a counterfactual game structure that introduces more "finality" to an event, which would lead to larger levels of thrill over the course of a game, and assess the viewership implications.

A *Effect Sizes and Revenue Implications*

The empirical analysis assessing viewership responses to skill and thrill finds effect sizes of approximately 11% and 7-30%, respectively, depending on specification. In particular, an increase of 7-30% corresponds to viewership increases of 187,830 - 804,987 individuals during a 15-minute programming interval, and the 11% initial viewership increase associated with a doubling of skill corresponds to approximately 295,162 additional viewers. For comparison, a one standard deviation increase in 15-minute level viewership is approximately 92% of 15-minute interval mean viewership (2.46 million individuals). Playoff games experience approximately 93% higher viewership than regular season games, and holiday games experience 54% higher viewership than non-holiday games. Additionally, viewership increases by approximately 45% on average from the start to the end of a game.

Examining the effect of other characteristics on television viewership provides further evidence that both skill and thrill are highly important economic factors in driving demand for NBA games. Next, I assess league revenue implications associated with skill and thrill. Table 7 presents the projected season-level value in both ticket sales and television viewership settings for the highest skill NBA players. The impacts in column 3 are based on results presented in Kaplan (2020), which uses a difference-in-differences approach to examine the ticket price reductions on a secondary marketplace associated with superstar player absence announcements for specific games, extrapolated over an entire NBA season. The impacts in column 4 are using the results from Table 2, again extrapolated over an entire season. One can see that from ticket sales alone, the impacts associated with the presence of superstars range from millions to tens of millions of dollars over the course of a season, with LeBron James leading at $69 million. The viewership impacts are slightly smaller on average, but still on the order of millions to tens of millions of dollars over the course of a season, with a maximum player value (which once again corresponds to LeBron James) of $24.5 million. The differences in magnitudes between ticket sales and television ratings may be due to a number of factors, but one likely contributor is the heightened allure of skill when watching in person.

Table 7: Season-Level Ticket Price and TV Viewership Player Impacts

Player	All-Star Votes	WTP Impact (Millions of $)	Initial WTW Impact (Millions of $)
LeBron James	4,620,809	69.06	24.51
Giannis Antetokounmpo	4,375,747	-1.57	23.21
Luka Doncic	4,242,980	30.13	22.51
Kyrie Irving	3,881,766	8.09	20.59
Stephen Curry	3,861,038	48.18	20.48
Kawhi Leonard	3,580,531	10.76	19.00
Derrick Rose	3,376,277	2.09	17.91
Kevin Durant	3,150,648	7.50	16.72
Paul George	3,122,346	29.03	16.56
James Harden	2,905,488	12.98	15.41
Joel Embiid	2,783,833	13.99	14.77
Anthony Davis	2,520,728	5.73	13.37
Dwyane Wade	2,208,598	41.86	11.72
Kemba Walker	1,395,330	23.74	7.40
Dirk Nowitzki	394,622	32.19	2.09

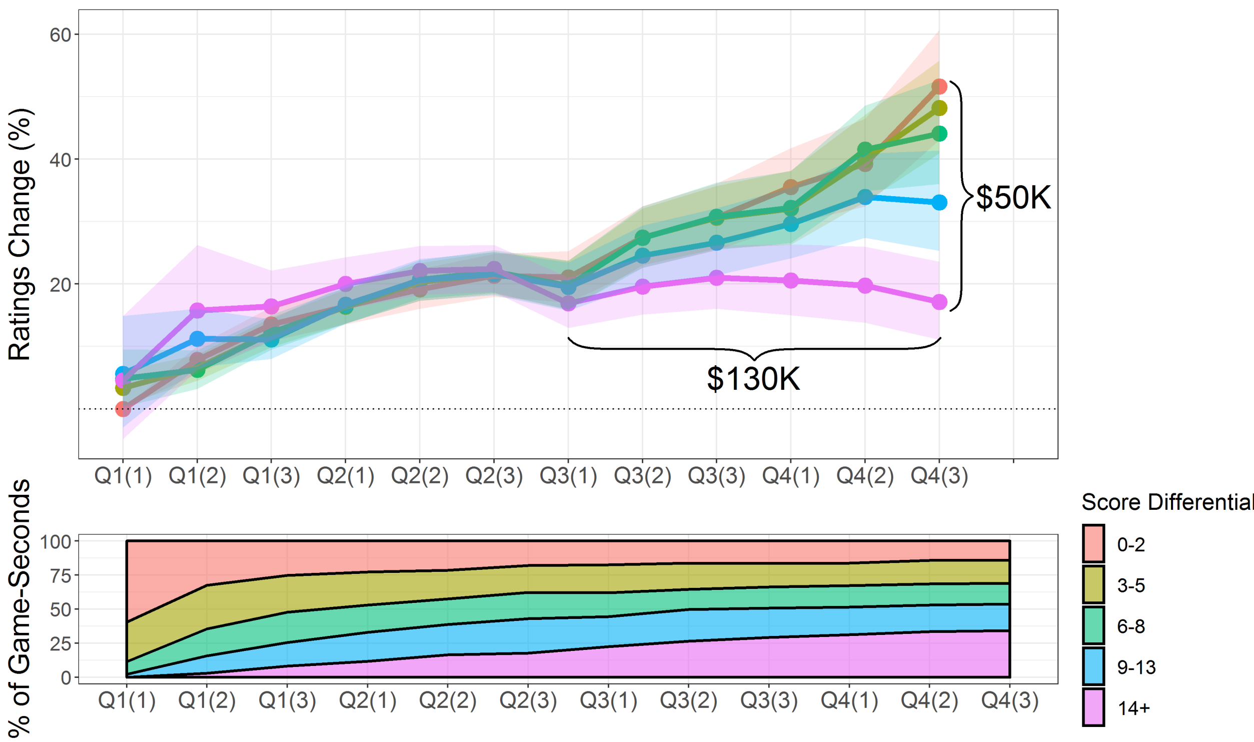
Note: These estimates represent the season-level monetary impacts each player had based on the difference-in-differences (DID) estimations in Kaplan (2020) for secondary marketplace ticket data (column 3) and initial viewership estimations for the TV viewership data (column 4). For the DID estimates from Kaplan (2020), this meant multiplying by 20,000 people on average per arena and 82 games over the course of a season. The initial viewership estimates were estimated via a log-log specification. So, the season-level impacts were determined using the player-specific % total of the average cumulative number of All-Star votes present for all players in a specific game (3.8 million), the approximate total value of television broadcasting for the NBA during a season (~$2.7 billion; Sports-Illustrated 2014), and the total number of regular season games each team plays (82).

To assess estimated revenues from thrill, I use changes in network revenues from advertising associated with differences in thrill across games. Figure 8 presents viewership change estimates associated with observable thrill, and is identical to Figure 6. 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 revenue between a 0-2 point game versus a 14+ point game in the final quarter segment is approximately $50,000.[20] Aggregating this

[20]The five absolute score differential bins presented 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.

difference over the course of an entire second-half, I find that network 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 the true value of thrill since they do not account for increases in consumer surplus of inframarginal viewers due to enhanced thrill.

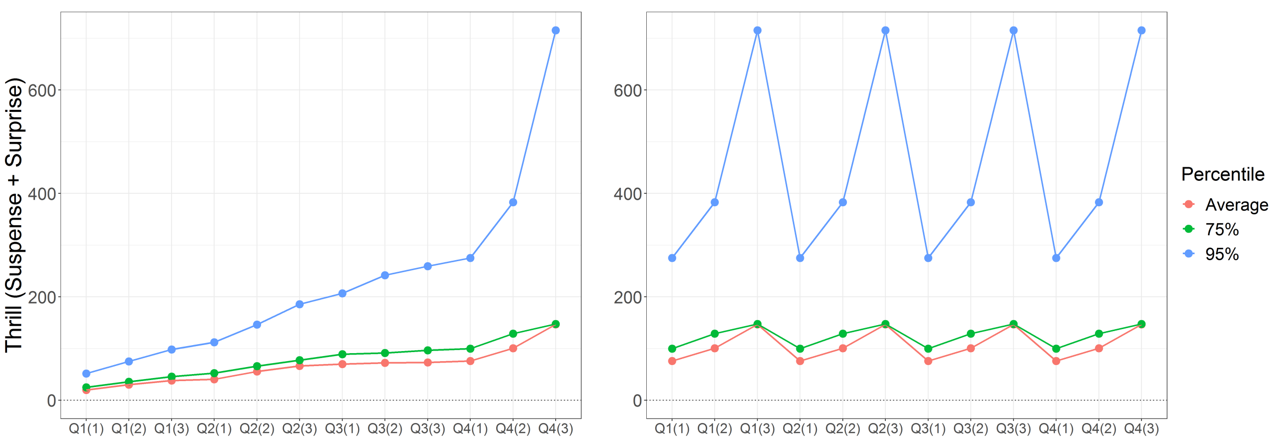
Figure 8: Estimated Advertising Revenues from Thrill



B Counterfactual Game Structures

Sports leagues are always discussing and considering different measures and rule changes that have the potential to enhance the fan experience. Understanding how counterfactual structures may affect viewership is important to better understand the economic implications of proposed adjustments. In this section, I present and analyze a counterfactual game structure that introduces more "finality" into a game. Examining Table 3 and Figure 6, it is clear that much of the thrill that takes place during a game happens towards the end. This is quite intuitive – on average, the impending final outcome of an event generates larger swings in the outcome probability than earlier stages of a game. Figure 9 shows this explicitly – in the left-pane, I plot the average, 75^{th}, and 95^{th} percentiles of thrill (suspense + surprise) within each quarter segment. It is very apparent that thrill is increasing monotonically over the course of a game at these points in the thrill distribution.[21] The right-pane presents a visual depiction of a scenario enhancing the finality of an event. For instance, suppose instead of a single meaningful outcome in a game (i.e. whichever team wins and loses the game), each quarter of a game represents a meaningful outcome. Under this scenario, each game would include four meaningful outcomes. The right-pane of Figure 9 portrays the distribution of thrill over the course of a game *extrapolated from the fourth quarter distribution of thrill*. I take the distribution of thrill from the fourth and final quarter presented in the left-pane, and extrapolate it to the first three quarters.

Figure 9: Full-Game Thrill Trajectories (left) and Fourth-Quarter Extrapolated Thrill Trajectories (right) by Percentile



One can see that this exercise generates substantial additional thrill in a game, especially for the 95th percentile of thrill observed in this sample of games. Table 8 presents changes in viewership-minutes associated with this counterfactual scenario. I perform two different extrapolations: (i) extrapolating the thrill trajectory from the fourth quarter to the previous

[21] Lower percentiles of the thrill distribution do not exhibit this monotonic pattern. This is due to the fact that games featuring less thrill experience the peak of their thrill trajectory earlier in a game. Figures 4 and 5 show this clearly for the bottom quintiles of the absolute score differential distribution.

three quarters, and (ii) extrapolating the thrill trajectory from the second half to the first half. In the first scenario, I increase the number of final outcomes in an event from one to four, and in the second from one to two. I assess changes in viewership-minutes within a game (i.e. at the quarter or half level, depending on the scenario), at the level of a game, and over an entire NBA season, which encompasses 1,230 total regular season games (not including the playoffs).

Table 8: Viewership Changes from Increased "Finality" (1000's of Viewership-Minutes)

			Level of Thrill		
			Average	75^{th} Percentile	95^{th} Percentile
Quarters					
	Game-Level		1,207.86 (0.60)	1,159.12 (0.57)	1,791.94 (0.87)
		First Quarter	632.18 (1.33)	629.28 (1.33)	868.20 (1.80)
		Second Quarter	367.21 (0.68)	359.92 (0.67)	589.74 (1.09)
		Third Quarter	208.47 (0.37)	169.93 (0.30)	333.99 (0.58)
		Fourth Quarter	–	–	–
	Season-Level		1,485,671 (0.60)	1,425,716 (0.57)	2,204,084 (0.87)
Halves					
	Game-Level		818.04 (0.41)	841.96 (0.42)	1,168.05 (0.58)
		First Half	818.04 (0.82)	841.96 (0.85)	1,168.05 (1.15)
		Second Half	–	–	–
	Season-Level		1,006,195 (0.41)	1,035,616 (0.42)	1,436,698 (0.58)
Full Game			–	–	–

Note: Percent-changes in viewership-minutes are indicated in parentheses.

Looking at Table 8, one can see that when extrapolating the thrill trajectory from the fourth quarter to the first three quarters, viewership-minutes increases between 1.16 - 1.79 million minutes over the course of an entire game, which corresponds to a 0.60-0.87% increase. At a season-wide level, which corresponds to 1,230 total games played during the regular season, increases in viewership-minutes range between 1.43 - 2.20 billion. Viewership-minutes increase differentially more in the first quarter, since the typical thrill trajectory is at its lowest during the earliest portions of a game.[22] Comparing the second-half extrapolation and fourth quarter

[22]There is an implicit assumption here that viewers are treating each quarter as an independent outcome, and

extrapolation scenarios, viewership minutes increase by a lower amount in the second-half case, which is intuitive given that we are introducing less finality in this scenario.

Contextualizing the effect sizes observed from this counterfactual, Figures 5 and 6 show that thrill can enhance viewership by up to 30% in the fourth quarter, and 5-10% over the course of an entire game. In the counterfactual, thrill enhances viewership between 0.4-1.8%, which is significantly lower. It is clear from this comparison that the evolution of thrill within a game outweighs a structural modification to a game's structure (without compromising the integrity of the outcome) from the standpoint of increasing viewership. It also provides important insight into the nature of thrill itself – people enjoy thrill because of it's stochastic nature within a game, and the magnitude of viewership increases associated with games featuring more versus less thrill reflects this.

This research suggests a deeper set of questions about how to optimally design contests to maximize viewer attention. One natural extension of this is to examine different designs of game endings to induce additional thrill – an example of this is the difference in overtime formats between professional and collegiate football in the U.S. Future work should aim to carefully assess proposed changes in these leagues, as well as implications for other forms of entertainment, particularly ones that feature elements of skill and thrill.

V Conclusion

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, and the skill associated with the performers. I conduct several empirical analyses to assess the impact of suspense, surprise, and skill on viewership.

that there are no differential responses to thrill based on the timing of when the outcome takes place. For instance, if four quarters are played in a game and each counts equally as an outcome, viewers may still respond more to thrill in the final quarter, as it represents the last remaining outcome in a game.

There are three primary findings from this study. First, skill is an important driver of a viewer's initial decision to watch a game, while expected thrill has no significant impact. In particular, for a doubling of skill present in a game, initial viewership increases by approximately 11%. For context, the presence of LeBron James alone results in an approximately 13.5% increase in initial TV viewership. These results are remarkably similar to those found in Kaplan (2020), which uses secondary ticket marketplace data to assesses the impact of a superstar absence announcement for a specific game on listed prices. The analysis finds that the absence of LeBron James leads to a 13% ($42/ticket) average reduction in ticket prices.

Second, I measure thrill using the evolution of absolute score differential during a game. I 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% (1.2%) in the third (fourth) quarter, strongly supporting the idea that viewers relish thrilling games, not just games that are close. Contextualizing these results further, second half ratings are 8.2-20.5% lower 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. I extend this analysis to look at absolute score differential during a game in reference to the closing point spread. I find 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).

Third, I directly implement the structural definitions of suspense and surprise from Ely et al. (2015). I find that a doubling of suspense during a game increases viewership by 0.4-0.6%, and a doubling of surprise by 0.6-1.0%, not accounting for any additional impacts associated with skill. For additional context, in the last segment of the fourth quarter a 0-2 point game averages 18 times more suspense and 14 times more surprise than a 14+ point game. In this case, viewership would be approximately 6.8-10.8% higher only through suspense and 9.0-13.4% only through surprise. Additionally, a doubling of skill on the court during a specific portion of the game leads to a 1.9-2.4% increase in viewership. Interestingly, I find a negative interactive effect between suspense and skill, suggesting that heightened suspense leads to differentially higher viewership with lower skill on the court. This supports the traditional notion that spectators may only turn on games featuring lesser-known players (or teams) if they are nearing the end and exhibiting sufficiently high suspense.

There are several avenues of future work based on the findings and implications presented here. First, micro-level data on individual viewership that can be linked to demographic information would provide a rich assessment of heterogeneity in viewership patterns in response to entertainment characteristics, particularly in response to within-game information updating. A complementary experiment could measure consumer attentiveness to advertisements in response to skill and thrill at a specific point during a game, and assess purchasing conversion rates for advertised products and services. Individuals' opportunity cost of leisure time can also be measured using exogenous variation in the thrill of games experienced in different locations around the world at different times of the day.

A different set of analyses should examine the outlay of non-instrumental information in different domains. For example, individuals gain enjoyment from being informed about important local, state, and national elections, often using different entertainment platforms to garner information. In the case of politics, many individuals are consuming politically-relevant information simply for the sake of entertainment. But there is an interesting dimension of civic engagement that may result depending on the thrill of the information. Specifically, how might social media engagement, donations, and even voting activity respond to the thrill of an election? Understanding these impacts has never been more important.

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.

Badenhausen, K. and M. Ozanian (2019). NBA valuations. *Forbes*. link here, (last accessed 2020-01-30).

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.

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.

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 dont 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)*.

Sports-Illustrated (2014). NBA announces 9-year TV deal with ESPN, Turner Sports. *Sports Illustrated*. link here, (last accessed 2020-01-30).

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.

Appendix

A Additional Empirical Strategies for Assessing Thrill

A.1 Stakes-Dependency

To understand the interplay between suspense and the stakes of an event, I examine viewership responses to suspense in regular season versus playoff games. The stakes are much higher in playoff games, since a single win or loss carries substantially higher consequences than a single win or loss during the regular season.[23] The empirical strategy to analyze stakes and suspense will be an extension of the strategy for studying viewership responses to suspense in general. I use the following estimating equation:

$$V_{it} = \gamma(|D_{it}| * \text{Playoffs}_i) + (|D_{it}| * \mathbf{Q_{it}})\mathbf{\Gamma} + (|D_{it}| * \mathbf{Q_{it}} * \text{Playoffs}_i)\mathbf{\Lambda} + \alpha_i + \eta_t + \epsilon_{it} \tag{13}$$

In equation 13, $\mathbf{\Lambda}$ represents the vector of time-varying, differential impacts of score differential during the playoffs on viewership. Again, if stakes are important in heightening sensitivity to suspense, estimates in $\mathbf{\Lambda}$ should be negative and increasingly large for later segments of a game.

A.2 Underdog Margin

Underdog margin represents the score differential in reference to the "underdog," which is the team not favored to win a game at the onset. Thus, the underdog margin variable can be positive (if the underdog has more points than the favored team) or negative. Again, I estimate impacts of the underdog margin on viewership while controlling for absolute score differential

[23] The regular season schedule in the NBA consists of 82 games. Thus, the marginal contribution of each game to a team's final record and playoff chances is quite low.

at different stages of a game.

$$V_{it} = (\text{UnderdogMargin}_{it} * \mathbf{Q_{it}})\mathbf{\Lambda} + (|D_{it}| * \mathbf{Q_{it}})\mathbf{\Gamma} + \alpha_i + \eta_t + \epsilon_{it} \tag{14}$$

A.3 Consecutive Points Scored

Another element of surprise, particularly in sporting events or other types of competitions, is the "run effect." This effect takes place when one team performs in a way that during a specific portion of the game, there is relatively large updating in beliefs about an outcome. A useful proxy for the run effect is the total number of consecutive points scored by a single team during a specific portion of the game.

To estimate the impact of this effect on viewership, I subset games to those that had a run of at least R consecutive points scored by a single team during a single period of the game, testing impacts for different values of R.[24] Again, I estimate impacts of consecutive points scored on viewership for games with ConsecPoints $> R$ and during different segments of the game, controlling for absolute score differential.

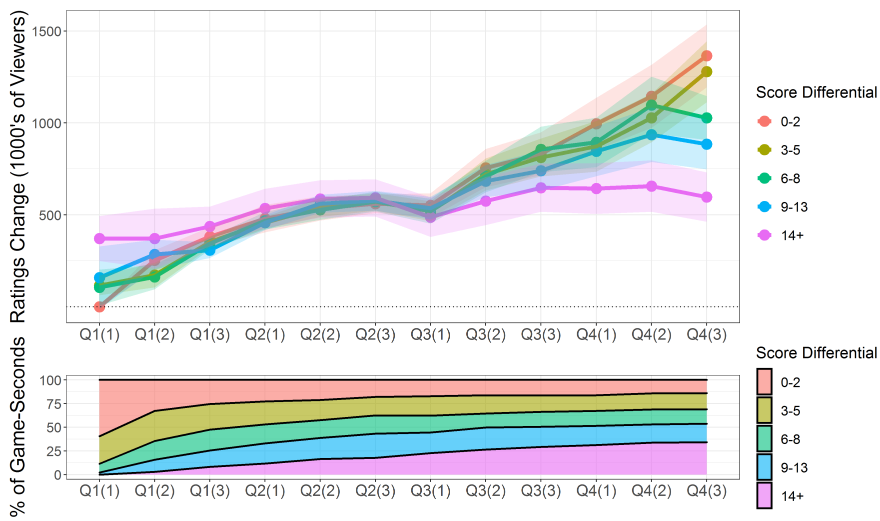
$$V_{it} = (\text{ConsecPoints}_{it} * \mathbf{Q_{it}})\mathbf{\Lambda} + (|D_{it}| * \mathbf{Q_{it}})\mathbf{\Gamma} + \alpha_i + \eta_t + \epsilon_{it} \tag{15}$$

[24]For context, $R = 15$ makes up approximately 10% of games in the sample while $R = 13$ approximately 25% of games.

B Additional Estimation Results

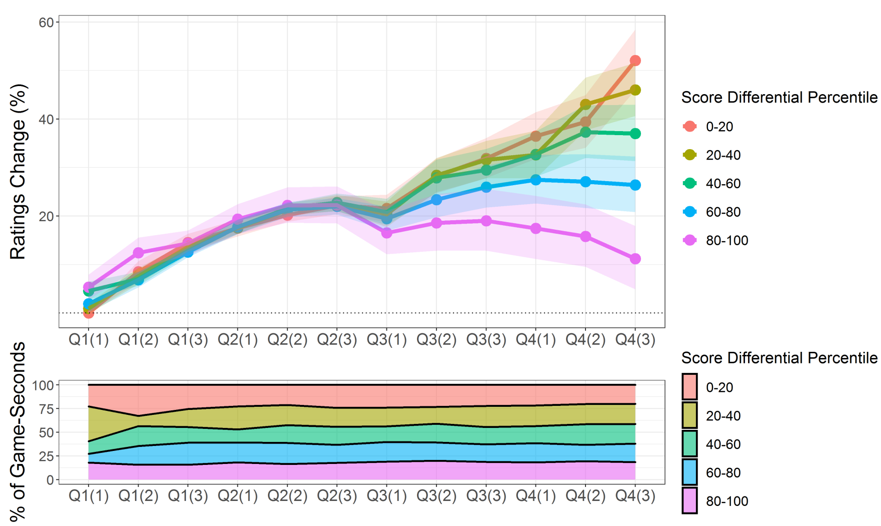
B.1 Absolute Score Differential

Figure 10: Individual Viewership Results by Score Differential Bin by Quarter Segment (Level Change)



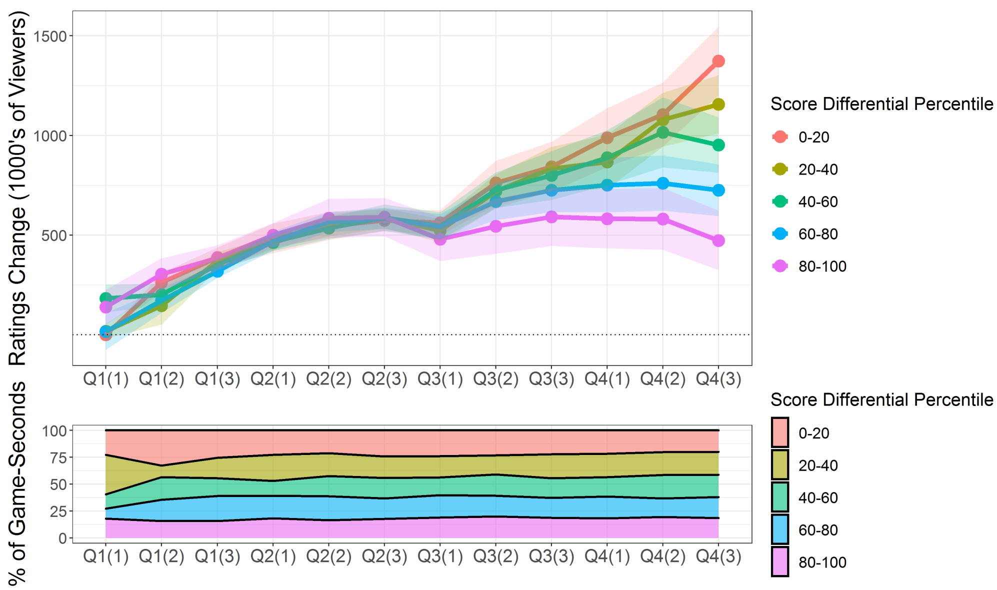
Note: Average 15-minute viewership was 2,694,597 individuals across entire sample.

Figure 11: Individual Viewership Results by Score Differential Percentile (Within Quarter Segment) by Quarter Segment



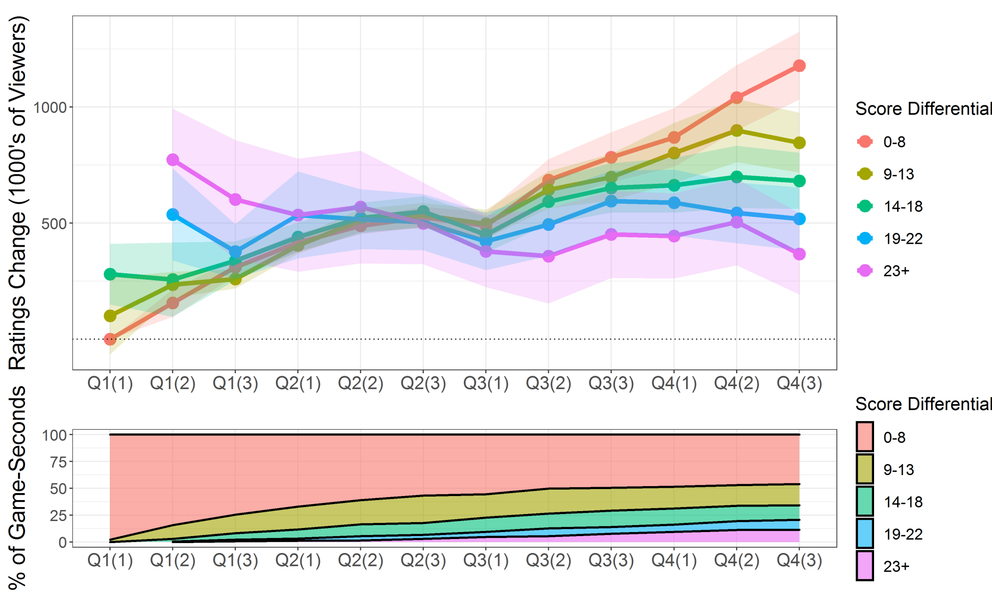
Note: Average 15-minute viewership was 2,694,597 individuals across entire sample.

Figure 12: Individual Viewership Results by Score Differential Percentile (Within Quarter Segment) by Quarter Segment (Level Change)



Note: Average 15-minute viewership was 2,694,597 individuals across entire sample.

Figure 13: Individual Viewership Results by Score Differential Bin by Quarter Segment (Tails, Level Change)



B.2 *Stakes-Dependency*

Finally, I examine the stakes associated with an event, hypothesizing that games with different stakes (i.e. playoff games versus regular season games) exhibit different viewership responses to suspense. Table 9 presents the results examining viewership responses to absolute score differential in playoff versus non-playoff games. Column (1) presents the naive estimation and column (2) the heterogeneous by period results aimed to capture suspense-driven effects. Both specifications include game and quarter segment fixed effects.

Table 9: Impact of Stakes on TV Ratings

	Dependent Variable: log(Total Proj. Viewers Watching)	
Absolute Score Diff.	-0.0078^{***}	0.0001
	(0.0018)	(0.0021)
Absolute Score Diff. * Q2		-0.0002
		(0.0019)
Absolute Score Diff. * Q3		-0.0049^{*}
		(0.0025)
Absolute Score Diff. * Q4		-0.0105^{***}
		(0.0030)
Absolute Score Diff. * Playoffs	0.0069^{**}	0.0057
	(0.0030)	(0.0043)
Absolute Score Diff. * Q2 * Playoffs		-0.0044
		(0.0036)
Absolute Score Diff. * Q3 * Playoffs		-0.0052
		(0.0046)
Absolute Score Diff. * Q4 * Playoffs		-0.0062
		(0.0048)
Period x Playoff Controls	No	Yes
Game FE	Yes	Yes
Quarter Segment FE	Yes	Yes
Observations	1,381,357	1,381,357
R^2	0.9453	0.9497
Adjusted R^2	0.9453	0.9497
Note:		*p<0.1; **p<0.05; ***p<0.01

In column (1), the term of interest is the interaction between Absolute Score Diff. and Playoffs, where Playoffs is an indicator variable = 1 for playoff games (and = 0 for regular season games). One can see that on average for regular season games, a one-point increase in the absolute score differential decreases viewership by 0.78%, while for playoff games that effect is not statistically different from zero. These findings suggest that viewers are much more responsive to how close a game is if it takes place during the regular season versus the playoffs. One potential mechanism is that for select subsets of viewers, substitution from nationally televised games towards local market games is possible during the regular season, where there are times when nationally-televised games overlap with strictly locally televised games. On the other hand, in the playoffs all games are nationally-televised and there is almost no overlap of games.[25]

In column (2), I examine heterogeneous viewership impacts of absolute score differential across periods in playoff versus regular season games. Thus, if viewers respond to suspense differently when stakes are higher, the effects would be witnessed in the triple interaction terms. One can see that for regular season games, the interaction between absolute score differential and time remaining in the game has the same magnitude and direction of impacts as those in Table 3. In addition, the sign of the interaction between Absolute Score Diff. and Playoffs is positive similar to column (1), but no longer statistically significant. Importantly, examining this coefficient along with the coefficients on the triple interaction terms suggests that playoff-level stakes do not statistically significantly enhance the viewership response to suspense, although the signs and ordering of the coefficients are in the expected direction.

[25] The only exception to this is during weekdays when there are 3 games scheduled. Since all games begin after a certain time, there is small overlap between games, where one of the games is typically shown on a less-viewed national network (e.g. NBA TV).

B.3 Underdog Margin

Table 10 presents results from estimations of the impact of underdog margin on viewership. Columns (1) and (2) examine the naive estimation of impacts of underdog margin on viewership, while columns (3) and (4) estimate differential effects by quarter and represent the model in equation 14. Columns (2) and (3) control for the average impact of score differential on viewership, while column (4) controls for the differential impacts by quarter segment. In columns (1) and (2), one can see that the average impact of underdog margin on viewership is positive and statistically significant, whereas column (2) suggests that a one point increase in the underdog score differential margin increases viewership by 0.21%. Thus, the naive model suggests that viewers do respond positively as the score differential margin favors the underdog.

Table 10: Impact of Underdog Margin on TV Ratings

	Dependent Variable: log(Total Proj. Viewers Watching)			
Underdog Margin	0.0033***	0.0021**	−0.0008	−0.0002
	(0.0009)	(0.0009)	(0.0016)	(0.0016)
Underdog Margin * Q2			0.0005	0.0007
			(0.0011)	(0.0011)
Underdog Margin * Q3			0.0023	0.0018
			(0.0015)	(0.0015)
Underdog Margin * Q4			0.0044**	0.0026
			(0.0017)	(0.0016)
Score Differential Control	No	Yes	Yes	Yes
Score Differential x Quarter Segment Control	No	No	No	Yes
Game FE	Yes	Yes	Yes	Yes
Quarter Segment FE	Yes	Yes	Yes	Yes
Observations	1,381,357	1,381,357	1,381,357	1,381,357
R^2	0.9440	0.9450	0.9455	0.9470
Adjusted R^2	0.9440	0.9449	0.9455	0.9470

Note: *p<0.1; **p<0.05; ***p<0.01

In columns (3) and (4), it is clear that the impact of the underdog margin on viewership depends on the time remaining in a game, where less time remaining increases the impact of the underdog margin on viewership, which is indicative of surprise. The effects are actually quite different across the game and in the expected direction based on the definition of surprise – the impact of a one point increase in the underdog margin in the fourth quarter on viewership is nearly double the impact witnessed in the third quarter. Again, this can be explained by the notion that the impact of a marginal underdog score differential change in later stages of a game leads to wider swings in outcome probabilities. When accounting for heterogeneous absolute score differential controls (column 4), the statistical significance disappears, however the signs and magnitudes of the coefficients by quarter support the argument that underdog margin provides meaningful surprise that viewers react to in the expected way. The magnitudes of the estimates are smaller than those seen in characteristics of suspense, albeit still economically meaningful. A one-standard deviation increase in the underdog margin (approximately 10 points) increases viewership 1.6-3.7%, where the effects are monotonically increasing as a game reaches its end.

B.4 Consecutive Points Scored

Next I examine the impact of the "run effect," as measured by consecutive points scored by a single team during a specific portion of the game, on viewership. Table 11 presents results from both the naive (columns 1 and 2) and surprise-focused (columns 3 and 4) estimations. As pointed out in section C, this analysis only includes games with $R \geq 15$ points, which makes up approximately 10% of all games in this sample.

One can see in the naive estimation, a one-point increase in consecutive points scored during a game leads to an average increase in viewership of 0.35-0.46%. These average effects suggest that people enjoy watching teams go on runs, but do not tell a story about runs driving surprise. In the estimations in columns (3) and (4), which draw from the model presented in equation 15, one can see that consecutive points scored does not have a significant impact

Table 11: Impact of Consecutive Points Scored on TV Ratings

	Dependent Variable: log(Total Proj. Viewers Watching)			
Consecutive Points	0.0035*	0.0046*	0.0029	−0.0050
	(0.0019)	(0.0022)	(0.0032)	(0.0033)
Consecutive Points * Q2			−0.0009	0.0056
			(0.0036)	(0.0033)
Consecutive Points * Q3			−0.0020	0.0058
			(0.0028)	(0.0032)
Consecutive Points * Q4			0.0075*	0.0154***
			(0.0035)	(0.0043)
Score Differential Control	No	Yes	Yes	Yes
Score Differential x Quarter Segment Controls	No	No	No	Yes
Game FE	Yes	Yes	Yes	Yes
Quarter Segment FE	Yes	Yes	Yes	Yes
Observations	170,959	170,959	170,959	170,959
R^2	0.9410	0.9431	0.9434	0.9483
Adjusted R^2	0.9409	0.9431	0.9434	0.9482

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

on viewership during the first three quarters, but that runs during the fourth quarter are differentially appealing to viewers. One can see that a one-point increase in consecutive points scored during the fourth quarter results in an approximately 0.75-1.5% increase in viewership. The time-dependent nature of the run effect connects directly to the definition of surprise – runs in the fourth quarter are likely to lead to larger swings in outcome probabilities compared to runs in earlier parts of games, and the relationship is almost completely monotonic. So, for a 15-point run in the fourth quarter, viewership increases during that portion of the game by approximately 15% compared to a game in the first quarter without any such run.[26]

[26] The assumed mechanism for these viewership changes is through individuals keeping track of games while not watching (on their phones, for instance) or receiving notifications updating them about a game, and tuning in as a result of this surprise event. In addition, because the viewership data is at the 15-minute interval level, it may be the case that I'm capturing viewers that opt-in at the end of or after a specific run, but still fall into the same 15-minute rating interval. The viewership data provides the average number of viewers during a 15-minute interval, and so these results may be an underestimate of the true viewership impact of a run.

Table 12 provides robustness by looking at games with $R \geq 13$ points, making up approximately 25% of all games in the sample. The results are consistent across the two sub-samples.

Table 12: Impact of Consecutive Points Scored on TV Ratings (Games with Maximum Consecutive Points > 12)

	Dependent Variable: log(Total Proj. Viewers Watching)			
Consecutive Points	0.0023*	0.0033**	0.0025	−0.0039
	(0.0012)	(0.0015)	(0.0020)	(0.0028)
Consecutive Points * Q2			−0.0016	0.0034
			(0.0021)	(0.0028)
Consecutive Points * Q3			−0.0016	0.0043
			(0.0017)	(0.0027)
Consecutive Points * Q4			0.0055**	0.0116***
			(0.0022)	(0.0034)
Score Differential Control	No	Yes	Yes	Yes
Score Differential x Quarter Segment Controls	No	No	No	Yes
Game FE	Yes	Yes	Yes	Yes
Quarter Segment FE	Yes	Yes	Yes	Yes
Observations	367,375	367,375	367,375	367,375
R^2	0.9324	0.9347	0.9349	0.9386
Adjusted R^2	0.9323	0.9347	0.9348	0.9386

Note: *p<0.1; **p<0.05; ***p<0.01