Entertainment Utility from Skill and Thrill*

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Abstract

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 information-conveying agents. Relying on the theory presented in Ely et al. (2015), I produce an empirically testable conceptual framework that examines the effect of suspense and surprise on consumer attention, incorporating spectator preferences for starmight of the information-conveying agents. Utilizing game-specific, high-temporal frequency secondary ticket marketplace and television ratings data from the National Basketball Association (NBA) during the 2017-18 and 2018-19 seasons, I measure spectator responses to suspense, surprise, and starpower. I find that suspense and starmight each enhance willingness-to-pay (WTP) and willingness-to-watch (WTW) between 4-30% depending on specification, while surprise induces a smaller viewership response. Interestingly, I find a negative interactive effect between suspense and starmight, suggesting that heightened suspense leads to differentially higher viewership with lower starmight on the court. These findings have important implications for entertainment companies, including leagues and television broadcasters, and advertisers.

Keywords: non-instrumental information, suspense, surprise, starmight, entertainment, consumer attention, difference-in-differences, event study

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I Introduction

Access to information is a crucial component of an economic agent’s decision-making process. Often, one thinks about information as instrumental in making economically meaningful decisions, where contingent actions await after becoming informed. For example, information about a tax implemented on sugar-sweetened beverages has important implications for an individual’s decision to buy regular soda. Yet, there is an entire class of non-instrumental information that does not have direct consequences for economic decision-making under constraints, but provides utility nonetheless. For instance, one can imagine waking up to read the news reviewing a political debate from the previous night, finding that a certain candidate performed much better than expected, while a different candidate may have essentially eliminated themself from the race. Or a tennis fan turning on the television to see that a top ranked player is about to be upset in the first round of the U.S. Open. One important distinction between these two types of information is the notion of uncertainty—in the case of instrumental information, uncertainty poses an economic burden for agents, while provision of non-instrumental information with uncertainty can often lead to utility gains.

One can think of the outlay of non-instrumental information as the “thrill” associated with an event. Thrill is broadly characterized as adjustments in a spectator’s belief state as a result of new information about an outcome. Ely et al. (2015) define and theoretically examine two primary characteristics associated with non-instrumental information during entertainment: suspense and surprise. Qualitatively, they define suspense as the variance in future beliefs over a state of the world, and surprise as the difference in current beliefs about an outcome state compared to previous beliefs. For instance, suppose a professional 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 massive change in the belief state about the golfer’s chances to win.

Yet, there is an important piece of information missing from these events: the performers themselves. Clearly, the extent to which thrill is meaningful depends on which golfer, or tennis player, or political candidate is conveying the information. Tiger Woods approaching the final back nine of a major tournament with a chance to clinch a victory is surely different than an identical scenario featuring a relatively less known golfer. If Serena Williams was about to be upset in the first round of Wimbledon, that would be much more surprising than a lesser known player. A political debate between Joe Biden and Donald Trump would carry a different level of thrill than a debate between candidates for a local election.

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 agents involved. Relying on the theory presented in Ely et al. (2015), I produce an empirically testable conceptual framework that examines the effect of suspense and surprise on consumer attention, incorporating spectator preferences for characteristics of the performing agents. Utilizing game-specific, high-temporal frequency secondary ticket marketplace and television ratings data from the National Basketball Association (NBA) during the 2017-18 and 2018-19 seasons, I measure willingness-to-pay (WTP) and willingness-to-watch (WTW) in response to suspense, surprise, and starpower.

I rely on two primary empirical strategies to measure these impacts. First, I use plausibly exogenous star-player absence announcements for specific games to measure WTP responses on a secondary ticket marketplace. Next, I utilize within-game play-by-play data at the second-of-game level, where I observe the level of starpower on the court, score differential, and real-time win probabilities for each team to assess television viewership responses to suspense, surprise, and starpower. While there are many different avenues of entertainment to study
these characteristics, live sports is a natural application since (i) performance and popularity
statistics of players are 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.

The findings suggest that suspense, surprise, and stardom are each important in generat-
ing consumer attention. In particular, there are statistically significant price declines due to
absences of the most popular stars, which include LeBron James, Stephen Curry, and Dwyane
Wade, among others, ranging from 4-16% ($7-$42) per ticket. I also analyze differential absence
impacts in home vs. away games, finding that away effects for LeBron James and Stephen Curry
are even larger, at 21% ($75) per ticket for LeBron and 18% ($55) per ticket for Curry. These
findings are notable because teams play at most two times in other cities, suggesting there is
a measurable scarcity impact associated with watching star players live. I compare these esti-
mates to the impact of starpower on initial television ratings for each matchup, finding similar
magnitudes in WTW as I do in WTP.

Next, I use the evolution of absolute score differential over the course of a game to measure
viewership responses to thrill. This analysis provides a more observable measure of suspense
and surprise (which cannot be independently examined here) before employing the structural
definitions in a joint analysis of suspense, surprise, and starpower. 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 1.2% in the fourth quarter, strongly supporting the idea
that viewers relish suspenseful 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 margin compared to a 0-8 margin, 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, finding that for every one-point increase in the
score differential from the closing spread, viewership declines by 0.69-0.79%. 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 star-
power. Directly implementing the structural definitions of suspense and surprise, I find that a
one-hundred percent increase in suspense during a game increases viewership by 0.4-0.6%, and a
one-hundred percent increase in surprise by 0.6-1.0%, not accounting for additional or differential
impacts associated with starpower. 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%. This range of estimates is quite similar to the 4-16% reduction in prices associated
with absences of the most popular superstar players, suggesting that starpower, suspense, and
surprise are each important in driving WTP and WTW.

In the fully interacted model accounting for within-game variation in starpower, I find that
a one hundred percent increase in starpower on the court at a given time during the game
(as measured by the cumulative number of All-Star fan votes) leads to a 1.9-2.4% increase in
viewership. While the starpower WTP and WTW estimates presented above reflect the exten-
sive margin of adjustment, these estimates represent an intensive margin measure of viewership
response to starpower. Interestingly, I find a negative interactive effect between suspense and
starpower, suggesting that heightened suspense leads to differentially higher viewership with
lower starpower 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 starpower 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.

There are several notable bodies of literature this research contributes to. First and foremost, there is a relatively small, albeit highly relevant, 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. They determine the optimal suspense and surprise information policies that maximize expected utility. Their study incorporates examples from practical entertainment and socially-relevant settings, including novels, political races, and live sports. Yet, they do not discuss utility implications from 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 game shows (Chan et al. 2009) and using the Hangman’s Paradox (Geanakoplos et al. 1989, Geanakoplos et al. 1996; Borwein et al. 2000). An adjacent and relatively rich literature examines physiological responses to stimuli classified as surprising, emphasizing that animals are genetically driven to respond to such occurrences (Itti and Baldi 2009; Ranganath and Rainer 2003; Fairhall et al. 2001; Ebstein et al. 1996).

To the best of my knowledge, there have been two 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 feature 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 magnitudinal impacts of suspense and surprise on viewership—a one standard deviation in both suspense and surprise increase audience viewership by 1.2%.

This paper aims to expand on 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 WTP and WTW, providing evidence of the relative magnitude impact of “skill” and “thrill.” In particular, I introduce data from a secondary ticket marketplace, which has the benefit of high temporal frequency observations before an event, to complement analyses on television viewership. Second, 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. Finally, I examine viewership responses to thrill over alternative game outcomes, which may be unrelated to the final outcome of which team/player 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.

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 aim to expand on this work by discussing and evaluating preferences for non-instrumental information, especially in the context of outcome resolution. In particular, evaluating the psychological and emotional attributes of entertainment is important in understanding the types of information individuals desire (Fowdur et al. 2009). For instance, studies have shown that story “spoilers” have large impacts on demand for entertainment goods, even suggesting that they have the potential to increase consumer enjoyment (Leavitt and Christenfeld 2011; Johnson and Rosenbaum 2015; Levine et al. 2016; Ryoo et al. 2020). Naturally, there has also been significant research assessing the impact of outcome uncertainty on demand for live sports (Rottenberg 1956; Knowles et al. 1992; Humphreys and Miceli 2019; Alavy et al. 2010; Forrest et al. 2005).¹ I aim to 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 highly relevant body of literature is in hedonic pricing. Rosen (1974) developed a theoretical framework that described the total value of a good as a combination of the values of its attributes, which has led to a rich body of literature applying the concept to a wide range of products (Busse et al. 2013; Sallee et al. 2016; Currie and Walker 2011; Chay and Greenstone 2005; Luttik 2000). This work focuses on two primary attributes of entertainment goods—the skill of the performers and the thrill of the event itself. Secondary ticket marketplace and television ratings data are natural avenues to explore WTP and WTW impacts, as there is important existing research examining dynamic pricing schemes in a wide variety of secondary marketplaces (Jiaqi Xu et al. 2019; Williams et al. 2017; Sweeting 2012; Blake et al. 2018).

¹It is important to note that while suspense and outcome uncertainty are related, they characterize different processes. Outcome uncertainty examines probabilities of different outcomes happening at different times, while suspense looks more fundamentally at the variance in the evolution of beliefs over the course of an event.
Levin et al. 2009; Oskam et al. 2018; Mills et al. 2016; Courty and Davey 2020) as well as in viewership responses to well-defined programming characteristics on television (Fournier and Martin 1983; Anstine 2001; Livingston et al. 2013). In particular, 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). However, there is a dearth of research exploring and measuring consumer WTP to experience star performers live and on television using a causal inference approach, which this paper aims to address. Furthermore, to the best of my knowledge, there is no existing research jointly measuring the impact of skill and thrill on WTP and WTW.

The fourth and final highly relevant 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 particular, there are important parallels between skill and thrill and brand personality content, and measuring in a
revealed preference manner how consumer attention responds to such information is important in understanding how to better engage audiences with different advertising strategies.

Understanding and evaluating audience preferences for skill- and thrill-based attributes of entertainment has important economic consequences. 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. For instance, an individual may be more willing to listen to a speech or read an article from Barack Obama compared to a lesser known and reputable figure. The ability to retain consumers through media outlets allows them to remain informed about important, economically consequential issues.

The remainder of this paper proceeds as follows. First, I develop a model of spectator utility from entertainment in section II. I then provide an overview of the data used and useful summary statistics in section III. Section IV presents the empirical strategy to identify willingness-to-pay and willingness-to-watch in response to suspense, surprise, and stardom, and section V presents the estimation results. Finally, section VI concludes.

II Model of Utility from Entertainment

This section presents a conceptual framework to understand consumer demand for “skill,” which represents the starpower of the primary entertainers, and “thrill,” which corresponds to the updating of beliefs that takes place during an event. While measuring “skill” is relatively straightforward, since it primarily depends on observable characteristics of the players involved (e.g. performance statistics, endorsement money, popularity as measured by number of All-Star votes, etc.), measuring “thrill” requires a more structured definition of what specific characteristics lead to the excitement that transpires during the course of a game. Specifically,
I characterize thrill into two components: suspense and surprise. I rely on a modified structure from Ely et al. (2015) to formally develop a mathematical interpretation of suspense and surprise that can be used in conjunction with starpower to assess spectator preferences.

A Defining Suspense and Surprise

Suppose there are two teams, A and B. Teams as entities can be broadly applied to 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 \( t \). Each potential outcome probability pair at time \( t \) falls within a state space \( \Omega \), where a state in that space is denoted \( \omega \). Put differently, \( \omega \) represents a specific pair of probabilities \( P_t \in \Omega \) that may be realized 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 \( t = T \).

It is necessary to introduce structure on beliefs about future outcome probabilities. Specifically, 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:
\[ X_t = \mathbb{E}_t \sum_{\omega} (\bar{\mu}_{t+1} - \mu_t)^2 \]

Thus, there is higher suspense at time \( t \) the higher the 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 (\textit{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:

\[ Y_t = (\mu_t - \mu_{t-1})^2 \]

Thus, there is higher surprise at time \( t \) the larger the squared difference in the realized probability pair at 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**

The model of spectator utility derived from entertainment combines suspense, surprise, and starpower to assess behavior of spectators. I begin by developing a framework that encompasses spectator utility for individual \( i \) from an entertainment event \( j \). I assume two primary components of entertainment that drive utility: “skill,” which corresponds to the level of starpower present in an event, and “thrill,” which is some convex combination of suspense and
surprise that occurs over the course of an event. Denote the starpower of an event as $S_j$, which I assume to be time invariant and continuous, and the thrill during some portion of an event as $H_j(r) = \gamma X_j(r) + (1 - \gamma) Y_j(r)$, where $r$ is a continuous measure of time remaining in an event. Thus, the expected thrill of an entire event can be written $\int_{r=0}^{r=R} E[H_j(r)]$ 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 event $j$ can be written as follows:

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

where $\psi$ and $\phi$ are average marginal utilities from “skill” and “thrill,” respectively. I also allow for an interactive effect of skill and thrill on utility, where $\theta$ represents the average marginal 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 starpower of an event linearly with time spent watching, although this assumption will be relaxed.\(^3\) $B_j$ represents some baseline average utility from event $j$, $\xi_i$ an individual utility shifter, and $\epsilon_{ij}$ 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 $\frac{\partial E[r[H_j(r)]]}{\partial r} < 0$, which suggests that expected thrill (at time remaining \(^2\)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 analogous for a setup using discrete time.

\(^3\)This assumption can (and will) be relaxed in different ways. For instance, starpower in an event can actually be measured as “starpower-minutes,” which accounts for the length of time a star player is actually playing in a game and how that overlaps with time spent watching.
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. With this structure, \( t^* \) is the solution to the following:

\[
\begin{align*}
(4) \quad \arg \max_t U_{ij}(t) &= -C(t, X_j) + \psi(S_j \ast t) + \int_0^t \phi \mathbb{E}[H_j(r)]dr + \theta [ (S_j \ast t) \ast \int_0^t \mathbb{E}[H_j(r)]dr ] \\
(5) \quad \frac{\partial C(t, X_j)}{\partial t} &= \psi S_j + \phi \mathbb{E}[H_j(t^*)] + \theta [ S_j \ast \int_{t^*}^t \mathbb{E}[H_j(r)]dr + (S_j \ast t^*) \ast \mathbb{E}[H_j(t^*)] ]
\end{align*}
\]

This result suggests that the optimal time spent watching is determined when the marginal opportunity cost of time spent watching equals the marginal benefit of additional starpower from watching, plus the marginal benefit of additional thrill experienced from time spent watching, plus the marginal benefit associated with an interactive effect between skill and thrill. The empirical analysis will directly estimate the marginal utilities from skill, thrill, and the interaction of the two, providing insight as to the relative importance to spectators.

*C A Note About Alternative Outcomes and Viewership Response Mechanisms*

As constructed, the model assumes thrill manifests itself with respect to beliefs about the final outcome of an event, which takes place at \( T \). 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

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

\[\text{Note that with the assumption } \frac{\partial E_{r=\mu[H_j(r)]}}{\partial r} < 0, \text{ time spent watching } t \text{ and time remaining } r \text{ are identical.}\]
that Team A makes a half-court buzzer beater at time $t$. Specifically, suppose that such a shot takes place at time $t - 1$ and the outcome of whether or not the shot goes in at $t$. The same definitions of suspense and surprise would apply: an agent would experience suspense during $t = \{0, ..., t - 1\}$ as to whether or not there will be a half-court buzzer-beater, 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 $t$. Such a generalization 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 starpower. There are two primary ways viewership may respond: through viewer addition and viewer retention. In the case of suspense, both viewer addition and viewer 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. Viewer retention is also likely, as a game that becomes more suspenseful is likely to retain viewers who were already tuned in before suspense increased. In the case of surprise and starpower, viewer retention is a more likely mechanism 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.

III Overview of Data

There are two primary sets of data used in the analysis: (i) high temporal frequency microdata from a large online secondary ticket marketplace, and (ii) high temporal frequency television viewership data from The Nielsen Company. This section presents an overview of this data and other complementary datasets used in this analysis.

A Data

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 Absence Announcements

Player absence announcements were collected from a popular fantasy basketball website, which provides detailed injury information and other reports for all players. This website provides regular updates on announcements from teams regarding player absences. I examined announcements pertaining to each All-Star player for the 2017-18 and 2018-19 NBA seasons,

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6Data 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.
documenting the exact time an announcement was made and for which game(s). When announcements were vague about the expected duration of missed time for a player (for example, if a player was announced to be out for “several weeks”), a very conservative lower bound horizon of the expected number of missed games was used.

A.3 Secondary Ticket Marketplace Data

An integral component of this project was collecting ticket-listing data from a large, online secondary ticket marketplace that offers tickets for events ranging from concerts to sporting events. The analysis relies on this willingness-to-pay data since sellers and buyers can react instantaneously to announcements about player absences. This data was accessed by routinely querying a REST (Representational State Transfer, a protocol built on-top of the standard web protocols) service provided by the secondary ticket marketplace every 30 minutes (or a total of 48 collections per day) for every remaining NBA matchup during the regular season (excluding playoffs).\(^7\) For each ticket listing, metadata on the corresponding NBA game was collected (e.g. home and away teams as well as date and time of matchup), data on the listing characteristics (listing price, quantity available, and a listing identifier), and identifiers for the time of data collection. This data provided high granularity snapshots for observing price changes before and after superstar absence announcements.

The empirical analysis relies on ticket listing observations within 3 days of a matchup, since this is when the majority of single-game superstar absence announcements and buyer/seller activity on the secondary market occurs. Additionally, ticket buyers and sellers may exhibit different responses (in terms of timing) depending on the amount of time between the announcement and affected game. Announcements impacting games within this window are likely to facilitate

\(^7\)A REST service is an HTTP-backed protocol that defines a set of rules for querying, updating, adding, and deleting data on a website. The REST protocol is how a website can securely expose its database without giving everyone unlimited control over the data.
more immediate changes, and thus make for clearer analysis of WTP impacts.\(^8\)

A.4 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 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.5 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.

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\(^8\) An interesting and important avenue of future research is to examine ticket price movements in response to longer-term absence announcements.

\(^9\) 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 \texttt{locfit} package in \texttt{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.
B  Summary Statistics

B.1  Secondary Ticket Marketplace

A summary of relevant variables collected from the secondary ticket marketplace microdata is presented in Table 1. Note that these are the primary summary statistics of the per-game averages for continuous variables (listing price and quantity per listing), and the per-game counts for count variables (number of observations, listing IDs, section IDs, and collection IDs). The data spans 2,330 NBA matchups, corresponding to 95% of the total number of regular season games played over two NBA seasons (2,460).\footnote{Reasons for missing data for certain matchups include server restarts and changes of event-names mid-season on the secondary ticket marketplace that were not automatically identified by the data collection program.} The “Listing Price” refers to the price posted by a seller for a specific listing. The “Quantity per Listing” denotes the number of seats available in a specific listing posted by a seller. The “Listing ID” is a unique listing-specific identifier, the “Collection ID” is a unique identifier corresponding to when the data was collected (i.e. each 30 minute collection gets a unique identifier), and “Section ID” corresponds to the section of the arena where the listing is located. Finally, “Number of Observations” corresponds to the number of unique listing-by-collection ID data points for each matchup.

<table>
<thead>
<tr>
<th>Data Characteristic</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Num. Obs.</td>
<td>37,660.88</td>
<td>26,648.85</td>
<td>70</td>
<td>215,346</td>
</tr>
<tr>
<td>Listing Price</td>
<td>$157.12</td>
<td>$107.06</td>
<td>$12.75</td>
<td>$995.01</td>
</tr>
<tr>
<td>Quantity per Listing</td>
<td>3.39</td>
<td>0.73</td>
<td>1.92</td>
<td>5.69</td>
</tr>
<tr>
<td>Listing IDs</td>
<td>826.80</td>
<td>682.10</td>
<td>28</td>
<td>5,357</td>
</tr>
<tr>
<td>Collection IDs</td>
<td>114.31</td>
<td>29.43</td>
<td>4</td>
<td>139</td>
</tr>
<tr>
<td>Section IDs</td>
<td>113.30</td>
<td>35.66</td>
<td>18</td>
<td>228</td>
</tr>
</tbody>
</table>

Table 1 shows that there is an average of 114.31 collection times for each matchup, which corresponds to approximately 57.16 hours prior to each matchup. There is an average of 826.80 unique listings per matchup across an average of 113.30 different arena sections. The average
per-matchup listing price is $157.12 with a quantity per listing of 3.39.

Because of the high temporal frequency of this microdata, I observe the time trends of average listing price and quantity of tickets posted to a secondary marketplace for each matchup. Figure 1 presents three different quantity time trends in terms of “hours to game”: the top pane presents the average total quantity of tickets available on the secondary marketplace for each matchup, the second pane presents the average number of tickets added (i.e. posted by sellers) to the marketplace per matchup, and the third pane the average number of tickets sold on the marketplace per matchup. I assume the disappearance of a listing implies that this listing was sold, either to a buyer or to the “seller” of the listing who decided to go themselves.\footnote{In other words, a seller may have their tickets purchased by another buyer, or decide to purchase their own tickets (i.e. remove the listing and go to the game themselves).} It is clear that the quantity of tickets available for a matchup declines as it approaches, which is intuitive as these tickets represent a “perishable good” and have no value following a matchup. Interestingly, the average number of tickets posted to the marketplace is significantly more uniform in terms of hours to game than the average number of tickets sold, which spikes in the five or so hours before a game.

Figure 2 plots the average listing price by hours to game. There is a downward trend in prices as a matchup approaches, decreasing from around $145/ticket two days before a matchup to around $100/ticket just before the start. The volatility in prices also substantially increases as game-time approaches, which may be attributed to an increase in activity on the marketplace—there are matchups where sellers may be trying to offload tickets and continuing to lower prices, and others where buyers are trying to obtain tickets, causing prices to increase.\footnote{Please note the different y-axis scale for each pane.}
B.2 Player Absence Announcements

Figure 3 presents the distribution of announcements for all analyzed All-Star players across the 2017-18 and 2018-19 NBA seasons in terms of hours to game. In the case of announcements
referring to multiple games, I only include observations corresponding to announcements within three days of a game to maintain consistency with the chosen time window.\textsuperscript{14}

Figure 3: Distribution of Player Absence Announcements by Hours to Game

Figure 3 shows there are 192 announcement-matchup pairs within three days of a matchup. Most announcements occur within 12 hours of a game, some coming only a few minutes beforehand.\textsuperscript{15} There are also noticeable declines in announcements 12-20 hours prior to a game, as these times often fall during the middle of the night. Rarely do announcements for a player absence for a specific matchup occur more than 36 hours prior to a game.\textsuperscript{16}

Table 2 presents the names of each starting All-Star player (or players that would have been voted a starter had the fan vote counted for 100%), how many “qualifying” games they missed (i.e. an explicit announcement for a matchup indicating the exogenous nature of a player’s

\textsuperscript{14}Table 2 provides both the “total number of games missed” (not just the most immediate game corresponding to a given announcement) for each All-Star player corresponding to all documented announcements, as well as the “total number of games analyzed” in our analysis.

\textsuperscript{15}This inherently limits the sample size of games that can be analyzed, since there needs to be an adequate timeframe pre- and post-announcement to witness ticket price changes.

\textsuperscript{16}As mentioned previously, our analysis does not consider the effect of a long-term injury announcement on games more than 3 days into the future.
Table 2: Count of Qualifying Missed-Games for each Starting-Caliber All-Star Player

<table>
<thead>
<tr>
<th>Player</th>
<th>Injury</th>
<th>Rest</th>
<th>Other</th>
<th>Total</th>
<th>Total Analyzed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anthony Davis</td>
<td>26</td>
<td>3</td>
<td>1</td>
<td>30</td>
<td>21</td>
</tr>
<tr>
<td>DeMar DeRozan</td>
<td>4</td>
<td>3</td>
<td>0</td>
<td>7</td>
<td>0x</td>
</tr>
<tr>
<td>DeMarcus Cousins</td>
<td>35</td>
<td>6</td>
<td>0</td>
<td>41</td>
<td>0x</td>
</tr>
<tr>
<td>Giannis Antetokounmpo</td>
<td>17</td>
<td>0</td>
<td>0</td>
<td>17</td>
<td>16</td>
</tr>
<tr>
<td>James Harden</td>
<td>10</td>
<td>2</td>
<td>0</td>
<td>12</td>
<td>6</td>
</tr>
<tr>
<td>Joel Embiid</td>
<td>12</td>
<td>6</td>
<td>0</td>
<td>18</td>
<td>13</td>
</tr>
<tr>
<td>Kemba Walker</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Kevin Durant</td>
<td>17</td>
<td>1</td>
<td>0</td>
<td>18</td>
<td>16</td>
</tr>
<tr>
<td>Kyrie Irving</td>
<td>35</td>
<td>1</td>
<td>1</td>
<td>37</td>
<td>27</td>
</tr>
<tr>
<td>Paul George</td>
<td>8</td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>7</td>
</tr>
<tr>
<td>Stephen Curry</td>
<td>42</td>
<td>1</td>
<td>0</td>
<td>43</td>
<td>20</td>
</tr>
<tr>
<td>Luka Doncic</td>
<td>10</td>
<td>0</td>
<td>0</td>
<td>10</td>
<td>9</td>
</tr>
<tr>
<td>Dwyane Wade</td>
<td>3</td>
<td>0</td>
<td>7</td>
<td>10</td>
<td>8</td>
</tr>
<tr>
<td>Dirk Nowitzki</td>
<td>2</td>
<td>2</td>
<td>0</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>LeBron James</td>
<td>22</td>
<td>3</td>
<td>0</td>
<td>25</td>
<td>16</td>
</tr>
<tr>
<td>Kawhi Leonard</td>
<td>6</td>
<td>14</td>
<td>1</td>
<td>21</td>
<td>21</td>
</tr>
<tr>
<td>Derrick Rose</td>
<td>32</td>
<td>0</td>
<td>0</td>
<td>32</td>
<td>19</td>
</tr>
</tbody>
</table>

* I did not analyze games in which DeMarcus Cousins or DeMar DeRozan missed, as both of them did not make the All-Star Team during the 2018-19 season (despite being All-Star starters during the 2017-18 season). The criteria for a player to be analyzed was that they were an All-Star during both seasons, a starter during at least one of the two seasons, or would have been voted an All-Star starter with 100% weight on the fan vote at least one of the two seasons.

absence) as a result of injury, rest, or “other” reasons, and the number of games for each player that was included in the analysis on ticket price changes. For each listed player, I am able to analyze most, if not all, of the qualifying games they were absent for.17

B.3 Television Viewership and Game Characteristics

Table 3 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

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17Reasons for not being able to analyze certain qualifying games include if the announcement occurred too close or too far from a matchup, missing ticket price data as a result of event-name changes on the secondary marketplace, or if another superstar was also announced absent for that qualifying game.
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 the least-viewed games attract hundreds of thousands of viewers every 15 minutes, and the most-viewed games receive tens of millions of viewers every 15 minutes.¹⁸

Table 3: Summary Statistics

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

Figures 4 and 5 show the average viewership trajectories by absolute score differential quintile and initial 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 5 is that initial point spread appears to predict viewership, at least in the final stages of a game.

Figure 6 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

¹⁸It cannot be determined from the data the number of unique viewers tuning in at any point during a game. I rely on total individual viewership for each 15-minute interval of a matchup.
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 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 6: 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 7 and 8 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. Figure 7 examines the one-period forward-looking variance in real-time win probability differences between the two competing teams, which corresponds to suspense, while Figure 8 examines the one-period backward looking variance, corresponding to surprise.\(^{19}\)

Figure 7: Variance in One-Period Forward-Looking Real-Time Win Probability Differential by Score Differential (Suspense)

![](image)

In Figure 7, 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 2-18 times more suspense than a 14+ point game, depending on the stage of the game.

Figure 8 depicts a somewhat different 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 occurring.

\(^{19}\)Figures 7 and 8 use a forward-(backward-)looking window of three minutes of game time (180 seconds). However, in section V I examine viewership impacts for one, three, and five minute windows. The results are largely unchanged when using these different window sizes.
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 probability differences. Section V 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 7 and 8.

**IV Empirical Strategy**

The empirical analysis in this paper attempts to understand the impact of suspense, surprise, and starpower on willingness-to-pay (WTP) and willingness-to-watch (WTW). First, I describe the empirical models associated with measuring WTP for superstars using the secondary ticket marketplace and player absence announcement data. Next, I construct a model to estimate television viewership responses to thrill as it evolves within a game. Finally, I provide a framework that attempts to jointly measure suspense, surprise, and starpower using television viewership.
A Empirical Models of Stardom

To obtain a plausibly causal effect of ticket price responses to a player’s absence, I construct a counterfactual group that models ticket price movements without a player’s absence, and compare those movements to the “treated” games, where a specific superstar player is announced to be out. This is important because there are underlying trends in ticket prices for NBA games that may bias the estimate of a player’s absence if not controlled for with an appropriate counterfactual. The counterfactual used in this analysis is denoted the same team counterfactual, which compares games for the team of a specific superstar where that superstar was absent, to games of that specific team not confounded by any superstar absences. For example, Golden State Warriors guard Stephen Curry missed the game on December 6, 2017 against the Charlotte Hornets. The same team counterfactual would consist of a subset of other Golden State Warriors games where Stephen Curry played and no other superstar players were announced to be absent. This counterfactual is preferred for the analysis since it controls for team-specific trends of ticket prices and their movements that may be common across many of their games.

A.1 Primary Estimating Equations

To measure the effect of star player presence on WTP, I use difference-in-differences (DID) and event-study estimations for each qualifying superstar player. Using the same-team counterfactual, the DID estimating equation is written as follows:

---

20 A different counterfactual could be a same day counterfactual, which would use ticket listings from all other games on the same day and compare their price movements to ticket listings for the treated game on that day. There are pros and cons to this method. On one hand, I am comparing games that occur during the same point in the season. On the other hand, there are a different number of games each day, which could limit the size of the counterfactual group, as well as completely different teams and markets involved each day.

21 This only includes “qualifying games” for other superstars, as defined in the Data Characteristic section. Namely, I do include games that another superstar may have missed, but that weren’t explicitly announced (for example, if another superstar was known to be out for the rest of the season prior to the treated game being analyzed).
\[
\ln(Price_{ish}) = \beta_1 Absence_i + \beta_2 PostAnn_h + \beta_3 (Absence \ast PostAnn)_{ih} + \alpha_{is} + \alpha_h + \epsilon_{ish}
\]

where \(Price_{ish}\) represents the average listed price for tickets in section \(s\) for matchup \(i\) at hours-to-game \(h\). So, an observation for the left-hand side variable would be the average listed price of tickets in section 201 for the Golden State Warriors vs. Houston Rockets matchup on October 17, 2017 listed on October 17, 2017 four hours before the game. \(Absence_i\) is a binary variable \(= 1\) if there was a superstar absence for matchup \(i\), and \(PostAnn_h\) is a binary variable \(= 1\) if the announcement had already been made at hours-to-game \(h\). Hours-to-game is used as the measure of time since matchups occur at different times during the day (e.g. 7:30pm EST or 10:30pm EST) and across days (e.g. October 16th vs. October 17th). Additionally, average ticket price trajectories are heavily dependent on the number of hours before gametime, as quantity of tickets available and prices on the secondary marketplace are very time-dependent (see Figures 1 and 2). The DID treatment coefficient is represented by \(\beta_3\), which approximately represents the percentage change in ticket prices associated with a superstar absence. Finally, \(\alpha_{is}\) represents arena section-by-matchup fixed-effects, and \(\alpha_h\) is an hours-to-game fixed effect.

Because I am attempting to determine the causal impact of a superstar absence on ticket prices, I estimate an event study to i) confirm parallel pre-trends in ticket prices for the treatment and counterfactual matchups, and ii) to determine the effect of a superstar absence on ticket prices in each time-period following the announcement. This strategy provides compelling identification, since I am able to examine “within-matchup” changes in prices in response to plausibly exogenous announcements.

Employing the same-team counterfactual, the primary empirical specification can be written:
\begin{equation}
\ln(Price_{i,ht}) = \sum_{t=-14}^{14\{-1\}} D_t Absence_{t,ih} + \alpha_{ih} + \alpha_{h} + \epsilon_{isht}
\end{equation}

Absence_{t,ih} is a vector of binary variables indexed by event-time t. Event-time t is in the half-hours-to-game unit, but is normalized to t = 0 based on the half-hours-to-game value when the announcement of a superstar’s absence takes place. As is standard in event study estimations, each variable takes a value = 1 if the observation in the data refers to a matchup i where a superstar was absent and the observation of data corresponds to event-time t. D_t is a vector of estimated coefficients distinguishing the price differential between the treated game and counterfactual games at event-time t compared to an omitted period (which for this analysis will correspond to t = −1). As can also be seen in the estimating equation, I restrict the event-time horizon to t = [−14, 14], where the left (right) binned endpoint coefficient represents the average treatment effects for all pre- (post-) periods not included in t = (−14, 14). The dependent variable and fixed-effects remain identical to the simple DID estimating equation.

In addition to estimating an effect for each individual matchup that experienced a superstar absence, I also estimate an aggregate absence effect for each superstar. Because each “treated” matchup for a specific player has a different announcement time in terms of hours-to-game, I cannot simply assign the same announcement time to all matchups in the counterfactual as was done in the individual matchup case. Rather, announcement times are randomly assigned for all matchups in the counterfactual by sampling from the pool of announcement times observed for the treated matchups. For example, James Harden was absent from six qualifying matchups that were analyzed (1/3/18, 3/11/18, 3/26/18, 4/11/18, 10/25/18, and 2/23/18), and was announced absent for these matchups at 47.5, 22, 26.5, 1.5, 33.5, and 2 hours-to-game, respectively. For each of these 6 treated matchups, I randomly pair a proportional number
of counterfactual matchups based on the total set of eligible counterfactual matchups for the Houston Rockets, and assign the announcement time (in hours-to-game) of the treated matchup to each counterfactual matchup with which it was paired. In the case of Harden, there are 148 eligible, untreated matchups in the counterfactual group, so 4 treated matchups receive 25 counterfactual matchups each and the remaining two matchups receive 24 counterfactual matchups. Once the pairings are assigned, the same announcement time is assigned to the group and the announcement time of each grouping is normalized to 0. The estimating equations remain the same as in the case of the individual matchup analysis with one key difference – for matchups in the counterfactual, $PostAnn_{ih}$ is determined based on the assigned announcement time within each grouping.\(^{22}\)

Finally, it is important to note that listed prices are used in this analysis. While a listed price does not necessarily indicate a seller’s true willingness-to-sell (i.e. the reservation price of attending the game), since the choice of the listing price is a function of the prices of other listings of comparable seats, changes in listed prices due to superstar absences should reflect a combined effect of sellers’ and buyers’ lower value of attending the corresponding matchup. In addition, I restrict the sample to tickets listings that eventually “sold,” since these are listings that at some point reflect a market-clearing equilibrium price between sellers and buyers.

### A.2 Identification Concerns

With any empirical estimation, there are concerns over identification of a causal estimate. In this estimation, I am inherently assuming that there are no omitted variables correlated with announcements that also affect ticket prices, namely:

\[
E[\epsilon_{ish}] | Absence_{t,ih}, X_{ish}] = 0
\]

\(^{22}\)To ensure robustness of the random counterfactual matchup-pairing algorithm, the aggregate-matchup analysis for each player is performed 3 times, each with a different random counterfactual pairing.
where $X_{ishl}$ represents the vector of covariates controlled for. However, because injury announcements are plausibly random (the occurrence of an injury is not predictable), and I only look at price movements 3 days prior to a matchup, there is only concern if a confounding event occurs that adjusts the price trajectory of a treated game differently than counterfactual games during this time horizon. One potential threat to identification is if an absence announcement of a player is correlated with having already made the playoffs and their team’s seeding set. This may occur if the propensity to sit a superstar due to injury is higher once a team’s playoff seeding is already known. In this case, it would be difficult to disentangle the price effect associated with a team having already made the playoffs and determined their seeding, and the price effect due to the injury of a superstar player.

While it is difficult to imagine important identification issues with respect to injury announcements, announcements about superstars being intentionally rested likely face a different set of concerns. First, decisions to rest superstar players may be dependent on several factors, for example the second night of back-to-back games or third game in four nights may exhibit a higher likelihood of superstars resting (e.g. Joel Embiid all of the 2017-18 season), competitiveness of the opponent, home vs. away games, etc. However, to the extent these characteristics are known prior to the three-days before a matchup, they would be accounted for in the matchup-specific fixed-effect.

B Empirical Models of Suspense and Surprise

Measuring suspense and surprise, which evolve during the course of a game, requires both a different source of data and different modeling strategy. Section II characterizes suspense and surprise in a structural way, relying on outcome probabilities at a granular level that are not directly observed by spectators. However, I first want to analyze viewership responses to suspense and surprise 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 view 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 that impacts the extent to which beliefs can change across periods. Equation 9 provides a general empirical model to measure viewership impacts in response to observed absolute score differential and time remaining in an event.

\[ V_{it} = (C_{it} \times Q_{it}) \Lambda + X_{it} \Gamma + \alpha_i + \eta_t + \epsilon_{it} \]

\( V_{it} \) represents total viewership for game \( i \) at time-of-game \( t \). \( C_{it} \) denotes the specific game characteristic impacting suspense and surprise (e.g. absolute score differential), and \( Q_{it} \) is a time-of-game indicator (e.g. a minute of a game). \( \Lambda \) represents a vector of time-varying coefficients that reflect the impact of \( C_{it} \) on viewership.

One important distinction to make is the difference between a close game and a thrilling game. A game featuring a 0-2 point score differential in the first quarter would be characterized as close, but not suspenseful, since the variance in beliefs about the outcome probabilities in the next period is quite low.\(^{23}\) On the other hand, a 0-2 point game in the fourth quarter would be considered both close and suspenseful. Intuitively, the differential viewership impacts across the horizon of a game for similar score differentials is the variation necessary to separate the impact of suspense on viewership versus the impact of a close game.\(^{24}\)

\(^{23}\)See Figure 7 for a visual depiction of this.

\(^{24}\)It is also clear that a close and suspenseful game is likely to feature substantial surprise as well. Given a winner needs to be decided, there may be a relatively large swing in outcome probabilities. For instance, a
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, $\mu_0$.

\[ |D_{t+1}| \sim \mathcal{N}(|D_t|, \sigma^2 | \mu_0) \]

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 $\mu_0$.

**B.1 Suspense and Surprise over Alternative Outcomes**

Individuals may 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 matchup-specific propositions (Salaga and Tainsky 2015). In order 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.\textsuperscript{25} The specific example of such an outcome that will be examined here is which team covers the closing point

\textsuperscript{25}This may be a strong assumption if individuals that care about these outcomes have an explicit financial stake, and thus suspense is endogenously chosen.
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 suspense, rather the absolute score differential in reference to the closing point spread.

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

$$|D_{it}'| = |D_{it} + P_{iT}|$$

where both $D_{it}$ and $P_{iT}$ use the same team as the reference point for scoring. For instance, if the home team is always used as the reference point, $D_{it} > 0$ implies the home team is leading, and $P_{iT} > 0$ 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 were the home team. If the closing point spread was -7, and the score at the end of the third quarter was 85 - 82 favoring Cleveland, then the absolute score differential from the 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 actual 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

---

26 Note that I index strength here at the matchup level, allowing for strength for a specific team to differ across matchups.
over time within games). The authors note that it is important to de-confound estimates from viewership corresponding to the actual game outcome (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 $G_{t>0.5T} = 0.4$, namely games must meet the criteria where at halftime, the difference in win probabilities of each team winning is $\geq 0.6$, 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:

\[
V_{it} = (|D_{it}'| * Q_{it}) \Lambda + (|D_{it}| * Q_{it}) \Gamma + \alpha_i + \eta_t + \epsilon_{it}
\]

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

C Joint Model of Suspense, Surprise, and Stardom

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:
\[ V_{it} = \mu X_{it} + \rho Y_{it} + \psi S_{it} + \lambda (X_{it} \ast S_{it}) + \nu (Y_{it} \ast S_{it}) + Z_{it} \Gamma + \alpha_i + \eta_t + \epsilon_{it} \]

\( V_{it} \) represents total viewership for game \( i \) at time-of-game \( t \). \( X_{it} \) denotes the structurally defined suspense parameter, \( Y_{it} \) the structurally defined surprise parameter, and \( S_{it} \) a cumulative measure of starpower.\(^{27}\) \( Z_{it} \) includes a set of controls that evolve within-game, and matchup and time-of-game fixed effects are denoted as \( \alpha_i \) and \( \eta_t \), 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 starpower, since it relies on within-game variation in the cumulative starpower of all players playing at a given point in a game. Finally, it allows for the inclusion of an interaction term between skill and thrill, which is useful in understanding differential viewership impacts to thrill depending on the presence of starpower. The following section will present the results from each of the empirical models discussed here.

V Results

This section presents estimation results from the empirical models of suspense, surprise, and starpower posed in section IV.

\(^{27}\)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 V, 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.
A Starpower Estimations

Figure 9 presents the results of the DID estimation as seen in equation (6). Each estimate reflects the average treatment effect on listed ticket prices from the entire sample of analyzed absences for each qualifying superstar. The confidence intervals presented are at the 95% level. Importantly, I only include players where pre-trends in ticket prices between the counterfactual and treated matchups prior to a superstars injury announcement are parallel, satisfying the identifying assumption that the DID estimate is causal. Absences for LeBron James and Stephen Curry result in the largest magnitude decrease in ticket prices at $42 and $29 per ticket, respectively. There are a number of other players whose absences lead to economically meaningful and statistically significant price reductions, including Dwyane Wade, Dirk Nowitzki, Luka Doncic, Paul George, Kemba Walker, and Kawhi Leonard, each of whom lead to price reductions between $7-$26 per ticket. Somewhat surprisingly, there are no statistically significant price reductions associated with James Harden’s or Giannis Antetokounmpo’s absences, who are the reigning MVPs from the previous two seasons. Figure 16 in the Appendix presents the results of the DID estimation as seen in equation (6) in percentage terms.

Furthermore, Figure 10 presents two distinct DID estimators for each player: one for home games missed and another for away games missed.\textsuperscript{28} One can see there are some striking differences in effects for certain players. For example, Stephen Curry and LeBron James’ absence effects are sizably larger and much more negative for away absences than for home absences. LeBron’s average away-game effect is $75/ticket, while Stephen Curry’s is $55/ticket. This suggests that the value of these players in away arenas is higher than in their home arena, likely because they only play in opposing arenas at most two times per year, and so there is a geographic scarcity effect of not being able to substitute towards a different game. On the

\textsuperscript{28}Note that Kemba Walker was not absent for any qualifying home games, and Dwyane Wade was not absent for any qualifying away games.
other hand, Luka Doncic and, to a lesser extent, James Harden both exhibit the opposite effect, where their absences are more meaningful for home games than for away games. This is also quite intuitive – both of these players are not just entertaining to watch, but without them their teams become much less competitive and much more likely to lose a game. The same argument could be made for LeBron James’ impact on the Lakers, who also exhibits a negative effect for home game absences, but his transcendent superstardom leads to an even larger away absence effect. Figure 17 in the Appendix exhibits these changes in percentage point terms.

To gain a better understanding of how starpower factors into the magnitudes of these estimates, Figure 11 visualizes the relationship between average player absence impact (as seen in Figure 9) on their maximum single-season All-Star vote total over the two seasons analyzed, and fits a quadratic approximation to showcase the general shape. The convex relationship between each player’s impact and their fan votes supports the economic theory of superstars.29

29This figure omits Dwyane Wade, Dirk Nowitzki, and Kemba Walker. Wade and Nowitzki were “legacy picks” by the NBA commissioner to take part in the All-Star game because of their career achievements, and thus
had lower fan vote totals but large impacts on prices when they missed games. Despite Walker’s significant impact on prices, his vote total was half the size of the next lowest vote-getter, and only missed two games over the course of these two seasons (both of which were at home), which was the lowest missed game total among all players analyzed here. His somewhat large effect is likely due to a small sample size of missed games and the fact that those games were missed in one of the NBA’s smallest markets (Charlotte).
To capture different measures of starpower, and in particular “career-long” popularity (which weights legacy players relatively more than recently popular stars), Figure 12 plots the player-specific ticket price impacts on both total number of career All-Star appearances (left) and championships won (right), which also exhibit a relatively convex relationship with superstar impacts on ticket prices.\textsuperscript{30}

Figure 12: Difference-in-Difference Results by All-Star Appearances (left) and Championships (right)

A.1 Event Studies

The event study results present coefficients for each of the 30-minute intervals before and after an absence announcement takes place. Figure 13 shows the results for the top three impact players with respect to ticket price declines as a result of their absences, again using the aggregate estimation, and Kawhi Leonard, who is the reigning NBA Finals MVP.\textsuperscript{31} Each point on the graph can be interpreted as the differential effect on listed ticket prices of a superstar absence announcement on the treated group vs. the counterfactual group. Coefficients statistically insignificantly different from zero prior to an absence announcement, which is indicated by the vertical red line, suggest that parallel pre-trends in ticket prices hold in each of these cases. The

\textsuperscript{30}The left pane is slightly more U-shaped, which is largely due to the significant global popularity of Luka Doncic, who played internationally for several seasons as a highly-renowned teenager before coming to the NBA but has not had a chance to accumulate All-Star appearances.

\textsuperscript{31}The event study results for the remaining eligible players are presented in the Appendix.
event study estimates exactly when prices change as a result of an announcement. One can see that there is a slight delay in the full responsiveness of listed ticket prices to the announcement of a superstar’s absence – typically the effects are smaller closer to the announcement time and larger further away. This is intuitive, as many sellers and buyers do not have immediate access to announcement information or the ability to immediately change their listing on the secondary marketplace. The endpoints are binned at −7 and +7 hours in event-time with respect to when the announcement occurs (at $t = 0$).

Figure 13: Event Study Results for Top Impact Superstars

(a) LeBron James

(b) Stephen Curry

(c) Dwyane Wade

(d) Kawhi Leonard
Table 4 presents the impact of several time invariant game characteristics on initial TV ratings (ratings at the start of a game) for nationally televised games, including the level of starpower as measured by cumulative All-Star fan votes for all players playing in a game.

Table 4: Impact of Starpower on Initial TV Ratings

<table>
<thead>
<tr>
<th>Dependent Variable: log(Total Proj. Individuals Watching) (Matchup-Level)</th>
<th>All Games</th>
<th>Reg. Season Only</th>
<th>Playoffs Only</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(Ag. All-Star Votes)</td>
<td>0.1197***</td>
<td>0.1580***</td>
<td>-0.0393</td>
</tr>
<tr>
<td></td>
<td>(0.0321)</td>
<td>(0.0276)</td>
<td>(0.0742)</td>
</tr>
<tr>
<td>log(Ag. PER)</td>
<td>-0.1280</td>
<td>-0.0049</td>
<td>0.0381</td>
</tr>
<tr>
<td></td>
<td>(0.1564)</td>
<td>(0.2018)</td>
<td>(0.2411)</td>
</tr>
<tr>
<td>log(Avg. Current Win PCT)</td>
<td>0.2756**</td>
<td>0.0838</td>
<td>0.6932***</td>
</tr>
<tr>
<td></td>
<td>(0.1274)</td>
<td>(0.1497)</td>
<td>(0.2501)</td>
</tr>
<tr>
<td>Absolute Pt. Spread (APS)</td>
<td>-0.0007</td>
<td>-0.0020</td>
<td>0.0035</td>
</tr>
<tr>
<td></td>
<td>(0.0049)</td>
<td>(0.0051)</td>
<td>(0.0115)</td>
</tr>
<tr>
<td>log(Ag. Team Value)</td>
<td>0.1753**</td>
<td>0.1112</td>
<td>0.3631*</td>
</tr>
<tr>
<td></td>
<td>(0.0721)</td>
<td>(0.0706)</td>
<td>(0.1950)</td>
</tr>
</tbody>
</table>

Month FE | Yes | Yes | Yes |
Day-of-Week FE | Yes | Yes | Yes |
Time-of-Day FE | Yes | Yes | Yes |
Streak FE | Yes | Yes | Yes |
TV Network FE | Yes | Yes | Yes |
Db1 Header FE | Yes | Yes | Yes |
Holiday FE | Yes | Yes | Yes |
Playoff Gm FE | Yes | No | No |
Clustered Robust SEs (Home + Away) | Yes | Yes | Yes |
Observations | 477 | 329 | 148 |
R² | 0.7448 | 0.6494 | 0.7084 |
Adjusted R² | 0.7155 | 0.5922 | 0.6068 |

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

There are three different specifications: column (1) includes all nationally-televised games from the 2017-18 and 2018-19 seasons, while columns (2) and (3) include only regular season and playoff games, respectively. Each of these specifications uses an “aggregate team value” continuous control variable to account for the number of people that may be expected to watch
independent of other important factors. 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). One can see that aggregate popularity, average current team quality, and aggregate team value are the only statistically significant estimates. The findings in specification (1) suggest that for a 100% increase in the cumulative number of All-Star votes in a matchup, initial rating increases by 12%, and similarly for a 100% increase in the average current win percentage of the two competing teams, ratings increase by nearly 0.28%. Additionally, in limiting the sample to regular season games (about 70% of the sample), the estimate on starpower increases to 16%, suggesting that player popularity may be a more important factor in the regular season than the playoffs. In fact, the estimate of the coefficient on the aggregate popularity variable becomes insignificant when subsetting the set of games to include only playoff matchups. One potential explanation for this is that playoff games have an “elimination” component, and so encompass a different viewership utility function that downweights preference for starpower. All specifications are clustered at the “Home Team + Away Team” level.

The effect of starpower on ticket prices and initial TV ratings are consistent and of similar magnitudes. Table 4 shows that in the presence of a player holding 100% of the average cumulative All-Star votes for a specific matchup, TV ratings were on average 12% higher, where ticket price reductions due to superstar player absences were on the order of 4-16% on average. For context, LeBron James averaged just over 3.6 million fan votes over the 2017-18 and 2018-19 seasons, which corresponds to approximately 95% of the average aggregate number

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32 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.

33 Note that I reset each team’s record for the playoffs, and so the “Avg. Current Win PCT” variable simply reflects that better teams move to future rounds by construction, where each subsequent playoff round experiences higher viewership.
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 below the total number of All-Star votes of all players in an average game. Using the results from the panel analysis, the presence of LeBron alone results in a 11.37-12.6% increase in ticket prices and TV ratings. The DID analysis yields a very similar result – the absence of LeBron leads to a 13% average reduction in ticket prices.

B Suspense and Surprise Estimations

The primary observable characteristic of suspense and surprise in these matchups is the absolute score differential in matchup \( i \) at time \( t \), \( D_{it} \). Table 5 shows two separate estimations. Column (1) presents the “naive” estimation, 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).\(^{34}\) Column (2) presents time-varying impacts of absolute score differential on viewership, which corresponds to equation 9.

One can see that on average across an entire game, a one point increase in the absolute score differential reduces television viewership by 0.55%, and so close games are important in raising viewership. Column (2) breaks 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 a 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 larger variance in beliefs, either forward- or backward-looking. As shown in Table 3, which depicts summary statistics of the play-by-play data, the mean and standard

\(^{34}\) As mentioned previously, it is important not to conflate the effect of a close game versus suspense and surprise on viewership.
Table 5: Impact of Absolute Score Differential on TV Ratings

<table>
<thead>
<tr>
<th>Absolute Score Diff.</th>
<th>Dependent Variable: log(Total Proj. Viewers Watching)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Absolute Score Diff.</td>
<td>-0.0055***</td>
</tr>
<tr>
<td></td>
<td>0.0015</td>
</tr>
<tr>
<td></td>
<td>(0.0013)</td>
</tr>
<tr>
<td>Absolute Score Diff.</td>
<td>-0.0012</td>
</tr>
<tr>
<td>* Q2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0017)</td>
</tr>
<tr>
<td>Absolute Score Diff.</td>
<td>-0.0059**</td>
</tr>
<tr>
<td>* Q3</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.0024</td>
</tr>
<tr>
<td>Absolute Score Diff.</td>
<td>-0.0116***</td>
</tr>
<tr>
<td>* Q4</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.0025</td>
</tr>
</tbody>
</table>

| Game FE | Yes       |
| Quarter Segment FE | Yes       |
| Observations | 1,381,357 |
| R^2      | 0.9466    |
| Adjusted R^2 | 0.9462 |

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

deviation of absolute score differential is 8.14 and 7.02, suggesting that viewership changes in response to changes in absolute score differential are quite sensitive.

Figure 14 depicts thrill impacts using absolute score differential at an even more granular level. Each game is split up into twelve equally spaced quarter segments, and absolute score differential is divided into five bins using the quintiles of the distribution in the data. All points in Figure 14 represent coefficients from an estimation taking the form of equation 9 using binned score differential, and can be interpreted as relative to the omitted score differential bin-by-quarter segment (the 0-2 bin in the first quarter segment, Q1(1)). First, this graph confirms that average viewership over the course of a game is increasing, as shown in Figures 4 and 5. It is also clear that there are heterogeneous impacts of absolute score differential on viewership as a game progressed to 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.

Figure 14: Household Viewership Results by Score Differential Bin by Quarter Segment (% Change)

It is clear that the 14+ absolute score differential bin exhibits the most stark impacts on viewership. Figure 15 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.
Table 6 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 spread, while columns (3) and (4) show thrill-driven impacts. Additionally, columns (2) and (3) control for the average impact of score differential on viewership, while column (4) controls for differential impacts of score differential on viewership by time of game.

In the naive model, the hypothesized sign of the coefficient on absolute score differential from the spread is negative, namely the further the absolute score differential gets from the point spread, the lower viewership becomes. One can see from columns (1) and (2) that controlling for absolute score differential is important, since it is likely correlated with absolute score differential
Table 6: Impact of Uncertainty Around Point Spread on TV Ratings

<table>
<thead>
<tr>
<th></th>
<th>Dependent Variable: log(Total Proj. Viewers Watching)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute Score Diff. From Spread</td>
<td>-0.0035* -0.0041 0.0021 0.0025</td>
</tr>
<tr>
<td></td>
<td>(0.0016) (0.0024) (0.0021) (0.0020)</td>
</tr>
<tr>
<td>Absolute Score Diff. From Spread * Q3(2)</td>
<td>-0.0003 -0.0010**</td>
</tr>
<tr>
<td></td>
<td>(0.0002) (0.0004)</td>
</tr>
<tr>
<td>Absolute Score Diff. From Spread * Q3(3)</td>
<td>-0.0022** -0.0023**</td>
</tr>
<tr>
<td></td>
<td>(0.0006) (0.0007)</td>
</tr>
<tr>
<td>Absolute Score Diff. From Spread * Q4(1)</td>
<td>-0.0031** -0.0021</td>
</tr>
<tr>
<td></td>
<td>(0.0010) (0.0014)</td>
</tr>
<tr>
<td>Absolute Score Diff. From Spread * Q4(2)</td>
<td>-0.0061*** -0.0055**</td>
</tr>
<tr>
<td></td>
<td>(0.0012) (0.0015)</td>
</tr>
<tr>
<td>Absolute Score Diff. From Spread * Q4(3)</td>
<td>-0.0100*** -0.0094***</td>
</tr>
<tr>
<td></td>
<td>(0.0013) (0.0018)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>No Yes Yes Yes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Score Differential Control</td>
<td>No Yes Yes Yes</td>
</tr>
<tr>
<td>Score Differential x Quarter Segment Control</td>
<td>No No No Yes</td>
</tr>
<tr>
<td>Game FE</td>
<td>Yes Yes Yes Yes</td>
</tr>
<tr>
<td>Quarter Segment FE</td>
<td>Yes Yes Yes Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>40,588 40,588 40,588 40,588</td>
</tr>
<tr>
<td>R²</td>
<td>0.9821 0.9821 0.9857 0.9859</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.9821 0.9821 0.9857 0.9859</td>
</tr>
</tbody>
</table>

*Note:*

*p<0.1; **p<0.05; ***p<0.01

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 this 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 through 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 result has an identical explanation to the results found in Table 5 and Figures 14 and 15. 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 -.0069 in specification (4), suggesting that for every one-point increase in the score differential from the
spread, viewership declines by 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 spread during the final quarter segment (9.3 points) can still have an economically meaningful impact viewership (6.4-7.3% reduction).

C Joint Estimation of Suspense, Surprise, and Stardom

The next set of estimations assesses the joint impact of suspense, surprise, and starpower on television viewership. This analysis relies on the structurally defined suspense and surprise parameters, as well as within-game changes in the level of starpower 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 7 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.\(^{35}\) 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 starpower with the goal of measuring differential viewership responses to thrill under varying levels of starpowr.

There are several notable takeaways from Table 7. First, it is important to contextualize the magnitudes of the suspense and surprise impacts on viewership. The estimates suggest that a one hundred percent increase in suspense increases viewership by 0.38-0.6%. However, as exhibited in Figure 7, 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

\(^{35}\)The results are not sensitive to reasonable window size adjustments.
Table 7: Impact of Suspense, Surprise, and Stardom on TV Ratings

<table>
<thead>
<tr>
<th></th>
<th>Dependent Variable: log(1000’s of Total Viewers)</th>
<th>1 Minute Window</th>
<th>3 Minute Window</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(Surprise)</td>
<td>0.0075***</td>
<td>0.0064***</td>
<td>0.0074</td>
</tr>
<tr>
<td></td>
<td>(0.0011)</td>
<td>(0.0010)</td>
<td>(0.0146)</td>
</tr>
<tr>
<td>log(Suspense)</td>
<td>0.0056***</td>
<td>0.0038**</td>
<td>0.0424**</td>
</tr>
<tr>
<td></td>
<td>(0.0015)</td>
<td>(0.0013)</td>
<td>(0.0153)</td>
</tr>
<tr>
<td>log(All-Star Votes)</td>
<td>0.0236**</td>
<td>0.0237**</td>
<td>0.0203***</td>
</tr>
<tr>
<td></td>
<td>(0.0082)</td>
<td>(0.0078)</td>
<td>(0.0052)</td>
</tr>
<tr>
<td>Absolute Score Diff.</td>
<td>−0.0021**</td>
<td>−0.0023**</td>
<td>−0.0022**</td>
</tr>
<tr>
<td></td>
<td>(0.0010)</td>
<td>(0.0010)</td>
<td>(0.0010)</td>
</tr>
<tr>
<td>log(Surprise) * log(All-Star Votes)</td>
<td>−0.0002</td>
<td>0.0017</td>
<td>−0.0025**</td>
</tr>
<tr>
<td></td>
<td>(0.0010)</td>
<td>(0.0010)</td>
<td>(0.0010)</td>
</tr>
</tbody>
</table>

|                      | log(Suspense) * log(All-Star Votes)              | −0.0026**       | −0.0029**       | −0.0029**       | −0.0029**       | −0.0029**       |
|                      | (0.0010)                                        | (0.0010)        | (0.0010)        | (0.0010)        | (0.0010)        | (0.0010)        |

Game FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
Quarter Segment FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | 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 | 1,381,973 | 1,381,973 | 1,381,973 | 1,381,973 | 1,381,973 | 1,381,973 | 1,381,973 | 1,381,973 | 1,381,973 |
R² | 0.9470 | 0.9471 | 0.9474 | 0.9471 | 0.9473 | 0.9473 | 0.9474 | 0.9474 | 0.9474 | 0.9474 | 0.9474 | 0.9474 | 0.9474 | 0.9474 | 0.9474 |
Adjusted R² | 0.9470 | 0.9471 | 0.9474 | 0.9471 | 0.9473 | 0.9473 | 0.9474 | 0.9474 | 0.9474 | 0.9474 | 0.9474 | 0.9474 | 0.9474 | 0.9474 | 0.9474 |

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

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 one hundred percent increase in 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 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 stardpower, the impact of surprise on viewership is no longer statistically significant. It is fairly intuitive that for a sport like basketball, which features frequent scoring and smooth updating
in outcome probabilities, surprise would have a lesser impact on viewer attention.

There are a couple of interesting and intuitive takeaways regarding the impact of starpower on viewership. First, examining the average impact of starpower while holding suspense and surprise constant, all specifications suggest that a one hundred percent increase 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 ticket price and initial TV viewership analyses examining stardom, the source of variation, and therefore interpretation of the coefficient magnitudes, is different. While the aforementioned analyses look at the time invariant impact of starpower prices and viewership, this estimation relies on within-game changes in the level of starpower on the court at any given time, and thus they complement one another in interpreting the impact of starpower on entertainment demand. One can think of the starpower-induced viewership changes estimated in Table 7 as occurring on the intensive margin (within games), while the larger estimates found in the ticket price and initial TV viewership analyses as occurring on the extensive margin (across games). It may be the case that spectators face two different decisions with respect to starpower: the likelihood of watching a game at all because of the aggregate starpower of players playing, and whether to continue watching a game when it features changes in starpower on the court at a given time.

Table 8 translates the coefficient on starpower from specification (3) to the corresponding within-game viewership impact for each of the specific superstars analyzed. 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 starpower impact translates to a 140% increase in on-court popularity, increasing within-game viewership by 2.83% when he is on the court playing.
Table 8: Within-Game Superstar Viewership Impacts

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

The second important takeaway from Table 7 related to starpower are the results from the fully interacted estimations in columns (3) and (6). Most interesting is the relationship between starpower and suspense. While suspense (holding starpower constant) continues to have a significant and meaningful impact on viewership, the interactive effect between starpower and suspense is negative and of smaller magnitude importance than the individual coefficients on suspense and All-Star votes. In words, the impact of heightened suspense on viewership falls with more starpower. Yet, a more intuitive way to interpret this differential impact is that suspense leads to differentially higher viewership with lower starpower 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 starpower. 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.
VI Conclusions

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 information-conveying agents. Relying on the theory presented in Ely et al. (2015), I produce an empirically testable conceptual framework that examines the effect of suspense and surprise on consumer attention, incorporating spectator preferences for characteristics of agents involved. Utilizing game-specific, high-temporal frequency secondary ticket marketplace and television ratings data from the National Basketball Association (NBA) during the 2017-18 and 2018-19 seasons, I measure willingness-to-pay (WTP) and willingness-to-watch (WTW) in response to suspense, surprise, and starpower.

The findings suggest that suspense, surprise, and starpower are each important in generating consumer attention. In particular, there are statistically significant price declines due to absences of the most popular stars, which include LeBron James, Stephen Curry, and Dwyane Wade, among others, ranging from 4-16% ($7-$42) per ticket. I also analyze differential absence impacts in home vs. away games, finding that away effects for LeBron James and Stephen Curry are even larger, at 21% ($75) per ticket for LeBron and 18% ($55) per ticket for Curry. I compare these estimates to the impact of starpower on initial television ratings for each matchup, finding similar magnitudes in WTW as I do in WTP.

Next, I measure thrill using the evolution of absolute score differential during a game, which is a more observable characteristic to viewers and exhibits much of the same information as the structural definitions of suspense and surprise. 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 1.2% in the 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 on average for games with a 14+ score differential margin compared to a 0-8 margin, 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, finding that for every one-point increase, viewership declines by 0.69-0.79%. 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 rely on the television viewership data to assess within-game viewership impacts of suspense, surprise, and starpower, which evolve over the course of a game. Directly implementing the structural definitions of suspense and surprise individually, I find that a one-hundred percent increase in suspense during a game increases viewership by 0.4-0.6%, and a one-hundred percent increase in surprise by 0.6-1.0%, not accounting for any additional impacts associated with stardom. However, these results deserve further context, since as defined 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%. This range of estimates is quite similar to the 4-16% reduction in prices associated with absences of the most popular superstar players, suggesting that starpower, suspense, and surprise are independently important in driving WTP and WTW.

Additionally, I find that a one hundred percent increase in the number of All-Star fan votes on the court at a given time during the game leads to a 1.9-2.4% increase in viewership. While the WTP and WTW estimates presented above reflect the extensive margin of adjustment,
these estimates represent an intensive margin measure of viewership response to starpower. Interestingly, I find a negative interactive effect between suspense and starpower, suggesting that heightened suspense leads to differentially higher viewership with lower starpower 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.

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 study of heterogeneity in viewership patterns in response to entertainment characteristics, particularly in response to within-game information updating. A complementary experiment to this proposed heterogeneity analysis could be to insert advertisements at different points of a game and measure attention retention, which may depend on the trajectory of the game leading up to the point of advertisement, as well as the current state of the game. A different set of analyses should examine the outlay of non-instrumental information in a different, yet highly relevant, domain, namely a political election. Many individuals are attracted and aim to be informed with respect to important local, state, and national elections, often using different entertainment platforms to garner information. In the case of politics, there is actually a contingent action that awaits this information, yet each vote only makes a marginal impact on the final outcome. Understanding how non-instrumental information over the course of an election cycle affects civic engagement is a more important question than ever.

References


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. 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:

\[ V_{it} = \gamma(|D_{it}| \times \text{Playoffs}_i) + (|D_{it}| \times Q_{it})\Gamma + (|D_{it}| \times Q_{it} \times \text{Playoffs}_i)\Lambda + \alpha_i + \eta_t + \epsilon_{it} \] (14)

In equation 14, \( \Lambda \) 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 \( \Lambda \) 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.

\[36]\text{The regular season schedule in the NBA consists of 82 games. Thus, the marginal contribution of each game to a team's final record and playoff chances is quite low.}\]
at different stages of a game.

\[ V_{it} = (\text{UnderdogMargin}_{it} \times Q_{it})\Lambda + (|D_{it}| \times Q_{it})\Gamma + \alpha_i + \eta_t + \epsilon_{it} \]  

(15)

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 \( R \).\(^{37}\) 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.

\[ V_{it} = (\text{ConsecPoints}_{it} \times Q_{it})\Lambda + (|D_{it}| \times Q_{it})\Gamma + \alpha_i + \eta_t + \epsilon_{it} \]  

(16)

B Additional Estimation Results

B.1 Stardom Willingness-to-Pay Estimations

Figure 16 presents the results of the DID estimation as seen in equation (6) in percentage terms. The reduction in prices due to absence announcements is highest for Dwyane Wade, Kemba Walker, and Dirk Nowitzki, all resulting in 14-16% reductions in prices associated with their

\(^{37}\)For context, \( R = 15 \) makes up approximately 10% of games in the sample while \( R = 13 \) approximately 25% of games.
absence announcements. Differences in the magnitudes of estimates between Figures 16 and 9 are due to differences in average ticket prices for different teams.

Figure 16: Difference-in-Difference Results for Superstar Absences (Percentage Change in Prices)

Figure 17 presents the results of the home vs. away DID estimation in percentage terms.
Figure 17: Difference-in-Differences Estimator by Home vs. Away Matchup Absence (Percentage Change in Prices)
B.2 Absolute Score Differential

Figure 18: Household Viewership Results by Score Differential Bin by Quarter Segment (Level Change)

Note: Average viewership was 2,694,597 households across entire sample.
Figure 19: Household Viewership Results by Score Differential Percentile (Within Quarter Segment) by Quarter Segment

Note: Average viewership was 2,694,597 households across entire sample.
Figure 20: Household Viewership Results by Score Differential Percentile (Within Quarter Segment) by Quarter Segment (Level Change)

Note: Average viewership was 2,694,597 households across entire sample.
Figure 21: Household Viewership Results by Score Differential Bin by Quarter Segment (Tails, Level Change)
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

<table>
<thead>
<tr>
<th></th>
<th>Dependent Variable: log(Total Proj. Viewers Watching)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absolute Score Diff.</td>
<td>$-0.0078^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.0018)</td>
</tr>
<tr>
<td>Absolute Score Diff. * Q2</td>
<td>$-0.0002$</td>
</tr>
<tr>
<td></td>
<td>(0.0019)</td>
</tr>
<tr>
<td>Absolute Score Diff. * Q3</td>
<td>$-0.0049^{*}$</td>
</tr>
<tr>
<td></td>
<td>(0.0025)</td>
</tr>
<tr>
<td>Absolute Score Diff. * Q4</td>
<td>$-0.0105^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.0030)</td>
</tr>
<tr>
<td>Absolute Score Diff. * Playoffs</td>
<td>$0.0069^{**}$</td>
</tr>
<tr>
<td></td>
<td>(0.0030)</td>
</tr>
<tr>
<td>Absolute Score Diff. * Q2 * Playoffs</td>
<td>$-0.0044$</td>
</tr>
<tr>
<td></td>
<td>(0.0036)</td>
</tr>
<tr>
<td>Absolute Score Diff. * Q3 * Playoffs</td>
<td>$-0.0052$</td>
</tr>
<tr>
<td></td>
<td>(0.0046)</td>
</tr>
<tr>
<td>Absolute Score Diff. * Q4 * Playoffs</td>
<td>$-0.0062$</td>
</tr>
<tr>
<td></td>
<td>(0.0048)</td>
</tr>
<tr>
<td>Period x Playoff Controls</td>
<td>No</td>
</tr>
<tr>
<td>Game FE</td>
<td>Yes</td>
</tr>
<tr>
<td>Quarter Segment FE</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>1,381,357</td>
</tr>
<tr>
<td>R²</td>
<td>0.9453</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.9453</td>
</tr>
</tbody>
</table>

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.\footnote{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).}

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 5. 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.
B.4 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 15. 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

<table>
<thead>
<tr>
<th></th>
<th>Dependent Variable: log(Total Proj. Viewers Watching)</th>
<th>Underdog Margin</th>
<th>Underdog Margin * Q2</th>
<th>Underdog Margin * Q3</th>
<th>Underdog Margin * Q4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0.0033***</td>
<td>0.0021**</td>
<td>−0.0008</td>
<td>−0.0002</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0009)</td>
<td>(0.0009)</td>
<td>(0.0016)</td>
<td>(0.0016)</td>
</tr>
<tr>
<td>Underdog Margin * Q2</td>
<td></td>
<td>0.0005</td>
<td>0.0007</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0011)</td>
<td>(0.0011)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Underdog Margin * Q3</td>
<td></td>
<td>0.0023</td>
<td>0.0018</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0015)</td>
<td>(0.0015)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Underdog Margin * Q4</td>
<td></td>
<td>0.0044**</td>
<td>0.0026</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0017)</td>
<td>(0.0016)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Score Differential Control</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Score Differential x Quarter Segment Control</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Game FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Quarter Segment FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>1,381,357</td>
<td>1,381,357</td>
<td>1,381,357</td>
<td>1,381,357</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.9440</td>
<td>0.9450</td>
<td>0.9455</td>
<td>0.9470</td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.9440</td>
<td>0.9449</td>
<td>0.9455</td>
<td>0.9470</td>
<td></td>
</tr>
</tbody>
</table>

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.5 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 IV, 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 16, one can see that consecutive points scored does not have a significant impact
Table 11: Impact of Consecutive Points Scored on TV Ratings

<table>
<thead>
<tr>
<th></th>
<th>Dependent Variable: log(Total Proj. Viewers Watching)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consecutive Points</td>
<td>0.0035* 0.0046* 0.0029 −0.0050</td>
</tr>
<tr>
<td></td>
<td>(0.0019) (0.0022) (0.0032) (0.0033)</td>
</tr>
<tr>
<td>Consecutive Points * Q2</td>
<td>−0.0009 0.0056</td>
</tr>
<tr>
<td></td>
<td>(0.0036) (0.0033)</td>
</tr>
<tr>
<td>Consecutive Points * Q3</td>
<td>−0.0020 0.0058</td>
</tr>
<tr>
<td></td>
<td>(0.0028) (0.0032)</td>
</tr>
<tr>
<td>Consecutive Points * Q4</td>
<td>0.0075* 0.0154***</td>
</tr>
<tr>
<td></td>
<td>(0.0035) (0.0043)</td>
</tr>
</tbody>
</table>

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 |
R² | 0.9410 | 0.9431 | 0.9434 | 0.9483 |
Adjusted R² | 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.\textsuperscript{39}

\textsuperscript{39} 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)

<table>
<thead>
<tr>
<th></th>
<th>Dependent Variable: $\log$(Total Proj. Viewers Watching)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Consecutive Points</td>
<td>0.0023* 0.0033** 0.0025 $-0.0039$</td>
</tr>
<tr>
<td></td>
<td>(0.0012) (0.0015) (0.0020) (0.0028)</td>
</tr>
<tr>
<td>Consecutive Points * Q2</td>
<td>$-0.0016$ $0.0034$</td>
</tr>
<tr>
<td></td>
<td>(0.0021) (0.0028)</td>
</tr>
<tr>
<td>Consecutive Points * Q3</td>
<td>$-0.0016$ $0.0043$</td>
</tr>
<tr>
<td></td>
<td>(0.0017) (0.0027)</td>
</tr>
<tr>
<td>Consecutive Points * Q4</td>
<td>$0.0055^{<strong>}$ $0.0116^{</strong>*}$</td>
</tr>
<tr>
<td></td>
<td>(0.0022) (0.0034)</td>
</tr>
</tbody>
</table>

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 |
R²                             | 0.9324 0.9347 0.9349 0.9386 |
Adjusted R²                     | 0.9323 0.9347 0.9348 0.9386 |

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