Celebration Beats Frustration: Emotional Cues and Alcohol Use During Soccer Matches*

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Emotions significantly influence human behavior during decision-making. While lab evidence is abundant, field studies are limited, often with rough measures or temporal gaps between triggers and behavior. Using high-frequency beer sales, in-play match data, and betting odds in a soccer stadium, we study the immediate impact of emotional cues on alcohol consumption. We integrate the emotional constructs *Surprise* and *Suspense*, considering positive and negative states. *Surprise* consistently increases beer sales, suggesting alcohol consumption in emotionally charged situations. *Suspense* mainly reduces beer sales. The positive emotional state dominates over the negative one regarding effect sizes, offering evidence that "celebration beats frustration."

JEL Codes: C11, D12, D91, I12

Key Words: immediate emotions; alcohol consumption; in-play betting odds; reference point; surprise; suspense; emotional state; bayesian hierarchical modeling.

For many years, economic research has extensively addressed the emotions that people might experience *after* making a decision, such as regret (Loomes and Sugden, 1982, for example), but it has rarely considered the effects of *immediate* emotions on decision-making. More recent studies explicitly incorporate cues, such as the smell of alcohol, into models of human behavior though (e.g., Laibson, 2001). Loewenstein (2000) elaborates on the theoretical relevance of immediate emotions and the consequences of a wide range of visceral factors, such as anger or fear, for human behavior, which leads him to conclude that "visceral factors play an essential (probably the dominant) role in human behavior" (p. 427). But investigating such a claim empirically is challenging, so most studies of how emotions influence decision-making have relied on lab experiments, which by their very nature cannot induce (or control) intense emotions (Tymula and Glimcher, 2018). One solution might be to leverage settings that induce strong emotional responses, such as weather extremes, terrorist attacks, political conflicts, or sporting events.

*This project is funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy - EXC number 2064/1 - Project number 390727645.
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In recent years, especially sporting events have become an area of interest because they typically have two key advantages over other settings (Palacios-Huerta, 2023). First, the psychological mechanism can be clearly identified, which is much more difficult (if not impossible) in the other settings, where direct physical or financial consequences also influence behavior. Second, sporting events in general, and regular league games in particular, are present in everyday life and as such are associated with a more "normal" set of intense emotions.

Edmans, Garcia, and Norli (2007), identifying negative domestic stock market reactions following losses of national soccer teams, were among the first to investigate the effects of sports sentiment. Others have more explicitly focused on reference point-based behavior by exploiting upsets. For instance, upset losses in the National Football League (NFL) increase family violence (Card and Dahl, 2011), and those in college football leagues apparently increase the sentence lengths imposed by juvenile court judges (Eren and Mocan, 2018), while upset wins in colleague football increase excessive partying and reports of rape (Lindo, Siminski, and Swensen, 2018). Overall, focused on post-match behavior, these studies exploit settings in which the temporal lag between the emotional trigger and observed behavior is comparably large. This is different in our paper, in which we explore the immediate behavioral response to emotional triggers.

Our conceptual framework builds on Ely, Frankel, and Kamenica (2015) who seek to explicitly model dynamics in this context by introducing two constructs pertaining to emotional cues: *Surprise* and *Suspense*[1]. We propose adopting and extending this framework to support our attempt to provide the first field evidence of the effects of immediate emotions on alcohol use[2]. Alcohol use in general is deeply rooted in society, widely recognized as a leading risk factor for death and disability (e.g., Griswold et al., 2018), and a major contributor to criminal behavior such as family violence (Klostermann and Fals-Stewart, 2006). However, even though "virtually all major theories of drinking behavior and alcohol problems include an important role for emotional factors" (Lang, C. J. Patrick, and Stritzke, 1999, p. 328ff.), field evidence of the immediate effects of

[1]In detail, *Surprise* is a backward-looking emotion that relates events, such as goals scored during the match, to anterior beliefs about the final outcome of a match, for instance. *Suspense* instead is a forward-looking emotion attributed to the variance in the next period's beliefs. Previous studies explore the effects of *Surprise* and *Suspense* on sports demand, in the context of Wimbledon tennis (Bizzozero, Flepp, and Franck, 2016), Premier League soccer (Buraimo et al., 2020), UEFA Champions League matches (Richardson, Nalbantis, and Pawlowski, 2023), and eSports events (Simonov, Ursu, and Zheng, 2023). Kessler et al. (2022) examine how short-term fluctuations in incidental happiness affect economic behavior by conducting a series of experiments in a sports bar, but the authors consider self-reported measures of surprise and excitement.

[2]By exploiting variation in Major League Baseball (MLB) match duration between the last alcohol call at the end of the seventh inning and the end of the match, Klick and MacDonald (2021) provide some indirect evidence for the impact of game-related alcohol consumption on crime near the stadium.

emotions on alcohol use as a mass phenomenon is largely missing.

To investigate this link, we combine high-frequency transaction data on beer sales during almost 100 matches played by a first division soccer team in Germany with the corresponding in-play event information and betting odds. These data allow us to measure *Surprise* and *Suspense* and to account for potential negative and positive emotional states during a match. For example, a home team fan might likely make different consumption decisions following a goal by the home team than an away team goal. Our proposed random intercept model is estimated by means of Hamiltonian Monte Carlo and has two levels. Level 1 (within-level) consists of match minute-specific information. Level 2 (between-level) contains match-specific data to control for differences in alcohol sales across matches.

This empirical design may help to justify the conditional independence assumption. However, it raises concerns about issues of reverse causality. In principle, if alcohol use influences fan behavior, it also might affect relevant match events. Home advantage is a well-established phenomenon in sports, and it can be attributed, at least partly, to crowd noise and social pressure on referees (Garicano, Palacios-Huerta, and Prendergast, 2005). Fan support tends to be dynamic during a match, and some of that dynamism might reflect the alcohol level consumed by the crowd, such that alcohol use at time t might drive outcome probabilities (cues) in the future. However, the likelihood of alcohol-induced enthusiastic cheering altering key events during the match seems negligible, given the average of 88.5 beers sold per minute during the match in our sample.

We find stable effects for *Surprise* increasing beer sales, yet we find almost no effects when we replace beer by shandy and weaker effects on soft drink purchases as the dependent variable. Thus, people seem to turn specifically to alcohol in emotionally charged situations, which is in line with psychological theories suggesting that alcohol may facilitate positive emotional experiences (Cooper et al., 1995) and reduce tension or stress (Greeley and Oei, 1999).

In contrast, we find *Suspense* to predominantly decrease beer sales, which could be explained by both the fear of missing important plays when the tension is high, and the desire to alleviate boredom by drinking alcohol when the tension is low (M. Patrick and Schulenberg, 2011). In particular, this finding lends some credibility to the claim by Wood, McInnes, and Norton (2011) that sports event-related traffic fatalities after close matches are due to aggressive driving caused by high levels of testosterone rather than excessive drinking during the match.

Finally, we find larger effects for the positive emotional state than the negative state, leading us to conclude that "celebration beats frustration" in our research. This finding may help to explain why, as Wood, McInnes, and Norton (2011, p. 617) infer, "losers are more likely to drive home safely."

I. DATA AND MEASURES

The underlying data consist of three pools. The first pool gathers transaction data (second-by-second sales of beer, water, hot wine punch, and so on) from VfB Stuttgart, a German first division soccer club. For the second pool, we obtain data regarding the sports betting market and basic match facts (e.g., minute-by-minute in-play and closing odds, date of the match, kickoff time) from NowGoal and OddsPortal. The third pool includes key match events, match day information, and further information on the teams (e.g., goals, red cards, ten minute-by-ten minute weather) from OptaSports, kicker.de, transfermarkt.de, Deutscher Wetterdienst (German weather service), Google Maps, kalender-online.com, schulferien.org, and cannsatter-volksfest.de. For more details and exact sources see online appendix tables B1 and B2, respectively.

A. Setting

We observe spectator behavior in the Mercedens-Benz Arena, where the soccer club VfB Stuttgart plays its home matches. Exploiting real in-play match events and using rarely accessed in-play transaction data (excluding sales during halftime, pre- and post-match) from the Mercedes-Benz Arena offers a promising approach, for several reasons. First, VfB Stuttgart's home matches draw some of the highest average attendances in Europe (e.g., 51.862 in season 2015/16[3]), so our analysis should be resilient, due to the high number of transactions. To track transactions, the club uses TCPOS[4] (point-of-sell technology), which documents every transaction taking place at any cash point in the stadium in a fully coherent, self-contained system.

Second, during the observed seasons, no stadium construction projects were taking place. Thus, no selection effects arise due to the unavailability of certain stands, for example. Moreover, no unexplained heterogeneity can arise as the result of changing beer vendors; for the entire sample, the vendor is the same, namely, Krombacher.

Third, this stadium imposes a strict segregation of spectators in sectors, surrounded by fences, during all matches, which is unlike the situation in many other stadiums in the Bundesliga. Across five areas, spectators cannot flow easily[5], though they can enter the catacombs in their section, which feature screens that allow them to watch the match and its key evens even if they are not in the stands, such that in-play information could affect their consumption decisions even when they are waiting in line to make their purchases.

[3]See https://www.transfermarkt.com/bundesliga/marktwerte/wettbewerb/L1, for example (retrieved on May 23, 2023).

[4]TCPOS is one of the global leading providers in the point-of-sell technology sector for hospitality and retail industries and is the official service provider in the Mercedes-Benz Arena.

[5]For some matches, the away fan area is extended by seats in the Untertürkheimer Kurve (opposite of the Cannstatter Kurve). We address this anomaly in the data preparation stage.

This segregation enables us to estimate effects for different stands and isolate home team versus away team fans, who likely experience diametrically opposed emotions for the same match events.

Fourth, cashpoints in the stadium are located close to every stand, but it takes some time to reach them. Still, contemporaneous or shortly delayed effects, such as in the same minute of or shortly after a signal, could occur if people who are already at a cashpoint impulsively decide to purchase. The same holds true for spectators on their way, such that they are in closer proximity to a cashpoint. Beer sales also might decrease in the short time span surrounding an event if consumers and salespeople spontaneously turn their attention to a monitor to see a replay. To explore such temporal patterns in behavior, we estimate contemporaneous effects, as well as effects up to 9 minutes after the signal.

Fifth, we can rule out inaccuracy due to the absence of real-time information. We are able to perfectly match real time with the match minute, such that delayed kickoffs do not lead to mismatched data points.

Sixth, though we cannot draw conclusions at the individual level, the investigation of alcohol use as a mass phenomenon is beneficial, especially as a form of reference point behavior. According to wisdom-of-the-crowd effects, the real expectations of people in aggregate should be closer to rationally expected reference points than individual appraisals, which tend to be highly biased. Research analyzing the individual effect of emotional cues must consider this deviation, which can be challenging.

B. Beverage Sales

We operationalize alcohol consumption first in relation to beer sales, as the main dependent variable. Subsequently, we also consider shandy and soft drinks to test for the relevance of alcoholic strength. Water and hot wine punch sales provide controls for baseline consumption and substitution effects, respectively. Table I summarizes beverage sales on a per minute basis.

Table I. Descriptive Statistics: Beverage Sales Per Minute

	count	mean	std	min	25%	50%	75%	max
Beer	8,820	88.5	57.4	0	44	76	123	320
Hot Wine	8,820	2.19	6.28	0	0	0	1	69
Shandy	8,820	8.64	8.35	0	3	6	12	68
Soft Drinks	8,820	16.7	17.1	0	5	11	23	130
Water	8,820	2.89	5.24	0	0	1	3	68

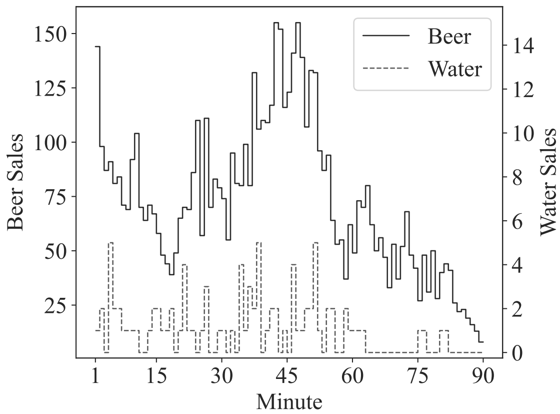
This table presents basic summary statistics of beverage sales on a per minute basis. The count variable is calculated by the number of matches (98 in the main specification) times 90 match minutes (halftime break excluded). On average there are 88.5 beer sales per minute in our sample. The number of beer sales serves as the dependent variable in the main specification and is substituted by shandy and soft drink sales in two alternative specifications. Water and hot wine (punch) control for baseline consumption and substitution effects, respectively. No minutes exhibit zero beer sales, after taking lags in the main specification. Percentages of 25%, 50%, and 75% denote the respective quantiles.

Clearly, beer accounts for the most transactions, with an average of 88.5 per minute.

The corresponding, relatively high standard deviation of 57.4 give rise to the question of why beer sales vary so much during matches. For all beverages, we also observe match minutes with no sales. However, taking the lags, all observed minutes in the main specification actually exhibit beer sales; the empty minutes occur at the very beginning of the match. A typical match in our sample exhibits 76 beer, 0 hot wine punch, 6 shandy, 11 soft drink, and 1 water sale(s) per minute (see 50% quantile in table I). The fewest transactions actually involve water, taking into account that hot wine punch is only sold in winter months.

Figure 1 illustrates the numbers in table I by depicting the time series of beer and water sold in the whole stadium, except for the away fan areas, during a match between VfB Stuttgart and SC Freiburg on Sunday, February 3, 2019, at 6:00 PM.

Figure 1. Beer and Water Sales, Exemplary Match



This figure shows the development of beer and water sales over time for an exemplary German first division soccer match between VfB Stuttgart and SC Freiburg on February 3, 2019 at 6:00 PM. The underlying data reflect the whole stadium, except for away fan areas. Sales during the break are excluded. The figure depicts a typical movement of beer sales, which first decrease, then peak around the half time break, and decrease towards the end of the match.

For beer, we identify a third-degree polynomial sales pattern over time (sales during the break excluded), which is typical a motion across all matches. Immediately after kickoff, beer sales begin to decrease signifying that fans who have paid to see live sports leave the cashpoint areas where they can buy alcohol. The observed delay likely reflects the queues at the cashpoints due to a high demand before kickoff. Also, fans arriving too late or just before kickoff and not wanting to forgo a beer can contribute to this pattern.

Then, just before halfway through the first half, beer sales reach their local minimum before they rise and find a maximum right after halftime break. Obviously, there is nothing to miss during the break in terms of live sports; halftime shows are either not presented or rather unattractive in German soccer (cf. many U.S. sports). Directly after halftime (right next to the 45th minute), sales remain at their overall maximum, again likely due to delay effects. We attribute the increase in the first half to anticipation effects, such that consumers likely expect high demand and long lines during the break. Economically speaking, people with lower opportunity costs of missing out go to buy early.

In the second half, beer sales drop considerably. This overall decline in sales in the second half might occur because fans leave before the end of the match to avoid crowds or traffic jams (congestion). An unfinished beer extends time in the stadium, because there is a deposit for returned cups. Especially in cold winter months, people could substitute a drink in the second half with one after the match in a bar near the stadium or at home, which arguably is more comfortable than in the stadium.

All in all, water sales do not exhibit a clear pattern like beer sales. However, we can see a typical decreasing volume towards the end of the match. More relevant for our research, we find that water and beer sales exhibit systematically different dynamics. By explaining beer sales, we are not summarizing transactions in general but alcohol sales in particular.

C. Emotional Cues

Emotional cues, as we construct and calculate them for this research, refer implicitly to reference point-based behavior. In this regard, we complement recent papers that use professional sports data in empirical tests of the theoretical prediction by Kőszegi and Rabin (2006) that utility from deviations between rationally expected references points and actual outcomes influence behavior under uncertainty (e.g., Card and Dahl, 2011; Eren and Mocan, 2018; Lindo, Siminski, and Swensen, 2018). Whereas these prior studies focus on post-match sentiment, we explore the effects of emotional cues during a match.

As noted, we focus on the emotional cues *Surprise* and *Suspense*, theoretically introduced by Ely, Frankel, and Kamenica (2015). With respect to their formulation for a soccer context, we follow Buraimo et al. (2020). Our key explanatory variables are

$$Surprise_t = u\left(\sum_{m \in H,D,A} \left[p_t^m - p_{t-1}^m\right]^2\right) \text{ and } \tag{1}$$

$$Suspense_t = u\left(\sum_{m \in H,D,A} p_{t+1}^{HG}\left[\left(p_{t+1}^m \mid p_{t+1}^{HG}\right) - p_t^m\right]^2 + p_{t+1}^{AG}\left[\left(p_{t+1}^m \mid p_{t+1}^{AG}\right) - p_t^m\right]^2\right) \tag{2}$$

$$\text{with } u(\cdot) = \sqrt{\cdot} \tag{3}$$

in which variable p represents a probability. The match minute is given by t. The path $m \in M = \{H, D, A\}$ can refer to home (H), draw (D), or away (A). Superscript HG indicates a "Home Goal", such that $p_{t+1}^D \mid p_{t+1}^{HG}$ is the conditional probability in minute $t+1$ of the match ending in a draw given the home team scores in minute $t+1$, for example. The equivalent AG indicates an "Away Goal."

As equation (1) specifies, *Surprise* is a backward-looking measure. It is based on the path-specific difference between the current outcome probability and the outcome probability in the period just before the current one, which serves as reference point. To capture the entire movement of changes, we can square and sum the differences between probabilities over all possible outcomes. Squaring the components within the sum prevents the path-specific parts from canceling each other out and also weights large deviations more heavily. *Surprise* is high if the current match situation does not align with former expectations, such as when an underdog scores an opening goal just before the end of the match.

In contrast, *Suspense* is a forward-looking measure, suggesting a what-if scenario that reflects the difference between the current outcome probability and the outcome probability in the next minute, given that teams score in the next minute. Very unlikely goals might influence the outcome probabilities strongly, which is why deviations from the reference points are weighted by the probability of the event happening. Summing over the weighted probability space (home win, draw, and away win) shows the expected value character of *Suspense*. Finally, *Suspense* is high if the variance of potential outcomes for the next period is large. For example, toward the end of the match, the two teams might equally likely score with a high probability in the next period, and the current score indicates a draw.

The underlying utility function in equation (3) controls for the curvature, reflecting the relative valuation of low versus high values. An exponent close to 1 implies that low cue portions are of similar importance to high portions. Low values near 0 instead denote strongly diminishing utility.

Both cues are based on match outcome probabilities, for which we use transformed in-play betting odds (see online appendix section A.1 for the exact procedure). Endogeneity seemingly might be a concern, because emotions could trigger odds and therefore emotional cues. But we obtain the odds from the Asian bookmaker Crown, which should be irrelevant for the typical fan of VfB Stuttgart (in contrast with a regionally popular bookmaker like tipico). Therefore, even when liquidity is low, emotionally involved people are unlikely to account for significant betting volume. Instead, betting odds generally are likely to stem from the high stakes of professional bettors (or syndicates) that use statistical models to determine underpriced odds.

Outcome probabilities based on in-play betting odds inherently exhibit missing values, because the market closes around important match events like goals when the odds are updated. Another reason for missing odds is the low liquidity that occurs when a match is practically decided before the end. For the imputation of these values, we use a gated recurrent unit (GRU) network via TensorFlow (Abadi et al., 2015), which includes goals, red cards, and previous outcome probabilities as features. In online appendix section A.2.1, we describe this imputation procedure in detail.

1. Emotional States. We distinguish between negative and positive emotional states, according to the perspective of home fans. To be precise, we employ endogenous state switching (indicated by S), where

$$\begin{aligned} p_t^H < p_{t-1}^H \quad &\Rightarrow \quad S = 0 \quad \text{and} \\ p_t^H > p_{t-1}^H \quad &\Rightarrow \quad S = 1 \end{aligned} \tag{4}$$

and the current state is maintained for $p_t^H = p_{t-1}^H$. If $p_1^H = p_0^H$, we choose the starting state at random, and both states have the same probability to be selected (p_0^H denotes the pre-match outcome probability for a home win). Online appendix table B3 provides descriptive statistics pertaining to how the states are represented in the sample; online appendix figure B1 illustrates the distribution of the states during matches.

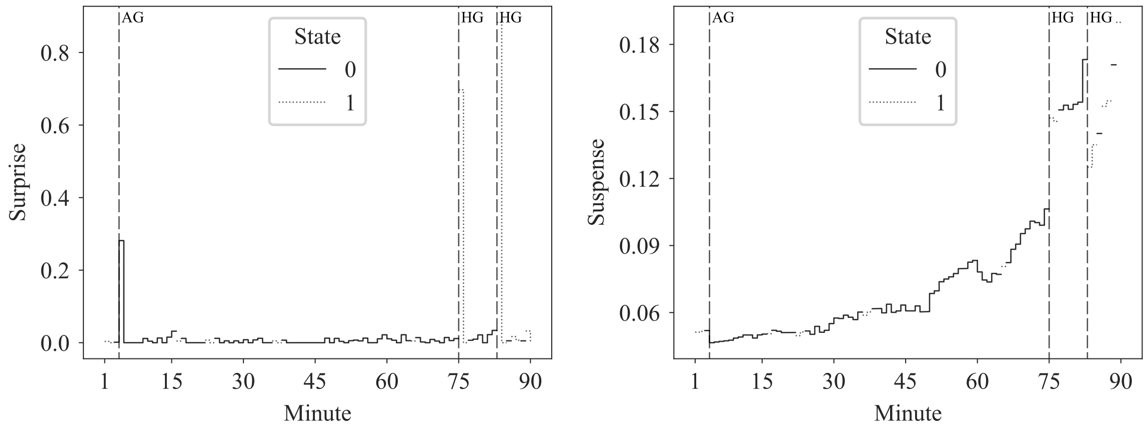
The state switching criteria in equation (4) based on changes in outcome probabilities are closely related to *Surprise*, as defined in equation (1). Although the sign of *Surprise* is strictly positive, we can think of $S = 0$ and $S = 1$ as negative and positive *Surprise*, respectively, because the marginal effect is free to switch signs, depending on the best fit.

We do not explicitly distinguish between negative and positive *Suspense*. Instead, we assume that people are affected by *Suspense* regardless of the match event and the team they support. This implies that, independent of any preferences about the timing of the resolution of uncertainty during the match (Palacios-Huerta, 1999; Dillenberger, 2010), realized relief after a tension phase is likely important for defining the emotional direction (i.e., negative or positive) rather than the expectation. As such, the emotional state in which people experience *Suspense* in t depends on the terminated and non-stochastic cue *Surprise*.

2. Visualization. In this subsection, we explicitly consider the entire stadium, excluding away fan areas. This sample is the largest possible block of data, accounting for emotional direction, and therefore smooths potential idiosyncrasies.

Figure 2 reveals how cues reflect key match events like goals (*HG* and *AG*), which change the outcome probability of the match. The data depicted by figure 2 refers to the same match between VfB Stuttgart and SC Freiburg, which ended in a draw (in stoppage time, which we do not consider in our analysis).

FIGURE 2. EMOTIONAL CUES FOR EXEMPLARY MATCH



This figure shows the development of emotional cues over time for an exemplary German first division soccer match between VfB Stuttgart and SC Freiburg on February 3, 2019 at 6:00 PM. Although VfB Stuttgart is the favorite, both cues exhibit a smaller jump when the away team scores at the beginning of the match (denoted AG) compared with the home team goals at the end (denoted HG). Key events like goals are more decisive when less time remains. Goals by the away team evoke the negative emotional state 0, from the perspective of home fans. Finally, the match ended in a draw (in stoppage time), but because we do not consider stoppage time, the last goal of the match is not depicted.

As we can see, *Surprise* as an adaptive variable returns to its pre-goal level very quickly after Freiburg scores in the first half, due to the varying reference point p_{t-1}. A goal for SC Freiburg (away) leads to the negative state 0 for home team fans. Stuttgart was favored in the match, so an away goal changes the match situation considerably. However, with a lot of time remaining, the jumps are higher when Stuttgart first equalizes and then breaks the tie deep in the second half.

For *Suspense*, the obvious pattern is its characteristic upward trend over time. The less time that remains, and the more information that is revealed, the greater the effect of a large variance of potential events in the next period; every goal becomes more crucial with respect to the final result.

II. MODEL

A. Formulae and Dimensions

To deal with the longitudinal multilevel data, we follow Asparouhov, Hamaker, and Muthén (2017) in determining

$$Y_{it} = Y_{1it} + Y_{2i} \ , \tag{5}$$

where i is the match index, and the match minute is captured by t. That is, equation (5) represents the orthogonal decomposition of the dependent variable Y_{it} into two components, in which Y_{2i} (between-level) is the time average of Y_{it}, and Y_{1it} (within-level) is oscillating around Y_{2i}, such that $Y_{1it} = Y_{it} - Y_{2i}$. The explained variable $\boldsymbol{Y}$ is a matrix that comprises the number of beverage sales across matches in its N rows and the number of units sold over time, i.e., during the matches in it's T columns. The same applies to

$\boldsymbol{Y_1}$. In contrast, $\boldsymbol{Y_2}$ is a $N \times 1$ vector, reflecting the lack of time specificity at level 2.

Having introduced the main components of the model, we can establish the within-level equation as

$$\begin{aligned}[Y_{1it} \mid S_{it} = s] = \nu_{1i} + \sum_{l=1}^{L} Y_{1i(t-l)}\phi_{1sl} + \sum_{l=0}^{L} \left(\boldsymbol{X_{1i(t-l)}\beta_{1sl}} + \boldsymbol{Z_{1i(t-l)}\gamma_{1sl}}\right) \\ + W_{1it}\psi_{1ts} + \varepsilon_{1it} \ . \end{aligned} \tag{6}$$

Then at the between-level, we set up

$$\nu_{1i} = \boldsymbol{Z_{2i}\gamma_2} + \upsilon_{2i} \ ,$$

which is a random intercept model. In other words, mean sales vary between matches, which we explain with a fixed-effects vector ($\boldsymbol{Z_{2i}}$) and a random component (υ_{2i}).

We choose hierarchical modeling over a classical fixed-effects estimator because it offers a higher number of degrees of freedom and thus increased model precision. The slope parameters are more flexible, in the sense that they are not tied to a single intercept. The first-difference estimator, as common alternative, is not suitable, due to the trend-stationary dependent variable; to use it, we would have to take multiple differences to obtain a stationary time series, and data are costly in our rather small sample. Instead, we introduce match minute dummies, using $\boldsymbol{W_1}$, to capture general sales patterns, unrelated to events in the match (see section I.B).

Intercept $\boldsymbol{\nu_1}$ and random term $\boldsymbol{\upsilon_2}$ are $N \times 1$ vectors; the match minute dummy vector $\boldsymbol{W_1}$ is $N \times T$ and its coefficient vector $\boldsymbol{\psi_1}$ is $1 \times T$. Cues collected in $\boldsymbol{X_1}$ ($N \times T \times G_{1,1}$) share a marginal effect object $\boldsymbol{\beta_1}$ with dimensions $G_{1,1} \times 1$. The fixed-effects in $\boldsymbol{Z_1}$ and $\boldsymbol{Z_2}$ are $N \times T \times G_{1,2}$ and $G_2 \times N$ objects, such that $G_{1,2}$ and G_2 are the number of covariates in $\boldsymbol{Z_1}$ and $\boldsymbol{Z_2}$. The marginal effect objects ϕ_1, $\boldsymbol{\gamma_1}$, and $\boldsymbol{\gamma_2}$ have corresponding dimensions: 1×1, $G_{1,2} \times 1$, and $G_2 \times 1$, respectively. Finally, the residual $\boldsymbol{\varepsilon}$ is a $N \times T$ matrix[6].

As equation (6) illustrates, the whole model is conditional on the state $S_{it} = s$. Lagged marginal effects thus apply to sales in t, given a certain state s, irrespective of whether the system was in a different state in the previous period.

B. Main Specification

For the main model specification, we use 98 matches from 6 seasons, spanning from 2013/14 to 2018/19.[7] We limit the set to league matches (i.e., Bundesliga and 2. Bun-

[6] Throughout this paper, we represent vectors, matrices, and higher dimensional objects with bold letters to distinguish them from scalars.

[7] A regular season consists of 34 matches or 17 home matches per season. Subtracting the 4 high risk matches we exclude thus yields 98 matches.

desliga, which are Germany's first and second divisions) to keep the sample homogeneous with respect to length and point in time at which the match outcome is determined. Cup matches, with potential overtime and penalty shootouts, thus are excluded. In addition, we do not consider stoppage time, so each time series lasts 90 minutes and has the exact same length for all matches. Next, we eliminate 4 high risk matches, for which the league decided that no alcohol, or only light beer, would be sold. The dependent variable includes beer sales and this main model specification refers to the entire stadium except for away fan areas.

1. Covariates. We control for weather conditions and substitutions at the within-level. For example, rain could simultaneously alter both the relative strength between teams and drinking behavior. Also, except for the potentially negligible effect of the entering player, there can be no updates to outcome probabilities during substitutions. That is, the systematic absence of match key events like goals and red cards during substitutions clearly affects outcome probabilities and simultaneously offers fans an opportunity to go for a drink. Therefore, we add substitutions as covariates. Other critical variables at the between-level include the total number of spectators and the price of beverages, which can improve model precision. For justifications of this model identification and additional details on the covariates, please see online appendix section A.3 and online appendix table B1.

2. Data Engineering. We standardize all explanatory variables (including the lagged dependent variable and all dummy variables). Standardization is highly recommended when using Markov chain Monte Carlo methods. Especially in a regularization context, it is important that large-scale features do not overwhelm features of smaller scales. For our data, varying scales are very prominent (e.g., air pressure in hPa versus emotional cues). The dependent variable is demeaned (following the basic idea of the decomposition described in section II.A) and transformed by the inverse hyperbolic sine (IHS) to allow a ceteris paribus comparison between the different specifications[8]. We do not log-transform, because for the alternative specifications Die-Hard Fans, Shandy, Soft Drinks, and Seasons in section III.B we observe match minutes with no sales even after taking the lags. Yet we obtain marginal effects in %. Finally, we drop the first match minute dummy, due to perfect multicollinearity, resulting in a total of $T-1$ minute dummies for which coefficient ψ_{11} serves as reference group.

3. Priors. For the main specification, we use several prior distributions. Without any theoretical guidance related to most of the parameters, and considering that the level-1 sample size which is not extremely small, we apply weakly informative priors in most

[8]The slope of $\sinh^{-1}(y) = \ln\left(y^2 + \sqrt{y^2+1}\right)$ is approximately equal to that of $\ln(y)$ for $y \geq 2$, so we interpret the coefficients as for a log-transformed dependent variable, because the scale of our dependent variable is large enough.

cases. First, we choose

$$\boldsymbol{\varepsilon} \sim \mathcal{N}\left(0, \sigma^2\right) \text{ with } \sigma \sim \mathrm{C}^+(0,1) \ ,$$

where C^+ denotes the Half-Cauchy distribution. Second, we specify

$$\boldsymbol{\upsilon_2} \sim \mathcal{N}\left(\mathcal{N}(0,1), \mathcal{N}^+(0,1)\right) \ ,$$

where N^+ is the truncated normal distribution. Third, we use a continuous version of the spike-and-slab prior (Mitchell and Beauchamp, 1988; George and McCulloch, 1993; Ishwaran and Rao, 2005), such that

$$\begin{aligned} \theta_j \mid \lambda_j, c &\sim \mathcal{N}\left(0, c^2\lambda_j\right) \text{ where } \theta_j \in \{\boldsymbol{\phi_{1s}}, \boldsymbol{\beta_{1s}}, \boldsymbol{\gamma_{1s}}, \boldsymbol{\psi_{1s}}, \boldsymbol{\gamma_2}\} \ , \\ \text{such that } \lambda_j &\sim \mathrm{Beta}(0.5, 0.5) \text{ for } j = 1, \ldots, J, \text{ and} \\ c^2 &\sim \Gamma^{-1}(3,1) \ . \end{aligned} \tag{7}$$

Except for $\boldsymbol{\psi_1}$ (no lags) and $\boldsymbol{\gamma_2}$ (no states), all vectors affected by the spike-and-slab design contain lagged values and are state-dependent. The feature space is comparably large, and it is difficult to foresee which variables explain variation in the dependent variable, so we choose to regularize all parameters, which also helps prevent overfitting.

The spike-and-slab prior uses a binary indicator variable λ that determines whether the coefficient is zero (i.e., it comes from a "spike", $\lambda \to 0$) or non-zero ("slab", $\lambda \to 1$). The slab width is denoted by the parameter c. It is generally not flexible to fix c, so a common practice entails placing a hyperprior on c to allow for heavy-tailed slabs. The sparsity information of the coefficient vector can be controlled with the parameters of the Beta prior in equation (7).

4. Estimation. We estimate the model using the probabilistic programming package PyMC (Salvatier, Wiecki, and Fonnesbeck, 2016), which relies on Theano in its computational backend.[9] In particular, we apply the No-U-Turn (NUTS) sampler (Hoffman and Gelman, 2014), a recursive algorithm for continuous variables based on Hamiltonian mechanics that extends Hamiltonian Monte Carlo (HMC) by eliminating the need to set a number of steps through the inbuilt automatic stoppage once the sampler starts to make a U-turn. We set a comparably large acceptance probability of 0.975 (default value is 0.8), which is associated with a small step size, so that we can achieve non-diverged trajectories for the samples. We run 4 chains with 2000 iterations each and an additional 1000 burn-in samples per chain that we discard. The Gelman-Rubin statistic $\hat{R}$ (Gelman and Rubin, 1992; Brooks and Gelman, 1998) monitors convergence.

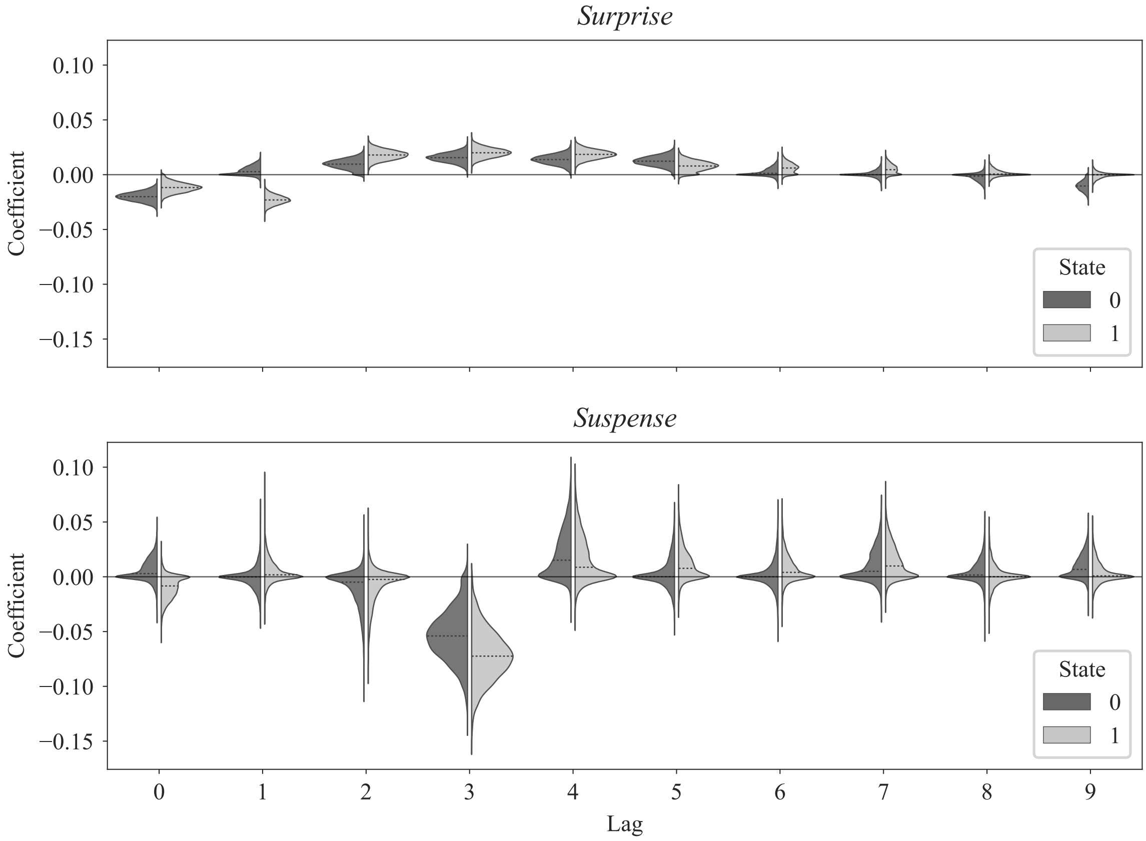
[9]Common frequentist approaches using linear algebra are not feasible, because the objects lack fitting dimensions, due to the emotional states.

III. EMPIRICAL RESULTS

A. Main Specification

Figure 3 depicts the main model posterior distributions of marginal effects $\boldsymbol{\beta_{11}}$ (*Surprise*) and $\boldsymbol{\beta_{12}}$ (*Suspense*) separately for negative (0) and positive (1) states. In addition to the contemporaneous effects ($l = 0$), we present all effects up to nine minutes after the signal ($L = 9$).

FIGURE 3. MAIN MODEL POSTERIOR DISTRIBUTIONS OF COEFFICIENTS FOR *SURPRISE* AND *SUSPENSE*



This figure shows the posterior distributions of the coefficients for *Surprise* and *Suspense*, based on the main specification. The posteriors are depicted for all lags in both states (negative state 0 and positive state 1). For example, a positive effect for *Surprise* appears in both states 3 minutes after a key match event (see distributions for the third lag in the upper panel). The median depicted by the dashed line, equal to 0.02 for positive state 1, implies that a one standard deviation increase in *Surprise* in positive state 1 increases the conditional mean of the number of beers sold during minute 3 after a key match event by approximately 2%, ceteris paribus.

The statistically and economically significant effects for *Surprise* and *Suspense* on the number of beer sales are most pronounced for $l = 3$. We use the median (dashed line) of the $l = 3$ marginal effect in positive state 1 for *Surprise* (upper panel) as an example; it is equal to 0.02. A one standard deviation increase in positive *Surprise* then increases the conditional mean of the number of beers sold during minute 3 after a key match event by approximately 2%, ceteris paribus. If we take the average value of 85.5 from table I as a basis, this increase corresponds to roughly two additional beers. At first glance, this effect might not seem notable, except that–as the exemplary match between

VfB Stuttgart and SC Freiburg in figure 2 reveals–the leading goal for Stuttgart increases *Surprise* more than 0.8. Considering the standard deviation of 0.07 for *Surprise* in state 1 (see online appendix table B5), the marginal effect in this numerical example increases by a factor of approximately 10, such that 17 additional beers are sold (20% of 85.5).

This effect for $l = 3$ corresponds to just a single minute; the total effect is longer lasting. For example, we find positive posterior distributions for *Surprise* when $l = 2$, $l = 4$, and $l = 5$ as well. Besides, not all people in the stadium drink alcohol (e.g., children, teetotalers, pregnant women).

The coefficients for *Suspense* (lower panel) follow the same reasoning, but the main effect when $l = 3$ is clearly larger than that of *Surprise* for both states. Due to the lower relative increase of *Suspense* for the second home goal though (figure 2), we calculate that approximately 10 beers less are sold in $l = 3$ at state 1, if we follow the same procedure described for *Surprise*. Also, the posteriors are wider (less precise), so our conclusions with respect to *Suspense* reflect greater uncertainty. Overall though, we yield several notable findings.

First, *Surprise* increases and *Suspense* decreases the number of beer sales in both states, aggregated over $l = 0$ to $l = 9$. For *Surprise* (top), $l = 2$ to $l = 5$ dominate the negative impact that appears at the beginning ($l = 0$ for both states, and $l = 1$ for state 1). This evidence indicates that both positive *Surprise* and negative *Surprise* have a positive impact in total. With regard to *Suspense* (bottom), the slight positive tendency (e.g., for $l = 4$ in both states and $l = 5$ in positive state 1) is overwhelmed by the negative effects for $l = 3$. The immediate effects for *Suspense* are negligibly small or non-existent.

Second, the positive state 1 dominates over the negative state 0 with respect to effect sizes for both cues, considering the main direction of action (i.e., positive for *Surprise* and negative for *Suspense*). In other words, "celebration beats frustration." For *Suspense* (bottom), this comparison is trivial, in that we only identify clear effects at $l = 3$. With respect to *Surprise* (top), we note that for 3 out of 4 time points, we find a positive effect ($l = 2$ to $l = 5$), with especially strong effects for the positive state 1.

Third, as a whole, the impacts degrade toward the end of the observed time window except for $l = 9$ in negative state 0 for *Surprise*. This result is also clearer for *Surprise*. In addition, *Surprise* initially decreases the number of beer sales unambiguously, in contrast with *Suspense*.

Fourth, for *Surprise*, the sign switch from negative to positive occurs one period earlier for negative state 0, such that people seem to react more quickly to negative signals than to positive signals.

Online appendix table C1 contains the posteriors of all variables used in the main specification. The most important covariates for both states at the within-level are the first half dummy and the lagged dependent variable. The first half dummy is contemporaneously negatively associated with beer sales. The coefficients for the lagged dependent variable are positive and mostly decreasing in size with higher-order lags. Furthermore, we identify some isolated non-zero posterior distributions across lags in positive state 1 like the coefficients related to the number of hot wine punch units sold (positive), the dummy for home substitutions (negative), and the number of water units sold (first positive, then negative). Alcohol consumption in negative state 0 seems rather unaffected by covariates other than the beforementioned first half dummy and the lagged dependent variable, which both control general time series pattern. Intuitively, people seem to seek out a "frustration beer" no matter what[10].

At the between-level, the dummy for a first division match (negative), some dummies for kickoff times (positive), and the number of spectators (positive) offer relatively great explanatory power with regard to the number of beer sales. In addition, the pre-match probabilities that the joint score exceeds 0.5 and 4.5 (negative and positive, respectively), the prices for beer and hot wine punch (both positive), the number of active cashpoints (positive), and the dummies for the match taking place on Saturday (positive) or Sunday (negative) exhibit non-zero but more moderate coefficients. For a visualization of between-match variation in the number of beer sales, please see online appendix figure C1[11].

B. Alternative Specifications

We assess the robustness of our findings by exploring alternative or extended specifications and considering different estimation issues. In this section, we briefly describe each specification and focus on the observable differences when describing the results.

1. Regularized Horseshoe. Prior distributions can strongly determine the empirical results in Bayesian estimation, which may be a particular concern in relation to our comparably small sample setting with a lot of weakly informative priors. Therefore, we test different distributions to determine if the results change. In particular, we replace the spike-and-slab prior of the main specification with another regularization prior, namely, the regularized horseshoe prior (Piironen and Vehtari, 2017). In turn, the definitions

[10]Contrary to our intuition about substitution effects, hot wine punch sales exhibit a positive coefficient, similar to water sales. Apparently, when people are willing to buy beer, they also turn to hot wine punch, or else hot wine punch drinkers drive excess demand. Furthermore, substitutions of players during the match do not seem to serve as opportunities to go for a drink. In contrast, the negative association of home substitutions suggests fans are interested in who is being substituted or that substitutions are systematically conducted at crucial points of the match.

[11]We explain the positive coefficient of beer price with a combination of inflation and increasing sales figures over the years. Moreover, the slight negative association for first division matches might suggest that the prestige of matches (if relevant at all) is outweighed by more positive experiences in the second division, in which the average winning probability for VfB Stuttgart is significantly higher ("celebration beats frustration").

become

$$\begin{aligned}
\theta_j \mid \lambda_j, \tau, c \sim \mathcal{N}\left(0, \tau^2 \tilde{\lambda}_j^2\right) \text{ where } \theta_j \in \{\boldsymbol{\phi_{1s}}, \boldsymbol{\beta_{1s}}, \boldsymbol{\gamma_{1s}}, \boldsymbol{\psi_{1s}}, \boldsymbol{\gamma_2}\} \ , \\
\text{with } \tilde{\lambda}_j^2 = \frac{c^2 \lambda_j^2}{c^2 + \tau^2 \lambda_j^2} \ , \\
\lambda_j \sim \mathrm{C}^+(0,1) \text{ for } j = 1, \ldots, J \ , \\
\tau \sim \mathrm{C}^+(0, \tau_0^2) \text{ using } \tau_0 = \frac{\frac{J}{2}}{J - \frac{J}{2}} \frac{\sigma}{\sqrt{n}} \ \text{, and} \\
c^2 \sim \Gamma^{-1}(3,1)
\end{aligned} \tag{8}$$

relative to equation (7). The regularized horseshoe shrinks large signals (coefficients far from zero) and therefore prevents flat posterior distributions. The largest parameters are regularized according to $\mathcal{N}(0, c^2)$. For small coefficients (in absolute value), the horseshoe estimator applies (Carvalho, Polson, and Scott, 2009), because $\tilde{\lambda}_j^2 \to \lambda_j^2$. Generally, we follow Piironen and Vehtari (2017) with respect to distributional choices and their values. We assume a share of 50% of all features to be relevant (cf. $\frac{J}{2}$ in equation (8), in which J denotes the size of the feature space). When we apply the regularized horseshoe, we find consistent support for our four main findings (online appendix figure C2).

2. Normal Prior. To investigate the effect of regularization, we also run a model with unregularized prior distributions, such that we consider

$$\phi_1, \boldsymbol{\beta_1}, \boldsymbol{\gamma_1}, \boldsymbol{\psi_{1s}}, \boldsymbol{\gamma_2} \sim \mathcal{N}\left(\mathcal{N}(0,1), \mathcal{N}^+(0,1)\right)$$

in contrast with the main specification. We again confirm our four main findings for the most part, though the third finding (degraded impacts toward the end) holds only for *Surprise* and not for *Suspense* (online appendix figure C3).

3. Seasons. Most of our data cover two additional seasons, that is, 2011/12 and 2012/13. Unfortunately, we lack bookmaker in-play odds for these two seasons (to the best of our knowledge). As a robustness check, we leverage these two seasons and predict the in-play odds for 2011/12 and 2012/13, using a feedforward neural network (online appendix table A2) in TensorFlow (Abadi et al., 2015), which entails an added set of 34 league matches. We describe the exact imputation procedure in online appendix section A.2.2. With this larger sample, we reaffirm our four main findings (online appendix figure C4). In addition, we can identify more steeply peaked distributions for *Surprise*.

C. Are Updating Beliefs Important?

Buraimo et al. (2020) propose another cue, *Shock*, which is similar to *Surprise* but applies to a different reference point. In concrete terms, the reference point in

$$Shock_t = \left(\sum_{m \in H,D,A} [p_t^m - p_0^m]^2 \right)^{0.5} \tag{9}$$

is p_0, which refers to the fixed pre-match outcome probability at the start of the match before any in-play information is revealed. Therefore, *Shock* is backward looking like *Surprise* but persistently affected by key match events. Often, *Shock* exhibits a long-term upward or downward trend, reflecting the low scores that characterize soccer. The more time that goes by, the lower the likelihood for changes, which reinforces the direction in which *Shock* already moves.

Imagine a match in which the underdog (away team) scores an opening goal just before the end of the match. In this fictional scenario, the reference point of *Surprise* (p_{t-1}) incorporates in-play information, and a draw is the most likely match outcome. In contrast, based on p_0, people expect a clear win for the favorite (home win). The indignation experienced by home fans, in view of the potentially impending defeat, might be better reflected as *Shock*. We therefore include *Shock* as regressor to identify the implications for *Surprise* and *Suspense*. Again though, we find consistent results (online appendix figure C5). That is, *Shock* does not appear relevant for explaining the number of beer sales, across all combinations of states and lags.

D. Does Involvement Matter?

Including the whole stadium (cf. away fan areas) creates a trade-off between sample size and accuracy. Most transactions considered in the main specification involve home fans, but there is a margin for diffusion, because in some stands, away fans can mingle with home fans. To gain greater accuracy with respect to the direction of the effect of emotional cues on beer, we thus focus on the Cannstatter Kurve only, which represents a smaller but more homogeneous sample of home fans. We adjust variables related to the target stand accordingly. For example, the number of cashpoints is limited to those in the Cannstatter Kurve only, rather than the whole stadium. Roughly speaking, we find a similar pattern, if slightly weaker, of effects for *Surprise* (online appendix figure C6). Moreover, the effects for *Surprise* do not vanish, and the temporal pattern across states is rather diffuse. Thus, we find further support for our first two findings but not for the latter two.

E. Is it About Alcohol Use?

1. Shandy. In the main specification, we do not combine beer and shandy, due to their distinct alcoholic content and taste. If we include shandy as dependent variable, we can test if people consciously turn to alcohol to deal with sport-related emotions during the match, such that we expect smaller effects (in absolute terms) or generally less clear signals for the cues in this analysis. With the exception of *Surprise* when $l = 4$ (positive) in negative state 0, no effects differ unambiguously different from zero (online appendix figure C7), so we do not find evidence for any of our main findings with this alternative dependent variable.

2. Soft Drinks. Analogously, we consider soft drinks as dependent variable, using aggregated sales of Coca-Cola, Coca-Cola Zero, Fanta, Mezzo Mix, Sprite, and Lift Apfelschorle (apple spritzer). Again, we seek to determine if people specifically turn to alcohol in emotional situations during the match or instead buy beverages in general when the match is not suspenseful, for example. In negative state 0, the rather positive posteriors for the *Surprise* coefficients are largely compensated for by the mainly negative posteriors of similar shape, such that we cannot deduce a net increase in sales without doubt (online appendix figure C8). Furthermore, "celebration beats frustration" does not hold for *Surprise*; no effects unambiguously differ from zero for the positive state 1. Although we find evidence for the third finding, related to diminished impacts over time, none of the other findings hold in this case.

F. Summary

These robustness checks and alternative or extended specifications allow us to complement and update our findings. First, *Surprise* increases the number of beer sales, while *Suspense* decreases them, in both states when aggregating over $l = 0$ to $l = 9$. Second, effect sizes in the positive state 1 are generally larger than those in the negative state 0. Thus, we consistently conclude that "celebration beats frustration" in our setting. Third, it is important to consider updating beliefs. Fourth, involvement seems important for the consumption decision, guided by emotional cues. Fifth, these trends indicate that the key factor is alcohol use, rather than general consumption. We cannot offer clear conclusions about temporal patterns though (when do effects decay and how are effects between the two states shifted exactly).

IV. DISCUSSION

A. Identification

At level 1, the missing control for different numbers of spectators during a match could be a source of endogeneity. If a very unbalanced outflow of either home or away team fans occurs, fan support for each team changes, relative to the other team, over the course of the match. The number of spectators at level 1 thus is an omitted variable that changes both the cues (outcome probabilities) and the number of beer sales. However, we logically anticipate that dynamic fan support is responsive to the match, not the other way around.

Toward the end of a match, a systematic, not beverage-related difference might arise, such as more purchases of bottled water instead of beer. A bottle is easier to take home than a cup. In this case, water consumption would not be an appropriate control variable for baseline consumption. However, we consider this issue largely irrelevant, because all nonalcoholic beverages are poured into cups in our sample.

In addition to fixed cashpoints, mobile cashpoints and beer runners are available, whose locations and numbers vary across matches. Beer runners (exclusively) sell beer in the stands. After the match, they clear their transactions at a single master cashpoint. Before the 2017/18 season, mobile cashpoints deposited their cumulative transactions with the master cashpoint too, but after this season, each of them was equipped with their own cash register systems. Because sales through mobile cashpoints are labeled though, we can segregate them. Our main dependent variable does not refer to any sales through mobile cashpoints or beer runners. Although we lack minute-by-minute data about beer runner sales, the club indicated that they are substantial. Because we can only control for the availability of beer runners, which reflects heterogeneity in supply, we assume that the null aggregated post-match numbers imply their absence.

Adding beer runner sales at level 1 seems unlike to systematically adjust differently to emotional cues and thus alter our main results substantially, but the estimates could change. That is, we might identify stronger immediate effects, because fans do not have to walk to the cashpoint; the opportunity costs for buying from a runner also are lower. A longer wait time also could even observed consumption back in time. Thus our findings represent lower bound estimates, because they exclude transactions by people with higher opportunity costs.

Arguably, the model also should include goal dummies, because they change the match outcome and could affect alcohol use, whether emotionally or indirectly due to the occasion, for example. But cues paint a clearer picture than goal dummies, in that they reflect the match situation (probabilities rather than each goal treated equally) and depend on a reference point. A specification with both goal dummies and cues would likely undermine the significant effects, due to multicollinearity. We believe our model captures the effects of the key match events effectively through the cues, conditional on the match situation, which implies they are more fine-tuned. For example, if we assume that the effect of a goal reflects both the occasion and an emotion, and they both lead to alcohol use, the occasion part (long versus short lines) and the level of emotion depend on the match situation, such that they still can be better captured by cues rather than a rough goal dummy, which exists irrespective of the score.

B. Fan Reaction

Some emotional threshold may need to be surpassed to spark a consumption decision. This threshold could depend on the composition of the group of consumers. We attribute the overall strongest effects in 1 to "celebration beats frustration" and assume a negligible share of alcohol addicts[12], who might have different motives to drink. The systematic difference between positive and negative emotions for consumption decisions, which "celebration beats frustration" describes, is reflected by Wood, McInnes, and Norton (2011), who not only conclude that losers drive home safer, but also emphasize the importance of psychological factors such as emotional trends.

The absence of consistent direct effects for *Shock* illustrates the importance of shifting reference points. When deciding whether to consume alcohol, people seem to update their beliefs based on what they observe on the field instead of holding on to pre-match expectations, according to the significant effects we find for *Surprise* and *Suspense*. On the one hand, fans might not buy alcohol during suspenseful phases, due to the fear of missing out. On the other hand, people might systematically turn to alcohol (social drinking) when they are bored to make the experience more entertaining (M. Patrick and Schulenberg, 2011). Both can explain the negative effects for *Suspense* and the in-play behavior before the post-match study of Wood, McInnes, and Norton (2011), who relate traffic fatalities after close matches to aggressive driving due to an increased testosterone level rather than drinking during the match.

Moreover, the weaker effects for *Surprise* in the die-hard fans specification likely reflects their greater emotional involvement. If the average die-hard fan is more involved than other fans and imposes a higher emotional threshold to be passed, because their opportunity costs of not watching (fear of missing out) are higher, a certain amount of *Surprise* would lead to fewer beer sales. Furthermore, the die-hard fans in the standing room might systematically turn to mobile beer runners, to avoid higher opportunity costs and also in response to the poorer accessibility of cashpoints. This behavioral choice decreases the observed number of beer sales. Then, the effects of the cues would be underestimated, because there are sales we do not see at level 1.

Regarding whether alcohol is important for the effects of the cues, we can only confirm the necessary condition. The sufficient condition is open for discussion, in that the zero-centered cue effects for shandy and soft drinks may be related to differences in consumers. For example, perhaps a larger share of women prefer shandy, and a higher share of children

[12]We recognize that the definition of alcohol addiction can apply to a lot of people, depending on the design of the test. Here, we refer to excessive drinkers who clearly stand out from the average of the population.

would imply more sales of soft drinks. If groups of people react systematically differently to emotional cues, external validity diminishes, and it already is limited in that we only access data pertaining to one club playing league matches. In the absence of selection effects, our results suggest the importance of alcoholic strength at least in positive state 1, in that we do not find any clear effects on shandy sales and only effects for negative state 0 if soft drinks is the dependent variable. This finding contrasts with the "celebration beats frustration" finding for soft drinks but supports it for alcohol if people in negative state 0 substitute beer with sugary drinks like cola, for example.

Theoretical underpinnings for the special position of alcohol are given by Cooper et al. (1995) and Greeley and Oei (1999). Greeley and Oei (1999) provide an overview of the tension reduction theory (TRT), according to which negative (emotional) stress/tension increases alcohol use, because individuals consume alcohol for its stress-response dampening effects. Cooper et al. (1995) stress the importance of considering different psychological motives for drinking. While TRT focuses on alcohol as a potential moderator of negative affective states, they find alcohol to be used to regulate positive emotions as well.

Considering that *Surprise* increases and *Suspense* decreases alcohol sales most of the time, fans apparently postpone consumption in suspenseful phases, then react to match key events when the suspense gets resolved. Note that we explain the wider posteriors for *Suspense* by acknowledging that *Suspense* is a hypothetical measure, with more uncertainty by construction.

Negative immediate effects can result from tumult or distraction in the stands and at the cashpoints. After a key match event, people need time to stand up, go to the cashpoint, maybe wait in the line, and finish the transaction. Accordingly, we often observe the strongest cue effects after a couple of minutes. In most specifications, the effects get weaker or switch signs toward the end of the observation period. We can explain these shifts according to a saturation effect: Once a fan has bought a beer, they are not likely to buy another one immediately.

V. CONCLUSION

We investigate the effects of emotional cues on alcohol sales during soccer matches, using real data pertaining to both emotional cues and alcohol use. We find robust evidence against the null hypothesis that *Surprise* and *Suspense* have no impact on beer sales. Instead, our effects are statistically and economically significant. Irrespective of the emotional state, *Surprise* primarily increases and *Suspense* predominately decreases beer sales. In addition, a positive emotional state dominates the negative state with respect to effects size for both cues. Thus, "celebration beats frustration."

Broadly speaking, by providing empirical evidence for the influences of emotions experienced during the decision-making process for consumption decisions, we highlight the importance of short-term emotions in determining economic behavior. More specifically, we contribute to the sparse empirical literature on emotions and alcohol use as a mass phenomenon.

While one might be inclined to view the chosen setting of this study as not providing representative evidence, it is important to note that the key issue for any such choice should be the ability to observe and isolate the effects of interest (Falk and Heckman, 2009). Furthermore, "Angrist and Pischke (2010) remind us that empirical evidence on any causal effect is always local." (Palacios-Huerta, 2023, p. 5). We thus hope to encourage economists and psychologists to model utility as a function of both preferences and emotions and to further test reference point-dependent constructs of emotions in sports settings in the future.

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Online Appendix for

Celebration Beats Frustration: Emotional Cues and Alcohol Use During Soccer Matches

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September 12, 2023

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Contents

A Additional Information on Estimation

A.1 Calculation of Emotional Cues

To calculate the emotional cues *Shock*, *Surprise*, and *Suspense*, we need match outcome probabilities, because all three emotional cues reflect in-play probabilities for the three potential outcomes H (home win), D (draw), and A (away win) in each minute of the match. Furthermore, *Shock* and *Surprise* call for pre-match outcome probabilities, again for H, D, and A, in that the reference point for *Shock* is p_0 (equation (9)) and that for *Surprise* in match minute 1 requires p_0 as reference point as well; *Suspense* also needs a starting point to simulate different potential match outcomes, as we clarify subsequently. The simulation for *Suspense* needs pre-match probabilities for the combined score to exceed a certain amount of goals.

We use betting odds to approximate these probabilities. In particular, we apply in-play odds from NowGoal (bookmaker Crown) and pre-match closing 1X2 (H, D, A) odds, as well as pre-match closing over/under odds[1] from OddsPortal (the sources are detailed in table B2). Our use of in-play odds diverges from the approach of Buraimo et al. (2020), who estimate outcome probabilities based on the time remaining, the current score, and the number of red cards. That is, they simulate different match outcomes by using historic goal distributions for the respective league and use the relative frequencies for H, D, and A from the scorelines at the end of the match as outcome probabilities. In contrast, we obtain the implied probabilities by taking the reciprocal of the odds, which usually add up to a value greater than 1, called the over-round. Then, we remove the difference between this over-round and 1 (considered the bookmaker commission or margin) that is inversely proportional to the size of the odds so that the resulting pseudo-probabilities, which we call normalized odds, sum up to 1.

For the unconditional probabilities p_{t+1}^{HG} and p_{t+1}^{AG}, as well as the conditional probabilities $p_{t+1}^{m} \mid p_{t+1}^{HG}$ and $p_{t+1}^{m} \mid p_{t+1}^{AG}$ in *Suspense* (equation (2)), instead, we follow the simulation approach proposed by Buraimo et al. (2020). Both the unconditional probabilities and the conditional probabilities specify hypothetical scenarios we cannot directly derive from bookmaker odds.

We refine their simulation approach though. Buraimo et al. (2020) estimate the scoreline of each encounter by exploiting a priori information about the teams' strengths, past performances, coaches, venue, and all other factors that have predictive power for the score. This information is embedded in pre-match odds. We use the last odds quoted before the match starts, referred to as closing odds. Closing odds most precisely reflect the market's assessment of the match outcome by accommodating more information than

[1] Over/under odds work as follows: If a bettor thinks there will be one or more goals for a given match, they will bet on over 0.5 and win the wager if at least one team scores. If they anticipate that there will be not more than two goals, they place their money on under 2.5.

any other, previously quoted odds. Then we take the average across multiple bookmaker odds, to avoid possible idiosyncrasies linked to individual bookmakers. Thus, the data contain closing odds from up to 36 bookmakers and over/under odds from up to 34 bookmakers. To increase the number of over/under odds, we also collect data about the combined score to exceed/subceed the statistics ±0.5, ±1.5, ±2.5, ±3.5, ±4.5, and ±5.5 goals.

Although Buraimo et al. (2020) proposes independent Poisson distributions to estimate the number of goals scored by each team, we use a bivariate Poisson distribution to estimate the scoreline and thereby relax the harsh independence assumption. Consequently, we assume that the number of goals scored by the home team, denoted by the random variable R_1, and the number of goals scored by the away team, denoted by the random variable R_2, are jointly Poisson distributed such that

$$P\left(R_1 = k_1, R_2 = k_2\right) = \exp\left(-\delta_1 - \delta_2 - \delta_3\right) \frac{\delta_1^{k_1}}{k_1!} \frac{\delta_2^{k_2}}{k_2!} \sum_{k=0}^{\min(k_1,k_2)} \begin{pmatrix} k_1 \\ k \end{pmatrix} \begin{pmatrix} k_2 \\ k \end{pmatrix} k! \left(\frac{\delta_3}{\delta_1 \delta_2}\right)^k$$

in which k_1 and k_2 are realizations of R_1 and R_2, respectively. Moreover, δ_1 and δ_2 refer to the scoring rates of the teams and

$$Cov(R_1, R_2) = \delta_3 \ .$$

If $\delta_3 = 0$, we end up at the independent Poisson distributions.

We use this in-play model to generate the probabilities for every scoreline of a given match. In addition, we calculate the probabilities for the match outcomes H, D, and A by summing the scoreline probabilities. Note that we restrict k_1 and k_2 to a maximum of 10, so we estimate the joint probabilities of all reasonable hypothetical scorelines for which the number of goals of each team does not exceed 10, such that $P(R_1 = 10, R_2 = 10)$ is the last probability estimated.

To estimate the scoring rates δ_1, δ_2, and δ_3, we minimize the squared difference between the transformed bookmaker odds and our estimated probabilities from the in-play model. The function we minimize is

$$F = \sum_{m \in H,D,A} \left(\boldsymbol{q}_m - \boldsymbol{p}_m\right)^2$$

where $\boldsymbol{p}_m$ is a vector of probabilities obtained from our model, and $\boldsymbol{q}_m$ denotes the vector of normalized pre-match match win and over/under bookmaker odds. The match win odds provide information about which scoring rate should be larger; the over/under odds help reveal the exact size of the scoring rates when minimizing. For a match in which VfB Stuttgart is the clear favorite, for example, their scoring rate is naturally higher. However, the information on who is expected to win does not suffice to determine the magnitude of δ_1, δ_2, and δ_3.

In a next step, we distribute the estimated scoring rates $\delta_1+\delta_3$ and $\delta_2+\delta_3$ across minutes of the match. With the assumption that goals are uniformly distributed throughout a match, we could evenly split up the scoring rates, resulting in $\delta/90$ for each minute. However, scoring rates are not constant; more goals are scored toward the end and fewer goals at the beginning. Buraimo et al. (2020) propose spreading the scoring rates in proportion to the empirical distribution of goals per minute, which they generate by gathering the timing of goals scored by many teams in the past.

Although this empirical distribution better captures the average scoring patterns, it generally fails to represent the scoring patterns of an individual team adequately, which depend on the team's individual strength, its way of playing, and its coach's philosophy. The teams at the tails of the distribution can reveal scoring behaviors far away from the average. Therefore, we propose team-specific empirical goal distributions to distribute the scoring rates across the minutes, reflecting all goals scored by a given team during all games played before the current encounter.

To guarantee a smooth distribution, we use a 10-minute moving average and linearly extrapolate missing values at the beginning of the time-series. The underlying data for the empirical goal distributions come from kicker (see table B2) and cover seasons 2013/14 to 2018/19 (inclusive). That is, the goal distribution for VfB Stuttgart consists of all league goals scored during that period (considering league affiliation due to relegations and promotions). The same is true for all opponents, such that each team takes its own weighting for the individual scoring rate. The squad and the way teams play can change significantly over the years, so it would be preferable to use goal data from the last few matches but due to the limited number of matches per season, we need to extend the observation period. Otherwise, we end up with a very sparse empirical goal distribution, with no observed goals for many match minutes.

With the per minute scoring rates, we can simulate the number of goals occurring in each minute of the match. We draw from a Bernoulli distribution with success probability equal to the per minute scoring rate in t and sum the final scoreline that thus results. To account for red cards, we rely on Vecer, Kopriva, and Ichiba (2009) who find that a red card decreases the affected team's scoring rate by $\frac{2}{3}$, while the opposite team's scoring rate increases by a factor of 1.2. For each match, we repeat this simulation 100,000 times so that there are $90 \times 100,000 = 9,000,000$ simulations per match. Then we can determine the probabilities required for the calculation of *Suspense* in t by evaluating the probabilities for the match outcome, given that the home or the away team, respectively, scores in the next minute. Without any next minute in regular match time in the 90th minute, we cannot calculate *Suspense* for it, such that we drop observations for this time point from the sample.

A.2 Imputation of In-Play Probabilities

A.2.1 Seasons 2013/14 to 2018/19. The betting market is closed when odds are updated or liquidity is low, so data on in-play odds exhibit missing values by nature, which in turn lead to missing in-play outcome probabilities. For the affected time points, we cannot transform the odds to obtain the outcome probabilities.

We handle the missing in-play outcome probabilities for seasons 2013/14 to 2018/19, as used in the main specification, by predicting their values using gated recurrent units (GRUs) and a separate training sample of approximately 4000 matches, played during the seasons 2013/14 to 2019/20 in the German first and second division. These GRUs represent an extension to recurrent neural networks (RNNs) that can account for dynamic behavior in the data by processing sequences of inputs.

As introduced by Cho et al. (2014), a GRU consists of two gates, an update gate and a reset gate. The update gate determines which new information is added and which is discarded, similar to the forget and input gate of a long-short-term-memory (LSTM); the reset gate determines how much past information to forget. Because the GRU lacks the LSTM's output gate, there are fewer parameters to train, which promises less computational effort with similar or better performance than LSTMs. Our GRU networks consist of an input layer, 3 hidden GRU layers, a hidden dense layer, and an output layer. Moreover, we make use of bias nodes and alternate activation functions in the hidden layers between rectified linear unit (ReLU) and hyperbolic tangent (tanh). Table A1 displays the model configuration.

TABLE A1. GATED RECURRENT UNIT NETWORK MODEL CONFIGURATION

Layer	Input	Units	Bias	Kernel Init.	Bias Init.	Activation	L2 Kernel
gru_1_input	(None, 10, 7)	NaN	NaN	NaN	NaN	NaN	NaN
gru_1	(None, 10, 7)	128	True	GlorotUniform	Zeros	relu	NaN
gru_2	NaN	96	True	GlorotUniform	Zeros	tanh	NaN
gru_3	NaN	64	True	HeUniform	Zeros	relu	NaN
gru_4	NaN	32	True	GlorotUniform	Zeros	tanh	NaN
dense	NaN	32	True	HeUniform	Zeros	relu	NaN
output	NaN	3	True	GlorotUniform	Zeros	softmax	0.0010

This table presents the configuration for the GRU network used to impute missing in-play outcome probabilities for seasons 2013/14 to 2018/19. The separate training sample consists of approximately 4000 matches from seasons 2013/14 to 2019/20 in the German first and second division. For each minute we, train 1 GRU network. The GRU networks include an input layer, 3 hidden GRU layers, a hidden dense layer, and an output layer. "Init." in columns 5 and 6 is short for "Initialization", and NaN ("Not a Number") labels unspecified parameters. As the first entry in the second column "(None, 10, 7)" shows, we use a full batch approach with a time series length of 10 and 7 features, namely, number of goals scored and red cards received by each team in t, as well as transformed in-play odds for the match outcome. Furthermore, the activation functions for the hidden layers are ReLU and tanh, alternating (column 7). The output layer squeezes the data between 0 and 1, according to the softmax function and is regularized by an L2 penalty term (last column).

For each minute, we train one GRU network, separately. The features (see "7" in "(None, 10, 7)" - second column of table A1) include the number of goals scored and red cards received by each team in t, as well as transformed in-play odds for the match outcome prior to t (for $t = 1$, transformed pre-match odds are used). The input sequences comprise this information in the last 10 minutes (see “10” in “(None, 10, 7)” - second column of table A1). Consequently, we use the information in $t - 10$ to t to predict the probabilities in t. For the periods prior to the 10th minute, this sequence reduces to t_0 to t. Note that there are no betting odds for stoppage time, and NaN (“Not a Number”) denotes parameters that are not specified.

In-play odds are available to us on a minute-by-minute basis. However, these odds are obviously not synchronized with the match minutes. If multiple odds updates occur per match minute, we use the most recent update. Should there be a goal or a red card in a certain minute but the odds remain unchanged, because they were placed before the match event, we replace the odds by NaN and predict it using a GRU network. The underlying assumption is that goals or red cards must change outcome probabilities and odds. For the whole match, the last updated odds are also the last usable odds. We replace all odds after them by NaN, because we do not know whether the odds do not change due to the course of the match or because the markets are closed because the match is almost decided, for example.

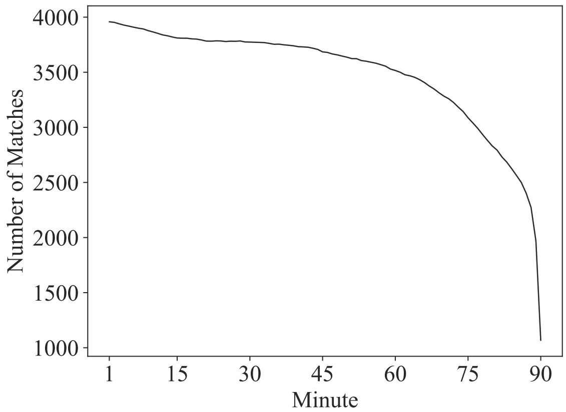
We standardize all features so that they are on the same scale, such that each feature has zero mean and unit variance. Specifically, we standardize the data by fitting parameters on the training set, then reuse them to transform the test data. In this way, we ensure there is no test set information in the training process, and, assuming training and test data come from the same distribution, we obtain more precise estimates for the mean and variance in the test set, because of the larger sample size of the training set. We carry out this transformation for each minute, separately. The targets are a vector of normalized odds, such that they give rise to a regression problem. Therefore, and because we want to penalize large deviations more strongly, we choose the mean squared error (MSE) as the objective loss function that needs to be minimized during the training process.

For the optimization, we use the AMSGrad variant (Reddi, Kale, and Kumar, 2019) of Adam (Adaptive Moment) Estimation (Kingma and Ba, 2014), which features stochastic gradient descent, based on the adaptive estimation of first-order and second-order moments. It thus is appropriate for settings with a relatively large number of parameters.

The number of epochs depends on the current match minute and is evenly spaced over the interval $[250, 500]$, rounded to the nearest integer, so that the network for minute 1 uses 250 epochs, and the network for minute 90 uses 500 epochs, because the higher the match minute, the more missing values there are, creating inaccuracies in prediction that stack over time. The batch size is equal to the size of the training data, such that the full data set is processed as one chunk (see “None” in “(None, 10, 7)” - second column of table A1). To prevent overfitting, we impose an L2 penalty of size 0.001 on the weights of the output layer.

Figure A1 displays the number of matches available to train the GRU networks for each minute.

Figure A1. Gated Recurrent Unit Network Available Observations

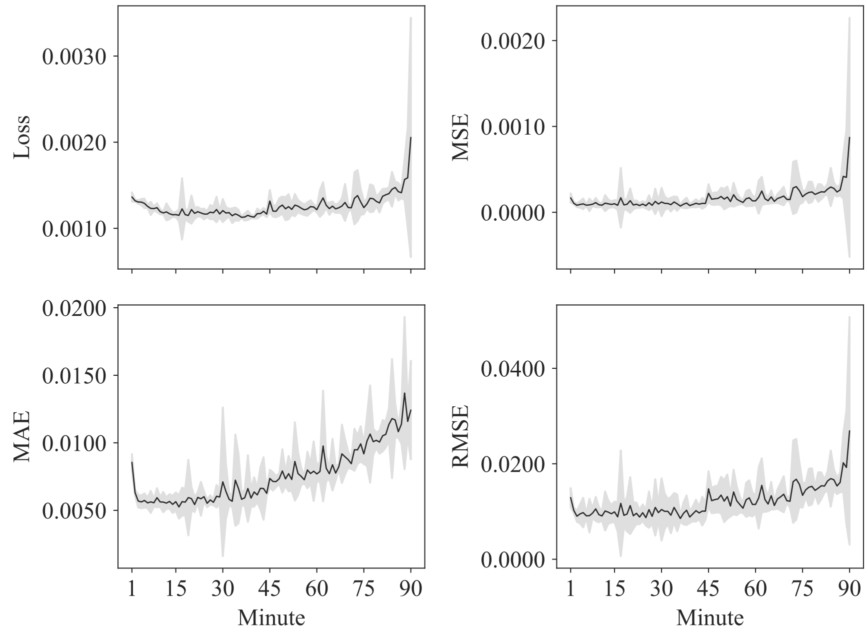


This figure shows the available number of observations (matches) in the training sample for the GRU network. We clearly observe a decrease in the number of matches the higher the match minute.

The number of matches available decreases over time, because the betting market is often closed toward the end of a match, especially if the winner is clear before the very end but not if scorelines are close. As matches with close scorelines at the end tend to result in a draw, we confront a self-selection problem regarding missing in-play odds. Therefore, we randomly over-sample underrepresented scorelines (e.g., 4-0, 4-1, 0-4, or 1-4) by drawing samples with replacement from these minority classes until their relative frequencies are equal to the relative frequencies of the occurrence of the cases in the training sample in each minute. Analogously, we randomly over-sample the underrepresented red cards, to ensure the algorithm does not ignore red cards as feature.

To evaluate the accuracy of the predictions, we randomly split the data set into 5 folds and apply cross-validation. Figure A2 displays various performance metrics, along with their 95% confidence intervals.

Figure A2. Gated Recurrent Unit Network Performance Metrics



This figure shows GRU network performance metrics loss (top left), mean squared error (top right), mean absolute error (bottom left), and root mean squared error (bottom right) with their associated 95% confidence intervals (CI), based on 5-fold cross validation with the training set.

The blue line depicts the metric, averaged across the five folds; the blue-shaded area illustrates the associated confidence bounds. The upper left and right panel belong to loss and MSE, respectively. The lower left panel depicts the mean absolute error (MAE), and the lower right panel indicates the root mean squared error (RMSE). All metrics exhibit a general increasing trend over time. We offer three reasons for this pattern. First, the number of matches in the training set decreases over time. Second, prediction errors increase over time, because closing odds offer lower predictive power the more time goes by. Third, the number of key events (goals and red cards) increases toward the end of the match, which extends the directions a match can develop. All three aspects make the prediction more difficult.

Because the targets are probabilities, we can focus on the MAE. However, similar deduction applies to the other performance metrics. The MAE can be interpreted as the mean absolute deviation between actual and predicted targets in percentage points. Consequently, predicted probabilities differ between 0.53 (minute 16) and 1.37 (minute 88) percentage points from the actual probabilities, with standard deviations of 0.04 (in minute 16) and 0.29 (in minute 88) percentage points. The MAE averaged across all minutes is 0.0076 (0.76 percentage points deviant from actual probabilities) with an average standard deviation of 0.0006 (0.06 percentage points).

A.2.2 Seasons 2011/12 and 2012/13. We find no in-play bookmaker odds available for seasons 2011/12 and 2012/13, from which probabilities could be derived. Therefore, we train a feedforward neural network (FFNN) for each minute to impute the missing probabilities. The training data are the same as for the GRU networks (section A.2.1). Our predictors are normalized pre-match closing odds on the result (see section A.1 on normalization) and in-play key events goals and red cards.

The FFNNs consist of an input layer, 3 hidden layers, and an output layer. The number of units in each layer declines from 128 to 32. The output layer contains 3 units, reflecting the number of desired outcomes. We use a bias vector in each layer. The activations are alternately ReLU and tanh, as well as a softmax in the output layer to get results between 0 and 1, which then sum to 1. Generally, we initialize the weights using a Xavier uniform initialization (Glorot and Bengio, 2010). For the hidden ReLU layers, however, we use He uniform to initialize, as proposed by He et al. (2015). To prevent overfitting, we impose an L2 penalty of size 0.001 on the weights of the output layer. As for the GRU networks, the number of epochs depends on the current match minute; the value is evenly spaced over the interval $[250, 500]$, rounded to the nearest integer, so that the network for minute 1 uses 250 epochs, and the network for minute 90 uses 500 epochs. Furthermore, we use full batch learning here.

We standardize the features to have zero mean and unit variance, analogous to section A.2.1. Again, we apply this transformation for each minute, separately. The targets are a vector of normalized in-play probabilities for the potential outcomes H, D, and A, such that we face a regression problem. To minimize the MSE, we again use the AMSGrad variant of Adam Estimation. Moreover, we oversample underrepresented scores and red cards, as described for the GRU networks in section A.2.1.

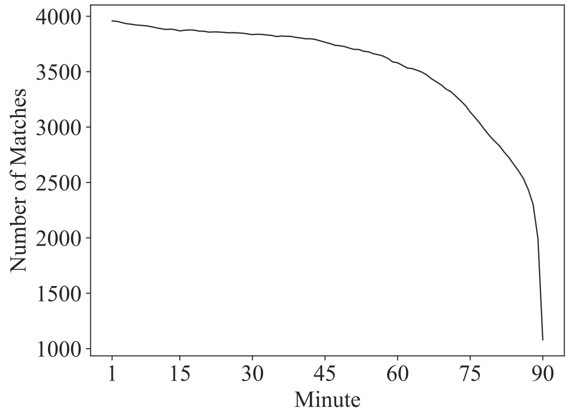
Table A2 displays the complete architecture. Figure A3 reveals the number of matches available to train the FFNN for each minute. Figure A4 depicts several performance metrics and their associated 95% confidence intervals, which we obtain from 5-fold cross-validation.

Table A2. Feedforward Neural Network Model Configuration

Layer	Input	Units	Bias	Kernel Init.	Bias Init.	Activation	L2 Kernel
dense_1_input	(None, 7)	NaN	NaN	NaN	NaN	NaN	NaN
dense_1	(None, 7)	128	True	GlorotUniform	Zeros	relu	NaN
dense_2	NaN	64	True	GlorotUniform	Zeros	tanh	NaN
dense_3	NaN	32	True	HeUniform	Zeros	relu	NaN
dense_4	NaN	16	True	GlorotUniform	Zeros	tanh	NaN
output	NaN	3	True	GlorotUniform	Zeros	softmax	0.0010

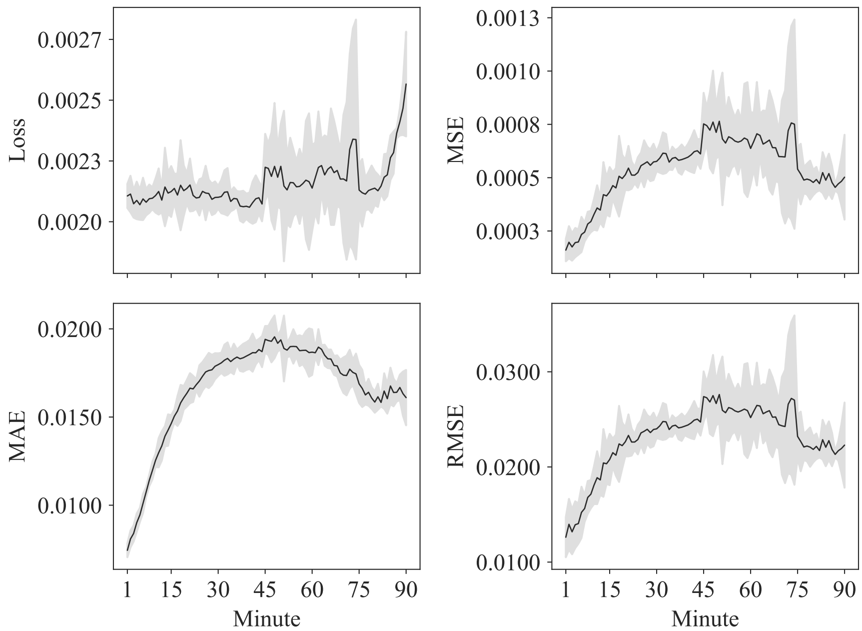
(Equivalent description as for table A1, but using a feedforward neural network and transformed pre-match odds instead of in-play odds as features to predict transformed in-play odds for seasons 2011/12 and 2012/13).

Figure A3. Feedforward Neural Network Available Observations



(Equivalent description as for figure A3, but using a feedforward neural network).

Figure A4. Feedforward Neural Network Performance Metrics



(Equivalent description as for figure A2, but using a feedforward neural network).

According to the MAE, the predicted probabilities on average differ between 0.74 (minute 1) and 1.95 (minute 48) percentage points from the actual probabilities, with standard deviations of 0.02 (minute 1) and 0.06 (minute 48) percentage points. The MAE averaged across all minutes is 1.66 percentage points deviance from actual probabilities, with an average standard deviation of 0.04 percentage points.

A.3 Covariates

In addition to the cues, we add variables for air pressure, precipitation (dummy), relative humidity, temperature, and wind speed at level 1. These covariates aim to capture weather conditions around the stadium, which we consider relevant for drinking behavior and match outcome. For example, Ventura-Cots et al. (2019) find a positive association between alcohol consumption and colder weather, as well as fewer sunlight hours. Lakshmana Rao and Mohan (2021) provide evidence that injuries occur mostly when the weather conditions are hot and humid, cold, and/or wet and rainy. Adverse weather conditions also create opportunities to consume, because people tend to retreat further into the catacombs, where the cashpoints are.

Weather data are measured in 10 minute steps, instead of a minute-by-minute basis. Therefore, we linearly interpolate air pressure, temperature, relative humidity, and wind speed. The precipitation dummy uses information on precipitation duration. Whenever the 10-minute precipitation duration is 0 or 10, the precipitation dummy is 0 or 1, respectively. If precipitation duration lies between 0 and 10 minutes (e.g., 8 minutes), we split the dummy into two blocks, comprised of one block with zero values and another block with ones, such that the order of the blocks is assigned at random. For example, for 8 minutes of rain, for the first minutes of a 10-minute interval, the precipitation dummy equals 1, and then for the last 2 minutes the dummy takes a value of 0.

In winter months, spectators can buy hot wine punch in addition to the other drinks, so we include hot wine punch sales to control for substitution effects.

Furthermore, a dummy variable separating the first and second half of each match is necessary, because the two halves are structurally different, as figure 1 depicts.[2]

In addition to the substitutions discussed in section II.B.1, water sales at level 1 control for baseline consumption, such that any effect on beer sales is more clearly attributable to the conscious decision to buy alcohol. That is, the effects on alcohol sales become cleaner when we also measure the sales of fans who are "just thirsty". Model precision increases too, such that baseline consumption reflects any global trend of variation on beverage sales.

At level 2, we include several probability estimates based on average closing over/under odds (normalized over/under odds). By adding the variables adapted from over/under odds, we seek to cover different spectator sentiments across matches. Pre-match sales and sales at the beginning of the match (due to delay effects) likely exhibit heterogeneity, reflecting the different levels of excitement in expectation of high versus low scoring matches.

We calculate pre-match outcome probability estimates using average closing odds for away team wins and draws (we drop home team wins due to multicollinearity). A match with a clear favorite is fundamentally different than a match with an uncertain outcome. These variables aim to account for the fan's basic state of mind. For example, fans who

[2]Analyzing both halves completely separate from each other would be interesting. Due to the restricted length of the time series though, this approach is not feasible.

usually buy one beer might skip it when they anticipate a very close match, if their fear of missing out exceeds the loss of a beer not consumed, which results in a systematic difference in mean sales between matches.

Beer prices also could be an important driver for demand and are therefore included at match level, to refine the (sports) seasonal dummies. Beer prices are stable within each season, but there is some variation between seasons over time.

The geodesic distance, defined as the shortest path between two points on a surface (the earth), between the away team's stadium and the home stadium of VfB Stuttgart (latitude-longitude data) can affect match relevance, due to its strong correlation with local rivalries (derbies). Barry et al. (2014) and Neal and Fromme (2007) find that the importance of a match (e.g., due to a rivalry) increases alcohol consumption by college football fans. We control for seasonal patterns beyond weather by using monthly dummies. For example, match relevance likely varies between the start of the season in autumn and its end in spring, which is not perfectly reflected by weather (e.g., snow in April). Pre-match team rankings and the round further contribute to match relevance. In general, matches between similarly ranked teams toward the end of the season are more important, because they can be decisive for how the teams will be ranked.

A dummy indicates whether the match is a first or second division match. During the observation period, VfB Stuttgart played in both divisions. The second division holds less prestigious matches, which might lead to systematic heterogeneity. For example, important first division matches might prompt additional consumption, due to perceptions that the event is special.

Two further dummies indicate whether the day after the match is a public holiday and if the match takes place during school holidays. Public holidays likely lead to disparities in drinking behavior. People might alter their drinking habits when the following day is a public holiday, during which excursions and festivities are popular pastimes. Zonda et al. (2009) identify a significant increase in alcohol consumption during holidays. Furthermore, people do not have to work on holidays, or on Sundays, so the public holiday dummy only refers to weekdays in this regard. School holidays likely change the composition of spectators, because family vacations typically take place during school holidays, which might alter per capita alcohol use.

Another potential factor influencing in-play consumption is the pre-match alcohol level, so we add a dummy denoting when the Cannstatter Volksfest and the Stuttgart Spring Festival take place. These festivals, hosted by the Cannstatter Wasen, a 35 hectare area near the stadium, are of great regional importance. With more than four million visitors (pre COVID-19), the Cannstatter Volksfest is considered the second largest beer festival in the world (after the Oktoberfest in Munich). We also control for systematic substitution effects when people forgo their beer in the stadium to drink later at the festival.

Drinking behavior also depends on the time of day (Room et al., 2013), such that across cultures, it is more common after 5:00 p.m. Therefore, we include the kickoff time. Another potential source of significant differences might be the interval between meals.

With the recognition that supply potentially drives demand, we control for the number of cashpoints where people can buy drinks and food. Wait times likely are longer if fewer cashpoints are open, ceteris paribus, which might decrease transactions due to higher opportunity costs. Variance in the number of cashpoints mainly occurs when single cashpoints open or close only for certain matches, rather than due to newly constructed cashpoints, for which the seasonal dummies would be sufficient, assuming the construction occurs between seasons.

In any case, the number of spectators relates to alcohol sales (assuming enough variation). We add the information at level 2, because VfB Stuttgart does not collect this data at level 1.

Next, we add (sports) seasonal dummies to deal with several sources of heterogeneity over years. Rule changes across seasons, such as shifting definitions of accidental handballs, can lead to more or less controversial referee decisions. According to Meij et al. (2015), fans exhibit more aggressive behavior when they perceive the match as unfair. Another source of heterogeneity over seasons involves payment options, such that during the 2011/12 season, fans could only pay with a so-called fan card. In 2012/13, cash was added as an option. From 2013/14 onward, people could pay cash or with a credit card.

We use weekday dummies to account for the structural difference between a match on Saturday versus Friday, for example. Playing simultaneously with a lot of other teams on Saturday probably evokes a different excitement level, because the consequences (e.g., rankings) of simultaneous scores can be incorporated immediately into consumption decisions. Moreover, people tend to drink more on weekends (Room et al., 2013).

Tables B1 and B2 present the entire feature space of the main specification (including further variables) with descriptions, sources, and additional remarks.

B Data Overview

Table B1. Variable Summary

Name	Description	Comment	Source
Shock	Shock	Generated from in-play odds and closing odds	7
Surprise	Surprise	Generated from in-play odds and closing odds	7
Suspense	Suspense	Generated from in-play odds, closing odds, historical scoring rates, timing of goals, and red cards	5, 6, 7, and 8
BeerSls	Number of beverage units sold	Dependent variable; considered are the sales of a certain drink (beer, shandy or soft drinks depending on the specification) within the target stand(s) (e.g., whole stadium except for the away fan area)	11
AirPress	Air pressure (in hPa)	Linearly interpolated, because the measuring station (5km away from the stadium) records in 10-minute steps	2
HotWineSls	Number of hot wine punch units sold	Considered are only the sales within the target stand	11
Is1stHalf	Dummy for first half	Generated from match data	6
IsPrecip	Dummy for precipitation	Derived from precipitation duration on a 10-minute basis with the measuring station (5km away from the stadium) recording in 10 minute steps	2
IsSubAway	Dummy for an away substitution		8
IsSubHome	Dummy for a home substitution		8
RelHumid	Relative humidity (in %)	Linearly interpolated, because the measuring station (5km away from the stadium) records in 10-minute steps	2

Temp	Temperature (in Celsius)	Linearly interpolated, because the measuring station (5km away from the stadium) records in 10-minute steps	2
WaterSls	Number of water units sold		11
Wind	Wind speed (in m/s)	Linearly interpolated, because the measuring station (5km away from the stadium) records in 10-minute steps	2
AvgClsOver05Prob	Pre-match probability that joint score exceeds 0.5	Uses average closing odds (multiple bookmakers)	7
AvgClsOver15Prob	Pre-match probability that joint score exceeds 1.5	Uses average closing odds (multiple bookmakers)	7
AvgClsOver25Prob	Pre-match probability that joint score exceeds 2.5	Uses average closing odds (multiple bookmakers)	7
AvgClsOver35Prob	Pre-match probability that joint score exceeds 3.5	Uses average closing odds (multiple bookmakers)	7
AvgClsOver45Prob	Pre-match probability that joint score exceeds 4.5	Uses average closing odds (multiple bookmakers)	7
AvgClsOver55Prob	Pre-match probability that joint score exceeds 5.5	Uses average closing odds (multiple bookmakers)	7
AvgClsProbAway	Pre-match probability that away team wins	Uses average closing odds (multiple bookmakers)	7
AvgClsProbHome	Pre-match probability that home team wins	Uses average closing odds (multiple bookmakers)	7
BeerPrice	Price of beverage (in Euro)	The corresponding beverage is beer, shandy or soft drink depending on which one is set as dependent variable in the underlying specification	11
GeoDist	Geodesic distance between home and away team's stadium (in km)	Generated using latitude and longitude of each team's stadium	3
HotWinePrice	Price of hot wine punch (in Euro)		11
Is1stDiv	Dummy for a first division match		6
IsMobCpoint	Dummy for the availability of mobile cashpoints	Generated from the number of units sold by mobile cashpoints; considered are the mobile cashpoints within the target stand(s) (e.g., whole stadium except for the away fan area) using the assumption that no sales imply no availability	11
IsPromoAway	Dummy for the away team promoted last season		10
IsPromoHome	Dummy for the home team promoted last season		10

IsPubHoliday	Dummy for a legal or church holiday at the day after the match		4
IsRelegAway	Dummy for the away team relegated last season		10
IsRelegHome	Dummy for the home team relegated last season		10
IsRunner	Dummy for the availability of mobile salesmen	Generated from the number of units sold by mobile salesmen (beer runners) who sell beer and soft-drinks only (no shandy, for example); considered are the sales in the whole stadium (due to the data at hand) using the assumptions that no sales imply no availability and non-zero sales indicate availability in every stand	11
IsSchlHoliday	Dummy for school holidays at the match day		9
IsSoldOut	Dummy for a sold-out match		5
IsVar	Dummy for the presence of a video assistant referee		6
IsWasen	Dummy for Wasen - a local festival		1
Kickoff15:30	Dummy for kickoff time 15:30		6
Kickoff15:45	Dummy for kickoff time 15:45		6
Kickoff17:30	Dummy for kickoff time 17:30		6
Kickoff18:00	Dummy for kickoff time 18:00		6
Kickoff18:30	Dummy for kickoff time 18:30		6
Kickoff20:00	Dummy for kickoff time 20:00		6
Kickoff20:15	Dummy for kickoff time 20:15		6
Kickoff20:30	Dummy for kickoff time 20:30		6
MonthAug	Dummy for the match taking place in August		6
MonthDec	Dummy for the match taking place in December		6
MonthFeb	Dummy for the match taking place in February		6
MonthJan	Dummy for the match taking place in January		6
MonthMar	Dummy for the match taking place in March		6
MonthMay	Dummy for the match taking place in May		6
MonthNov	Dummy for the match taking place in November		6

MonthOct	Dummy for the match taking place in October		6
MonthSep	Dummy for the match taking place in September		6
NumCpoints	Number of active cashpoints	Considered are the cashpoints within the target stand(s) (e.g., whole stadium except for the away fan area)	11
NumSpects	Number of spectators	Refers always to all spectators in the whole stadium	5
RankAwayLast	Final rank of the away team last season		10
RankAwayPre	Rank of the away team before the match		5
RankHomeLast	Final rank of the home team last season		5
RankHomePre	Rank of the home team before the match		5
Round	Round of the season		5
Season2014/15	Dummy for season 2014/2015		6
Season2015/16	Dummy for season 2015/2016		6
Season2016/17	Dummy for season 2016/2017		6
Season2017/18	Dummy for season 2017/2018		6
Season2018/19	Dummy for season 2018/2019		6
WkdayMo	Dummy for the match taking place on a Monday		8
WkdaySa	Dummy for the match taking place on a Saturday		8
WkdaySu	Dummy for the match taking place on a Sunday		8
WkdayTu	Dummy for the match taking place on a Tuesday		8
WkdayWe	Dummy for the match taking place on a Wednesday		8

This table presents details on dependent and independent variables, used in the main specification, excluding the match minute dummies. Note that, depending on the specification, isolated variables may be discarded due to multicollinearity. Also, the set of variables might differ slightly in specifications where the sample changes, such as in the Seasons specification (e.g., additional kickoff time or season dummies). We code all binary indicators 0: false and 1: true. The reference groups for kickoff time, month, season, and weekday are 13:30, Apr, 2013/14, and Fr, respectively. Table B2 particularizes the numbered data sources in the last column.

Table B2. Data Sources

Source	Name	URL	Retrieved On
1	cannstatter-volksfest.de	https://www.cannstatter-volksfest.de/de/landing-page/	October 02, 2019
2	Deutscher Wetterdienst	https://www.dwd.de/	November 9, 2021 at 11:50:34 AM
3	Google Maps	https://www.google.de/maps/	September 26, 2019
4	kalender-online.com	https://kalender-online.com/	November 12, 2021 at 8:43:36 PM
5	kicker	https://www.kicker.de/	October 21, 2020 at 8:08:46 PM
6	NowGoal	https://www.nowgoal.com/	September 8, 2020 at 10:55:08 to October 21, 2020 12:03:04 PM
7	OddsPortal	https://www.oddsportal.com/	October 22, 2020 4:34:22 PM
8	OptaSports		August 16, 2021 12:45:28 PM
9	schulferien.org	https://www.schulferien.org/	November 13, 2021 5:14:34 PM
10	transfermarkt.de	https://www.transfermarkt.de/	September 26, 2019
11	VfB Stuttgart		November 7, 2018 and July 12, 2019

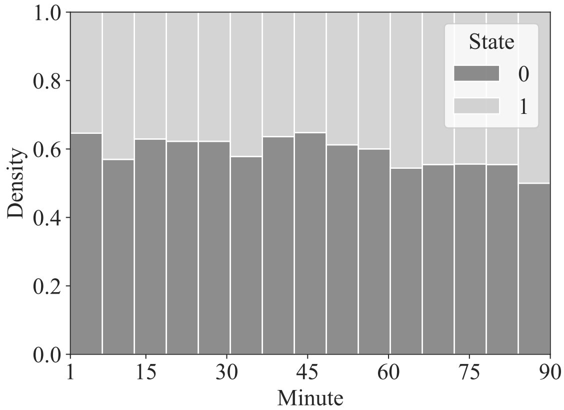
This table presents information on the data sources specified in table B1.

Table B3. Descriptive Statistics: States

	count	sum	mean	std	min	25%	50%	75%	max
State 0	98	5,218	53.2	18.5	18	38.2	55.5	69.5	89
State 1	98	3,602	36.8	18.5	1	20.5	34.5	51.8	72

This table presents basic summary statistics for the negative and the positive state 0 and 1, respectively. Overall, we observe the positive state 1 3,602 times (sum) in 98 matches (count). There is at least 1 match in which we record the negative state 0 only 18 times; 25%, 50%, and 75% denote the respective quantiles.

Figure B1. In-Play Distribution of States



This figure shows kernel density estimates of both negative state 0 and positive state 1 during matches. Overall, we observe the negative state 0 more often. Positive state 1 exhibits a slight positive trend, whereas the occurences of the negative state 0 slightly decrease.

Table B4. Descriptive Statistics: Explanatory Variables Per Minute in State 0

		count	mean	std	min	25%	50%	75%	max
Shock	$X_{1,0}$	5,218	0.2874	0.2287	0.0011	0.0717	0.2604	0.4435	0.9617
Surprise	$X_{1,1}$	5,218	0.0148	0.0599	0	0	0.0040	0.0115	0.9684
Suspense	$X_{1,2}$	5,166	0.0731	0.0417	0.0100	0.0513	0.0622	0.0861	0.2495
AirPress	$Z_{1,0}$	5,218	980	9.31	948	976	981	986	998
HotWineSls	$Z_{1,1}$	5,218	2.45	6.80	0	0	0	1	69
Is1stHalf	$Z_{1,2}$	5,218	0.5228	0.4995	0	0	1	1	1
IsPrecip	$Z_{1,3}$	5,218	0.1083	0.3108	0	0	0	0	1
IsSubAway	$Z_{1,4}$	5,218	0.0255	0.1671	0	0	0	0	2
IsSubHome	$Z_{1,5}$	5,218	0.0305	0.1795	0	0	0	0	2
RelHumid	$Z_{1,6}$	5,218	68	17.4	24.7	57.2	66.8	82.6	99.2
Temp	$Z_{1,7}$	5,218	10.8	7.18	-3.16	5.06	10.4	15.3	31
WaterSls	$Z_{1,8}$	5,218	2.86	4.97	0	0	1	3	61
Wind	$Z_{1,9}$	5,218	3.16	1.46	0.2000	2.17	2.96	4	8.44
AvgClsOver05Prob	$Z_{2,0}$	5,218	0.9182	0.0148	0.8787	0.9084	0.9193	0.9286	0.9513
AvgClsOver15Prob	$Z_{2,1}$	5,218	0.7693	0.0371	0.6706	0.7465	0.7730	0.7958	0.8450
AvgClsOver25Prob	$Z_{2,2}$	5,218	0.5486	0.0540	0.4165	0.5144	0.5474	0.5835	0.6682
AvgClsOver35Prob	$Z_{2,3}$	5,218	0.3407	0.0520	0.2285	0.3068	0.3413	0.3706	0.4672
AvgClsOver45Prob	$Z_{2,4}$	5,218	0.1884	0.0378	0.1145	0.1605	0.1888	0.2099	0.2851
AvgClsOver55Prob	$Z_{2,5}$	5,218	0.0995	0.0233	0.0541	0.0843	0.0983	0.1112	0.1605
AvgClsProbAway	$Z_{2,6}$	5,218	0.3208	0.1395	0.1376	0.2259	0.2778	0.3763	0.7721

AvgClsProbHome	$Z_{2,7}$	5,218	0.4203	0.1310	0.0772	0.3372	0.4495	0.5141	0.6481
BeerPrice	$Z_{2,8}$	5,218	4.18	0.0919	4	4.20	4.20	4.20	4.30
GeoDist	$Z_{2,9}$	5,218	294	141	55.6	152	326	398	536
HotWinePrice	$Z_{2,10}$	5,218	3.93	0.2862	3.50	3.50	4	4.20	4.30
Is1stDiv	$Z_{2,11}$	5,218	0.8678	0.3388	0	1	1	1	1
IsMobCpoint	$Z_{2,12}$	5,218	0.4293	0.4950	0	0	0	1	1
IsPubHoliday	$Z_{2,13}$	5,218	0.0163	0.1266	0	0	0	0	1
IsRelegAway	$Z_{2,14}$	5,218	0.0136	0.1159	0	0	0	0	1
IsRunner	$Z_{2,15}$	5,218	0.6225	0.4848	0	0	1	1	1
IsSchlHoliday	$Z_{2,16}$	5,218	0.1428	0.3499	0	0	0	0	1
IsSoldOut	$Z_{2,17}$	5,218	0.2192	0.4138	0	0	0	0	1
IsWasen	$Z_{2,18}$	5,218	0.1541	0.3611	0	0	0	0	1
Kickoff15:30	$Z_{2,19}$	5,218	0.6374	0.4808	0	0	1	1	1
Kickoff15:45	$Z_{2,20}$	5,218	0.0121	0.1092	0	0	0	0	1
Kickoff17:30	$Z_{2,21}$	5,218	0.0661	0.2485	0	0	0	0	1
Kickoff18:00	$Z_{2,22}$	5,218	0.0228	0.1493	0	0	0	0	1
Kickoff18:30	$Z_{2,23}$	5,218	0.0776	0.2676	0	0	0	0	1
Kickoff20:30	$Z_{2,24}$	5,218	0.0954	0.2938	0	0	0	0	1
MonthAug	$Z_{2,25}$	5,218	0.0715	0.2577	0	0	0	0	1
MonthDec	$Z_{2,26}$	5,218	0.1135	0.3172	0	0	0	0	1
MonthFeb	$Z_{2,27}$	5,218	0.1261	0.3320	0	0	0	0	1
MonthJan	$Z_{2,28}$	5,218	0.0816	0.2738	0	0	0	0	1
MonthMar	$Z_{2,29}$	5,218	0.1207	0.3259	0	0	0	0	1
MonthMay	$Z_{2,30}$	5,218	0.0707	0.2564	0	0	0	0	1
MonthNov	$Z_{2,31}$	5,218	0.0757	0.2645	0	0	0	0	1
MonthOct	$Z_{2,32}$	5,218	0.0849	0.2788	0	0	0	0	1
MonthSep	$Z_{2,33}$	5,218	0.1518	0.3588	0	0	0	0	1
NumCpoints	$Z_{2,34}$	5,218	157	20.5	113	135	157	178	188
NumSpects	$Z_{2,35}$	5,218	52,218	6,117	36,800	47,125	54,022	58,000	60,000
RankAwayLast	$Z_{2,36}$	5,218	7.56	4.87	1	3	7	12	18
RankAwayPre	$Z_{2,37}$	5,218	9.39	5.00	1	5	9	14	18
RankHomePre	$Z_{2,38}$	5,218	13.1	4.83	1	12	15	16	18
Round	$Z_{2,39}$	5,218	17	9.67	1	8	17	25	34
Season2014/15	$Z_{2,40}$	5,218	0.1801	0.3843	0	0	0	0	1
Season2015/16	$Z_{2,41}$	5,218	0.1844	0.3878	0	0	0	0	1
Season2017/18	$Z_{2,42}$	5,218	0.1573	0.3642	0	0	0	0	1
Season2018/19	$Z_{2,43}$	5,218	0.1729	0.3782	0	0	0	0	1
WkdayMo	$Z_{2,44}$	5,218	0.0481	0.2140	0	0	0	0	1
WkdaySa	$Z_{2,45}$	5,218	0.5958	0.4908	0	0	1	1	1
WkdaySu	$Z_{2,46}$	5,218	0.2125	0.4091	0	0	0	0	1
WkdayTu	$Z_{2,47}$	5,218	0.0061	0.0781	0	0	0	0	1
WkdayWe	$Z_{2,48}$	5,218	0.0065	0.0805	0	0	0	0	1

This table presents basic summary statistics of explanatory variables (table B1), excluding the lagged dependent variable and match minute dummies, on a per minute basis in negative state 0. For example, the minimum value of *Surprise* ($X_{1,1}$) per minute in state 0 is 0. Note that 25%, 50%, and 75% denote the respective quantiles.

Table B5. Descriptive Statistics: Explanatory Variables Per Minute in State 1

		count	mean	std	min	25%	50%	75%	max
Shock	$X_{1,0}$	3,602	0.3259	0.2054	0.0021	0.1829	0.3319	0.4512	0.8543
Surprise	$X_{1,1}$	3,602	0.0169	0.0718	0	0	0.0019	0.0097	1.06
Suspense	$X_{1,2}$	3,556	0.0621	0.0348	0.0083	0.0408	0.0570	0.0763	0.2242
AirPress	$Z_{1,0}$	3,602	980	9.05	948	975	981	986	998
HotWineSls	$Z_{1,1}$	3,602	1.80	5.42	0	0	0	1	60
Is1stHalf	$Z_{1,2}$	3,602	0.4670	0.4990	0	0	0	1	1
IsPrecip	$Z_{1,3}$	3,602	0.1177	0.3223	0	0	0	0	1
IsSubAway	$Z_{1,4}$	3,602	0.0389	0.2098	0	0	0	0	2
IsSubHome	$Z_{1,5}$	3,602	0.0297	0.1762	0	0	0	0	2
RelHumid	$Z_{1,6}$	3,602	68.4	19.3	24.9	54	71.7	85.4	100
Temp	$Z_{1,7}$	3,602	10.5	7.15	-3.14	4.66	10.1	15.2	30.8
WaterSls	$Z_{1,8}$	3,602	2.94	5.61	0	0	1	3	68
Wind	$Z_{1,9}$	3,602	3.09	1.44	0	2.10	3.02	4.01	8.50
AvgClsOver05Prob	$Z_{2,0}$	3,602	0.9203	0.0140	0.8787	0.9104	0.9201	0.9299	0.9513
AvgClsOver15Prob	$Z_{2,1}$	3,602	0.7743	0.0349	0.6706	0.7530	0.7790	0.7983	0.8450
AvgClsOver25Prob	$Z_{2,2}$	3,602	0.5560	0.0517	0.4165	0.5249	0.5576	0.5882	0.6682
AvgClsOver35Prob	$Z_{2,3}$	3,602	0.3473	0.0500	0.2285	0.3149	0.3430	0.3716	0.4672
AvgClsOver45Prob	$Z_{2,4}$	3,602	0.1930	0.0371	0.1145	0.1679	0.1905	0.2106	0.2851
AvgClsOver55Prob	$Z_{2,5}$	3,602	0.1025	0.0229	0.0541	0.0873	0.0985	0.1130	0.1605
AvgClsProbAway	$Z_{2,6}$	3,602	0.3306	0.1520	0.1376	0.2237	0.2788	0.3984	0.7721
AvgClsProbHome	$Z_{2,7}$	3,602	0.4143	0.1399	0.0772	0.3350	0.4489	0.5241	0.6481
BeerPrice	$Z_{2,8}$	3,602	4.18	0.0900	4	4.20	4.20	4.20	4.30
GeoDist	$Z_{2,9}$	3,602	288	142	55.6	152	326	398	536
HotWinePrice	$Z_{2,10}$	3,602	3.96	0.2680	3.50	3.99	4	4.20	4.30
Is1stDiv	$Z_{2,11}$	3,602	0.8168	0.3869	0	1	1	1	1
IsMobCpoint	$Z_{2,12}$	3,602	0.4275	0.4948	0	0	0	1	1
IsPubHoliday	$Z_{2,13}$	3,602	0.0014	0.0372	0	0	0	0	1
IsRelegAway	$Z_{2,14}$	3,602	0.0053	0.0724	0	0	0	0	1
IsRunner	$Z_{2,15}$	3,602	0.6724	0.4694	0	0	1	1	1
IsSchlHoliday	$Z_{2,16}$	3,602	0.1180	0.3226	0	0	0	0	1
IsSoldOut	$Z_{2,17}$	3,602	0.2821	0.4501	0	0	0	1	1
IsWasen	$Z_{2,18}$	3,602	0.2016	0.4012	0	0	0	0	1
Kickoff15:30	$Z_{2,19}$	3,602	0.6008	0.4898	0	0	1	1	1
Kickoff15:45	$Z_{2,20}$	3,602	0.0075	0.0863	0	0	0	0	1
Kickoff17:30	$Z_{2,21}$	3,602	0.0791	0.2700	0	0	0	0	1
Kickoff18:00	$Z_{2,22}$	3,602	0.0169	0.1290	0	0	0	0	1
Kickoff18:30	$Z_{2,23}$	3,602	0.0875	0.2825	0	0	0	0	1
Kickoff20:30	$Z_{2,24}$	3,602	0.0616	0.2405	0	0	0	0	1
MonthAug	$Z_{2,25}$	3,602	0.0464	0.2103	0	0	0	0	1
MonthDec	$Z_{2,26}$	3,602	0.1105	0.3135	0	0	0	0	1
MonthFeb	$Z_{2,27}$	3,602	0.1421	0.3492	0	0	0	0	1
MonthJan	$Z_{2,28}$	3,602	0.0566	0.2312	0	0	0	0	1
MonthMar	$Z_{2,29}$	3,602	0.0999	0.3000	0	0	0	0	1
MonthMay	$Z_{2,30}$	3,602	0.0974	0.2966	0	0	0	0	1

MonthNov	$Z_{2,31}$	3,602	0.0902	0.2865	0	0	0	0	1
MonthOct	$Z_{2,32}$	3,602	0.1019	0.3025	0	0	0	0	1
MonthSep	$Z_{2,33}$	3,602	0.1049	0.3065	0	0	0	0	1
NumCpoints	$Z_{2,34}$	3,602	158	20.1	113	140	155	178	188
NumSpects	$Z_{2,35}$	3,602	52,348	6,901	36,800	46,600	54,410	58,680	60,000
RankAwayLast	$Z_{2,36}$	3,602	7.99	4.85	1	3	8	12	18
RankAwayPre	$Z_{2,37}$	3,602	9.06	5.15	1	4	9	13	18
RankHomePre	$Z_{2,38}$	3,602	12.5	5.29	1	10	14	17	18
Round	$Z_{2,39}$	3,602	18.6	9.69	1	10	19	28	34
Season2014/15	$Z_{2,40}$	3,602	0.1388	0.3458	0	0	0	0	1
Season2015/16	$Z_{2,41}$	3,602	0.1577	0.3645	0	0	0	0	1
Season2017/18	$Z_{2,42}$	3,602	0.1968	0.3977	0	0	0	0	1
Season2018/19	$Z_{2,43}$	3,602	0.1494	0.3565	0	0	0	0	1
WkdayMo	$Z_{2,44}$	3,602	0.0802	0.2717	0	0	0	0	1
WkdaySa	$Z_{2,45}$	3,602	0.5611	0.4963	0	0	1	1	1
WkdaySu	$Z_{2,46}$	3,602	0.2418	0.4282	0	0	0	0	1
WkdayTu	$Z_{2,47}$	3,602	0.0161	0.1259	0	0	0	0	1
WkdayWe	$Z_{2,48}$	3,602	0.0155	0.1237	0	0	0	0	1

(Equivalent description as for table B4, but given positive state 1).

C Further Results

C.1 Main Specification

Table C1. Main Model Results

			mean	std	median	$hdi^{5\%}$	$hdi^{95\%}$	$\hat{R}$
Surprise	State 0	$\hat{\beta}_{1,1,0,0}$	-0.0200	0.0040	-0.0200	-0.0280	-0.0130	1
		$\hat{\beta}_{1,1,0,1}$	0.0030	0.0040	0.0030	-0.0020	0.0110	1
		$\hat{\beta}_{1,1,0,2}$	0.0090	0.0050	0.0100	0.0020	0.0170	1
		$\hat{\beta}_{1,1,0,3}$	0.0150	0.0040	0.0150	0.0090	0.0230	1
		$\hat{\beta}_{1,1,0,4}$	0.0140	0.0040	0.0140	0.0070	0.0210	1
		$\hat{\beta}_{1,1,0,5}$	0.0120	0.0050	0.0120	0.0050	0.0200	1
		$\hat{\beta}_{1,1,0,6}$	0.0020	0.0040	0.0010	-0.0030	0.0090	1
		$\hat{\beta}_{1,1,0,7}$	0.0010	0.0030	0.0000	-0.0040	0.0060	1
		$\hat{\beta}_{1,1,0,8}$	-0.0020	0.0040	-0.0010	-0.0090	0.0030	1
		$\hat{\beta}_{1,1,0,9}$	-0.0100	0.0050	-0.0100	-0.0180	-0.0020	1
	State 1	$\hat{\beta}_{1,1,1,0}$	-0.0120	0.0050	-0.0120	-0.0190	-0.0040	1
		$\hat{\beta}_{1,1,1,1}$	-0.0230	0.0040	-0.0230	-0.0300	-0.0160	1
		$\hat{\beta}_{1,1,1,2}$	0.0180	0.0050	0.0180	0.0100	0.0250	1
		$\hat{\beta}_{1,1,1,3}$	0.0200	0.0040	0.0200	0.0130	0.0270	1
		$\hat{\beta}_{1,1,1,4}$	0.0180	0.0040	0.0180	0.0110	0.0250	1
		$\hat{\beta}_{1,1,1,5}$	0.0080	0.0050	0.0080	0.0000	0.0150	1
		$\hat{\beta}_{1,1,1,6}$	0.0060	0.0050	0.0060	-0.0010	0.0130	1
		$\hat{\beta}_{1,1,1,7}$	0.0050	0.0040	0.0050	-0.0010	0.0120	1

		$\hat{\beta}_{1,1,1,8}$	0.0010	0.0030	0.0010	-0.0030	0.0070	1
		$\hat{\beta}_{1,1,1,9}$	-0.0010	0.0030	0.0000	-0.0060	0.0040	1
Suspense	State 0	$\hat{\beta}_{1,2,0,0}$	0.0050	0.0100	0.0030	-0.0080	0.0230	1
		$\hat{\beta}_{1,2,0,1}$	-0.0010	0.0100	0.0000	-0.0190	0.0140	1
		$\hat{\beta}_{1,2,0,2}$	-0.0100	0.0160	-0.0050	-0.0390	0.0090	1
		$\hat{\beta}_{1,2,0,3}$	-0.0540	0.0230	-0.0540	-0.0930	-0.0160	1
		$\hat{\beta}_{1,2,0,4}$	0.0200	0.0200	0.0150	-0.0050	0.0540	1
		$\hat{\beta}_{1,2,0,5}$	0.0030	0.0130	0.0000	-0.0180	0.0240	1
		$\hat{\beta}_{1,2,0,6}$	0.0010	0.0110	0.0000	-0.0160	0.0200	1
		$\hat{\beta}_{1,2,0,7}$	0.0090	0.0140	0.0050	-0.0090	0.0330	1
		$\hat{\beta}_{1,2,0,8}$	0.0040	0.0100	0.0020	-0.0090	0.0230	1
		$\hat{\beta}_{1,2,0,9}$	0.0090	0.0100	0.0070	-0.0040	0.0270	1
	State 1	$\hat{\beta}_{1,2,1,0}$	-0.0100	0.0110	-0.0080	-0.0270	0.0050	1
		$\hat{\beta}_{1,2,1,1}$	0.0050	0.0110	0.0020	-0.0100	0.0230	1
		$\hat{\beta}_{1,2,1,2}$	-0.0080	0.0160	-0.0020	-0.0360	0.0120	1
		$\hat{\beta}_{1,2,1,3}$	-0.0720	0.0230	-0.0720	-0.1100	-0.0340	1
		$\hat{\beta}_{1,2,1,4}$	0.0150	0.0200	0.0090	-0.0110	0.0490	1
		$\hat{\beta}_{1,2,1,5}$	0.0110	0.0140	0.0080	-0.0070	0.0350	1
		$\hat{\beta}_{1,2,1,6}$	0.0070	0.0120	0.0040	-0.0100	0.0270	1
		$\hat{\beta}_{1,2,1,7}$	0.0130	0.0150	0.0100	-0.0060	0.0380	1
		$\hat{\beta}_{1,2,1,8}$	0.0010	0.0100	0.0000	-0.0150	0.0180	1
		$\hat{\beta}_{1,2,1,9}$	0.0040	0.0100	0.0010	-0.0120	0.0200	1
AirPress	State 0	$\hat{\gamma}_{1,0,0,0}$	0.0010	0.0170	0.0000	-0.0240	0.0260	1
		$\hat{\gamma}_{1,0,0,1}$	0.0000	0.0180	0.0000	-0.0260	0.0270	1
		$\hat{\gamma}_{1,0,0,2}$	0.0010	0.0180	0.0000	-0.0260	0.0280	1
		$\hat{\gamma}_{1,0,0,3}$	0.0000	0.0180	0.0000	-0.0280	0.0250	1
		$\hat{\gamma}_{1,0,0,4}$	0.0060	0.0210	0.0030	-0.0230	0.0400	1
		$\hat{\gamma}_{1,0,0,5}$	-0.0050	0.0200	-0.0020	-0.0390	0.0220	1
		$\hat{\gamma}_{1,0,0,6}$	0.0000	0.0180	0.0000	-0.0270	0.0260	1
		$\hat{\gamma}_{1,0,0,7}$	-0.0020	0.0190	-0.0010	-0.0320	0.0230	1
		$\hat{\gamma}_{1,0,0,8}$	0.0050	0.0190	0.0020	-0.0230	0.0350	1
		$\hat{\gamma}_{1,0,0,9}$	-0.0050	0.0190	-0.0020	-0.0360	0.0230	1
	State 1	$\hat{\gamma}_{1,0,1,0}$	0.0000	0.0170	0.0000	-0.0290	0.0230	1
		$\hat{\gamma}_{1,0,1,1}$	0.0000	0.0180	0.0000	-0.0240	0.0290	1
		$\hat{\gamma}_{1,0,1,2}$	-0.0010	0.0180	0.0000	-0.0280	0.0250	1
		$\hat{\gamma}_{1,0,1,3}$	0.0000	0.0180	0.0000	-0.0260	0.0260	1
		$\hat{\gamma}_{1,0,1,4}$	-0.0070	0.0210	-0.0040	-0.0390	0.0240	1
		$\hat{\gamma}_{1,0,1,5}$	0.0050	0.0200	0.0020	-0.0220	0.0370	1
		$\hat{\gamma}_{1,0,1,6}$	0.0000	0.0180	0.0000	-0.0290	0.0260	1
		$\hat{\gamma}_{1,0,1,7}$	0.0030	0.0180	0.0010	-0.0240	0.0310	1
		$\hat{\gamma}_{1,0,1,8}$	-0.0040	0.0190	-0.0020	-0.0340	0.0240	1
		$\hat{\gamma}_{1,0,1,9}$	0.0040	0.0190	0.0020	-0.0260	0.0330	1
HotWineSls	State 0	$\hat{\gamma}_{1,1,0,0}$	0.0020	0.0060	0.0000	-0.0080	0.0120	1
		$\hat{\gamma}_{1,1,0,1}$	-0.0030	0.0060	-0.0010	-0.0160	0.0050	1
		$\hat{\gamma}_{1,1,0,2}$	0.0000	0.0060	0.0000	-0.0100	0.0100	1
		$\hat{\gamma}_{1,1,0,3}$	0.0000	0.0060	0.0000	-0.0110	0.0100	1

		$\hat{\gamma}_{1,1,0,4}$	-0.0070	0.0080	-0.0060	-0.0210	0.0040	1
		$\hat{\gamma}_{1,1,0,5}$	0.0060	0.0080	0.0050	-0.0050	0.0200	1
		$\hat{\gamma}_{1,1,0,6}$	-0.0010	0.0060	0.0000	-0.0110	0.0090	1
		$\hat{\gamma}_{1,1,0,7}$	-0.0020	0.0060	-0.0010	-0.0130	0.0080	1
		$\hat{\gamma}_{1,1,0,8}$	-0.0010	0.0060	0.0000	-0.0120	0.0080	1
		$\hat{\gamma}_{1,1,0,9}$	0.0050	0.0070	0.0040	-0.0040	0.0180	1
	State 1	$\hat{\gamma}_{1,1,1,0}$	0.0150	0.0100	0.0150	-0.0010	0.0310	1
		$\hat{\gamma}_{1,1,1,1}$	0.0040	0.0080	0.0020	-0.0070	0.0200	1
		$\hat{\gamma}_{1,1,1,2}$	0.0050	0.0080	0.0030	-0.0070	0.0200	1
		$\hat{\gamma}_{1,1,1,3}$	0.0030	0.0080	0.0010	-0.0090	0.0170	1
		$\hat{\gamma}_{1,1,1,4}$	-0.0050	0.0090	-0.0030	-0.0210	0.0070	1
		$\hat{\gamma}_{1,1,1,5}$	0.0010	0.0080	0.0000	-0.0110	0.0150	1
		$\hat{\gamma}_{1,1,1,6}$	-0.0020	0.0070	0.0000	-0.0150	0.0100	1
		$\hat{\gamma}_{1,1,1,7}$	-0.0060	0.0090	-0.0040	-0.0220	0.0060	1
		$\hat{\gamma}_{1,1,1,8}$	-0.0060	0.0080	-0.0030	-0.0210	0.0060	1
		$\hat{\gamma}_{1,1,1,9}$	-0.0070	0.0090	-0.0060	-0.0220	0.0040	1
Is1stHalf	State 0	$\hat{\gamma}_{1,2,0,0}$	-0.1290	0.0350	-0.1330	-0.1840	-0.0700	1
		$\hat{\gamma}_{1,2,0,1}$	-0.0010	0.0230	0.0010	-0.0370	0.0350	1
		$\hat{\gamma}_{1,2,0,2}$	0.0010	0.0140	0.0000	-0.0200	0.0240	1
		$\hat{\gamma}_{1,2,0,3}$	0.0030	0.0150	0.0000	-0.0200	0.0260	1
		$\hat{\gamma}_{1,2,0,4}$	0.0300	0.0250	0.0260	-0.0030	0.0710	1
		$\hat{\gamma}_{1,2,0,5}$	0.0140	0.0230	0.0050	-0.0150	0.0560	1
		$\hat{\gamma}_{1,2,0,6}$	0.0090	0.0200	0.0020	-0.0170	0.0420	1
		$\hat{\gamma}_{1,2,0,7}$	0.0230	0.0260	0.0150	-0.0080	0.0670	1
		$\hat{\gamma}_{1,2,0,8}$	0.0260	0.0270	0.0190	-0.0060	0.0720	1
		$\hat{\gamma}_{1,2,0,9}$	0.0210	0.0230	0.0170	-0.0100	0.0570	1
	State 1	$\hat{\gamma}_{1,2,1,0}$	-0.0560	0.0360	-0.0590	-0.1080	0.0030	1
		$\hat{\gamma}_{1,2,1,1}$	-0.0100	0.0240	-0.0030	-0.0460	0.0250	1
		$\hat{\gamma}_{1,2,1,2}$	0.0030	0.0150	0.0010	-0.0180	0.0260	1
		$\hat{\gamma}_{1,2,1,3}$	0.0060	0.0150	0.0010	-0.0150	0.0310	1
		$\hat{\gamma}_{1,2,1,4}$	0.0140	0.0240	0.0060	-0.0200	0.0560	1
		$\hat{\gamma}_{1,2,1,5}$	0.0180	0.0240	0.0100	-0.0090	0.0610	1
		$\hat{\gamma}_{1,2,1,6}$	0.0100	0.0200	0.0030	-0.0150	0.0450	1
		$\hat{\gamma}_{1,2,1,7}$	0.0170	0.0260	0.0080	-0.0140	0.0620	1
		$\hat{\gamma}_{1,2,1,8}$	0.0160	0.0260	0.0070	-0.0160	0.0630	1
		$\hat{\gamma}_{1,2,1,9}$	0.0240	0.0230	0.0200	-0.0060	0.0610	1
IsPrecip	State 0	$\hat{\gamma}_{1,3,0,0}$	0.0010	0.0060	0.0000	-0.0070	0.0120	1
		$\hat{\gamma}_{1,3,0,1}$	0.0060	0.0070	0.0040	-0.0050	0.0180	1
		$\hat{\gamma}_{1,3,0,2}$	-0.0010	0.0060	0.0000	-0.0110	0.0100	1
		$\hat{\gamma}_{1,3,0,3}$	0.0010	0.0060	0.0000	-0.0090	0.0120	1
		$\hat{\gamma}_{1,3,0,4}$	-0.0060	0.0080	-0.0040	-0.0200	0.0040	1
		$\hat{\gamma}_{1,3,0,5}$	0.0030	0.0070	0.0010	-0.0080	0.0140	1
		$\hat{\gamma}_{1,3,0,6}$	0.0030	0.0070	0.0010	-0.0060	0.0150	1
		$\hat{\gamma}_{1,3,0,7}$	0.0020	0.0060	0.0000	-0.0070	0.0130	1
		$\hat{\gamma}_{1,3,0,8}$	0.0030	0.0070	0.0010	-0.0060	0.0160	1
		$\hat{\gamma}_{1,3,0,9}$	-0.0030	0.0060	-0.0010	-0.0140	0.0060	1

	State 1	$\hat{\gamma}_{1,3,1,0}$	0.0020	0.0060	0.0000	-0.0080	0.0130	1
		$\hat{\gamma}_{1,3,1,1}$	-0.0040	0.0080	-0.0020	-0.0180	0.0070	1
		$\hat{\gamma}_{1,3,1,2}$	-0.0060	0.0080	-0.0040	-0.0190	0.0060	1
		$\hat{\gamma}_{1,3,1,3}$	-0.0010	0.0070	0.0000	-0.0120	0.0100	1
		$\hat{\gamma}_{1,3,1,4}$	0.0010	0.0070	0.0000	-0.0100	0.0130	1
		$\hat{\gamma}_{1,3,1,5}$	-0.0040	0.0070	-0.0020	-0.0160	0.0080	1
		$\hat{\gamma}_{1,3,1,6}$	0.0010	0.0070	0.0000	-0.0100	0.0120	1
		$\hat{\gamma}_{1,3,1,7}$	-0.0010	0.0060	0.0000	-0.0120	0.0100	1
		$\hat{\gamma}_{1,3,1,8}$	0.0000	0.0060	0.0000	-0.0110	0.0100	1
		$\hat{\gamma}_{1,3,1,9}$	0.0020	0.0060	0.0010	-0.0070	0.0120	1
IsSubAway	State 0	$\hat{\gamma}_{1,4,0,0}$	0.0000	0.0030	0.0000	-0.0050	0.0050	1
		$\hat{\gamma}_{1,4,0,1}$	0.0010	0.0030	0.0000	-0.0040	0.0070	1
		$\hat{\gamma}_{1,4,0,2}$	-0.0080	0.0050	-0.0080	-0.0150	0.0000	1
		$\hat{\gamma}_{1,4,0,3}$	0.0010	0.0030	0.0000	-0.0040	0.0070	1
		$\hat{\gamma}_{1,4,0,4}$	-0.0010	0.0030	0.0000	-0.0070	0.0040	1
		$\hat{\gamma}_{1,4,0,5}$	-0.0020	0.0030	-0.0010	-0.0080	0.0030	1
		$\hat{\gamma}_{1,4,0,6}$	-0.0090	0.0050	-0.0090	-0.0150	0.0000	1
		$\hat{\gamma}_{1,4,0,7}$	-0.0010	0.0030	0.0000	-0.0070	0.0040	1
		$\hat{\gamma}_{1,4,0,8}$	-0.0050	0.0050	-0.0050	-0.0130	0.0010	1
		$\hat{\gamma}_{1,4,0,9}$	-0.0010	0.0030	0.0000	-0.0070	0.0040	1
	State 1	$\hat{\gamma}_{1,4,1,0}$	0.0010	0.0030	0.0010	-0.0030	0.0080	1
		$\hat{\gamma}_{1,4,1,1}$	0.0000	0.0030	0.0000	-0.0050	0.0050	1
		$\hat{\gamma}_{1,4,1,2}$	0.0000	0.0030	0.0000	-0.0050	0.0050	1
		$\hat{\gamma}_{1,4,1,3}$	-0.0010	0.0030	0.0000	-0.0070	0.0030	1
		$\hat{\gamma}_{1,4,1,4}$	0.0050	0.0040	0.0040	-0.0010	0.0120	1
		$\hat{\gamma}_{1,4,1,5}$	0.0010	0.0030	0.0000	-0.0040	0.0070	1
		$\hat{\gamma}_{1,4,1,6}$	-0.0030	0.0040	-0.0020	-0.0100	0.0020	1
		$\hat{\gamma}_{1,4,1,7}$	-0.0020	0.0040	-0.0010	-0.0090	0.0030	1
		$\hat{\gamma}_{1,4,1,8}$	0.0000	0.0030	0.0000	-0.0040	0.0060	1
		$\hat{\gamma}_{1,4,1,9}$	0.0030	0.0040	0.0020	-0.0020	0.0100	1
IsSubHome	State 0	$\hat{\gamma}_{1,5,0,0}$	-0.0020	0.0030	-0.0010	-0.0070	0.0030	1
		$\hat{\gamma}_{1,5,0,1}$	0.0010	0.0030	0.0000	-0.0030	0.0070	1
		$\hat{\gamma}_{1,5,0,2}$	-0.0030	0.0040	-0.0030	-0.0100	0.0020	1
		$\hat{\gamma}_{1,5,0,3}$	0.0010	0.0030	0.0000	-0.0030	0.0070	1
		$\hat{\gamma}_{1,5,0,4}$	-0.0010	0.0030	0.0000	-0.0060	0.0040	1
		$\hat{\gamma}_{1,5,0,5}$	0.0010	0.0030	0.0000	-0.0030	0.0070	1
		$\hat{\gamma}_{1,5,0,6}$	-0.0010	0.0030	0.0000	-0.0060	0.0040	1
		$\hat{\gamma}_{1,5,0,7}$	-0.0020	0.0030	-0.0010	-0.0070	0.0030	1
		$\hat{\gamma}_{1,5,0,8}$	-0.0010	0.0030	0.0000	-0.0060	0.0030	1
		$\hat{\gamma}_{1,5,0,9}$	0.0000	0.0030	0.0000	-0.0040	0.0050	1
	State 1	$\hat{\gamma}_{1,5,1,0}$	0.0010	0.0040	0.0000	-0.0040	0.0070	1
		$\hat{\gamma}_{1,5,1,1}$	0.0090	0.0050	0.0090	0.0000	0.0170	1
		$\hat{\gamma}_{1,5,1,2}$	-0.0020	0.0040	-0.0010	-0.0090	0.0030	1
		$\hat{\gamma}_{1,5,1,3}$	0.0000	0.0030	0.0000	-0.0050	0.0060	1
		$\hat{\gamma}_{1,5,1,4}$	-0.0030	0.0040	-0.0020	-0.0110	0.0030	1
		$\hat{\gamma}_{1,5,1,5}$	-0.0180	0.0050	-0.0180	-0.0260	-0.0090	1

		$\hat{\gamma}_{1,5,1,6}$	-0.0070	0.0050	-0.0070	-0.0150	0.0010	1
		$\hat{\gamma}_{1,5,1,7}$	0.0010	0.0040	0.0000	-0.0050	0.0070	1
		$\hat{\gamma}_{1,5,1,8}$	-0.0030	0.0040	-0.0020	-0.0110	0.0030	1
		$\hat{\gamma}_{1,5,1,9}$	-0.0010	0.0040	0.0000	-0.0070	0.0050	1
RelHumid	State 0	$\hat{\gamma}_{1,6,0,0}$	0.0000	0.0170	0.0000	-0.0270	0.0240	1
		$\hat{\gamma}_{1,6,0,1}$	0.0010	0.0170	0.0000	-0.0250	0.0300	1
		$\hat{\gamma}_{1,6,0,2}$	-0.0040	0.0190	-0.0010	-0.0340	0.0230	1
		$\hat{\gamma}_{1,6,0,3}$	0.0040	0.0200	0.0020	-0.0220	0.0390	1
		$\hat{\gamma}_{1,6,0,4}$	0.0000	0.0180	0.0000	-0.0300	0.0260	1
		$\hat{\gamma}_{1,6,0,5}$	-0.0010	0.0180	0.0000	-0.0300	0.0230	1
		$\hat{\gamma}_{1,6,0,6}$	-0.0060	0.0200	-0.0030	-0.0380	0.0250	1
		$\hat{\gamma}_{1,6,0,7}$	-0.0040	0.0190	-0.0020	-0.0360	0.0220	1
		$\hat{\gamma}_{1,6,0,8}$	0.0020	0.0170	0.0000	-0.0230	0.0320	1
		$\hat{\gamma}_{1,6,0,9}$	0.0030	0.0170	0.0000	-0.0220	0.0290	1
	State 1	$\hat{\gamma}_{1,6,1,0}$	0.0040	0.0170	0.0010	-0.0210	0.0300	1
		$\hat{\gamma}_{1,6,1,1}$	0.0020	0.0170	0.0000	-0.0270	0.0270	1
		$\hat{\gamma}_{1,6,1,2}$	0.0040	0.0190	0.0010	-0.0220	0.0350	1
		$\hat{\gamma}_{1,6,1,3}$	-0.0070	0.0200	-0.0030	-0.0400	0.0220	1
		$\hat{\gamma}_{1,6,1,4}$	-0.0010	0.0180	0.0000	-0.0300	0.0260	1
		$\hat{\gamma}_{1,6,1,5}$	0.0000	0.0170	0.0000	-0.0250	0.0290	1
		$\hat{\gamma}_{1,6,1,6}$	0.0070	0.0200	0.0040	-0.0220	0.0400	1
		$\hat{\gamma}_{1,6,1,7}$	0.0050	0.0190	0.0020	-0.0200	0.0380	1
		$\hat{\gamma}_{1,6,1,8}$	0.0010	0.0170	0.0000	-0.0270	0.0270	1
		$\hat{\gamma}_{1,6,1,9}$	0.0020	0.0170	0.0000	-0.0250	0.0260	1
Temp	State 0	$\hat{\gamma}_{1,7,0,0}$	0.0050	0.0210	0.0020	-0.0260	0.0390	1
		$\hat{\gamma}_{1,7,0,1}$	-0.0040	0.0210	-0.0010	-0.0380	0.0250	1
		$\hat{\gamma}_{1,7,0,2}$	-0.0070	0.0230	-0.0040	-0.0480	0.0230	1
		$\hat{\gamma}_{1,7,0,3}$	-0.0030	0.0210	-0.0010	-0.0360	0.0270	1
		$\hat{\gamma}_{1,7,0,4}$	0.0000	0.0210	0.0000	-0.0310	0.0320	1
		$\hat{\gamma}_{1,7,0,5}$	0.0080	0.0220	0.0040	-0.0240	0.0440	1
		$\hat{\gamma}_{1,7,0,6}$	-0.0010	0.0210	0.0000	-0.0310	0.0330	1
		$\hat{\gamma}_{1,7,0,7}$	-0.0060	0.0230	-0.0030	-0.0430	0.0270	1
		$\hat{\gamma}_{1,7,0,8}$	0.0040	0.0200	0.0010	-0.0280	0.0340	1
		$\hat{\gamma}_{1,7,0,9}$	0.0000	0.0190	0.0000	-0.0270	0.0310	1
	State 1	$\hat{\gamma}_{1,7,1,0}$	-0.0060	0.0210	-0.0020	-0.0390	0.0250	1
		$\hat{\gamma}_{1,7,1,1}$	0.0040	0.0210	0.0010	-0.0240	0.0390	1
		$\hat{\gamma}_{1,7,1,2}$	0.0090	0.0230	0.0050	-0.0230	0.0490	1
		$\hat{\gamma}_{1,7,1,3}$	0.0050	0.0210	0.0010	-0.0240	0.0400	1
		$\hat{\gamma}_{1,7,1,4}$	0.0030	0.0200	0.0000	-0.0270	0.0350	1
		$\hat{\gamma}_{1,7,1,5}$	-0.0050	0.0220	-0.0020	-0.0410	0.0260	1
		$\hat{\gamma}_{1,7,1,6}$	0.0050	0.0210	0.0010	-0.0220	0.0410	1
		$\hat{\gamma}_{1,7,1,7}$	0.0100	0.0230	0.0060	-0.0240	0.0460	1
		$\hat{\gamma}_{1,7,1,8}$	-0.0020	0.0200	-0.0010	-0.0340	0.0290	1
		$\hat{\gamma}_{1,7,1,9}$	0.0010	0.0190	0.0000	-0.0290	0.0280	1
WaterSls	State 0	$\hat{\gamma}_{1,8,0,0}$	0.0020	0.0060	0.0000	-0.0070	0.0120	1
		$\hat{\gamma}_{1,8,0,1}$	-0.0010	0.0060	0.0000	-0.0120	0.0080	1

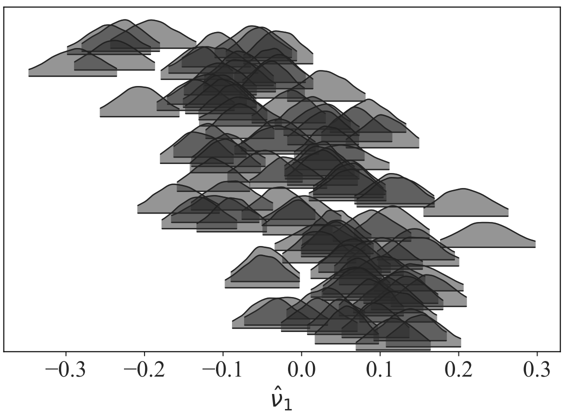
		$\hat{\gamma}_{1,8,0,2}$	0.0060	0.0070	0.0040	-0.0040	0.0190	1
		$\hat{\gamma}_{1,8,0,3}$	0.0000	0.0060	0.0000	-0.0100	0.0100	1
		$\hat{\gamma}_{1,8,0,4}$	0.0000	0.0060	0.0000	-0.0110	0.0090	1
		$\hat{\gamma}_{1,8,0,5}$	0.0000	0.0060	0.0000	-0.0090	0.0110	1
		$\hat{\gamma}_{1,8,0,6}$	-0.0010	0.0060	0.0000	-0.0120	0.0080	1
		$\hat{\gamma}_{1,8,0,7}$	0.0050	0.0070	0.0030	-0.0050	0.0170	1
		$\hat{\gamma}_{1,8,0,8}$	0.0040	0.0060	0.0020	-0.0050	0.0160	1
		$\hat{\gamma}_{1,8,0,9}$	0.0000	0.0050	0.0000	-0.0090	0.0100	1
	State 1	$\hat{\gamma}_{1,8,1,0}$	0.0190	0.0090	0.0190	0.0030	0.0340	1
		$\hat{\gamma}_{1,8,1,1}$	0.0060	0.0080	0.0040	-0.0050	0.0210	1
		$\hat{\gamma}_{1,8,1,2}$	-0.0060	0.0080	-0.0040	-0.0200	0.0040	1
		$\hat{\gamma}_{1,8,1,3}$	-0.0030	0.0070	-0.0010	-0.0160	0.0080	1
		$\hat{\gamma}_{1,8,1,4}$	-0.0010	0.0060	0.0000	-0.0130	0.0090	1
		$\hat{\gamma}_{1,8,1,5}$	0.0020	0.0060	0.0010	-0.0080	0.0140	1
		$\hat{\gamma}_{1,8,1,6}$	0.0000	0.0060	0.0000	-0.0110	0.0110	1
		$\hat{\gamma}_{1,8,1,7}$	0.0070	0.0080	0.0050	-0.0050	0.0210	1
		$\hat{\gamma}_{1,8,1,8}$	-0.0020	0.0070	0.0000	-0.0140	0.0080	1
		$\hat{\gamma}_{1,8,1,9}$	-0.0100	0.0080	-0.0100	-0.0240	0.0020	1
Wind	State 0	$\hat{\gamma}_{1,9,0,0}$	-0.0090	0.0130	-0.0070	-0.0300	0.0100	1
		$\hat{\gamma}_{1,9,0,1}$	0.0060	0.0160	0.0030	-0.0170	0.0340	1
		$\hat{\gamma}_{1,9,0,2}$	-0.0040	0.0140	-0.0020	-0.0300	0.0160	1
		$\hat{\gamma}_{1,9,0,3}$	0.0030	0.0140	0.0000	-0.0170	0.0260	1
		$\hat{\gamma}_{1,9,0,4}$	-0.0040	0.0160	-0.0020	-0.0320	0.0200	1
		$\hat{\gamma}_{1,9,0,5}$	0.0120	0.0180	0.0070	-0.0130	0.0410	1
		$\hat{\gamma}_{1,9,0,6}$	0.0010	0.0200	0.0000	-0.0310	0.0350	1
		$\hat{\gamma}_{1,9,0,7}$	0.0010	0.0150	0.0000	-0.0230	0.0260	1
		$\hat{\gamma}_{1,9,0,8}$	-0.0040	0.0140	-0.0010	-0.0270	0.0170	1
		$\hat{\gamma}_{1,9,0,9}$	-0.0070	0.0140	-0.0020	-0.0330	0.0110	1
	State 1	$\hat{\gamma}_{1,9,1,0}$	0.0030	0.0130	0.0010	-0.0140	0.0270	1
		$\hat{\gamma}_{1,9,1,1}$	-0.0150	0.0170	-0.0140	-0.0420	0.0080	1
		$\hat{\gamma}_{1,9,1,2}$	0.0060	0.0140	0.0030	-0.0140	0.0300	1
		$\hat{\gamma}_{1,9,1,3}$	0.0000	0.0140	0.0000	-0.0220	0.0220	1
		$\hat{\gamma}_{1,9,1,4}$	0.0090	0.0170	0.0060	-0.0140	0.0380	1
		$\hat{\gamma}_{1,9,1,5}$	0.0010	0.0180	0.0000	-0.0260	0.0310	1
		$\hat{\gamma}_{1,9,1,6}$	0.0200	0.0220	0.0170	-0.0090	0.0550	1
		$\hat{\gamma}_{1,9,1,7}$	-0.0060	0.0160	-0.0030	-0.0310	0.0170	1
		$\hat{\gamma}_{1,9,1,8}$	-0.0050	0.0150	-0.0010	-0.0290	0.0150	1
		$\hat{\gamma}_{1,9,1,9}$	-0.0070	0.0140	-0.0020	-0.0340	0.0100	1
AvgClsOver05Prob	-	$\hat{\gamma}_{2,0}$	-0.0200	0.0290	-0.0120	-0.0740	0.0180	1
AvgClsOver15Prob	-	$\hat{\gamma}_{2,1}$	-0.0100	0.0330	-0.0020	-0.0700	0.0420	1
AvgClsOver25Prob	-	$\hat{\gamma}_{2,2}$	-0.0110	0.0400	-0.0030	-0.0770	0.0570	1
AvgClsOver35Prob	-	$\hat{\gamma}_{2,3}$	0.0100	0.0430	0.0010	-0.0640	0.0820	1
AvgClsOver45Prob	-	$\hat{\gamma}_{2,4}$	0.0270	0.0420	0.0150	-0.0290	0.1010	1
AvgClsOver55Prob	-	$\hat{\gamma}_{2,5}$	0.0040	0.0320	0.0000	-0.0460	0.0610	1
AvgClsProbAway	-	$\hat{\gamma}_{2,6}$	-0.0040	0.0200	-0.0020	-0.0360	0.0240	1
AvgClsProbHome	-	$\hat{\gamma}_{2,7}$	0.0070	0.0190	0.0040	-0.0200	0.0370	1

BeerPrice	-	$\hat{\gamma}_{2,8}$	0.0170	0.0170	0.0150	-0.0060	0.0440	1
GeoDist	-	$\hat{\gamma}_{2,9}$	0.0070	0.0060	0.0070	-0.0010	0.0170	1
HotWinePrice	-	$\hat{\gamma}_{2,10}$	0.0170	0.0160	0.0150	-0.0050	0.0420	1
Is1stDiv	-	$\hat{\gamma}_{2,11}$	-0.0440	0.0220	-0.0430	-0.0830	-0.0090	1
IsMobCpoint	-	$\hat{\gamma}_{2,12}$	0.0000	0.0100	0.0000	-0.0170	0.0180	1
IsPubHoliday	-	$\hat{\gamma}_{2,13}$	0.0020	0.0050	0.0010	-0.0050	0.0110	1
IsRelegAway	-	$\hat{\gamma}_{2,14}$	0.0010	0.0050	0.0000	-0.0050	0.0100	1
IsRunner	-	$\hat{\gamma}_{2,15}$	0.0010	0.0080	0.0000	-0.0120	0.0150	1
IsSchlHoliday	-	$\hat{\gamma}_{2,16}$	0.0010	0.0060	0.0000	-0.0080	0.0110	1
IsSoldOut	-	$\hat{\gamma}_{2,17}$	0.0020	0.0060	0.0010	-0.0070	0.0140	1
IsWasen	-	$\hat{\gamma}_{2,18}$	-0.0020	0.0050	-0.0010	-0.0120	0.0050	1
Kickoff15:30	-	$\hat{\gamma}_{2,19}$	0.0290	0.0250	0.0250	-0.0050	0.0690	1
Kickoff15:45	-	$\hat{\gamma}_{2,20}$	0.0090	0.0080	0.0080	-0.0020	0.0220	1
Kickoff17:30	-	$\hat{\gamma}_{2,21}$	0.0110	0.0140	0.0070	-0.0060	0.0370	1
Kickoff18:00	-	$\hat{\gamma}_{2,22}$	0.0070	0.0090	0.0050	-0.0040	0.0240	1
Kickoff18:30	-	$\hat{\gamma}_{2,23}$	0.0300	0.0150	0.0290	0.0060	0.0540	1
Kickoff20:30	-	$\hat{\gamma}_{2,24}$	0.0430	0.0240	0.0410	0.0060	0.0830	1
MonthAug	-	$\hat{\gamma}_{2,25}$	0.0050	0.0080	0.0020	-0.0060	0.0190	1
MonthDec	-	$\hat{\gamma}_{2,26}$	0.0020	0.0060	0.0010	-0.0060	0.0130	1
MonthFeb	-	$\hat{\gamma}_{2,27}$	0.0000	0.0060	0.0000	-0.0100	0.0090	1
MonthJan	-	$\hat{\gamma}_{2,28}$	-0.0050	0.0060	-0.0040	-0.0160	0.0030	1
MonthMar	-	$\hat{\gamma}_{2,29}$	-0.0010	0.0050	0.0000	-0.0100	0.0060	1
MonthMay	-	$\hat{\gamma}_{2,30}$	0.0020	0.0050	0.0010	-0.0060	0.0120	1
MonthNov	-	$\hat{\gamma}_{2,31}$	-0.0050	0.0060	-0.0030	-0.0160	0.0040	1
MonthOct	-	$\hat{\gamma}_{2,32}$	0.0030	0.0070	0.0010	-0.0060	0.0140	1
MonthSep	-	$\hat{\gamma}_{2,33}$	0.0030	0.0080	0.0010	-0.0080	0.0170	1
NumCpoints	-	$\hat{\gamma}_{2,34}$	0.0140	0.0170	0.0110	-0.0100	0.0430	1
NumSpects	-	$\hat{\gamma}_{2,35}$	0.0490	0.0110	0.0490	0.0320	0.0680	1
RankAwayLast	-	$\hat{\gamma}_{2,36}$	0.0010	0.0040	0.0000	-0.0070	0.0080	1
RankAwayPre	-	$\hat{\gamma}_{2,37}$	-0.0010	0.0060	0.0000	-0.0110	0.0080	1
RankHomePre	-	$\hat{\gamma}_{2,38}$	-0.0010	0.0080	0.0000	-0.0150	0.0120	1
Round	-	$\hat{\gamma}_{2,39}$	0.0020	0.0100	0.0000	-0.0140	0.0160	1
Season2014/15	-	$\hat{\gamma}_{2,40}$	0.0010	0.0090	0.0000	-0.0130	0.0160	1
Season2015/16	-	$\hat{\gamma}_{2,41}$	0.0000	0.0100	0.0000	-0.0160	0.0150	1
Season2017/18	-	$\hat{\gamma}_{2,42}$	0.0040	0.0120	0.0010	-0.0130	0.0230	1
Season2018/19	-	$\hat{\gamma}_{2,43}$	0.0080	0.0150	0.0040	-0.0100	0.0330	1
WkdayMo	-	$\hat{\gamma}_{2,44}$	-0.0090	0.0120	-0.0060	-0.0310	0.0070	1
WkdaySa	-	$\hat{\gamma}_{2,45}$	0.0180	0.0220	0.0170	-0.0130	0.0540	1
WkdaySu	-	$\hat{\gamma}_{2,46}$	-0.0170	0.0180	-0.0150	-0.0470	0.0090	1
WkdayTu	-	$\hat{\gamma}_{2,47}$	-0.0030	0.0060	-0.0020	-0.0150	0.0050	1
WkdayWe	-	$\hat{\gamma}_{2,48}$	0.0040	0.0090	0.0010	-0.0100	0.0200	1
BeerSls	State 0	$\hat{\phi}_{1,0,1}$	0.1930	0.0100	0.1930	0.1770	0.2080	1
		$\hat{\phi}_{1,0,2}$	0.1690	0.0100	0.1690	0.1530	0.1850	1
		$\hat{\phi}_{1,0,3}$	0.0630	0.0100	0.0630	0.0460	0.0780	1
		$\hat{\phi}_{1,0,4}$	0.0280	0.0110	0.0280	0.0100	0.0460	1
		$\hat{\phi}_{1,0,5}$	0.0330	0.0100	0.0330	0.0160	0.0500	1

		$\hat{\phi}_{1,0,6}$	0.0150	0.0110	0.0150	-0.0010	0.0310	1
		$\hat{\phi}_{1,0,7}$	0.0090	0.0100	0.0080	-0.0040	0.0250	1
		$\hat{\phi}_{1,0,8}$	-0.0010	0.0060	0.0000	-0.0120	0.0080	1
		$\hat{\phi}_{1,0,9}$	-0.0080	0.0080	-0.0080	-0.0210	0.0030	1
	State 1	$\hat{\phi}_{1,1,1}$	0.1840	0.0100	0.1840	0.1670	0.2000	1
		$\hat{\phi}_{1,1,2}$	0.1800	0.0100	0.1800	0.1630	0.1960	1
		$\hat{\phi}_{1,1,3}$	0.0580	0.0100	0.0580	0.0410	0.0750	1
		$\hat{\phi}_{1,1,4}$	0.0230	0.0120	0.0230	0.0000	0.0390	1
		$\hat{\phi}_{1,1,5}$	0.0230	0.0110	0.0230	0.0000	0.0380	1
		$\hat{\phi}_{1,1,6}$	0.0170	0.0110	0.0170	-0.0010	0.0340	1
		$\hat{\phi}_{1,1,7}$	0.0220	0.0110	0.0220	0.0050	0.0400	1
		$\hat{\phi}_{1,1,8}$	0.0000	0.0060	0.0000	-0.0100	0.0100	1
		$\hat{\phi}_{1,1,9}$	-0.0020	0.0070	-0.0010	-0.0140	0.0080	1
Noise	-	$\hat{\sigma}$	0.2560	0.0020	0.2560	0.2530	0.2600	1
SlabWitdh	-	c^2	0.0110	0.0010	0.0110	0.0090	0.0130	1

This table presents summary statistics on the posterior distributions of the coefficients, estimated in the main specification. We exclude the match minute dummies for presentation reasons. Columns 7 and 8 include the 5% and 95% quantiles of the highest density interval, respectively. The last column provides the Gelman-Rubin statistic. Indices of coefficients denote the level, the variable, the state, and the lag. For ϕ, we drop the variable index, because it is redundant. The median for $\beta_{1,1,1,3}$ equal to 0.02 implies: a one standard deviation increase of *Surprise* in positive state 1 increases the conditional mean of beer sales during minute 3 after a key match event by approximately 2%, ceteris paribus.

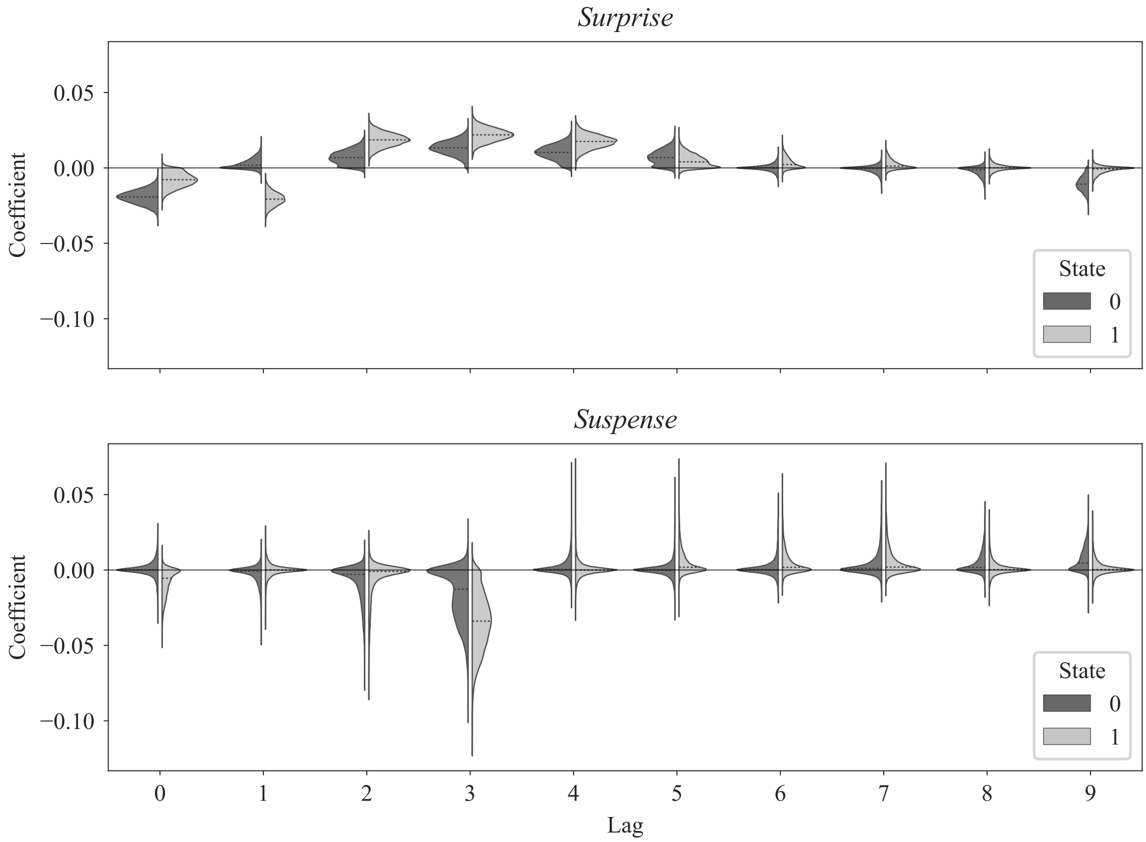
FIGURE C1. MAIN MODEL FOREST PLOT



This figure shows posterior distributions of the intercept $\hat{\nu_1}$ for each match. The matches are sorted chronologically from top to bottom (seasons 2013/14 to 2018/19).

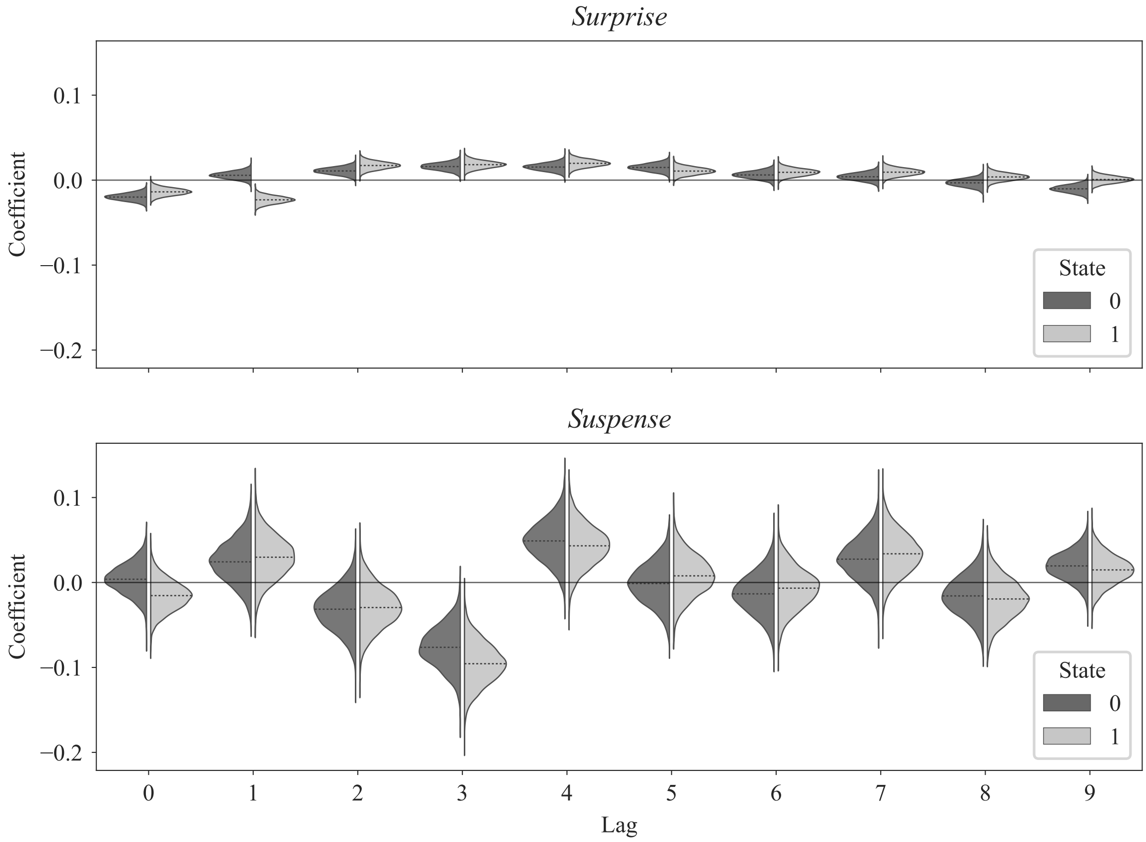
C.2 Extended Specifications and Robustness Checks

FIGURE C2. REGULARIZED HORSESHOE POSTERIOR DISTRIBUTIONS OF COEFFICIENTS FOR *SURPRISE* AND *SUSPENSE*



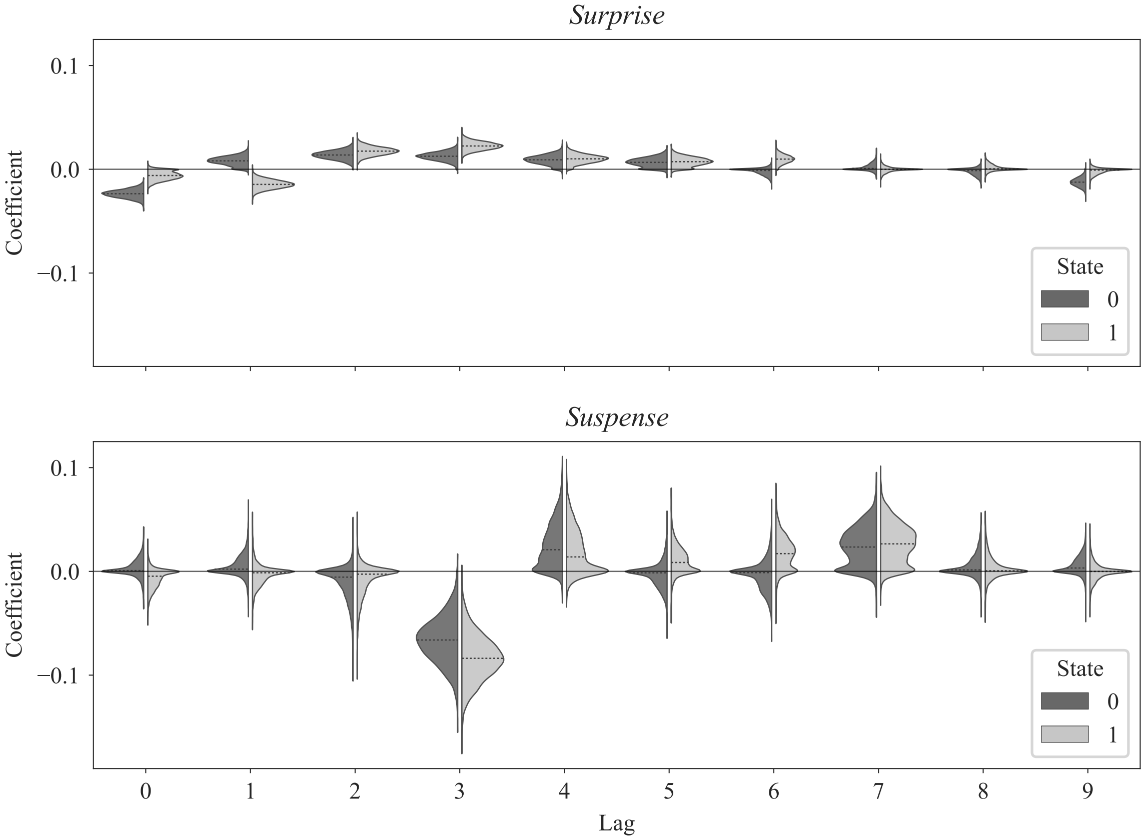
(Equivalent description as for figure 3, but for the regularized horseshoe specification).

Figure C3. Normal Prior Posterior Distributions of Coefficients for *Surprise* and *Suspense*



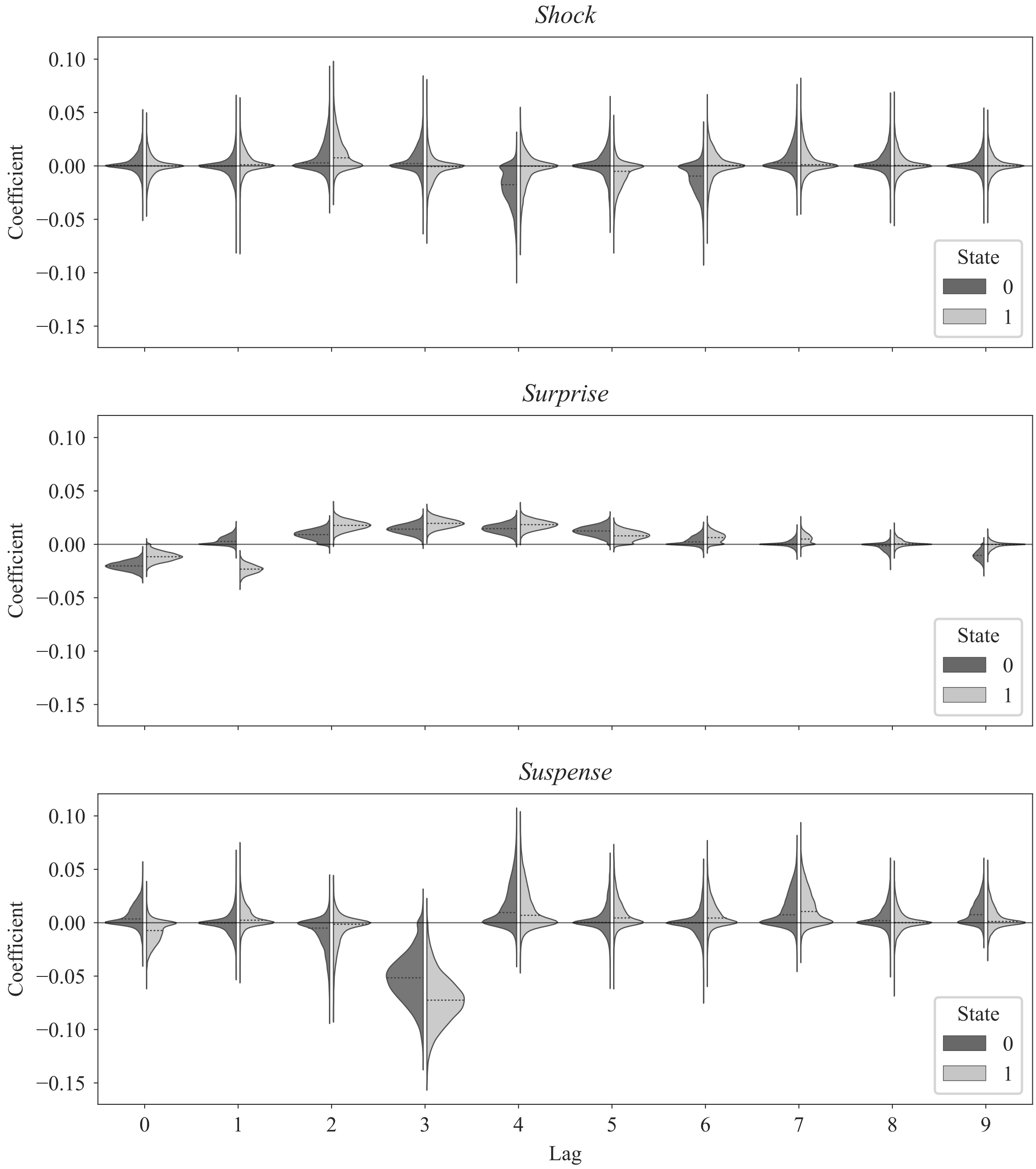
(Equivalent description as for figure 3, but for the normal prior specification).

Figure C4. Seasons Posterior Distributions of Coefficients for *Surprise* and *Suspense*



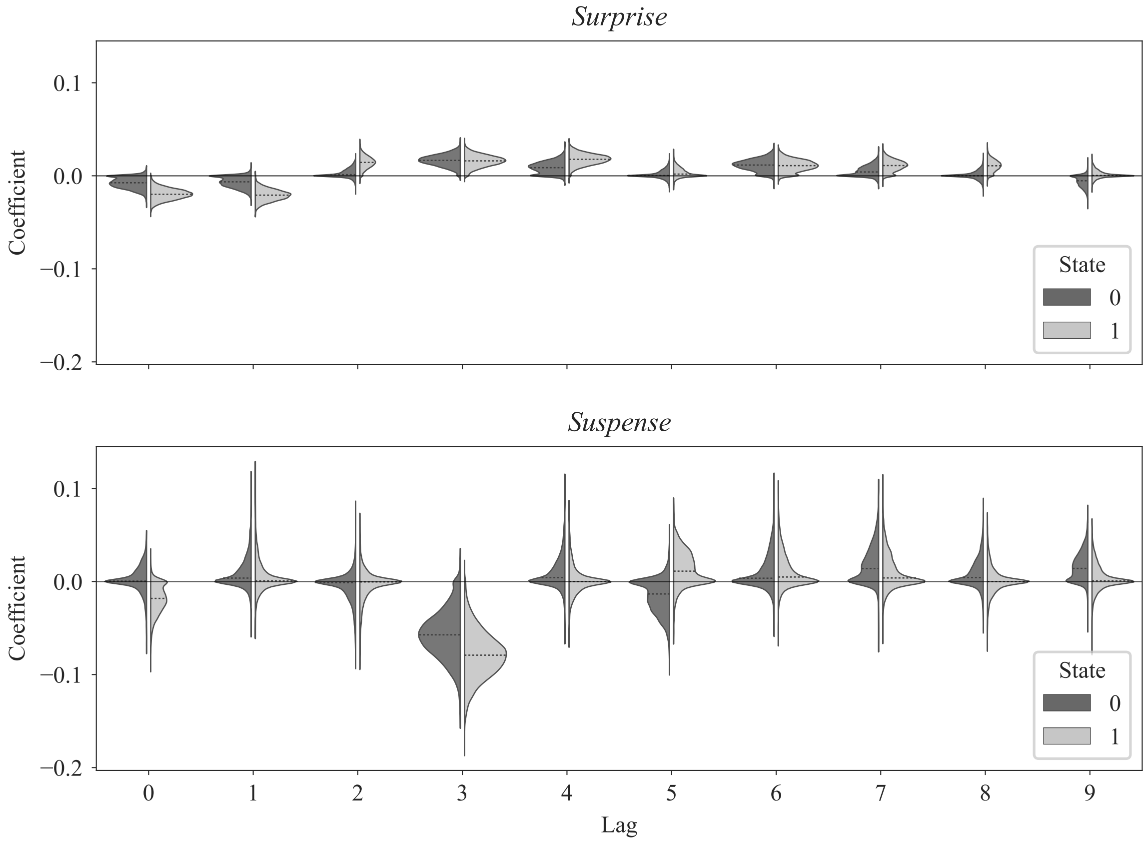
(Equivalent description as for figure 3, but for the seasons specification).

Figure C5. Shock Posterior Distributions of Coefficients for *Surprise* and *Suspense*



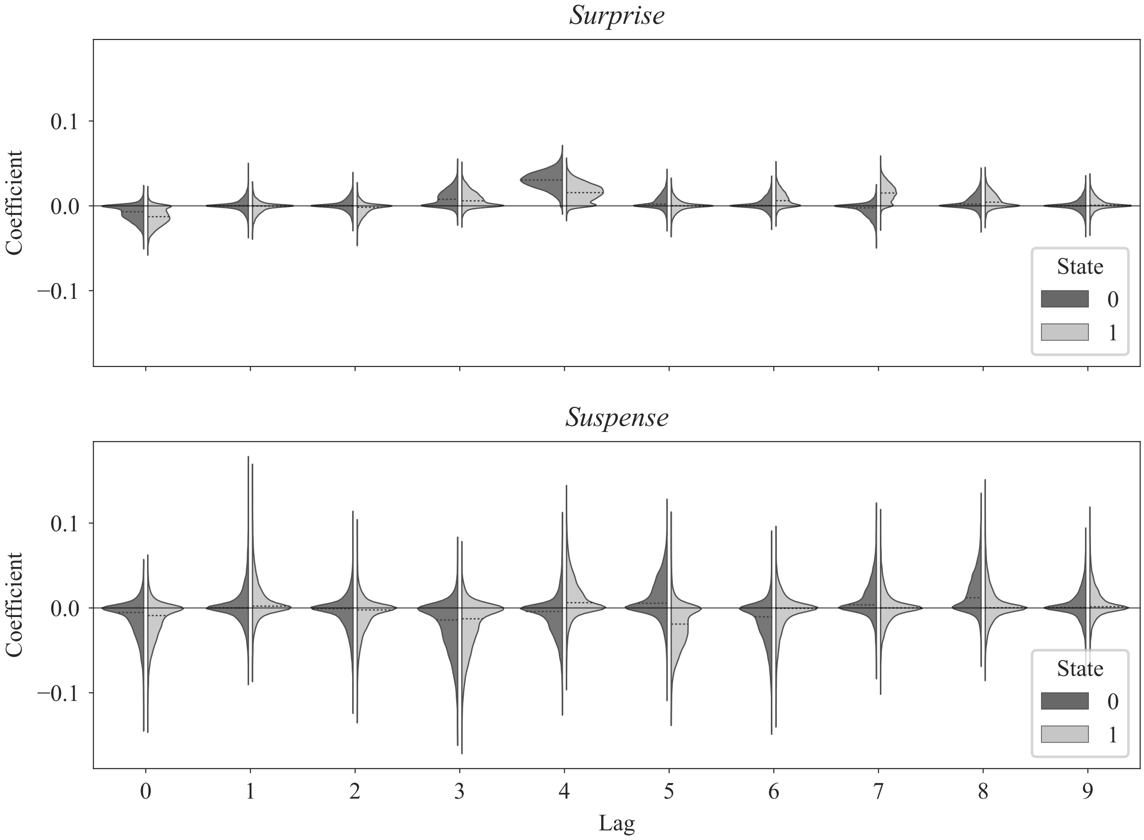
(Equivalent description as for figure 3, but for the shock specification).

Figure C6. Die-Hard Fans Posterior Distributions of Coefficients for *Surprise* and *Suspense*



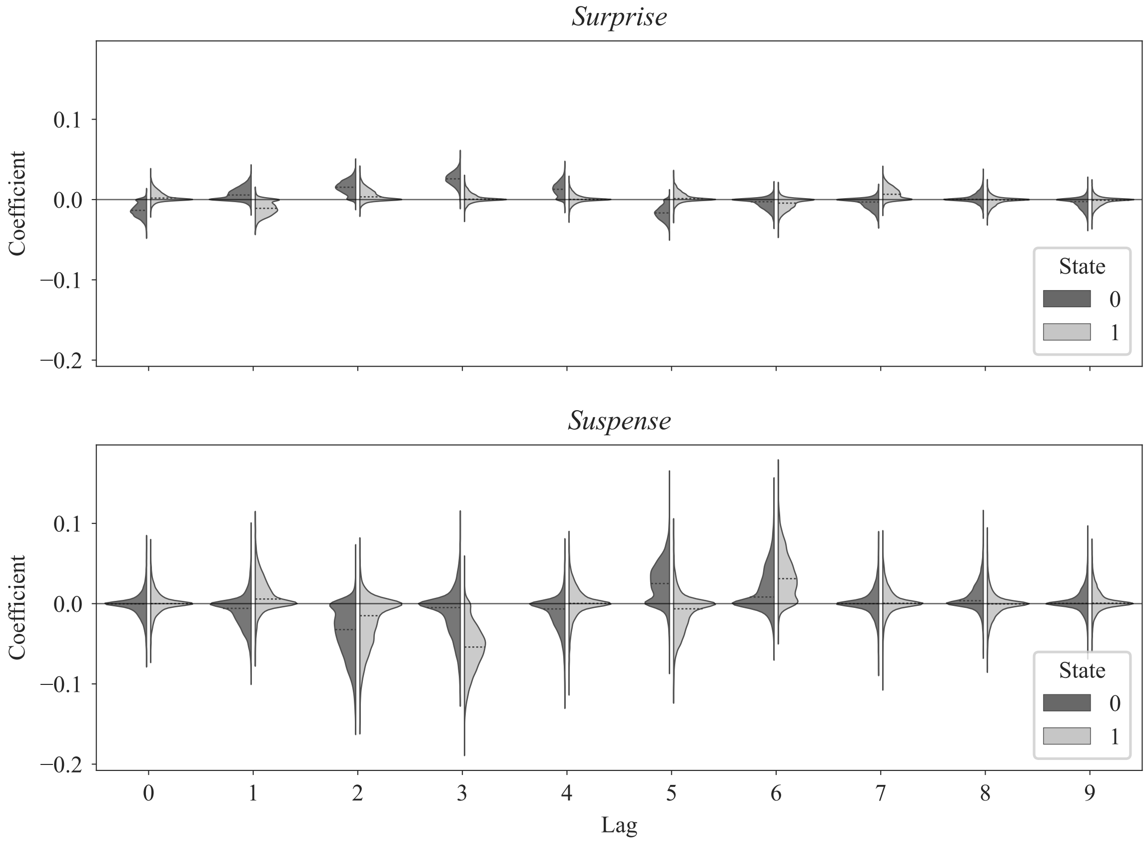
(Equivalent description as for figure 3, but for the die-hard fans specification).

Figure C7. Shandy Posterior Distributions of Coefficients for *Surprise* and *Suspense*



(Equivalent description as for figure 3, but for the shandy specification).

FIGURE C8. SOFT DRINKS POSTERIOR DISTRIBUTIONS OF COEFFICIENTS FOR *SURPRISE* AND *SUSPENSE*



(Equivalent description as for figure 3, but for the soft drinks specification).

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