

Belief dynamics in sport:
Exploring economic and behavioral
consequences of suspense, surprise, and
expectation violations

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Abbreviations

CB	Competitive Balance
EPL	English Premier League
GPS	Global Positioning System
NBA	National Basketball Association
NFL	National Football League
PPML	Pseudo-Poisson Maximum Likelihood
TMC	Traffic Message Channel
UCL	UEFA Champions League
UEFA	Union of European Football Associations
UOH	Uncertainty of Outcome Hypothesis

1 Introduction

This dissertation focuses on the role of belief dynamics, namely suspense, surprise, and expectation violations, in shaping the economic and behavioral consequences of sports. This introductory chapter presents the problem statement (Section 1.1), introduces belief dynamics as the conceptual entry point of the dissertation (Section 1.2), describes the three levels at which belief dynamics generate consequences (Section 1.3), and provides an overview of the dissertation's structure (Section 1.4).

1.1 Problem statement

Sport has long been recognized as an entertainment product, and the question of what makes a sporting contest compelling to spectators has attracted sustained attention in economics, behavioral science, and sports management. A central premise underlying much of this literature is that outcome uncertainty enhances the entertainment value of a contest and thereby drives demand. This premise, known as the uncertainty of outcome hypothesis (UOH) and originating in the foundational contributions of Rottenberg (1956) and Neale (1964), has carried substantial institutional weight: it serves as the primary justification for regulatory interventions in professional sports leagues, including revenue sharing, salary caps, and draft systems, which would be prohibited in most industries outside of sport (Budzinski, 2012; Fort & Quirk, 1995). Yet despite decades of empirical investigation, the evidence in support of this relationship remains strikingly inconsistent, particularly in the context of European football (Borland & MacDonald, 2003; Collins & Humphreys, 2022; Johnson & Fort, 2022; Pawlowski & Nalbantis, 2019).

This dissertation builds on a specific diagnosis of that inconsistency. Traditional outcome uncertainty measures are static: they reliably capture pre-match conditions but tell us little about what actually happens during a game and how spectators experience it moment by moment. More fundamentally, such measures bundle together two conceptually distinct mechanisms of entertainment utility that respond to uncertainty in opposite ways. The anxious excitement generated by a genuinely uncertain contest and the emotional jolt produced when an outcome departs from expectations are different experiences, aris-

ing at different moments during a match. A single pre-match uncertainty variable cannot distinguish between them, and a literature built on such variables should perhaps not be expected to produce consistent results.

At the same time, it is clear that sporting contests do generate powerful emotional and behavioral responses. Fans adjust their television viewing in real time as goals are scored and outcomes shift. Leagues structured around a small number of dominant clubs raise questions about whether competition attractiveness may be changing over time. And emotionally intense games leave traces that extend well beyond the final whistle, shaping behavior in contexts far removed from the stadium. These phenomena suggest that the mechanisms linking sporting uncertainty to economic and behavioral outcomes are more complex, and more consequential, than traditional approaches have captured.

This dissertation therefore adopts a different conceptual entry point: *belief dynamics*, the processes through which spectators form, update, and react to beliefs about contest outcomes as events unfold. Across three empirical studies, it examines how belief dynamics in sport, through suspense, surprise, and expectation violations, shape the entertainment value of sporting contests, influence consumer demand, and spill over into behavior beyond the sport and stadium.

1.2 Belief dynamics as the conceptual entry point

Why should the mere movement of beliefs generate utility at all? The preference to anticipate and understand future events is considered a fundamental motivator of human behavior, deeply rooted in the adaptive value of advance information (Bromberg-Martin & Hikosaka, 2009). Yet in the domains of music, film, literature, and sport, where information carries no instrumental value, consumers behave differently: they actively seek out experiences whose outcomes they do not know, and they appear to derive utility right from the resolution of that uncertainty (Gold et al., 2019). Sports represents perhaps the purest setting of this voluntary consumption of uncertainty: contests are genuinely unresolved, outcomes are produced in real time, and millions of people pay, in money, time, and attention, to watch uncertainty unfold. The conceptual foundations at the core of this dissertation formalizes exactly this phenomenon.

The theoretical foundation of this dissertation is the framework of Ely, Frankel, and Kamenica (2015), who formalize the entertainment utility consumers derive from non-instrumental information and, crucially, separate it into two dimensions that respond to uncertainty in opposite directions. Suspense is forward-looking — the anxious anticipation of what an unresolved contest may yield — and it rises with uncertainty; surprise is backward-looking — the jolt of a sharp revision in beliefs — and it requires a departure from what was expected. A contest can be suspenseful without ever being surprising, and surprising without ever having been suspenseful, which is precisely why the single pre-match uncertainty measure discussed in Section 1.1 cannot capture either. Chapter 2 develops these constructs formally; what matters here is that they supply the two distinct mechanisms whose conflation, as argued in Study 2, lies behind the inconsistent empirical record of the UOH.

A third construct, introduced by Buraimo, Forrest, McHale, and Tena (2020), *shock* — the deviation of current outcome probabilities from those held before the match began — is tested alongside these in Study 1 but proves marginal and is not carried forward; the evidence of this dissertation points to the moment-to-moment movement of beliefs, rather than the cumulative drift from a match’s pre-match script, as what drives engagement. What makes these constructs more than abstractions is that they can be measured: by approximating spectators’ beliefs with the outcome probabilities implied by betting markets, belief dynamics become observable at the minute level. A growing literature has exploited this across sports and media settings, reviewed in Chapter 2; the empirical studies here follow the operationalization of Buraimo et al. (2020).

Belief dynamics connect naturally to a second body of behavioral theory, and it is here that the framework matures as the dissertation moves outward. In the reference-dependent preferences of Kőszegi and Rabin (2006), expectations form the reference point against which a realized outcome is judged, so that deviations from it register as gains or losses in utility. The two frameworks are complementary stages of one process: Ely, Frankel, and Kamenica (2015) describe the utility generated while beliefs are still moving, as suspense anticipates and surprise revises, while Kőszegi and Rabin (2006) describe the utility consequences of where those beliefs finally resolve relative to where they began. A contest that sustains high suspense and then ends in disappointment combines the two:

prolonged arousal followed by a painful violation of what was expected. This anticipation–revision–resolution arc is the connective logic of the dissertation. The same belief dynamics that drive demand within a contest (Studies 1 and 2) can, once resolved against expectation, carry consequences beyond it (Study 3). Because the dynamic that matters at this third level is the gap between the expected and the realized outcome rather than its minute-by-minute path, Study 3 measures it accordingly, proxying pre-game expectation with the betting spread — a deliberate adaptation of the framework to the level at which it operates, not a departure from it.

1.3 The three levels of consequence

The three empirical studies that form the core of this dissertation demonstrate that belief dynamics in sport generate consequences at three distinct levels.

Level 1 — within the live event (Study 1). Belief dynamics unfold minute by minute during a match. Suspense builds as outcome uncertainty intensifies, and surprise spikes when goals shift the probabilities. These in-game belief dynamics directly shape consumer behavior, driving real-time TV audience size across two different markets. The consequence is immediate and measurable: viewers respond to what is happening on the pitch as it happens.

Level 2 — at the competition and policy level (Study 2). Belief dynamics accumulate across matches and seasons. Suspense and surprise, aggregated to the match level, capture how much entertainment value a competition actually delivers and whether that value is declining, stable, or growing over time. This reframes suspense and surprise not just as drivers of individual behavior but as diagnostic tools for league organizers and policymakers. The consequence is economic and structural: how attractive competitions are, and whether intervention is warranted.

Level 3 — beyond the sporting event (Study 3). Belief dynamics ultimately resolve through the realization of an outcome. As uncertainty resolves and expectations are either confirmed or violated, the emotional consequences of sport can extend beyond the event itself. This shifts the focus from the entertainment value generated within competitions

to the broader behavioral effects that sporting contests may produce in everyday life. The consequence at this level is societal: belief dynamics generated by sport have the potential to shape behavior outside the stadium and beyond the sporting context.

The dissertation moves from the most micro level (a single minute of a single match) through the structural level (14 seasons across five leagues) to the most macro and socially consequential level (risky driving behavior in the real world).

1.4 Structure of the dissertation

Chapter 2 develops the conceptual foundation that is the basis of all three studies. It moves from the uncertainty of outcome hypothesis through to the belief dynamics framework, reviews the empirical evidence on suspense and surprise in sports demand, and establishes the three research gaps that motivate the empirical studies. Chapter 3 translates those gaps into research objectives and introduces the three studies as a logical progression, explaining how each builds on and extends the preceding one. Chapter 4 presents the three empirical studies, each reproduced in the form in which it is published or currently under review. Chapter 5 synthesizes the findings across all three studies thematically, derives the cumulative theoretical contribution, discusses practical implications, and acknowledges limitations. Chapter 6 closes the dissertation, restates its core contribution, and points toward future research directions.

2 Conceptual Foundation and Literature Review

This chapter develops the conceptual foundation that is the basis of the dissertation and reviews the literature it builds on. It begins with the traditional economics of outcome uncertainty and works toward the belief dynamics framework used in the empirical studies, then identifies the research gaps that motivate them. Section 2.1 introduces competitive balance (CB), the uncertainty of outcome hypothesis (UOH), and the demand for sport, and explains why the empirical record on outcome uncertainty has remained inconsistent. Section 2.2 presents the belief dynamics framework and its core constructs of suspense and surprise. Section 2.3 reviews the empirical evidence applying this framework to sports demand. Section 2.4 turns to the measurement of competitive balance at the league level and its relevance for policy. Section 2.5 introduces reference-dependent emotions and the literature on behavioral spillovers from sporting events into real-world behavior. Section 2.6 synthesizes the review into the three research gaps that the empirical studies address.

2.1 The demand for sport

The economic study of spectator demand for sport begins with the seminal contributions of Rottenberg (1956) and Neale (1964). Their central insight is that sporting competitions are economically peculiar: teams are not ordinary competitors as they would be in regular business market competition, but mutually dependent producers of a joint product, the contest itself, which no single team can supply alone (Neale, 1964). Because the value of that product depends on its result being in doubt, a team cannot maximize its welfare by becoming overly dominant. As Rottenberg (1956) argued, fan interest is greatest when the differences in quality among teams is not too drastic. This reasoning gives rise to the uncertainty of outcome hypothesis, which states that demand for a sporting contest increases with the unpredictability of its result.

Competitive balance and outcome uncertainty are closely related but still quite distinct concepts. Competitive balance refers to the relative strengths of the teams in a competition, and is commonly understood along three dimensions: the uncertainty of individual

game outcomes (short-term balance), the closeness of in-season sub-competitions such as the championship or relegation race (mid-term balance), and the degree to which a small number of teams dominate over many seasons (long-term balance) (Szymanski, 2003). Outcome uncertainty is the manifestation of the short-term dimension: the unpredictability of a single result. The UOH, in its most studied form, concerns the relationship between this match-level outcome uncertainty and demand (Fort, 2022; Pawlowski, Nalbantis, & Coates, 2018).

The significance of the UOH is not limited to explaining spectator demand. Assumptions about the benefits of competitive contests have also informed the institutional design of professional sport and have been invoked to justify forms of coordination that would be unusual in conventional product markets (Budzinski, 2012; Fort & Quirk, 1995). Consequently, uncertainty has become not only an empirical object of study but also an implicit policy objective. As developed further in Study 2, presented in Section 4.2, this makes the choice of how competition attractiveness is measured especially consequential.

Given this importance, the hypothesis has been tested extensively. Early studies examined stadium attendance (Cairns, Jennett, & Sloane, 1986; Jennett, 1984), while the growth of broadcasting shifted attention toward television audiences, which offer larger samples and more fine-grained measurement of demand (Buraimo & Simmons, 2008, 2009; Forrest, Simmons, & Buraimo, 2005). Yet, despite decades of research and investigation, the overall empirical record is remarkably inconsistent. Some studies find support for the UOH, others find no effect, and then some others find that fans prefer a higher probability of a home win to genuine uncertainty (Buraimo & Simmons, 2015; Humphreys & Perez, 2019). Reviews of this phenomena have repeatedly concluded that the evidence is mixed at best, especially in European football (Collins & Humphreys, 2022; Johnson & Fort, 2022; Pawlowski & Nalbantis, 2019). If outcome uncertainty does not reliably drive demand, then monitoring it over time and treating it as a policy target appears misguided.

Why has a hypothesis so central to sports economics proved so difficult to confirm? Part of the answer, as the literature has noted, is that the relationship is moderated by context, varying with the stage of the season and the type of competition at stake (Forrest et al., 2005). But a more basic limitation, and the one this dissertation builds on, lies in the

measures themselves. Traditional outcome uncertainty measures are static: computed from pre-match win probabilities, they capture only the expected closeness of a contest before it begins, not how uncertainty actually evolves as the match is played. They are also one-dimensional, collapsing two distinct sources of entertainment utility, that respond to uncertainty in opposite ways, into one single quantity. The tension experienced while a result remains in doubt and the reaction provoked when a result departs from expectations are different responses, and a measure that combines them into one cannot separate their effects. This perspective suggests that the mixed support for the UOH may reflect not the absence of a relationship between uncertainty and demand, but the use of measures too coarse to detect mechanisms that pull in different directions (Pawlowski et al., 2018). The framework introduced in the next section is designed to draw exactly this distinction.

2.2 Belief dynamics and entertainment utility

As noted in Chapter 1, the preference to anticipate and understand future events is a fundamental human motivator, rooted in the survival value of advance information (Bromberg-Martin & Hikosaka, 2009). In areas such as music, literature, film, and sport, however, where information carries no instrumental value, consumers behave differently: they appear to prefer disruptions to their expectations (Gold et al., 2019). In their seminal work, Ely et al. (2015) formalize the entertainment utility derived from such non-instrumental information, distinguishing two dimensions: suspense and surprise.

Suspense is an ex-ante emotion, the feeling of anxious uncertainty experienced when the consumer or viewer looks forward to what might happen next. It is greatest when upcoming events carry decisive significance for the final outcome, and it is most aptly described as the juxtaposition of hope and fear (Madrigal, Bee, & Chen, 2022). Surprise, by contrast, is an ex-post emotion. Following Ely et al. (2015), a period is more surprising the further the current belief lies from the belief held in the previous moment, that is, the larger the change or revision in the spectator's expectations from one moment to the next. The two constructs are therefore quite distinct: suspense concerns the anticipation of events still to come, while surprise concerns the magnitude of belief revision once events have occurred. Recent neuroimaging evidence supports this separation,

showing that suspense and surprise produce independent effects on viewers' prefrontal brain activity during sports media consumption, with no apparent interaction between the two (Richardson et al., 2026). A growing body of psychological and neuroscientific work has examined the affective and cognitive foundation of these emotions in greater depth (Antony et al., 2021; Li, Bramley, & Gureckis, 2021; Madrigal, Bee, & Chen, 2023).

A central appeal of the framework is that these abstract constructs can be measured. Buraimo et al. (2020) operationalize suspense and surprise for football using in-play outcome probabilities, and introduce a third construct, shock, defined as the deviation of current outcome probabilities from those held before the match began. Whereas the reference point for surprise is the expectation held in the previous minute, the reference point for shock is the pre-match expectation.¹ Outcome probabilities are derived from a Poisson goal-scoring model calibrated to bookmaker odds (Maher, 1982), with red cards incorporated by adjusting the affected team's scoring rate (Vecer, Kopriva, & Ichiba, 2009). This approach converts the movement of beliefs over the course of a match into observable, minute-level quantities, and provides the measurement foundation on which the empirical studies of this dissertation build. Since Ely et al. (2015), the framework has been taken up across entertainment and sports settings as a more behaviorally grounded account of demand than the static outcome-uncertainty measures it improves upon, with the supporting evidence reviewed in Section 2.3. While this framework concerns the utility generated by the movement of beliefs during a contest, a distinct strand of behavioral theory concerns how the final outcome is evaluated against prior expectations, a question we return to in Section 2.5.

2.3 Empirical evidence on suspense and surprise

Empirical applications of the framework emerged relatively slowly despite its obvious relevance to several stakeholders in professional sport. Early work, therefore, focused on establishing whether audiences respond measurably to suspense and surprise before

¹The two therefore need not move together: a late goal that merely restores the widely expected favorite to a winning position generates surprise relative to the preceding minute but little shock relative to pre-match beliefs.

attention expanded to the conditions under which the relative importance of the emotional cues varies. The first application of the framework to sport was Bizzozero, Flepp, and Franck (2016), who used minute-by-minute television audience data from men's tennis matches at Wimbledon. They find that both suspense and surprise drive viewership, though surprise tends to matter more than suspense. Buraimo et al. (2020) reach a similar conclusion for English Premier League (EPL) football, with both constructs again significant, but report a proportionally smaller combined effect than in tennis.

Subsequent applications reveal that the relative importance of the two constructs varies across settings. Simonov, Ursu, and Zheng (2023) study streaming audiences for the eSports title Counter-Strike: Global Offensive and find that suspense is a significant driver of viewership while surprise has little to no effect. Kaplan (2021) reports a comparable pattern for the National Basketball Association, where heightened suspense raises viewership but surprise plays a more limited role. This heterogeneity, with surprise dominating in some settings and suspense in others, suggests that the balance between the two emotions depends on the structure of the sport and the nature of its audience, a question to which the cross-market comparison in Study 1 returns directly.

Beyond television and streaming demand, the framework has been extended to other measures of consumer response. Related work links suspense and surprise to advertising and sponsorship processing during broadcasts (Bee & Madrigal, 2012; Breuer, Rumpf, & Boronczyk, 2020) and to the broader entertainment gratifications that viewers derive from watching sport (Hall, 2015; Pawlowski, Rambaccussing, Ramirez, Reade, & Rossi, 2024). Together, this body of evidence establishes suspense and surprise as robust drivers of sport consumption, while leaving open how they operate in a supranational competition and how they compare across distinct national markets, the gaps addressed in Study 1.

2.4 Competitive balance measurement and league-level policy

Sections 2.2 and 2.3 concerned the short-term, match-level dimension of competitive balance and its link to demand. This section turns to the long-term dimension introduced in Section 2.1, namely the distribution of success across teams and seasons, and to how it has been measured and used as a target for policy.

Long-term CB has traditionally been measured from final standings, using the spread of wins, points, or championship titles across the teams in a league (Depken, 1999; Lee & Fort, 2012; Pawlowski, Breuer, & Hovemann, 2010).² These measures have been widely used to track CB over time and across leagues, and to assess whether interventions such as revenue sharing or financial regulation have made competitions more or less even (Avila-Cano & Triguero-Ruiz, 2023; Basini, Tsouli, Ntzoufras, & Friel, 2023; Poli, Ravenel, & Besson, 2018). More recent work has applied them specifically to European football and to the UEFA Champions League, in several cases finding little evidence of the decline in balance that is often assumed (Csató & Petróczy, 2025).

What these measures share is a top-down logic: they treat balance as a property of the season's results as a whole, rather than of the individual matches that produced them. This has two limitations as a guide for policy. First, such measures are only loosely connected to what fans actually value, since the distribution of points across a table does not necessarily reflect how much entertainment the underlying matches delivered. Second, because they aggregate from the top down, they are difficult to decompose: a single league-level index reveals little about which clubs or which kinds of matches drive an observed trend.

An alternative is to build the picture from the bottom up, beginning with the entertainment utility generated within individual matches and aggregating upward to the club, league, and season level (Basini et al., 2023). Match-level suspense and surprise are well suited for this purpose. They are grounded in the relative strengths of the teams, they are directly linked to demand, and because they are computed per match they can be averaged at any level of aggregation, allowing the sources of a trend to be located rather than merely overall observed. This bottom-up, demand-grounded approach to CB is developed in Study 2, which derives a normative benchmark for suspense and surprise and uses it to assess the level and evolution of competition attractiveness across Europe's top five leagues. The relevance of such monitoring for league design and regulation connects to a broader operational-research literature on the design of sporting contests (Budzinski,

²The most widely used such measure is the Herfindahl-Hirschman index, originally developed to gauge market concentration in industrial economics and adapted to sport by applying it to the distribution of wins or championship titles (Owen, Ryan, & Weatherston, 2007).

2012; Devriesere, Csató, & Goossens, 2025; Scarf, Parma, & McHale, 2019; Scarf, Yusof, & Bilbao, 2009; Szymanski, 2003).

2.5 Expectation violations and behavioral spillovers

The framework of Section 2.2 concerns the utility a spectator derives from the movement of beliefs while an event is unresolved. A separate branch of behavioral economics concerns itself with how the resolved outcome is evaluated, and it provides the foundation for the third level of this dissertation. A central insight is that outcomes are judged not in absolute terms but relative to the expectations. Prospect theory established that people evaluate gains and losses against a reference point, and that losses loom larger than equivalent gains (Kahneman & Tversky, 1979). Kőszegi and Rabin (2006) formalized this idea with an expectations-based reference point, in which the reference is determined by what someone would rationally expect to happen. When a realized outcome falls short of that expectation, the result is experienced as a loss and can provoke disappointment, frustration, or anger; when it exceeds expectations, the result is experienced as a gain and could lead to happiness or elation. Applied to sport, this framework implies that a fan's emotional response to a result depends not only on whether their team won or lost, but on how that result compares to what they rationally expected beforehand (Coates, Humphreys, & Zhou, 2014).

This expectation based behavior matters because the emotions generated by a sporting outcome do not necessarily remain confined to the context of the game. A substantial body of evidence documents emotional spillovers from sport into domains unrelated to the contest itself. Unexpected outcomes have been linked to movements in national stock returns (Edmans, García, & Norli, 2007), to harsher juvenile sentencing by judges whose local college team suffered an upset loss (Eren & Mocan, 2018), and to reduced voter turnout following emotionally engaging broadcasts (Potoski & Urbatsch, 2017). Most relevant to the present work, Card and Dahl (2011) show that unexpected losses by a local NFL team produce significant increases in family violence, an effect concentrated precisely in games the home team was expected to win, and Cardazzi, McCannon, Humphreys, and Rodriguez (2024) document a comparable pattern following unexpected NBA losses.

These studies establish that the disappointment generated by an expectation-violating event can translate into consequential real-world behavior, and that the effect is driven by the violation of what was expected rather than by the loss alone.

A parallel literature establishes why driving is particularly sensitive to emotional states. A driver's emotional condition bears directly on road safety: performance is best at moderate levels of arousal and worsens at the extremes (Braun, Weber, & Alt, 2021; Yerkes & Dodson, 1908).³ Among negative emotional states, anger appears particularly relevant because experimental and observational studies associate it with more aggressive vehicle operation and poorer responses to hazards (Deffenbacher, Deffenbacher, Lynch, & Richards, 2003; Mesken, Hagenzieker, Rothengatter, & De Waard, 2007; Roidl, Frehse, & Höger, 2014; Steinhauser et al., 2018). The scale of the effect can be large: Dingus et al. (2016) find that emotionally aroused drivers are nearly ten times more likely to be involved in a crash than those in a neutral state.

Despite this, large-scale field evidence on how emotional cues from sporting events affect driving remains scarce, and the little that exists is concentrated on aggregate outcomes. Redelmeier and Stewart (2003) documented a sharp rise in traffic fatalities following the Super Bowl, and Jakar, Gordon, and He (2023) found elevated crash counts around professional sporting venues, particularly after heavily attended games. Existing field evidence also leaves an important asymmetry unresolved. Wood, McInnes, and Norton (2011) associate closely contested games with subsequent fatalities around the winning team's location, providing evidence that highly activating sporting experiences may carry over into traffic behavior. Their design, however, cannot establish whether a different post-game emotional state—disappointment following a narrowly lost contest—produces a comparable response among losing supporters. Nor do event-level fatality counts reveal when or where any behavioral adjustment occurs. Study 3 addresses this limitation using road-segment speed observations that vary at much finer temporal and spatial resolutions.

³Consistent with this, in a naturalistic study of taxi drivers, negative emotional states such as anger and sadness were found to significantly increase driving speed in real traffic, whereas happy and relaxed states showed no such effect (Kadoya, Watanapongvanich, & Khan, 2021).

2.6 Summary and research gaps

The literature reviewed in this chapter establishes a clear progression. Traditional measures of outcome uncertainty have struggled to explain the demand for sport, and the belief dynamics framework of Ely et al. (2015) offers a more precise account by separating the forward-looking experience of suspense from the backward-looking experience of surprise. A growing body of evidence confirms that these constructs drive within-match demand across a range of settings, and a parallel literature shows that the emotions generated by sporting outcomes, particularly when those outcomes violate expectations, can spill over into behavior far removed from the game itself. Taken together, this work establishes suspense, surprise, and expectation violations as empirically consequential. Yet three issues central to this dissertation remain unaddressed.

Gap 1. The belief dynamics framework has been applied to several sports and broadcasting settings, but always to a single competition watched by a single national audience. No study has examined a setting where the same matches are followed simultaneously by distinct national markets, which is what a direct comparison of suspense and surprise effects across audiences requires. It therefore remains unknown whether these effects hold in a supranational competition and whether their magnitude is stable or varies with market context.

Gap 2. Suspense and surprise have been studied as drivers of demand within individual matches, but not as tools for evaluating the attractiveness of a competition over time. Doing so requires a reference point, some sense of what level of suspense and surprise a balanced competition should be expected to deliver, against which observed values can be judged. No such benchmark has been established, and no study has tracked suspense and surprise systematically across leagues, clubs, and seasons to assess whether competition attractiveness is declining, stable, or improving.

Gap 3. A substantial literature documents emotional spillovers from sport into real-world behavior, but it has relied almost entirely on aggregate, event-level outcomes such as crime reports and traffic fatalities. No study has used fine-grained behavioral data to examine whether the specific combination of sustained suspense and a disappointing outcome

leaves a spatially and temporally precise imprint on behavior beyond the stadium. The mechanism connecting belief dynamics to real-world risk therefore remains unobserved at the resolution needed to identify it.

These three gaps motivate the research objectives developed in the next chapter, which sets out how each is addressed by the empirical studies of this dissertation.

3 Research Objectives

This chapter describes the objectives and empirical approaches of the three studies that make up this dissertation, each of which is presented in full in Chapter 4. The studies address the research gaps identified in Section 2.6, moving from the within-match drivers of demand, through the use of belief dynamics as a competition-level diagnostic, to their behavioral consequences beyond the stadium. Together they aim to establish suspense, surprise, and expectation violations as empirically consequential forces in the economics of sport. What follows is a brief discussion of the objective pursued by each study.

Study 1: Richardson, T., Nalbantis, G., & Pawlowski, T. (2023). Emotional cues and the demand for televised sports: Evidence from the UEFA Champions League. *Journal of Sports Economics*, 24(8), 993–1025. <https://doi.org/10.1177/15270025231187067>

Study 1, presented in Section 4.1, focuses on the within-match drivers of television demand. Its main objective is to examine whether suspense and surprise, as formally defined by Ely et al. (2015), along with a third emotional cue, shock (Buraimo et al., 2020), drive minute-by-minute viewership of UEFA Champions League matches, and to test whether these effects differ across two distinct national markets. The study draws on minute-by-minute television audience data for matches broadcast in the United Kingdom and Spain,⁴ combined with detailed event data and pre-match betting odds. From the odds, match-specific scoring rates are estimated and used in a Poisson model of goal scoring, which is simulated 100,000 times per minute to generate the evolving outcome probabilities from which suspense, surprise, and shock are constructed. Their effects on minute-by-minute, within-match television demand are then estimated using Pseudo-Poisson Maximum Likelihood (PPML) with match fixed effects. In doing so, the study aims to extend the belief dynamics framework to a supranational competition for the first time, and to deliver the first direct comparison of how these effects operate across separate viewer markets. Study 1 thus establishes the empirical foundation on which the remainder of the dissertation builds.

⁴The minute-by-minute audience data were kindly provided by the Union of European Football Associations (UEFA).

Study 2: Flepp, R., Pawlowski, T., & Richardson, T. (2026). Suspense and surprise in European football. *European Journal of Operational Research*. <https://doi.org/10.1016/j.ejor.2026.07.017>

Study 2, presented in Section 4.2, takes the same constructs that Study 1 validates as drivers of within-match demand and shifts the focus from the individual match to the attractiveness of competitions over time. Its main objective is to develop match-level suspense and surprise as diagnostic tools for league organizers and policymakers, and to assess how the entertainment value of Europe’s top five leagues has evolved. The study draws on more than 25,000 men’s matches across the English, Spanish, German, Italian, and French first divisions over fourteen seasons, from which match-level suspense and surprise are computed using betting odds and an in-play model of scoring. To give these measures meaning, the study derives a normative benchmark through large-scale simulation of otherwise-balanced matches that retain a realistic home advantage, establishing the level of suspense and surprise that a genuinely competitive match would be expected to produce, against which observed values can be judged. It then analyzes the level and trend of these measures across leagues, clubs, and seasons. In doing so, the study aims to show that belief dynamics, aggregated from the bottom up, offer a more demand-grounded account of CB than traditional measures computed from final standings, and to determine whether intervention in any of these competitions is warranted.

Study 3: Richardson, T., Bickley, S., Chan, H. F., Torgler, B., Yasmin, S., & Pawlowski, T. (2026). Emotional driving: Reference-dependent emotions and risky driving behavior after sporting events. *Working paper*.

Study 3, presented in Section 4.3, extends the dissertation beyond the sporting event itself, to the resolution stage of the belief-dynamics arc, asking whether the emotions generated when an outcome is finally realized spill over into real-world behavior. Its main objective is to test whether game results that depart from pre-game expectations, that is, expectation violations, leave a measurable imprint on post-game driving around stadiums. The study draws on GPS-based vehicle speed data, aggregated to the Traffic Message Channel (TMC) road-segment level in ten-minute intervals, for road segments within five kilometers of five Florida stadiums, combined with statewide crash records

and pre-game betting spreads for the home teams' NFL and NBA games. As set out in Section 1.2, the belief dynamic that matters at this level is the gap between the expected and the realized outcome, and the betting spread serves as the proxy for pre-game expectation: a predicted-close game corresponds to high anticipated suspense, so that a narrow, disappointing loss combines sustained suspense with a negative resolution. By interacting the expectation category implied by the spread with the actual outcome, and comparing game-day speeds against matched non-game-day observations, the study isolates the behavioral effect of each expectation-outcome profile, under the identifying assumption, following Card and Dahl (2011), that the result of a game is as good as random once the pre-game spread is known. In doing so, the study aims to provide the first fine-grained behavioral evidence that the belief dynamics of sport can shape behavior beyond the stadium, with direct implications for road safety and event management.

Finally, beyond the objectives of the individual studies, the dissertation draws their findings together to derive the broader theoretical and practical implications of belief dynamics in sport for sports demand research, league governance, and public safety policy. This integrative aim is taken up in the discussion of Chapter 5.

4 Empirical Studies

This chapter contains the three empirical studies conducted within the scope of this dissertation. Each study follows the style guidelines of the journal in which it is published or currently under review, including paper structure, citation style, and wording, and is reproduced here in that form. Studies 1 and 2 are published in the *Journal of Sports Economics* and the *European Journal of Operational Research*, respectively. Study 3 is a working paper currently under review.⁵ Each study includes an introduction followed by sections on the data, variables, and empirical strategy, the results, and a discussion, and each closes with a reference list and an appendix containing further information on the data and additional results such as robustness checks.

⁵At the time of submission of this dissertation, Study 3 has been submitted to a journal and is available on arXiv at <https://arxiv.org/abs/2606.18805> (DOI: 10.48550/arXiv.2606.18805).

4.1 Study 1: Emotional Cues and the Demand for Televised Sports: Evidence from the UEFA Champions League

Richardson, T., Nalbantis, G., & Pawlowski, T. (2023). Emotional cues and the demand for televised sports: Evidence from the UEFA Champions League. *Journal of Sports Economics*, 24(8), 993–1025. <https://doi.org/10.1177/15270025231187067>

Emotional Cues and the Demand for Televised Sports: Evidence from the UEFA Champions League

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Abstract

This study provides first evidence on how belief dynamics are driving entertainment utility and consequently the demand for sports *across* markets by analyzing minute-by-minute audience data of UEFA Champions League (UCL) games televised in the UK and the Spanish market during a full (pre-COVID) cycle of broadcasting rights. Overall, we find that *suspense* and *surprise* are the main drivers of demand in both markets while *shock* only has marginal effects in the Spanish market. Interestingly, we find a combined impact of *suspense* and *surprise* in the UK market that is of similar magnitude as reported in a previous study for English Premier League matches in the UK. In the Spanish market, however, the combined impact is considerably larger.

Keywords

suspense, surprise, shock, emotional cue, TV demand, UEFA Champions League

JEL Classification Codes: C23, D12, L82, L83, Z20

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Introduction

The preference to understand and be aware of future events is seen as an influential motivator for survival (Bromberg-Martin & Hikosaka, 2009). Yet, in the realm of music, film, books, and sports, where information is non-vital, consumers seem to prefer disruptions to their expectations (Gold et al., 2019). In their seminal work, Ely et al. (2015) developed a comprehensive theoretical model on the demand for such non-instrumental information by focusing on entertainment utility from *suspense* and *surprise*.

Suspense is an ex-ante emotion; it is the feeling of anxious uncertainty and is experienced when the consumer is forward looking as to what could happen next. As such, *suspense* is greater when the upcoming events have a greater significance on the overall outcome. *Suspense* is most appropriately described as the juxtaposition of hope and fear (Madrigal et al., 2022). For instance, *suspense* can be experienced during the moments leading up to a penalty kick that would win the match, i.e., the hope to see a game-winning goal and the fear of a miss.¹ This is in distinction to *surprise*, which is an ex-post emotion that is present when an event occurs suddenly or unexpectedly and causes a shift in what the consumer previously thought the outcome would be. Ely et al. (2015) define a period to be more surprising when the current belief is further from the last period's belief, i.e., if the current events are vastly different from the previous events, the period is more surprising. For instance, *surprise* can be generated in a soccer match when a team opens the score against all odds.

Quite recently, Buraimo et al. (2020) have introduced a further entertainment utility factor: *shock*. *Shock* is similar to *surprise*. However, while the reference point for *surprise* is the (average) expectation over the outcome in the *minute before*, the reference point for *shock* is the (average) expectation over the outcome prior to *kick-off*. As such, *shock* is experienced when the current outcome probabilities are drastically different from those considered *prior* to the start of the match; For instance, when a heavily favored team is facing a high probability of losing to the pre-match underdog.

Despite the managerial relevance for broadcasters, sponsors, leagues, and clubs, empirical evidence on whether entertainment seeking sport consumers prefer *suspense*, *surprise* and/or *shock* elements in sports competitions is sparse. In a first application of these concepts to sports, Bizzozero et al. (2016) utilized minute-by-minute television audience data from international men's tennis matches played in Wimbledon (UK) broadcast in Switzerland on free-to-air networks. Overall, they find that both *surprise* and *suspense* are important drivers of demand. *Surprise*, however, tends to be more important than *suspense*. In a second application, Buraimo et al. (2020) modeled minute-by-minute television audience data from the English Premier League broadcast in UK on pay-TV networks. Similar to Bizzozero et al. (2016) they found that both *surprise* and *suspense* matter for viewership. However, in contrast to Bizzozero et al. (2016), the authors report a

proportionally smaller combined impact of both cues. Simonov et al. (2023) focus on eSports and analyze streaming viewers of the game Counter-Strike: Global Offensive (CS:GO). The authors find evidence that *suspense* is a significant indicator for viewership. On the contrary, however, *surprise* has little to no effect on streaming viewers' preference.² Similarly, Kaplan (2021), suggests that heightened *suspense* leads to a considerably higher viewership of a National Basketball Association (NBA) game; however, this is only found to have significant impact on viewership when the skill of the performers on the court is lower.

We contribute to this literature by implementing the seminal framework of Ely et al. (2015) in their construction and understanding of *suspense* and *surprise*. Following that framework, we replicate and extend its applications by Bizzozero et al. (2016) and Buraimo et al. (2020). Next to the growing consensus regarding the importance of replication studies in economics and business research (see Hamermesh, 2017; Krumer et al., 2022), we offer insights on a particularly relevant and surprisingly understudied supranational competition, i.e., the UEFA Champions League (UCL).³ Moreover, we explore two different markets at the same time, i.e., UK and Spain, and thus deliver some first evidence on the salience of emotional cues across markets. By analyzing minute-by-minute audience data of all UCL games televised in the UK and the Spanish market during a full (pre-COVID) cycle of broadcasting rights, we find that *suspense* and *surprise* are the main drivers of demand in both markets while *shock* only has marginal effects in the Spanish market. Interestingly, we find a combined impact of *suspense* and *surprise* in the UK market that is of similar magnitude as previously reported for English Premier League matches in the UK (see Buraimo et al., 2020). In the Spanish market, however, the combined impact is larger and closely resembles that reported for international tennis matches in Wimbledon (see Bizzozero et al., 2016).

Data and Measures

UEFA Champions League

We first begin with a brief description of our setting. The UCL, second only to the FIFA World Cup in worldwide football importance, is the most prestigious club football event in the world. Although the name might say otherwise, the UCL is not a league, rather, a pan-European tournament. This yearly, pre-eminent tournament was first held in the 1955–1956 season and has been played every year since. Its global audience, at about 1.7 billion viewers across all matches of a season, makes the UCL the second most viewed yearly sporting competition, only behind the Tour de France (Shazi, 2018). The Lisbon Final between Real Madrid and Atlético Madrid saw 380 million people tune from over 200 different countries around the globe (Ashby, 2014).

Since 1992, 32 teams qualify for the tournament and are drawn into eight groups of four. The number of qualifying teams varies by country/domestic league. For example, in England and Spain the teams finishing top four in their respective domestic leagues are allowed to join the tournament the following year. While smaller

countries, like Croatia or Cyprus, are only allotted one team in the qualification rounds of the tournament. Teams are divided into four pots based on their UEFA club coefficient ranking. Pot 1 consists of the highest-ranked teams, while Pot 4 consists of the lowest-ranked teams. The draw begins with Pot 1, with the eight teams drawn one at a time and placed into groups A to H. Once all teams in Pot 1 have been placed, the draw proceeds to Pot 2, and so on until all four pots have been emptied. Note that restrictions are placed to ensure clubs from the same nation are not drawn into the same group. The winners and runners-up from each of the eight groups then qualify for the round of 16 – which initiates the two-legged knock-out phases for the round of 16, quarter-finals, and semi-final. The final is a single match in a neutral, pre-selected location, with the winner ultimately becoming the UCL champion of the year. Between 1997/98 and 2017/18, the finals have only consisted of clubs from England, Spain, Germany, or Italy (with the exception of the season 2003/04 where AS Monaco [France] and FC Porto [Portugal] met in the Final).

Television Viewership

The viewership data was kindly provided by the Union of European Football Associations (UEFA) and contains a total of 296 (172) UCL games televised in the UK (Spanish) market during four seasons, i.e., from 2014/15 to 2017/18. During this period, Spain and the UK (specifically, England) were among the most relevant markets both with regard to the UEFA association club coefficients as well as to the overall distribution of the UCL's market pool money (see Table A1 in Appendix A). To purge the data from any inconsistencies that might have been caused by the shift of broadcasting rights between 2014/2015 and 2015/2016, we focus in our main estimations on seasons 2015/2016–2017/2018.⁴ This period corresponds to a full (pre-COVID) UCL broadcasting rights cycle, leaving us with a total of 180 (131) UCL games televised in the UK (Spanish) market.⁵

For both markets we use aggregate minute-by-minute viewership, due to instances of games being televised by two or more channels (e.g., on regional and national channels in Spain, see Table A3 in Appendix A). To obtain a balanced panel, we drop all observations that go beyond the regular time, thus we are left with 90 min-by-minute observations per game. Table 1 provides an overview of the televised games by season, stage, and market. On average (excluding extra time), between seasons 2015/2016 and 2017/2018 UCL telecasts in the UK attracted around 0.560 million viewers per minute, while in Spain the telecasts had an average minute-by-minute audience of around 2.607 million viewers. This difference in the audience figures may be partly explained by the fact that during the period of study UCL telecasts were available only on paid TV in the UK, whilst in Spain games were televised either on free-to-air channels or on paid TV with the share of free-to-air games being around 34% (see Table 2).⁶

Moreover, Spanish teams were more successful than UK teams in the competition during our observation window. Table 3 shows, by year and round, each team from the UK and Spain that competed in the UCL KO stages.

Table I. Overview of UEFA Champions League Telecasts by Season, Stage, and Market.

United Kingdom										
Stage	2014/15		2015/16		2016/17		2017/18		Total	
	N	Av. Aud.	N	Av. Aud.	N	Av. Aud.	N	Av. Aud.	N	Av. Aud.
Group	87	0.463	27	0.478	33	0.359	36	0.379	183	0.430
Round of 16	16 (8)	1.454 (1.567)	15 (8)	0.505 (0.522)	16	0.444 (0.447)	15 (8)	0.690 (0.669)	62 (32)	0.779 (0.801)
Quarter-finals	8 (4)	1.023 (1.059)	8 (4)	0.522 (0.496)	7 (3)	0.618 (0.678)	8 (4)	0.760 (0.759)	31 (15)	0.734 (0.753)
Semi-finals	4 (2)	2.735 (2.800)	4 (2)	1.105 (1.111)	4	0.621 (0.688)	4 (2)	1.582 (1.594)	16 (8)	1.511 (1.548)
Final	1	6.367	1	2.323	1	2.891	1	4.369	4	3.987
Total	116	0.768	55	0.571	61	0.470	64	0.637	296	0.641
Spain										
Stage	2014/15		2015/16		2016/17		2017/18		Total	
	N	Av. Aud.	N	Av. Aud.	N	Av. Aud.	N	Av. Aud.	N	Av. Aud.
Group	18	2.188	6	5.858	30	1.501	30	1.183	84	1.918
Round of 16	12 (6)	2.245 (2.154)	4 (2)	5.885 (5.568)	16 (8)	1.911 (1.903)	15 (8)	1.967 (1.648)	47 (24)	2.352 (2.186)
Quarter-finals	6 (3)	3.113 (3.559)	2 (1)	9.579 (10.010)	7 (3)	2.697 (2.763)	8 (4)	2.283 (2.340)	23 (11)	3.26 (3.490)
Semi-finals	4 (2)	4.952 (5.154)	2 (1)	8.742 (8.659)	4 (2)	4.342 (5.211)	4 (2)	4.121 (3.167)	14 (7)	5.082 (5.103)
Final	1	8.654	1	10.040	1	9.247	1	8.861	4	9.291
Total	41	2.767	15	7.049	58	2.089	58	1.976	172	2.645

Notes: In each UCL season (from group stage onwards) a total of 125 UCL games are staged. Numbers indicate the televised games in each market. In parenthesis are displayed the number of first leg games in the corresponding knock-out stage. Season 2014/15 is eliminated from our main estimations due to the shift of broadcasting rights. AV. Aud. is average audience in that round (in millions), while in parenthesis is the average audience figures for first leg games.

Emotional Cues

For modeling the effects of emotional cues on audience size, the exact timing of significant match events such as the beginning and ending of the first and second half, goals scored or red cards received is needed. This exact time stamp information was acquired through the British sports analytics firm, Opta/Stats Perform, allowing for the nontrivial task of synchronizing the audience dataset with the football dataset to be compatible and accurate with the expressed times and events during the games.

To define *suspense* and *surprise*, we closely follow the work of Ely et al. (2015) and shadow Buraimo et al. (2020) for the additional definition of *shock*. While *surprise* is about what just happened in the match and how outcome probabilities changed from minute $t-1$ to minute t , *shock* refers to the difference between outcome probabilities in minute t and the pre-match outcome probabilities $t=0$. Accordingly, p_t refers to the match's final outcome probabilities at minute t and H, D, and A identify a home win, draw, and away win, respectively. As such, we define *surprise* and *shock* as:

$$Surprise_t = \sqrt{(p_t^H - p_{t-1}^H)^2 + (p_t^D - p_{t-1}^D)^2 + (p_t^A - p_{t-1}^A)^2} \quad (1)$$

$$Shock_t = \sqrt{(p_t^H - p_0^H)^2 + (p_t^D - p_0^D)^2 + (p_t^A - p_0^A)^2} \quad (2)$$

Since *suspense* is a forward-looking emotion, additional measures are required. The changes in outcome probability are now hypothetical, in which they refer to what would happen if a team were to score a goal in the following minute. Further, the changes in probability must be weighted by the complementary probabilities of either team scoring so that *suspense* is subject to the significance and the likelihood of an event actually occurring. Due to this, we introduce p_{t+1}^{HS} and p_{t+1}^{AS} to specify the respective probabilities of either the home team or away team scoring in the next minute from t . As such, we define *suspense* as:

$$Suspense_t = \sqrt{\sum_{i \in H, D, A} p_{t+1}^{HS} [(p_{t+1}^i | p_{t+1}^{HS}) - p_t^i]^2 + p_{t+1}^{AS} [(p_{t+1}^i | p_{t+1}^{AS}) - p_t^i]^2} \quad (3)$$

Here, the terms $(p_{t+1}^i | p_{t+1}^{HS}) - p_t^i$ and $(p_{t+1}^i | p_{t+1}^{AS}) - p_t^i$ are the hypothetical change in outcome probabilities from minute t to $t+1$ if either team, home or away, were to score in the next minute.

In order to calculate *suspense*, *surprise* and *shock*, in-play outcome probabilities are required. Since available in-play betting odds might suffer from behavioral biases (see, for instance, Angelini et al., 2022), we mimic the approach proposed by Buraimo et al. (2020) and use in-play outcome probabilities calculated with the following model. Assuming independent Poisson distributions for goals scored by the

Table 2. Number of Games Shown on Television by Broadcaster.

	Operator	Type	2015/16			2016/17			2017/18			Total		
			GRP	KO	All	GRP	KO	All	GRP	KO	All	GRP	KO	All
UK	BT Group													
	BT	PAY	27	28	55	33	28	61	36	28	64	96	84	180
Spain	Atresmedia													
	Antena 3	FTA	6	9	15	6	9	15	6	8	14	18	26	44
	LaSexta	FTA	0	0	0	0	0	0	0	1	1	0	1	1
	Radiotelevisión Española													
	Teledeporte	FTA	0	0	0	0	0	0	0	0	0	0	0	0
	Televisió de Catalunya													
	TV3	FTV	6	9	15	6	9	15	5	9	14	17	27	44
	Esport3	FTV	0	0	0	0	0	0	1	0	1	1	0	1
	beIN Media Group & Mediapro													
	beIN	PAY	0	0	0	24	20	44	24	20	44	48	40	88

Notes: In the Spanish market 88 games were televised on pay TV. Since Atresmedia and Televisio de Catalunya televised the same games, the total number of games televised on free TV is 45. Note that two games were available on both pay and free TV. As such, the Spanish data cover overall 131 different games [88 (pay TV) + 45 (free TV) - 2 (overlapping)]. BT includes the channels: BT Sport 1-3, BT Sport ESPN, BT Sport Europe, BT Sport Showcase. beIN includes the channels: beIN Max 1, beIN Max 2, beIN Sports. GRP: Group stage games. KO: Games of knock-out stages and final. PAY: pay-TV platform. FTA: free-to-air; FTV: free-to-view, only available in certain regions of the country.

Table 3. UK and Spanish Teams' Participation in the Knock-Out Stages During the Study Period.

Stage	2015/16			2016/17			2017/18			Total	
	UK	Spain		UK	Spain		UK	Spain		UK	Spain
Round of 16	Arsenal Chelsea Manchester City	Atlético Madrid Barcelona Real Madrid		Leicester City Manchester City	Atlético Madrid Barcelona Real Madrid Sevilla		Chelsea Liverpool Manchester City Manchester United Tottenham Hotspur	Sevilla Real Madrid Barcelona		10	10
Quarter-finals	Manchester City	Atlético Madrid Barcelona Real Madrid		Leicester City	Atlético Madrid Barcelona Real Madrid		Liverpool Manchester City	Barcelona Real Madrid Sevilla		4	9
Semi-finals	Manchester City	Atlético Madrid Real Madrid		.	Atlético Madrid Real Madrid		Liverpool	Real Madrid		2	5
Final	.	Atlético Madrid Real Madrid		.	Real Madrid		Liverpool	Real Madrid		1	4

Notes: Typically, Spanish and English teams have four teams in the group stage. There is, however, an additional berth for UEFA Europa League title holders. In the estimation period, besides for the Round of 16, Spanish teams were more successful in the UCL than English teams, i.e., 42% of Round of 16 teams were from either the UK or Spain. However, in the quarter-finals, UK teams made up 17% of all teams, while Spain consisted of 38% of all teams. Moreover, the semi-finals in this period consisted of 17% UK teams and 31% Spanish teams. Likewise, the teams competing in the finals consisted of 17% English teams and 67% Spanish teams.

home team (X) and the away team (Y), i.e.,

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

we can estimate the two scoring rates λ_H and λ_A by minimizing the squared difference between the outcome probabilities o_i and m_i , i.e.,

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

using an optimization function in Python. In this regard, H , D , and A refer to the possible outcomes of a home win, a draw, or an away win respectively. Moreover, while o_i are the bookmaker implicit outcome probabilities based on pre-match closing odds on the three outcomes as well as over-under totals,⁷ m_i are outcome probabilities calculated from our Poisson model by simply summing the different scoreline probabilities for a given match.

After the scoring rates for each team have been estimated, the next step is to distribute these across the minutes of the match. A rudimentary way to achieve this would be to assume uniform distribution so that each minute was equal to $\lambda/90$. However, scoring rates are not evenly distributed throughout a match; for instance, more goals typically occur in the latter moments of a match rather than the opening minutes. To execute a more accurate method, we split the scoring rates in proportion to the empirical distribution of goals per minute, as suggested by Buraimo et al. (2020). The empirical goal distribution for the UCL between the tournament years of 1998/99 and 2020/21 can be seen in Figure 1. It is important to note that goals occurring in stoppage time of their respective half are included in the goal tally for the 45th and the 90th minutes, partially explaining the higher goal totals in those minutes. We use this approach in order to keep all games at exactly 90-min length. As such, any goal occurring in extra-time (i.e., when a knock-out match is tied after the original 90 min) was not included in the goal total.

Using these scoring rates per minute, we simulate the number of goals being scored in each minute of a specific match, then total the score and record the final result. This match-level simulation was repeated 100,000 times per minute, leading to 9 million simulations per match. In other words, each individual match of 90 min was simulated 100,000 times leading to 100,000 “matches” being played.

These simulations are also used to evaluate the probabilities of a home win, a draw, and an away win for calculating *suspense* by using “what if” scenarios: “What are the probabilities of a home win, draw, or away win if the home team scored in the next minute? What are the probabilities of a home win, draw, or away win if the away team scored in the next minute?”. Red cards are accounted for by following the methods of Vecer et al. (2009) – if a team received a red card, their goal scoring rate, for the rest of the game, was diminished to 2/3 of the original, while the opposition’s scoring rate was multiplied by 1.2.

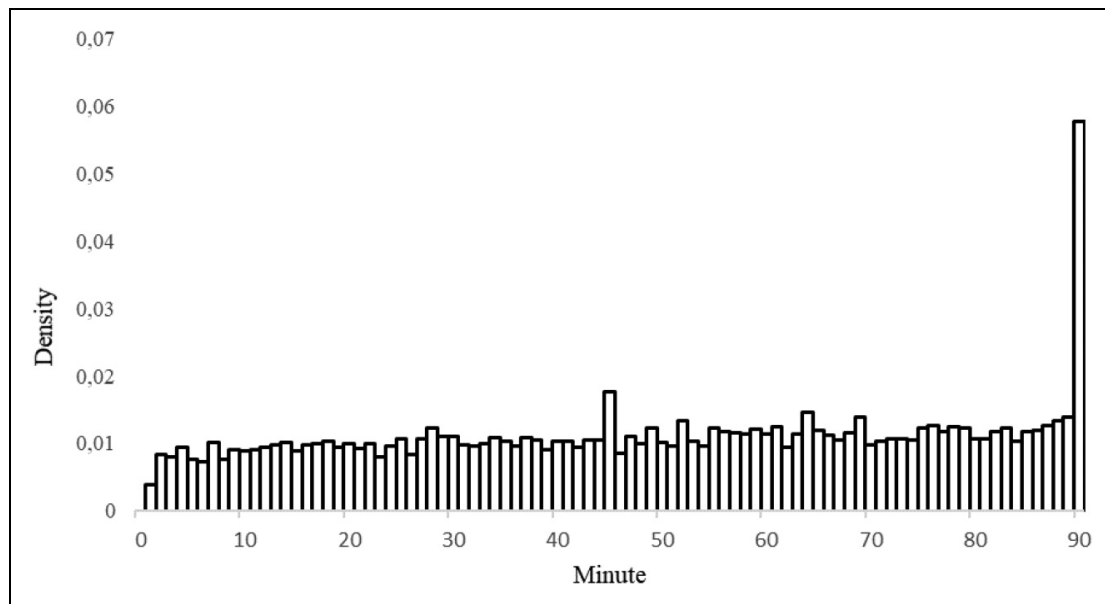


Figure 1. Empirical goal distribution in the UCL between 1998/99 and 2020/21.

Notes: Minute averages are based on all UCL games ($n = 2,957$) played between 1998/99 and 2020/21. In those games, 8,207 goals were scored. Historical goals data stemmed from fbref.com.

Example Games

For a better grasp and understanding of the data, we illustrate the evolution of our key measures during the course of an “exciting” match (Figure 2) and a kind of “routine” match (Figure 3) that were both televised in the UK and Spanish market. The criteria used to select the example games were as follows: First, the respective game needed to be broadcast in both the UK and Spanish market. Second, the respective game needed to follow the timeline of “routine” or “exciting” (based on the authors’ footballing opinion). Third, the respective game needed to be a group stage game to prevent any additional audience views caused by match relevance.

In the first example (Figure 2), a match played between Chelsea vs Roma (played on October 18, 2017) was selected as example of an “exciting” match due to the many goals (six in total) and the back-and-forth nature of the match (2-0; 2-3; 3-3). Chelsea (61% winning probability according to closing odds) opened the scoring with two early goals. *Suspense* remained at low levels due to the initial one-sided win probability for Chelsea. However, Roma managed to take the lead in the second half causing an increase in *suspense*. When Chelsea equalized shortly after, *suspense* in the game reached high levels nearing the final whistle - as a goal for either team would be decisive. Toward the latter minutes of the match when *surprise* and *shock* both saw increased yields due to major shifts in game events, both the UK and Spanish viewing audience follow suite and increase until the final moments.

The second example match (Figure 3) between Manchester City and Borussia Monchengladbach (played on September 14, 2016) was selected as an example of “routine” match. Manchester City (69% winning probability according to closing

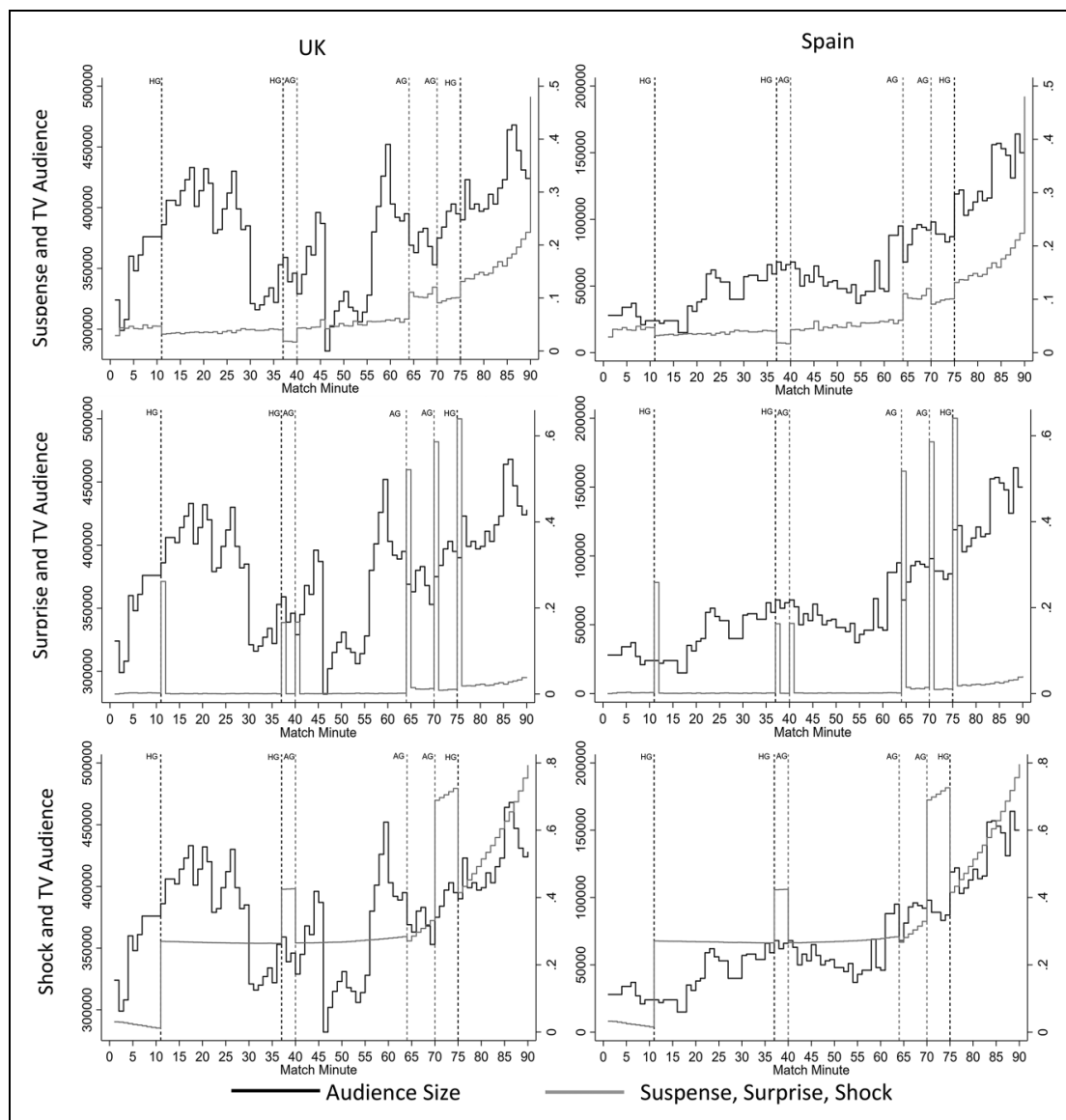


Figure 2. Audience size and emotional cues in an “exciting” match (Chelsea vs Roma, October 18, 2017).

Notes: Indicators HG and AG specify the minute of a home goal or away goal, respectively. The audience data was provided by the UEFA. Data on the exact betting timings of relevant game events and game halves stemmed from Opta / Stats Perform. Pre-match betting odds data used to estimate suspense, surprise and shock stemmed from oddsportal.com.

odds) routinely produced a 4-0 win, scoring twice in each half. For both *suspense* and *surprise*, the generated yields decreased after each goal was scored and practically disappeared after goal three and as full-time approached. Comparatively speaking, the *shock* levels were still low compared to our “exciting” example, however *shock*, rose until the very end, as the pre-match expectation of such a drastically one-side game was lower than the actual outcome. Interestingly, after halftime the UK viewership gradually decreased, while Spanish viewers were variable throughout the entire match with multiple spikes of audience interest.

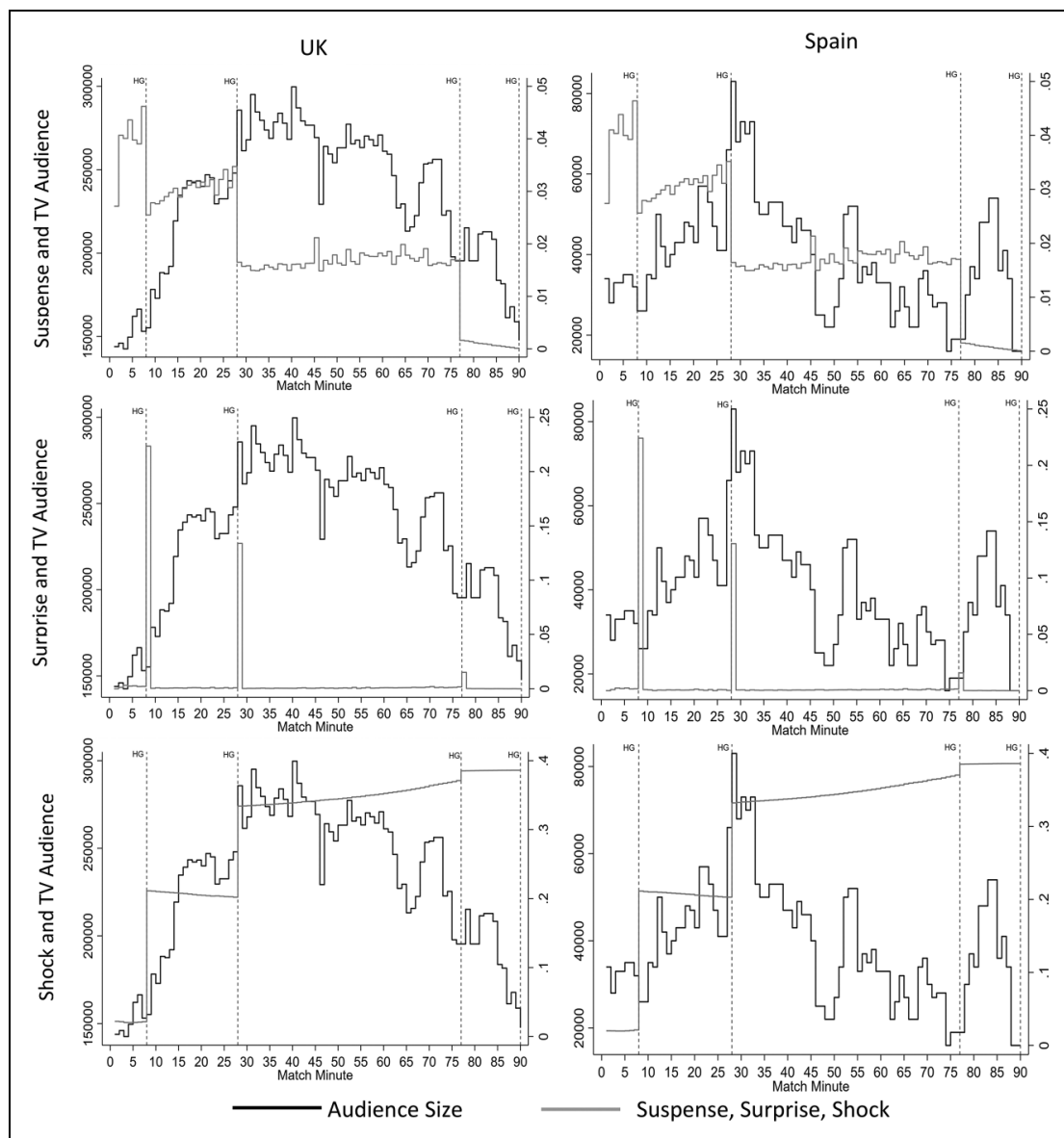


Figure 3. Audience size and emotional cues in a “routine” match (Manchester City vs Borussia Monchengladbach, September 14, 2016).

Notes: Indicators HG and AG specify the minute of a home goal or away goal, respectively. The audience data was provided by the UEFA. Data on the exact timings of relevant game events and game halves stemmed from Opta / Stats Perform. Pre-match betting odds data used to estimate suspense, surprise and shock stemmed from oddsportal.com.

Model Specification

In our main specification, we regress audience size of game i in minute t on all three emotional cue variables of game i in minute t as well as lagged audience size, a series of minute-of-match dummies and match fixed-effects. In this regard, we include minute-of-match dummies to account for common temporal patterns, such as the decreased viewership right after halftime due to the viewers switching back to the

game after ignoring the halftime show or commercials. Match fixed-effects account for all factors identifying individual matches, including the quality and appeal of teams, the relevance of the game, the location of the match, and the television station. Finally, lagged audience size proxies the inertia when viewing live football on television due to the assumption that our forecasts of audience figures depend on the events occurring in the same game.

In order to avoid spurious correlations, we need to check whether our audience measure is $I(1)$ or stationary. We test this using the full sample as well as different subsamples (e.g., all minute-by-minute observations vs first half only and second half only). Overall, Im–Pesaran–Shin Unit Root tests (2003) strongly reject the null hypothesis that all panels contain unit roots. Moreover, Maddala and Wu (1999) Panel Unit Root tests also strongly reject the null that the series is $I(1)$. Since these “first generation” tests are frequently criticized for assuming cross-sectional independence, we further implemented the Pesaran (2007) Panel Unit Root test which relaxes this assumption. Again, non-stationarity is strongly rejected.

For estimating the model, we must consider the distribution of our dependent variable is right-skewed and includes zero observations.⁸ As such, we opt for the Pseudo-Poisson Maximum Likelihood estimator (see Silva & Tenreiro, 2006) which is robust to any distribution (Wooldridge, 2010). Moreover, controlling for lagged audience – which is important in order to avoid any omitted variable bias (see Bizzozero et al., 2016; Buraimo et al., 2020) – might cause problems. While residual autocorrelation may cause a downward bias in models including a lagged dependent variable (Keele & Kelly, 2006), the inclusion of both fixed effects and a lagged dependent variable may raise concerns with regard to Nickell bias (Nickell, 1981). Since, however, the time dimension of our panel is comparably large ($T=90$ min), we argue that the bias (if any) is small (see Baltagi, 2008; Nickell, 1981).⁹

Findings

In our analysis we focus on two main panels. Panel A contains just group stage games. Panel B contains all group stage games (i.e., Panel A) plus all first leg games of the knock-out stage and the Final match. We do not consider second leg games since emotional cues are expected to be triggered by the probability of qualifying to the next stage rather than the actual outcome of the individual game. Table 4 displays the descriptive statistics for the UK (Spanish) market of the overall 96 (66) matches in Panel A and 140 (100) matches in Panel B.¹⁰

Table 5 displays our main results. Overall, our findings suggest that particularly *suspense* and *surprise* are driving the demand for UCL games in both markets. *Shock*, however, has a marginal impact on the demand for UCL games in both markets being statistically significant just for the Spanish one (Panel B).¹¹ Importantly, when estimating all models excluding *shock* the coefficients of *surprise*

and *suspense* hardly change (see Table A7 in Appendix A). As such, we conclude, like Buraimo et al. (2020), that *shock* does not absorb any effects of *surprise* or *suspense* and appears to be an additional – though in our setting less relevant – cue.¹²

In order to explore potential effect heterogeneity, we repeat our analysis using different specifications. To start with, we interact the variables of interest with stage of the competition, i.e., group stage or knock-out stages (see Table 6). Overall, our findings suggest that *suspense* and *surprise* seem to matter more for group stages than knock-out games in both markets while only the UK audience seems to value *shock* more when watching group stage games.

We further explore effect heterogeneity with regard to the halves of the match (see Table 7). In line with Bizzozero et al. (2016) we find audience, in both markets, to have a preference for *suspense* particularly in the second half. Interestingly, however, in the Spanish Panel B the interaction effect between first half and *suspense* is negative and statically significant. Additional subsample estimations suggest that this negative effect is primarily driven by knockout games televised on free-to-air channels (see Table A8 in Appendix A). Concerning *surprise*, in UK it seems that this cue is only a precise predictor of demand in the second half. In Spain, however, no differences arise with regard to the impact of *surprise* in both halves.

Finally, we return to the concept of uncertainty of outcome that dominated the empirical research during the last decades (see, for instance, Nalbantis & Pawlowski, 2019; Pawlowski et al., 2018), and estimate our main specification with additional variables directly measuring uncertainty of outcome. Theoretically, uncertainty of outcome as well as *suspense*, *surprise*, and *shock* are closely connected. While *suspense* is increasing with increasing uncertainty of outcome, both *surprise* and *shock* are increasing with decreasing (lagged) uncertainty of outcome. Moreover, an event with high levels of uncertainty will cater to the *suspense* that pleases TV viewers. This is due to *suspense* existing along a continuum in which the audience is aware of the endpoint that will produce an outcome; for each minute that occurs, that potential outcome becomes closer making the audience feel more *suspense* (Madrigal et al., 2023). Madrigal et al. (2023), also, find that uncertainty of outcome only creates *suspense* to the extent that there is an established and known endpoint.¹³

We measure outcome uncertainty by taking the absolute difference between the home and away win probability at minute t and further consider the probability to draw (e.g., Alavy et al., 2010). Moreover, we control for the number of goals at minute t as well as the goal difference between the contestants at minute t (e.g., Buraimo et al., 2020). Overall, while the effects of all three cues partly reduce, controlling for these measures does not change our main findings about *suspense* and *surprise*. Interestingly, however, *shock* becomes even significant for some specifications (see Table 8).¹⁴

Overall, our models support the notion that *suspense*, *surprise*, and *shock* are viable factors with respect to UCL football television audience demand. But are they also economically significant? For answering this question, we quantify the impact of the emotional cues based on our main results in Table 5 (Panel A). For

Table 4. Descriptive Statistics.

	UK						Spain									
	Panel A (N = 96 games)			Panel B (N = 140 games)			Panel A (N = 66 games)			Panel B (N = 100 games)						
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Suspense	0.058	0.048	0	0.521	0.058	0.046	0	0.521	0.055	0.046	0	0.521	0.056	0.045	0	0.521
Surprise	0.015	0.074	0	1.168	0.015	0.073	0	1.170	0.013	0.068	0	1.166	0.014	0.069	0	1.166
Shock	0.295	0.227	0	1.116	0.306	0.243	0	1.116	0.255	0.211	0.001	1.060	0.282	0.236	0	1.060
Audience	0.399	0.254	0	1.648	0.535	0.572	0	4.901	1.844	2.462	0	8.715	2.429	3.065	0	12.100

Notes: Panel A consists of group stage games. Panel B consists of group stage games and first leg games of the round of 16, quarter-finals, semi-finals as well as the finals. UK: United Kingdom; ESP: Spain. Audience is in millions. See Appendix A Table A4 for descriptive statistics of the UK and Spain markets including the 2014/15 season.

Table 5. Main Results.

	UK		ESP	
	Panel A	Panel B	Panel A	Panel B
Audience _{t-1}	1.215*** (0.142)	0.313** (0.122)	0.067*** (0.014)	0.053*** (0.011)
Suspense	0.294*** (0.096)	0.481*** (0.076)	0.613*** (0.116)	0.378*** (0.114)
Surprise	0.023*** (0.009)	0.021** (0.008)	0.020* (0.011)	0.023*** (0.006)
Shock	0.030 (0.019)	0.035 (0.023)	0.029 (0.026)	0.040* (0.021)
Observations	8,448	12,320	5,808	8,800
Number of game IDs	96	140	66	100
Log Pseudolikelihood	-4,850.58	-7,600.21	-4,816.79	-8,259.28

Notes: All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6. Effect Heterogeneity: Group Stage Games vs Knock-Out Games.

	UK	ESP
	Panel B	Panel B
Audience _{t-1}	0.361*** (0.133)	0.055*** (0.01)
Suspense × Group Stage	0.510*** (0.098)	0.593*** (0.111)
Suspense × Knock-out	0.296*** (0.092)	0.154 (0.158)
Surprise × Group Stage	0.028** (0.011)	0.023** (0.011)
Surprise × Knock-out	0.008 (0.011)	0.016* (0.008)
Shock × Group Stage	0.074*** (0.022)	0.029 (0.027)
Shock × Knock-out	-0.019 (0.035)	0.032 (0.033)
Observations	12,320	8,800
Number of game IDs	140	100
Log Pseudolikelihood	-7,599.87	-8,258.61

Notes: All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7. Effect Heterogeneity: First vs Second Half.

	UK		ESP	
	Panel A	Panel B	Panel A	Panel B
Audience _{t-1}	1.208*** (0.142)	0.308** (0.123)	0.062*** (0.015)	0.048*** (0.011)
Suspense × 1st half	−0.096 (0.279)	−0.115 (0.321)	−0.074 (0.273)	−0.585*** (0.192)
Suspense × 2nd half	0.286*** (0.095)	0.469*** (0.074)	0.613*** (0.117)	0.365*** (0.115)
Surprise × 1st half	0.017 (0.019)	0.011 (0.017)	0.022 (0.017)	0.024* (0.012)
Surprise × 2nd half	0.024*** (0.009)	0.024*** (0.009)	0.018 (0.013)	0.021*** (0.008)
Shock × 1st half	0.024 (0.029)	0.008 (0.032)	0.009 (0.034)	0.012 (0.025)
Shock × 2nd half	0.015 (0.027)	0.024 (0.028)	0.007 (0.028)	0.01 (0.023)
Observations	8,448	12,320	5,808	8,800
Number of game IDs	96	140	66	100
Log Pseudolikelihood	−4,850.56	−7,600.15	−4,816.57	−8,258.65

Notes: All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the UK market, an increase of one standard deviation in *suspense* (*surprise*) [*shock*] is predicted to increase audience by 1.4% (0.2%) [0.7%]. In the Spanish market, an increase of one standard deviation in *suspense* (*surprise*) [*shock*] would increase audience size by 2.9% (0.1%) [0.6%]. For both markets, the effects of *suspense* are larger compared to Wimbledon tennis (which was estimated at about 1.2%, see Bizzozero et al., 2016) while the effect of *surprise* is considerably lower (which was estimated at about 2.5%, see Bizzozero et al., 2016). If we take into account the joint effect of *surprise* and *suspense*, our estimates for the Spanish market are close to that reported for Wimbledon tennis. For the UK market, however, the joint effect is similar to that reported for the English Premier League (about 1.2%, see Buraimo et al., 2020).

To better apprehend the economic importance of the emotional cues, we also quantify the impact of *suspense*, *surprise*, and *shock* (based on UK Panel A coefficients, see Table 5) with the help of hypothetical (yet arguably realistic) scenarios. We start the simulations by considering two main scenarios (see Table 9). In scenario A, we closely follow Buraimo et al. (2020) and predict the audience of a group game where both contestants are fairly equally matched, yet the home team has a slight home advantage (outcome probabilities: 38% home win; 25% draw; 37% away

Table 8. Controlling for Game Uncertainty and Current State of Game.

	UK				ESP			
	Panel A		Panel B		Panel A		Panel B	
Audience _{t-1}	1.217*** (0.142)	1.210*** (0.145)	0.322*** (0.119)	0.316*** (0.118)	0.066*** (0.014)	0.057*** (0.014)	0.053*** (0.011)	0.047*** (0.012)
Suspense	0.303*** (0.095)	0.250*** (0.088)	0.501*** (0.101)	0.353*** (0.096)	0.527*** (0.146)	0.299*** (0.123)	0.373*** (0.123)	0.222*** (0.111)
Surprise	0.023*** (0.009)	0.022*** (0.01)	0.022*** (0.008)	0.021*** (0.009)	0.018 (0.012)	0.014 (0.013)	0.024*** (0.007)	0.016* (0.009)
Shock	0.035* (0.02)	0.045* (0.025)	0.065** (0.031)	0.097*** (0.033)	0.026 (0.03)	0.038 (0.029)	0.043*** (0.022)	0.072*** (0.027)
Abs(hwin-awin)	-0.014 (0.025)	-0.02 (0.024)	-0.059** (0.027)	-0.071*** (0.027)	0.018 (0.039)	-0.012 (0.032)	-0.006 (0.029)	-0.031 (0.026)
Draw prob	-0.021 (0.049)	-0.036 (0.049)	-0.081 (0.053)	-0.122** (0.057)	0.055 (0.075)	-0.016 (0.068)	-0.005 (0.064)	-0.063 (0.063)
Total goals		0.002 (0.005)		0.002 (0.005)		0.004 (0.009)		0.011 (0.007)
Goal difference		-0.006 (0.008)		-0.017** (0.008)		-0.023*** (0.008)		-0.023*** (0.007)
Observations	8,448	8,448	12,320	12,320	5,808	5,808	8,800	8,800
Number of game IDs	96	96	140	140	66	66	100	100
Log Pseudolikelihood	-4,850.57	-7,600.13	-4,850.57	-7,599.99	-4,816.76	-8,259.28	-4,815.78	-8,258.11

Notes: All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

win). Both teams have a scoring probability of 1.8 and the game starts with 500,000 viewers. We simulate this game with two different outcomes, i.e., the game ends in a goalless tie (A1) and both teams score a total of six goals and end up in a tie (A2). In A2, the home team scores in the 20th, 40th and 60th minute. The away team comes back after each home goal, scoring in the 30th, 50th and 70th minute. In scenario B, we consider a group game where the home team is a strong favorite (outcome probabilities: 80% home win; 13% draw; 7% away win). The home team has a score probability of 2.9 and the away team has a score probability of 0.8. As before, we simulate this game with two different outcomes and a starting audience of 500,000 viewers. In subscenario B1, it is a one-side game with the favorite scoring six times, on the 10th, 20th, 30th, 40th, 60th and 70th minute. In subscenario B2, the away team wins against all odds scoring twice in the 20th and 70th minute. Figure 4 provides the predicted audience based on the aforementioned scenarios.

First, both A1 and A2 are characterized by similar levels of *suspense*, yet A2 is characterized by higher amounts of *surprise* and *shock* around the time of goals. Figure 4 provides the predicted audience for these subscenarios. In the first 20 min both games have exactly the same viewership. After the first goal and up to the 70th minute, the A2 game attracts on average higher viewership than the A1 game. Comparing both subscenarios for the full game, the A2 game attracts extra 611,000 viewer-minutes in comparison to the A1 game. This equates to roughly an extra 6,865 viewers per minute.

Second, the B2 game is characterized by higher amounts of *suspense*, *surprise* and *shock* than the B1 game. In the first 20 min both games have exactly the same viewership. When the underdog scores, the B2 game starts to attract higher viewership

Table 9. Description of the Hypothetical Game Scenarios.

	Score probabilities		Pre-match outcome probabilities					
	Home	Away	Home	Draw	Away	Result	Min. of home [away] goals	Type of game
Scenario A								
A1	1.8	1.8	0.38	0.25	0.37	0-0		Evenly matched teams, no goals
A2	1.8	1.8	0.38	0.25	0.37	3-3	20, [30], 40, [50], 60, [70]	Evenly matched teams, many goals
Scenario B								
B1	2.9	0.8	0.80	0.13	0.07	6-0	10, 20, 30, 40, 60, 70	One-side game for the favorite
B2	2.9	0.8	0.80	0.13	0.07	0-2	[20], [70]	Underdog win

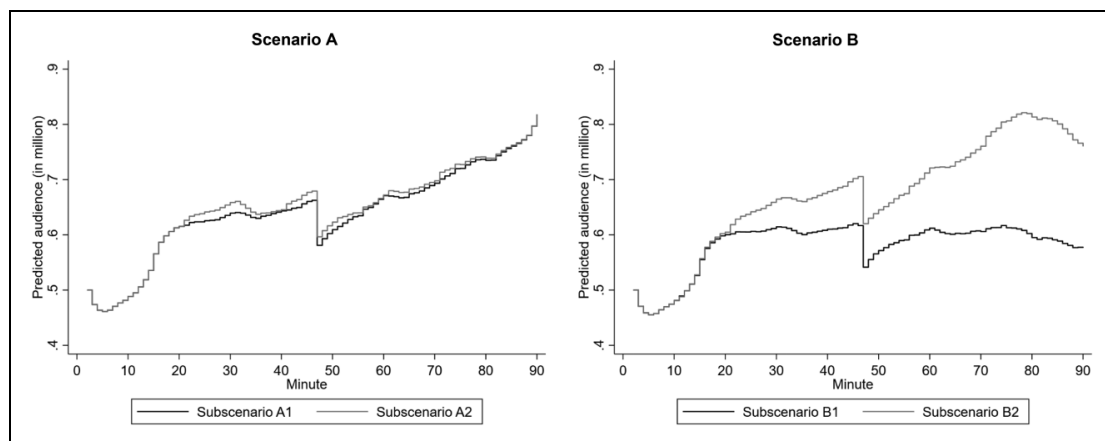


Figure 4. Predicted audience (in millions) based on four hypothetical group stage games. Notes: For a description of the (sub)scenarios see Table 9. All games start with 500,000 viewers. The predictions are based on the coefficients of the UK Panel A model (Table 5).

than the B1 game with the difference between both becoming substantially higher in the second half of the game. Comparing both subscenarios for the full game, the B2 game attracts extra 7.969 million viewer-minutes in comparison to the B1 game. This equates to roughly an extra 89,540 viewers per minute.

Finally, comparing scenarios A and B, both games A1 and A2 attract larger audiences than game B1, that is extra 5.185 and 5.796 million viewer-minutes respectively.¹⁵ However, game B2 has higher aggregate viewership than games A1 and A2, attracting extra 2.784 and 2.173 million viewer-minutes respectively. These simulations are suggestive that games between equally matched teams attract higher viewership than games in which the favorite win. At the same time, however, games where the underdog wins the match generate even higher audience levels. This is in line with notion that fans seem to have a preference for upsets which is frequently reported in the literature examining the impact of outcome uncertainty on viewership using aggregated audience data (Humphreys & Pérez, 2019) or survey data (Pawlowski et al., 2018). This result is also in line with Antony et al. (2021) who modeled belief-consistent against belief-inconsistent scenarios. The authors concluded that belief-inconsistent results of a game that contradicted the pre-match belief were better predictors of subjective event boundaries (or what the subject *thought* would happen).

Conclusion

We implemented the seminal framework of Ely et al. (2015) by replicating and extending its applications by Bizzozero et al. (2016) and Buraimo et al. (2020). In particular, we explored for the first time whether and how belief dynamics during the course of the *same* events are driving entertainment utility and, consequently, the demand for televised sports in *different* markets.

Overall, we find that *suspense* and *surprise* are statistically and economically significant drivers of demand for UCL matches in both the UK and Spanish market. These effects are not absorbed when controlling for traditional uncertainty of outcome measures. Moreover, our findings suggest that *suspense* and *surprise* matter more for group stage (rather than knock-out-stage) matches as well as in the second (rather than the first) half of a match.

Interestingly, we find the combined effects of *suspense* and *surprise* in UK to be fairly similar to those reported for the English Premier League (see Buraimo et al., 2020), while in the Spanish market the combined effects are fairly similar to those reported for Wimbledon tennis (Bizzozero et al., 2016). Buraimo et al. (2020) argued that any differences in effect sizes between their study and the study by Bizzozero et al. (2016) may be attributed to the fact that Wimbledon matches were shown on free-to-air television, while Premier League games are only accessible on pay-TV platforms. At first sight, our findings could be considered as suggestive evidence that this argument may hold. However, our sample size prohibits running sub-sample estimations focusing *just* on free-to-air games in the Spanish market to further support this argument. As such, we are cautious with any such conclusions.

Moreover, differences regarding the salience of emotional cues in the two markets could be also ascribed to distinct social/cultural contexts. For instance, Liddell and Williams (2019) find that response to emotional cues (or “emotional regulation strategies”, in their words) may depend on various contextual factors, including cultural differences. As such, future research focusing on cross-cultural differences could deliver some meaningful insights in this regard.

A further highly relevant line of future research is exploring effect heterogeneity with regard to fandom. Even though Madrigal et al. (2023) find that enjoyment differences are independent of “favorable” outcomes (see also Hall, 2015), behavioral responses to emotional cues could differ across the different types of viewers. Initially, we thought about exploring this in our setting by simply comparing the effects for UCL games involving (or not) domestic teams. Doing so, however, is problematic already from a theoretical perspective, since viewing figures probably consist of fans of a team hoping for a favorable outcome as well as “haters” that tune in to watch hoping for a poor outcome for a rival team. As such, individual level data is required. Such data would also allow delving into how emotional cues are related to a viewer’s tuning and switching behavior as well as their attention level (see Liu et al., 2020).

Overall, these results offer some implications for broadcasters, advertisers/sponsors, and league organizers/governing bodies.

In this regard, our findings could inform advertisers and sponsors on the proper timing of ads placement and sponsor messages during live sports content. More precisely, our findings suggest that advertisers and sponsors may benefit from increased visibility due to higher viewership after surprising moments (e.g., a goal of an underdog), when an upset seems very likely to happen, or when a game is very suspenseful. At first glance, this implication seems to be in line with the consumer psychology literature. For instance, Bee and Madrigal (2012) find that fans react more favorably to ads

shown after suspenseful games. Since, however, viewers are less attentive to sponsor messages in suspenseful situations (Breuer et al., 2020), the overall effectiveness of placing an ad or sponsor message when a game is suspenseful remains unclear.

Our findings also suggest that broadcasters should not be afraid to show a game with a clear favorite as long as there is still a chance for an upset to happen. Although it is difficult to predict which games may result in an upset, it may be possible to stimulate fan engagement by promoting one-sided games in a way that invokes a “David and Goliath” narrative.

Finally, wins of underdogs are rare in football and depend – amongst others – also on referee decisions. Hereto, there is an abundance of empirical findings showing that referees tend to favor the favorite team (e.g., Erikstad & Johansen, 2020; Lago-Peñas & Gómez-López, 2016). Such implicit biases can pose a barrier to the prospect of upsets. Consequently, any endeavors aimed at mitigating such bias could potentially yield a positive impact on viewership. Numerous leagues including the UCL have introduced video-assistant-referee systems to promote impartial and accurate decision making with notable success (see Holder et al., 2022). Increasing the level of impartiality even further and standardizing referee decision-making by revising rules that are open to subjective interpretation (e.g., stoppage time estimation) could be a step in the right direction.

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Authors' Note

Tim Pawlowski is also associated with LEAD Graduate School and Research Network, Tübingen, Germany and Interfaculty Research Institute for Sports and Physical Activity, Tübingen, Germany.

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Notes

1. To expand upon Ely et al. (2015), Li et al. (2021) empirically test the power to this *suspense* reward theory by designing a task-based casino game to experimentally induce *suspense* and to test if greater *suspense* (higher reward) motivates playing the game more. They find preliminary evidence that a more suspenseful experience enhances the patron's willingness to engage longer.
2. Next to these studies exploring the demand for sports *directly* there are some recent efforts in exploring behavioral responses to emotional cues from sports in other areas like Twitter activity (see Pawlowski et al., 2023) and alcohol use (see Fischer et al., 2023).
3. As of writing the paper, only two studies exist which have analyzed TV demand of UCL matches (Budzinski et al., 2022; Wills et al., 2022). However, both studies use match-level data and do not explore any effects of belief dynamics during the course of a match.
4. As a robustness check we run the main estimations using also the 2014/15 season (see Table A2 in Appendix A). Overall, our findings remain. *Surprise*, however, remains statistically significant just for the Spanish market.
5. In the UK, ITV broadcasting coverage of the UCL ended in 2015, because the broadcaster lost its 23-season agreement as the only provider. For the 2015/16 season, SKY became the UCL broadcaster, starting a new cycle of broadcasting rights in the country. Within the same time-frame, CanalTV+ lost their agreement to broadcast the tournament in Spain, with beIN Sport taking over as a sole provider. Note that for the 2015/16 season, Mediapro (operator of beIN) showed UCL games strictly on the agency's TotalChannel OTT platform. Indicating the lack of televised games in the data for the corresponding year. During this cycle, a total of 375 games were staged, of which 180 (131) games were televised in the UK (Spain).
6. Note that in the 2015/16 season, the average Spanish viewing audience was considerably larger when compared to other seasons in our dataset. This may rely on the fact that beIN showed exclusively most games on over-the-top (OTT) television while only a limited number of games were available on linear TV (and as such included in our data). Within the already limited number of games shown on linear TV, all but one game involved a Spanish team. Remarkably, in 2015/2016 three Spanish teams competed in the quarter-finals (see Table 3) with Barcelona being eliminated by Atlético Madrid in two tight games (aggregate score: 2–3), while similarly tight was also the final between Real Madrid and Atlético Madrid (1–1 draw at the end of extra time, 5–3 on penalties). This could potentially explain the high average television audience. As a robustness check for Spain, we run models excluding season 15/16 (due to the few game broadcasts and the extraordinarily large audiences). Our main findings largely remain. Results are available upon request.

7. Pre-match betting odds come from oddportal.com. We use average betting odds across multiple betting odds providers (up to ten different companies). All odds were transformed by taking the inverse of the betting odd to obtain implied probabilities. Over-round is removed by scaling the bookmaker implicit probabilities to one. Overall, these pre-match odds can be expected to reflect factors such as current form and match results, strength of the opposition, and other relevant factors that influence the outcome.
8. 0.45% (0.90%) of the game-minute observations in the UK Panel A (B) and 5.8% (4.3%) of the game-minute observations in the Spanish Panel A (B) contain zeros. Since games with zero audience at a given minute in our data are commonly games between relatively low-quality clubs, we posit that these zeros display “true” zero demand.
9. As a robustness check, we run models excluding lagged audience. Our main findings largely remain. Results available upon request.
10. In general, one could also think of exploring lagged effects in our setting. Theoretically, this seems relevant since, for instance, fans could watch their beloved team get scored on and angrily watch the replay and the next couple of minutes before switching off the TV. Econometrically, however, this raises concerns since the number of T would reduce substantially, thus eventually causing the Nickell bias as discussed before. As such, we refrain from exploring any lagged effects in our study.
11. As a robustness check we analyzed the data from UK and Spain all together (see Table A5 in Appendix A) and we further checked market specific heterogeneity with regard to the impact of emotional cues (see Table A6 in Appendix A). The results are in line with our original market specific models. There are no market specific differences concerning the impact of emotional cues for Panel A games. In Panel B games, however, *shock* seems to matter more in Spain.
12. Upon comparing the average cues reported by Buraimo et al. (2020; Table 1) for the EPL with those of our study (see Table 4), it appears that UCL group stage games exhibit on average lower cues. This is in line with the notion that – while featuring the best clubs in Europe – the level of predictability (in the UCL group stage) has increased over time (Schokkaert & Swinnen, 2014). However, given the data at hand it remains unclear whether this – or other issues such as design differences between both competitions – are driving the differences regarding the relevance of *shock* between both studies.
13. An attempt to test the interplay between uncertainty of outcome and the emotional cues is provided on Table A9 in Appendix A. As expected, we find that game uncertainty increases with increasing levels of *suspense*, while game uncertainty reduces with increasing levels of *shock*. While the sign for *surprise* is as expected (positive) suggesting that game uncertainty and *surprise* are negatively correlated, these estimates are not precise enough to be significant.
14. We further estimated models excluding the emotional cue variables (see Table A10 in Appendix A). Our findings suggest that only draw probability is statistically significant while the estimate for the absolute difference between home and away win probability at minute t still lacks in precision. These findings are suggestive of the cue measures “better” picking up the viewers’ preferences for UCL matches.
15. Due to the fact that our simulations include lagged audience, to derive the additional viewers per minute from the additional viewer-minutes, we use 89 instead of 90 minutes. That is, our predictions start from minute two, as we need minute one audience to predict minute two audience.

References

- Alavy, K., Gaskell, A., Leach, S., & Szymanski, S. (2010). On the edge of your seat: Demand for football on television and the uncertainty of outcome hypothesis. *International Journal of Sport Finance*, 5(2), 75–95.
- Angelini, G., De Angelis, L., & Singleton, C. (2022). Information efficiency and behavior within in-play prediction markets. *International Journal of Forecasting*, 38(1), 282–299. <https://doi.org/10.1016/j.ijforecast.2021.05.012>
- Antony, J. W., Hartshorne, T. H., Pomeroy, K., Gureckis, T. M., Hasson, U., McDougale, S. D., & Norman, K. A. (2021). Behavioral, physiological, and neural signatures of surprise during naturalistic sports viewing. *Neuron*, 109(2), 377–390. <https://doi.org/10.1016/j.neuron.2020.10.029>
- Ashby, K. (2014, May 28). Worldwide reach of the Lisbon final. *UEFA*. <https://www.uefa.com/uefachampionsleague/news/0250-0c510b7eb8f9-fbe1a8bb6fc2-1000-worldwide-reach-of-the-lisbon-final/>
- Baltagi, B. H. (2008). *Econometric analysis of panel data* (Vol. 4). John Wiley & Sons.
- Bee, C. C., & Madrigal, R. (2012). It's not whether you win or lose; It's how the game is played. *Journal of Advertising*, 41(1), 47–58. <https://doi.org/10.2753/JOA0091-3367410104>
- Bizzozero, P., Flepp, R., & Franck, E. (2016). The importance of suspense and surprise in entertainment demand: Evidence from Wimbledon. *Journal of Economic Behavior & Organization*, 130, 47–63. <https://doi.org/10.1016/j.jebo.2016.07.006>
- Breuer, C., Rumpf, C., & Boronczyk, F. (2020). Sponsor message processing in live broadcasts – A pilot study on the role of game outcome uncertainty and emotions. *Psychology & Marketing*, 38(5), 896–907. <https://doi.org/10.1002/mar.21481>
- Bromberg-Martin, E. S., & Hikosaka, O. (2009). Midbrain dopamine neurons signal preference for advance information about upcoming rewards. *Neuron*, 63(1), 119–126. <https://doi.org/10.1016/j.neuron.2009.06.009>
- Budzinski, O., Feddersen, A., & Kunz-Kaltenhäuser, P. (2022). Demand for TV broadcasts of UEFA Champions League games in Danish television – The impact of uncertainty, stardom, and local heroes. *Ilmenau Economics Discussion Papers*, 27(165). <https://doi.org/10.1016/j.neuron.2009.06.009>
- Buraimo, B., Forrest, D., McHale, I. G., & Tena, J. D. (2020). Unscripted drama: Soccer audience response to suspense, surprise, and shock. *Economic Inquiry*, 58(2), 881–896. <https://doi.org/10.1111/ecin.12874>
- Ely, J., Frankel, A., & Kamenica, E. (2015). Suspense and surprise. *Journal of Political Economy*, 123(1), 215–260. <https://doi.org/10.1086/677350>
- Erikstad, M. K., & Johansen, B. T. (2020). Referee bias in professional football: favoritism toward successful teams in potential penalty situations. *Frontiers in Sports and Active Living*, 2, <https://doi.org/10.3389/fspor.2020.00019>
- Fischer, L. E., Nagel, M., Kelava, A., & Pawlowski, T. (2023). Celebration beats frustration – emotional cues and alcohol use during soccer matches. University of Tübingen: Mimeo.
- Gold, B. P., Mas-Herrero, E., Zeighami, Y., Benovoy, M., Dagher, A., & Zatorre, R. J. (2019). Musical reward prediction errors engage the nucleus accumbens and motivate learning. *Proceedings of the National Academy of Sciences*, 116(8), 3310–3315. <https://doi.org/10.1073/pnas.1809855116>

- Hall, A. E. (2015). Entertainment-oriented gratifications of sports media: Contributors to suspense, hedonic enjoyment, and appreciation. *Journal of Broadcasting & Electronic Media*, 59(2), 259–277. <https://doi.org/10.1080/08838151.2015.1029124>
- Hamermesh, D. S. (2017). Replication in labor economics: Evidence from data, and what it suggests. *American Economic Review*, 107(5), 37–40. <https://doi.org/https://www.https://doi.org/10.1257/aer.p20171121>
- Holder, U., Ehrmann, T., & König, A. (2022). Monitoring experts: Insights from the introduction of video assistant referee (VAR) in elite football. *Journal of Business Economics*, 92(2), 285–308. <https://doi.org/10.1007/s11573-021-01058-5>
- Humphreys, B. R., & Pérez, L. (2019). Loss aversion, upset preference, and sports television viewing audience size. *Journal of Behavioral and Experimental Economics*, 78, 61–67. <https://doi.org/10.1016/j.socec.2018.12.002>
- Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, 115(1), 53–74. [https://doi.org/10.1016/S0304-4076\(03\)00092-7](https://doi.org/10.1016/S0304-4076(03)00092-7)
- Kaplan, S. (2021). Entertainment utility from skill and thrill. United States Naval Academy. <https://doi.org/10.2139/ssrn.3888785>
- Keele, L., & Kelly, N. J. (2006). Dynamic models for dynamic theories: The ins and outs of lagged dependent variables. *Political Analysis*, 14(2), 186–205. <https://doi.org/10.1093/pan/mpj006>
- Krumer, A., Otto, F., & Pawlowski, T. (2022). Nationalistic bias among international experts: Evidence from professional ski jumping. *The Scandinavian Journal of Economics*, 124(1), 278–300. <https://doi.org/10.1111/sjoe.12451>
- Lago-Peñas, C., & Gómez-López, M. (2016). The influence of referee bias on extra time in elite soccer matches. *Perceptual and Motor Skills*, 122(2), 666–677. <https://doi.org/10.1177/0031512516633342>
- Li, Z. W., Bramley, N. R., & Gureckis, T. M. (2021). Expectations about future learning influence moment-to-moment feelings of suspense. *Cognition and Emotion*, 35(6), 1099–1120. <https://doi.org/10.1080/02699931.2021.1932429>
- Liddell, B. J., & Williams, E. N. (2019). Cultural differences in interpersonal emotion regulation. *Frontiers in Psychology*, 10. <https://doi.org/10.3389/fpsyg.2019.00999>
- Liu, X., Shum, M., & Uetake, K. (2020). Passive and active attention to baseball telecasts: Implications for content (re-) design. New York University Stern School of Business. <https://doi.org/10.2139/ssrn.3717894>
- Maddala, G. S., & Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and Statistics*, 61(S1), 631–652. <https://doi.org/10.1111/1468-0084.0610s1631>
- Madrigal, R., Bee, C., & Chen, J. (2022). Hope and fear in the experience of suspense. *Cognition and Emotion*, 36(6), 1074–1092. <https://doi.org/10.1080/02699931.2022.2075327>
- Madrigal, R., Bee, C., & Chen, J. (2023). When the stakes are low: How key features of momentary suspense contribute to a global evaluation of enjoyment. *Communication Research*, 50(3), 287–311. <https://doi.org/10.1177/00936502221074645>
- Nalbantis, G., & Pawlowski, T. (2019). US Demand for European soccer telecasts: A between-country test of the uncertainty of outcome hypothesis. *Journal of Sports Economics*, 20(6), 797–818. <https://doi.org/10.1177/1527002518817598>

- Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, 49(6), 1417–1426. <https://doi.org/10.2307/1911408>
- Pawlowski, T., Nalbantis, G., & Coates, D. (2018). Perceived game uncertainty, suspense and the demand for sport. *Economic Inquiry*, 56(1), 173–192. <https://doi.org/10.1111/ecin.12462>
- Pawlowski, T., Rambaccussing, D., Ramirez, P., Reade, J. J., & Rossi, G. (2023). Exploring entertainment utility from football games. University of Tübingen: mimeo
- Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22(2), 265–312. <https://doi.org/10.1002/jae.951>
- Schokkaert, J., & Swinnen, J. (2014). Uncertainty of outcome is higher in the Champions League than in the European Cup. *Journal of Sports Economics*, 17(2), 115–147. <https://doi.org/10.1177/1527002514521628>
- Shazi, N. (2018, February 21). 10 most-watched events in the history of television. *Huffington Post*. https://www.huffingtonpost.co.uk/entry/10-most-watched-sport-events-in-the-history-of-television_uk_5c7e84e8e4b06e0d4c22eebc
- Silva, J. S., & Tenreiro, S. (2006). The log of gravity. *The Review of Economics and Statistics*, 88(4), 641–658. <https://doi.org/10.1162/rest.88.4.641>
- Simonov, A., Ursu, R. M., & Zheng, C. (2023). Suspense and surprise in media product design: Evidence from twitch. *Journal of Marketing Research*, 60(1), 1–24. <https://doi.org/10.1177/00222437221108653>
- Vecer, J., Kopriva, F., & Ichiba, T. (2009). Estimating the effect of the red card in soccer: when to commit an offense in exchange for preventing a goal opportunity. *Journal of Quantitative Analysis in Sports*, 5(1). <https://doi.org/10.2202/1559-0410.1146>
- Wills, G., Tacon, R., & Addesa, F. (2022). Uncertainty of outcome, team quality or star players? What drives TV audience demand for UEFA Champions League football? *European Sport Management Quarterly*, 22(6), 876–894. <https://doi.org/10.1080/16184742.2020.1836010>
- Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

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Appendix A

Table A1. Top 5 Market Pools, UEFA Association Club Coefficients and Number of Participating Clubs by Country.

2014/15			2015/16			2016/17			2017/18			
Market Pool	Rank	# Clubs	Market Pool	Rank	# Clubs	Market Pool	Rank	# Clubs	Market Pool	Rank	# Clubs	
England	€ 93,560,000	2	4	€ 142,676,000	2	4	€ 138,214,000	3	4	€ 147,663,000	3	5
France	€ 68,052,000	6	2 (3)	€ 68,141,000	6	2 (3)	€ 75,195,000	6	3	€ 68,077,000	5	2 (3)
Germany	€ 65,600,000	3	4	€ 68,334,000	3	4	€ 65,986,000	2	4	€ 61,335,000	2	3 (4)
Italy	€ 93,518,000	4	2 (3)	€ 100,785,000	4	2 (3)	€ 99,954,000	4	2 (3)	€ 115,178,000	4	3
Spain	€ 83,756,000	1	4	€ 89,124,000	1	5	€ 79,461,000	1	4 (5)	€ 90,013,000	1	4

Notes: The market pool is the share of TV money each participating club receives based on how relevant their market is. Data comes from UEFA yearly reports on revenue distribution, provided on uefa.com. The association club coefficients are based on the results of each association's clubs in the five previous UEFA Champions League and UEFA Europa League seasons. We present the number of teams participating in the UCL group stage by country. In parenthesis is the total number of teams including the clubs eliminated in the UCL play-off round (i.e., the last qualification round before the UCL group stage). For season 2014/15, the market pool data as reported by UEFA do not consider teams that fail to qualify to the group stage via the play-off round.

Table A2. Estimations Including All Four Seasons.

	UK		ESP	
	Panel A	Panel B	Panel A	Panel B
Audience _{t-1}	0.113*** (0.029)	0.095*** (0.018)	0.073*** (0.011)	0.054*** (0.008)
Suspense	0.623*** (0.144)	0.426*** (0.097)	0.603*** (0.102)	0.351*** (0.096)
Surprise	0.014 (0.022)	0.022 (0.014)	0.030** (0.012)	0.026*** (0.006)
Shock	0.080*** (0.029)	0.083*** (0.021)	0.03 (0.023)	0.045** (0.018)
Observations	14,872	20,064	7,392	11,440
Number of game IDs	169	228	84	130
Log Pseudolikelihood	-7,137.22	-11,024.85	-6,357.56	-11,010.76

Notes: All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3. Number of Channels a Game is Televised Simultaneously.

Channels	UK				Spain			
	Panel A		Panel B		Panel A		Panel B	
	N	Share	N	Share	N	Share	N	Share
1	82	85.4%	118	84.3%	.	.	.	.
2	14	14.6%	33	15.7%	48	72.7%	67	67%
3	.	.	.	.	18	27.3%	31	31%
4	.	.	.	.	.	.	2	2%

Notes: Panel A consists of group stage games. Panel B consists of group stage games and first leg games of the round of 16, quarter-finals, semi-finals as well as the finals. UK: United Kingdom; ESP: Spain. *Channels* is the number of channels that a game is televised. *N* is the number of games that are shown on the respective number of channels.

Table A4. Descriptive Statistics Including Season 2014/15.

	UK						Spain					
	Panel A (N = 169 Games)			Panel B (N = 228 Games)			Panel A (N = 84 Games)			Panel B (N = 130 Games)		
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Suspense	0.056	0.046	0.000	0.521	0.058	0.045	0.000	0.521	0.054	0.045	0.000	0.521
Surprise	0.014	0.074	0.000	1.185	0.015	0.073	0.000	1.170	0.013	0.065	0.000	1.166
Shock	0.298	0.232	0.000	1.116	0.307	0.243	0.000	1.116	0.254	0.213	0.000	1.060
Audience	0.466	0.834	0.000	5.985	0.631	1.072	0.000	7.233	1.918	2.496	0.000	12.100

Notes: Panel A consists of group stage games. Panel B consists of group stage games and first leg games of the round of 16, quarter-finals, semi-finals as well as the finals. UK: United Kingdom; ESP: Spain. Audience is in millions. The sample includes all four seasons, and excludes N = 14 games of season 2014/15 in UK that have zero audience across all 90 min.

Table A5. Regression Estimates – Combined UK and Spain Games.

	UK & Spain	
	Panel A	Panel B
Audience _{t-1}	0.077*** (0.080)	0.060*** (0.007)
Suspense	0.600*** (0.089)	0.381*** (0.086)
Surprise	0.023*** (0.009)	0.024*** (0.005)
Shock	0.038* (0.019)	0.041*** (0.016)
Observations	14,256	21,120
Number of game IDs	162	240
Log Pseudolikelihood	-9,673.83	-15,863.44

Notes: All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6. Effect Heterogeneity – Combined UK and Spain Games.

	UK & Spain	
	Panel A	Panel B
Audience _{t-1}	0.077*** (0.010)	0.058*** (0.009)
Suspense × UK	0.551*** (0.103)	0.408*** (0.082)
Suspense × Spain	0.614*** (0.112)	0.382*** (0.109)
Surprise × UK	0.032*** (0.012)	0.033*** (0.009)
Surprise × Spain	0.020* (0.011)	0.021*** (0.007)
Shock × UK	0.040 (0.029)	0.023 (0.023)
Shock × Spain	0.037 (0.027)	0.048** (0.021)
Observations	14,256	21,120
Number of game IDs	162	240
Log Pseudolikelihood	-9,673.84	-15,863.39

Notes: All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7. Regression Estimates – Excluding Shock.

	UK		ESP	
	Panel A	Panel B	Panel A	Panel B
Audience _{t-1}	1.224*** (0.142)	0.320** (0.120)	0.069*** (0.014)	0.054*** (0.011)
Suspense	0.307*** (0.096)	0.470*** (0.074)	0.627*** (0.120)	0.367*** (0.115)
Surprise	0.025*** (0.009)	0.024*** (0.007)	0.020* (0.011)	0.025*** (0.017)
Observations	8,448	12,320	5,808	8,800
Number of game IDs	96	140	66	100
Log Pseudolikelihood	-4,850.59	-7,600.26	-4,816.85	-8,259.53

Notes: All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8. Effect Heterogeneity: First vs Second Half – Pay TV Audience.

	ESP	
	Panel A	Panel B
Audience _{t-1}	0.555*** (0.074)	0.303*** (0.097)
Suspense × 1st half	-0.093 (0.702)	0.738 (0.498)
Suspense × 2nd half	0.764*** (0.247)	0.676*** (0.187)
Surprise × 1st half	0.050 (0.046)	0.016 (0.030)
Surprise × 2nd half	-0.014 (0.020)	0.017 (0.017)
Shock × 1st half	-0.022 (0.097)	-0.047 (0.069)
Shock × 2nd half	-0.078 (0.058)	-0.005 (0.062)
Observations	4,224	6,072
Number of game IDs	48	69
Log Pseudolikelihood	-2,043.29	-3,133.95

Notes: All models include game fixed effects and minute-of-game dummies. Dependent variable is audience of pay TV telecasts in Spain. Given the limited sample sizes with regard to free TV games we refrain from reporting free TV audience estimates. In parenthesis are displayed robust standard errors clustered at game level. ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9. Outcome Uncertainty Regressed on Emotional Cues.

	UK		ESP	
	Panel A	Panel B	Panel A	Panel B
Suspense	−5.295*** (0.704)	−5.179*** (0.608)	−5.497*** (0.808)	−5.267*** (0.098)
Surprise	0.027 (0.103)	0.077 (0.083)	0.178 (0.126)	0.179* (0.098)
Shock	1.567*** (0.244)	1.747*** (0.189)	0.989*** (0.311)	1.450*** (0.257)
Observations	8,640	12,600	5,940	9,000
Number of game IDs	96	140	66	100
Log Pseudolikelihood	−6,135.39	−8,811.05	−4,407.42	−6,489.21

Notes: Outcome variable: Absolute difference between the home and away win probability at minute t . All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A10. Regression Estimates on the Impact of Outcome Uncertainty – Excluding Emotional Cues.

	UK		ESP	
	Panel A	Panel B	Panel A	Panel B
Audience _{$t-1$}	1.246*** (0.141)	0.320*** (0.121)	0.071*** (0.015)	0.055*** (0.011)
Abs(hwin-awin)	0.027 (0.026)	0.016 (0.025)	0.067* (0.037)	0.043 (0.026)
Draw prob	0.089 (0.050)	0.113** (0.048)	0.243*** (0.067)	0.135** (0.059)
Observations	8,448	12,320	5,808	8,800
Number of game IDs	96	140	66	100
Log Pseudolikelihood	−4,850.68	−7,600.63	−4,817.37	−8,260.09

Notes: All models include game fixed effects and minute-of-game dummies. In parenthesis are displayed robust standard errors clustered at game level. UK: United Kingdom; ESP: Spain. Levels of statistical significance; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2 Study 2: Suspense and Surprise in European Football

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Football

ABSTRACT

A key criterion for evaluating sports competitions is their attractiveness to consumers. In this paper, we propose using match-level suspense and surprise, which capture the entertainment utility generated by competitive balance and outcome uncertainty for sports spectators, to assess attractiveness. Through simulations, we derive a benchmark range for suspense and surprise based on an otherwise balanced match with home advantage, before analyzing more than 25,000 matches from Europe's top five football leagues played between 2010/11 and 2023/24. Our findings reveal that mean match suspense is often lower than the benchmark range, particularly for top teams, while mean match surprise most often aligns with the benchmark. Moreover, we identify nuanced trends over time and highlight notable differences across leagues and clubs. These insights enhance our understanding of how the attractiveness of matches arises from competitive balance and carry important policy implications.

1. Introduction

Professional sports constitute an entertainment product, with many competitions and matches regularly attracting widespread attention. More generally, the attractiveness of a match in sports can be defined by its quality, its importance, or its competitive intensity (Devriesere et al., 2025). The latter is also referred to as outcome uncertainty, a concept rooted in the seminal works of Neale (1964) and Rotemberg (1956), who argue that the unpredictability of competitive outcomes enhances fan welfare. Conceptually, competitive balance, which refers to the relative strengths of teams, translates into outcome uncertainty at various levels: a single match (short-term perspective), a sub-competition such as the championship race (mid-term perspective), or the dominance of a few teams over time (long-term perspective) (e.g., Szymanski, 2003). Subsequently, greater outcome uncertainty is assumed to lead to higher demand for sports. This relationship is known in the literature as the Uncertainty of Outcome Hypothesis (UOH), which primarily refers to the relation between outcome uncertainty and demand at the match level (e.g., Fort, 2022; Pawlowski et al., 2018).

Based on the premise that outcome uncertainty enhances entertainment value and is desirable for sports fans, league organizers frequently (re)design competitions, and policymakers justify market interventions such as salary caps, draft systems, or revenue redistribution schemes (e.g., Fort & Quirk, 1995), which are prohibited or heavily restricted in most industries outside of professional sports (e.g., Budzinski, 2012; Mehra & Zuercher, 2006). Moreover, numerous studies investigate factors influencing outcome uncertainty, including competition design and tournament rules (e.g., Chater et al., 2021; Csató, 2022; Csató & Gyimesi, 2026; Devriesere et al., 2025; Scarf et al., 2009), sporting rules (e.g., Baker et al., 2022; Csató, 2023; Di Mattia & Krumer, 2023; Goller & Krumer, 2020), point-scoring systems (e.g., Percy, 2009), and scoring rates (e.g., Scarf et al., 2019). However, prior research has failed to provide consistent evidence that outcome uncertainty is a key driver of stadium attendance and TV viewership, particularly in European football (Collins & Humphreys, 2022; Johnson & Fort, 2022; Pawlowski & Nalbantis, 2019). Accordingly, monitoring outcome uncertainty over time and treating it as a policy target appears misleading.

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In this paper, we adopt a different perspective and propose suspense and surprise (Ely et al., 2015) as measures for assessing match attractiveness and, when averaged across matches, the mean match attractiveness of certain teams and competitions. Both measures capture the entertainment utility that originates from the relative strengths of the teams in a match and unfolds through the resolution of information during the game. In this regard, suspense is a forward-looking concept that reflects the excitement or anxiety about future events and arises from the variance in beliefs about the outcome of the game in the next period. Surprise, in contrast, is a backward-looking concept that captures the emotional response to an unexpected event, resulting from the shift between the current and previous beliefs about the game's outcome (Ely et al., 2015).

A key reason for employing both measures is their clear link to sports demand. Building on the framework of Ely et al. (2015), researchers have empirically investigated how viewers derive entertainment utility from suspense and surprise by approximating subjective beliefs with objective outcome probabilities and using within-game panel data, such as TV viewing figures (Bizzozero et al., 2016; Buraimo et al., 2020; Kaplan, 2021; Richardson et al., 2023), streaming data (Simonov et al., 2023), and social media activity (Pawlowski et al., 2024). A consistent finding across these studies is that within-game sports demand is driven by both suspense and surprise.

Moreover, both measures are closely tied to outcome uncertainty, albeit in opposite ways: suspense tends to increase with higher uncertainty, whereas surprise is more likely to arise when an outcome departs from what was previously expected. Consequently, distinguishing between suspense and surprise is theoretically valuable, as it captures two distinct dimensions of entertainment utility within the broader concept of outcome uncertainty. This perspective may help explain the mixed empirical support for the UOH, as it suggests that the relationship between match outcome uncertainty and demand operates through at least two distinct mechanisms. Finally, the calculation of suspense and surprise follows a bottom-up approach to competitive balance and outcome uncertainty (Basini et al., 2023). This enables analyses at different levels of aggregation, such as the club or league level, thereby allowing for a more precise examination of patterns and trends.

We examine the status quo and the development of suspense and surprise in European football, the most extensively analyzed context for the UOH (Collins & Humphreys, 2022), and pose three questions: (i) How do match-level suspense and surprise depend on the (relative) strengths of the teams? (ii) How do suspense and surprise in European football matches compare to a theoretical benchmark based on the maximum attainable levels of suspense and surprise? (iii) How have suspense and surprise evolved over time? Addressing these questions enables league organizers and policymakers to make informed regulatory and league design decisions by considering the origins, levels, and trends of demand-relevant suspense and surprise.

We begin by analyzing how match-level suspense and surprise are influenced by the strengths of the competing teams. This is important because team-strength variation captures competitive balance (Baker et al., 2022). To investigate this, we simulate matches between teams with varying scoring rates, which reflect the underlying strengths of the competing teams (Scarf et al., 2022). We refer to a match as being “perfectly balanced” when both teams have equal strength and their scoring rates just differ by home advantage. Our simulations reveal a key trade-off: suspense in a perfectly balanced match is higher when scoring rates are lower, whereas surprise increases with higher scoring rates. Based on this, we establish a benchmark range of suspense and surprise, derived from simulating perfectly balanced matches at varying scoring rates. In the second step, we derive empirical values of suspense and surprise from over 25,000 matches played in the top five European leagues: the English Premier League, the German Bundesliga, the Spanish La Liga, the Italian Serie A, and the French Ligue 1, covering the seasons from 2010/11 to 2023/24.

Our findings suggest that mean suspense across all matches is lower than the benchmark range. This pattern is particularly evident in matches involving top teams, whereas matches involving non-top teams are relatively less likely to exhibit mean suspense levels significantly below the lower benchmark bound. In contrast, mean surprise values typically remain within the benchmark range. Regarding time trends, we find no evidence of a general decline in suspense and surprise across European football. Instead, the results point to heterogeneous patterns across leagues, including downward trends, upward trends, and cases with no clear trend. In addition, some league-level trends are driven primarily by matches involving one or two clubs.

With this study, we contribute to the literature on the attractiveness of sports competitions. In particular, our analysis is closely related to the recent work of Buraimo et al. (2022), who demonstrate the relevance of match importance in terms of league outcomes for demand. In contrast, we focus on uncertainty surrounding the outcome of a specific match rather than on league outcomes and propose a measure of entertainment utility that is grounded in the relative strengths of the teams and evolves through the resolution of information during the game. As such, we argue that suspense and surprise provide complementary ways of assessing match attractiveness and, when averaged across matches, mean match attractiveness of certain teams and competitions.

The remainder of this paper is structured as follows: Section 2 conceptualizes suspense and surprise; Section 3 derives suspense and surprise from simulated matches involving teams of varying strength; Section 4 analyzes suspense and surprise in real matches; and Section 5 presents the discussion and conclusion.

2. General set-up

The procedures for determining suspense and surprise values in both simulated and real matches build on the conceptual framework proposed by Ely et al. (2015). In this framework, suspense is induced by the variance in beliefs about the next period, whereas surprise arises from the change in beliefs between the previous and current periods. In the context of football, these beliefs pertain to the final outcome of a match and can be approximated with objective winning probabilities.

In their seminal work, Ely et al. (2015) develop the corresponding model in a highly general framework with finite state and signal spaces. Although their main contribution is theoretical and design-oriented, i.e., they study the optimal way in which information should be revealed over time, they also provide several empirical illustrations of information revelation and the resulting suspense and surprise processes in different settings, including tennis, European football, blackjack, and the Clinton–Obama Democratic Party presidential primary. In contrast to this general theoretical framework, however, all of these empirical illustrations are based on binary outcomes only, namely winning or losing. For European football, where draws constitute a common third outcome, they collapse the draw and away-win categories in their illustration.

Buraimo et al. (2020) were the first to operationalize the model while jointly accounting for all three possible outcomes, namely a home win, a draw, and an away win. Building on their approach, we define the backward-looking measure of surprise as follows:

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

where p_t refers to the probability of a home team win (p_t^H), a draw (p_t^D), or an away team win (p_t^A) at minute t in a given match.¹ In contrast, suspense is a forward-looking measure that weights potential changes in outcome probabilities by the probabilities of either the home or away

¹ While we use this specification of surprise in our analysis, it is worth mentioning that the correlation between this specification and an alternative specification that omits the probabilities of a draw is 99%.

team scoring in the next minute, denoted by p_{t+1}^{HS} and p_{t+1}^{AS} , respectively. Accordingly, we define suspense in a given minute t as follows:

Suspense _{t}

$$= \sqrt{\sum_{j \in \{H, D, A\}} \left(p_{t+1}^{HS} \left[(p_{t+1}^j | HS_{t+1}) - p_t^j \right]^2 + p_{t+1}^{AS} \left[(p_{t+1}^j | AS_{t+1}) - p_t^j \right]^2 \right)} \quad (2)$$

where $(p_{t+1}^j | HS_{t+1}) - p_t^j$ and $(p_{t+1}^j | AS_{t+1}) - p_t^j$ reflect the hypothetical change in outcome probabilities from minute t to $t+1$, given that either team scores in $t+1$.

To calculate the required (conditional) outcome probabilities on a minute-by-minute basis for each match, we follow the approach outlined by [Buraimo et al. \(2020\)](#) and implement an in-play model. For each game, we assume that a European football match resembles a ‘‘Poisson match’’, where goals are scored independently by the home and away teams, following univariate Poisson distributions. The Poisson model has been suggested first by [Maher \(1982\)](#) and is a classical choice for the distribution of the number of goals in football (e.g., [Csat , 2023](#); [Scarf et al., 2022, 2019](#); [van Eetvelde & Ley, 2019](#)). Specifically, the number of goals scored by the home team, $X \sim \text{Poisson}(\lambda_H)$, and the number of goals scored by the away team, $Y \sim \text{Poisson}(\lambda_A)$. We distribute the team-specific scoring rates, λ_H and λ_A , across the match using historical, league-specific minute-by-minute empirical goal distributions to derive time-specific scoring rates. These minute-by-minute goal-scoring rates are combined with the timing of major in-game events, namely goals scored and red cards received, to estimate the outcome probabilities for each match at any given minute. Specifically, scoring in a given minute is simulated by drawing from a Bernoulli distribution, where the success probability is set to the estimated minute-by-minute scoring rate. That is, $G_t \sim \text{Bernoulli}(p_t^S)$, where G_t represents whether a goal is scored in minute t , and p_t^S denotes the estimated team-specific goal-scoring probability in that minute ([Chater et al., 2021](#)). The simulation exercise is repeated 100,000 times for each minute, resulting in 9 million simulated match-minutes.

One important consideration in this modeling process is the adjustment of scoring rates following red cards. [Vecer et al. \(2009\)](#) estimate the effect of a red card on scoring rates using betting data from matches played at the 2006 FIFA World Cup and UEFA EURO 2008. They find that, for the remainder of the match, the scoring rate of the team receiving a red card is reduced, on average, to $\frac{2}{3}$ of its original value, while that of the opposing team increases to 1.2 times its original value. We adopt these parameters in our modeling process.

However, because [Vecer et al. \(2009\)](#) use relatively old data from a small sample of national-team matches, we conducted robustness checks to assess whether our results are sensitive to alternative parameter values. To do so, we first selected, from the real-match data described in Section 4, the subsample of matches in which at least one red card was awarded. Using this subsample, we conducted sensitivity analyses with scoring-rate multipliers of 0.5, 0.66, and 0.8 for the team receiving the red card, and 1.1, 1.2, and 1.3 for the opposing team. Overall, our findings did not change materially. We therefore decided to retain the ratios originally proposed by [Vecer et al. \(2009\)](#) in our analysis.

A second important consideration in the modeling process is the treatment of injury time. Injury time is regularly added in both the first and second half, resulting in substantial variation in effective playing time across matches. In our modeling approach, we therefore introduce one additional injury-time minute in each half, namely 45 + 1 and 90 + 1, into which all events occurring during injury time are collapsed. While this remains an approximation, it allows us to distinguish more clearly between regular playing time and injury time in the analysis. Adding further injury-time minutes in the first half is problematic because injury time there is usually short. Likewise,

introducing multiple additional injury-time minutes in the second half would be somewhat arbitrary and would not materially improve our approach, as we cannot account for heterogeneity in injury-time length across matches in the simulation.

The resulting outcome probabilities from this modeling process are used to calculate suspense and surprise on a minute-by-minute basis, which are then aggregated over all minutes at the match level. Note, since we are missing a value for suspense in minute 90 + 1 (as suspense is forward-looking), we effectively use 91 minute-suspense values for calculating aggregated suspense. Moreover, surprise in minute 1 is always zero unless a goal or red card happened in minute 1, in which case we calculated surprise using the closing odds as reference category. As such, we effectively use 92 minute-surprise values for calculating aggregated surprise. Overall, this procedure yields one suspense and one surprise value per match.

3. Simulated matches

To investigate how suspense and surprise are influenced by team strengths, we simulate matches between teams with varying scoring rates. We consider 1326 unique scoring rate combinations, covering all pairings of λ_H and λ_A ranging from 0 and 5 in increments of 0.1. Since football is a low-scoring sport, with a mean scoring rate of approximately 1.5 goals per team per match (e.g., [Baker & McHale, 2018](#); [Scarf et al., 2022](#)), a scoring rate of 5 represents a really high value.

For each pairing, we simulate 100,000 matches, resulting in a total of 132,600,000 hypothetical matches. The simulations use historical minute-by-minute empirical goal distributions from the English Premier League to determine the minute-by-minute scoring rates.² Red cards are incorporated into the simulation framework in a manner identical to how goals are simulated. Using the historical data, we calculate the empirical minute-by-minute probability of a red card occurring separately for home and away teams across all 92 min (i.e., including minutes 45 + 1 and 90 + 1 as described before). In each simulated game, for every minute we draw from a Bernoulli distribution using these empirical probabilities to determine whether a red card occurs at that minute for each team. Once a red card is assigned to a team, its scoring rate is reduced by a factor of $\frac{2}{3}$, while the opposing team’s scoring rate is increased by a factor of 1.2 for all remaining minutes of the match. This red card state is tracked cumulatively so that if a team accumulates more red cards than the opposing team at any point, the scoring rate adjustments are applied from that minute onward for the remainder of the game.

Subsequently, we calculate the suspense and surprise values for each simulated match, following the methodology outlined in Section 2. [Fig. 1](#) presents the simulation results for the mean level of suspense ([Fig. 1\(a\)](#)) and surprise ([Fig. 1\(b\)](#)) across different combinations of scoring rates, λ_H and λ_A . Suspense is low (indicated in blue) when scoring rates are highly unequal, as one team is overwhelmingly dominant and almost certain to win the match. Conversely, suspense tends to be high (indicated in red) when scoring rates are equal. However, suspense is zero when $\lambda_H = \lambda_A = 0$, since the outcome of a draw is certain, even though the match is perfectly competitively balanced. This illustrates the fundamental distinction between competitive balance and outcome uncertainty, as also noted by [Scarf et al. \(2019\)](#).

Importantly, even in a perfectly balanced match, the level of suspense depends on the absolute values of the scoring rates. When both rates are close to zero, the probability of a draw is high, as neither team is likely to score. As the scoring rates increase together while remaining equal, the likelihood of a draw decreases, and the probability of either

² The empirical goal distributions across the top five European leagues are similar, and we do not expect that selecting the empirical goal distribution of another top five league would significantly affect our results.

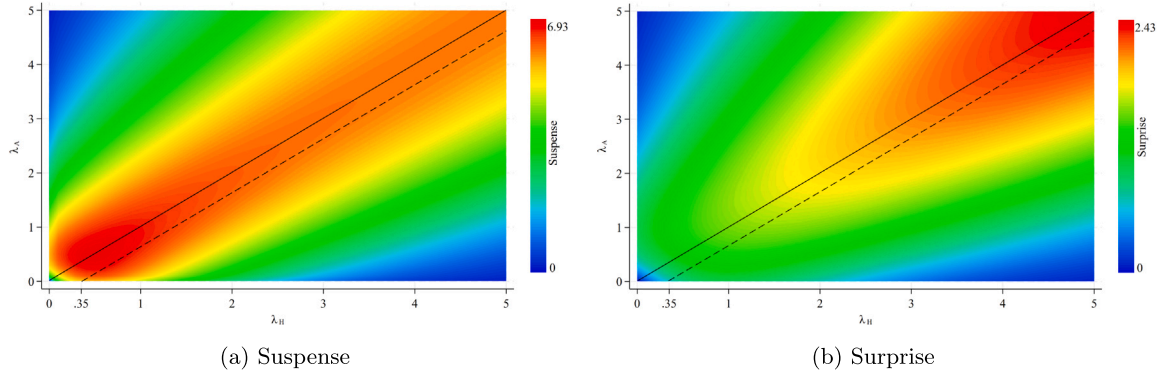


Fig. 1. Suspense and surprise as a function of teams' scoring rates.

Note: This figure plots match-level suspense (Fig. 1(a)) and surprise (Fig. 1(b)) values as a function of the scoring rates λ_H for the home team and λ_A for the away team, assuming a Poisson match where goals are scored independently following univariate Poisson distributions. The 45-degree line reflects match-level suspense and surprise in matches between teams of equal strength and with equal scoring rates. The parallel shifted dashed line reflects the corresponding values for otherwise balanced matches with a home advantage of 0.35 goals.

a home or away win increases (Scarf et al., 2022). Therefore, different levels of equal scoring rates translate into different levels of suspense. Suspense increases for $0 < \lambda_H = \lambda_A < 0.5$, reaches a maximum at $\lambda_H = \lambda_A = 0.5$, and decreases again for $\lambda_H = \lambda_A > 0.5$, as the two rates continue to rise together. This finding adds nuance to the conjectures of Scarf et al. (2019), who suggest that suspense strictly decreases as scoring rates increase.

Interestingly, surprise follows the opposite pattern, increasing strictly with higher and more equal scoring rates. It is zero when $\lambda_H = \lambda_A = 0$, as no goals are expected and a draw is certain. In our simulations, the maximum level of surprise occurs at $\lambda_H = \lambda_A = 5$. Because these are the highest scoring rates considered in our simulations, this should be interpreted as a local maximum within the simulated range. Remarkably, higher but unequal scoring rates can produce levels of surprise similar to those observed under lower but equal scoring rates. For example, the surprise generated in a match with $\lambda_H = \lambda_A = 1$ is similar to that in a match with $\lambda_H = 3$ and $\lambda_A = 1.5$.

These findings contradict the conjecture by Scarf et al. (2019), who suggest that higher scoring rates always reduce surprise. One possible explanation for this discrepancy is the simpler definition and operationalization of surprise used by Scarf et al. (2019), who classify a match as surprising if a team defeats another team whose win percentage is at least 20 percentage points higher, and as non-surprising otherwise. Their measure therefore captures only whether the final outcome was surprising, but not the within-match variations in outcome probability that contribute to surprise as originally defined by Ely et al. (2015).

More broadly, the simulation results in Fig. 1 highlight a trade-off between suspense and surprise when relative team strength is held constant. This pattern is clearest in perfectly balanced matches: suspense is higher at lower scoring rates, except when rates are close to zero, whereas surprise is higher at higher scoring rates. Intuitively, lower scoring rates tend to keep matches closer for longer, which increases suspense, while higher scoring rates generate more scoring events, creating more opportunities for surprising developments. Thus, for a given degree of team-strength imbalance, changes in the overall scoring environment can move suspense and surprise in opposite directions.

We further use the simulated matches to examine how suspense and surprise respond to changes in team-strength imbalance. We define team-strength imbalance as the absolute log difference in the two teams' scoring rates, $|\log(\lambda_H) - \log(\lambda_A)|$, and control for the average log scoring-rate level, $[\log(\lambda_H) + \log(\lambda_A)]/2$. We then separately regress mean suspense and mean surprise on team-strength imbalance and the average log scoring-rate level. The standardized coefficients on team-strength imbalance show that, conditional on the average scoring-rate level, suspense responds more strongly to imbalance than surprise. To illustrate, a one-standard-deviation increase in team-strength

imbalance is associated with a 1.12-standard-deviation decrease in suspense, compared with a 0.78-standard-deviation decrease in surprise. Thus, for the same increase in imbalance, the decline in suspense is about 44% larger than the decline in surprise.

To contextualize the current empirical values of suspense and surprise in European football (see Section 4), we use the simulation results to derive a benchmark range for both metrics for otherwise balanced matches with home advantage and varying absolute scoring rates. Under equal playing strength, the expected scoring differential between the home and away team should reflect home advantage in the standard double round-robin setting of the leagues under consideration. Using the empirical distribution of the mean number of goals scored per match by home and away teams, we estimate that home advantage corresponds, on average, to an increase of 0.35 in the home team's scoring rate. This home advantage is illustrated by a parallel shift of the 45-degree line in Fig. 1.

Since the scoring-rate levels that would prevail in a perfectly balanced match are not known ex ante, we choose a deliberately broad range of low and high scoring rates. For the low-scoring case, we choose a scoring rate of 0.5, which corresponds to the 10th percentile of the empirical distribution of the mean number of goals scored per team per match in our sample. Accordingly, when incorporating home advantage, we set $\lambda_H = 0.85$ and $\lambda_A = 0.5$. Likewise, for the high-scoring case, we choose a scoring rate of 2.5, which corresponds to the 90th percentile of the empirical distribution in our sample.³ Taking home advantage into account, we set $\lambda_H = 2.85$ and $\lambda_A = 2.5$.⁴

³ As a sensitivity check, we also use the 15th and 85th percentiles to define the low- and high-scoring-rate scenarios. The results remain qualitatively unchanged. We interpret this as a meaningful sensitivity check, while acknowledging that whether empirical suspense and surprise values fall below, within, or above the benchmark range necessarily depends on the width of that range. Much narrower percentile intervals would mechanically tighten the benchmark bands and could lead to more empirical values to fall outside them.

⁴ We additionally test whether home advantage varies with scoring rates using league-season observations. Specifically, we regress average home-away goal difference on mean-centered average total goals per match, weighted by the number of matches. The estimated relationship is small and statistically insignificant ($\beta = -0.036$, $p = 0.510$), indicating no systematic variation in home advantage across scoring rates. We also test whether home advantage differs across leagues. Pairwise comparisons show that La Liga has a somewhat higher average home-away goal difference (0.42) than several other leagues, significantly exceeding Ligue 1, the Premier League, and Serie A, but not the Bundesliga. Recalculating the La Liga benchmark bands using a home-advantage adjustment of 0.42 instead of 0.35 leaves the results virtually unchanged.

Table 1
Descriptive statistics for otherwise balanced matches with home advantage.

		N	Mean	Median	SD	Min	Max
Low scoring rates ($\lambda_H = 0.85$; $\lambda_A = 0.5$)	Suspense	100,000	6.70	7.15	1.68	0.24	9.31
	Surprise	100,000	1.34	1.11	0.68	0.62	6.68
High scoring rates ($\lambda_H = 2.85$; $\lambda_A = 2.5$)	Suspense	100,000	6.08	6.49	1.87	0.46	9.39
	Surprise	100,000	1.99	1.84	0.85	0.41	6.70

Notes: Suspense and surprise in simulated, otherwise balanced matches with a home advantage of 0.35 in λ_H , under low-scoring conditions ($\lambda_H = 0.85$, $\lambda_A = 0.5$) and high-scoring conditions ($\lambda_H = 2.85$, $\lambda_A = 2.5$).

Note that, in contrast to our approach, the literature often identifies unique upper and lower bounds of competitive balance indices based on the theoretically most equal or most unequal distribution of wins or points (e.g., [Avila-Cano et al., 2023, 2021](#); [Depken, 1999](#); [Owen et al., 2007](#)). Alternatively, realized concentrations are compared with established thresholds for market concentration set by authorities such as the European Commission or the U.S. Federal Trade Commission (e.g., [Avila-Cano & Triguero-Ruiz, 2023](#)). In addition, we derive the benchmark values endogenously from the premise that viewers value suspense and surprise. Under this premise, suspense is highest when scoring rates are low and equal (i.e., both equal to 0.5), whereas surprise is highest when scoring rates are high but still equal.

[Table 1](#) presents the descriptive statistics for suspense and surprise in otherwise perfectly balanced matches with home advantage and low ($\lambda_H = 0.85$, $\lambda_A = 0.5$) or high scoring rates ($\lambda_H = 2.85$, $\lambda_A = 2.5$). Within this benchmark range, suspense has a lower bound of 6.08 and an upper bound of 6.70, while surprise ranges from 1.34 to 1.99. These values define the benchmark range boundaries against which we compare the empirical values of suspense and surprise.

4. Real matches

4.1. Data and sample

Our empirical dataset comprises over 25,000 men's football matches played in the top five European leagues, i.e., the English Premier League, the German Bundesliga, the Spanish La Liga, the Italian Serie A, and the French Ligue 1, between the 2010/11 and 2023/24 seasons. Depending on the league, the dataset includes between 4284 and 5320 matches per league. Match information, including the timing of goals and red cards, was collected from fbref.com, while pre-match closing odds and over-under totals were obtained from oddsportal.com.

To estimate the scoring rates λ_H and λ_A for each game, we follow the methodology of [Buraimo et al. \(2020\)](#), which relies on betting odds and uses an optimization procedure based on the assumption that goals scored follow Poisson distributions. Betting odds have been shown to contain highly accurate information on football matches ([Wunderlich, 2025](#)) and to have higher predictive quality than alternative approaches to measuring team strength, such as Elo ratings ([Hvattum & Arntzen, 2010](#); [Wunderlich & Memmert, 2018](#)).

We adjust the pre-match betting odds for the overround to derive implied probabilities for a home win, draw, and away win. While these closing odds already capture some information about the expected number of goals, since a team more likely to win is also more likely to score more, over/under (O/U) odds provide additional, independent constraints on the distribution of total goals scored. Specifically, O/U odds for thresholds ranging from 0.5 to 5.5 goals are converted into implied probabilities and incorporated into the same optimization procedure, ensuring that the selected scoring rates not only match expected match outcomes but also align with market expectations about total goals. Using the procedure outlined in [Section 2](#), we calculate match-level suspense and surprise values for all 25,389 matches played.

To validate our assumption that match-level suspense and surprise are positively related to sports demand, we regress both measures on TV audience using the original dataset from [Buraimo et al. \(2022\)](#). This dataset comprises 790 English Premier League matches televised

between the second half of the 2013/14 season and the end of the 2018/19 season. In Columns 2 and 3 of [Table A.1](#) in [Appendix A](#), we show that suspense and surprise are positively associated with TV demand and help explain demand over and above league-outcome-specific measures proposed by [Buraimo et al. \(2022\)](#), namely match significance with respect to the championship, European qualification, and relegation. A detailed description of the analysis and results is provided in [Appendix A](#).

[Table 2](#) presents descriptive statistics for suspense and surprise across leagues. League comparisons reveal several differences, with mean suspense ranging from 5.78 in the Premier League to 6.05 in Ligue 1 over the observation period. Similarly, mean surprise varies from 1.41 in the Premier League and La Liga to 1.44 in the Bundesliga. Notably, the relatively large standard deviations indicate substantial variation over time and across matches. The last column of [Table 2](#) indicates whether mean suspense and surprise values fall significantly below the lower bound of the benchmark range for perfectly balanced matches as defined in [Section 3](#), based on a one-sided t-test. The results show that mean suspense values are significantly lower than the benchmark's lower bound for all leagues but Ligue 1. In contrast, mean surprise values across all five leagues remain above the lower bound of the benchmark range. This suggests that, while mean suspense in matches from the top five European leagues is comparatively low, mean surprise remains within the benchmark range. As a robustness check, we excluded the COVID-19-affected seasons 2019/20, 2020/21, and 2021/22 from our sample, and the results remained similar.

In the following analysis, we exploit the granularity of match-level suspense and surprise to examine trends within each league individually. Importantly, however, while we report observed trends, we cannot draw conclusions about the underlying mechanisms, whether COVID-19-related or otherwise.

4.2. Suspense and surprise trends in the English Premier League

We begin by examining the development of suspense and surprise in the English Premier League. [Fig. 2](#) presents box plots showing mean suspense and surprise per game across teams and seasons. We visualize the three top teams separately, defined as those that accumulated the most points during our observation period from 2010/11 to 2023/24, while grouping all remaining teams together. According to this definition, the top three teams in the Premier League were Manchester City, Liverpool, and Arsenal. The gray horizontal band represents the benchmark range for a perfectly balanced match as defined in [Section 3](#). An asterisk (*) indicates whether mean suspense or surprise values for a team in a given season are significantly below the lower bound of the benchmark range ($p < 0.05$), based on a one-sided t-test.

[Fig. 2\(a\)](#) shows that mean suspense values for Manchester City matches tend to be the lowest and are almost always significantly below the lower benchmark bound. For Liverpool and Arsenal, a similar pattern emerges, though it is less pronounced. While visual inspection of [Fig. 2\(a\)](#) suggests that mean suspense for all other teams only rarely falls below the benchmark range, [Panel A](#) of [Table B.1](#) in [Appendix B](#) shows that matches involving Chelsea, Manchester United, and Tottenham Hotspur also recorded multiple seasons with mean suspense values below the lower benchmark band. In addition, the 2018/19 season stands out, as 12 of the 20 teams exhibited low suspense values. With

Table 2

Descriptive statistics of suspense and surprise in men's European football matches.

League	Metric	N	Mean	Median	SD	Min	Max	BM	< BM
Top 5 leagues	Suspense	25,389	5.90	6.59	2.15	0.08	9.31	6.08	***
	Surprise	25,389	1.42	1.80	0.81	0.12	5.91	1.34	
Premier League	Suspense	5320	5.78	6.43	2.19	0.08	9.17	6.08	***
	Surprise	5320	1.41	1.17	0.82	0.14	5.36	1.34	
Bundesliga	Suspense	4284	5.85	6.47	2.19	0.26	9.11	6.08	***
	Surprise	4284	1.44	1.27	0.80	0.14	5.91	1.34	
La Liga	Suspense	5320	5.89	6.64	2.22	0.16	9.26	6.08	***
	Surprise	5320	1.41	1.16	0.82	0.12	5.69	1.34	
Serie A	Suspense	5320	5.92	6.60	2.13	0.23	9.15	6.08	***
	Surprise	5320	1.43	1.22	0.82	0.14	5.44	1.34	
Ligue 1	Suspense	5145	6.05	6.70	2.04	0.17	9.31	6.08	
	Surprise	5145	1.42	1.20	0.79	0.12	5.17	1.34	

Notes: Suspense and surprise values are calculated as described in Section 2. Fewer games are observed for Ligue 1 due to the unbalanced schedule during the COVID-19 pandemic and the league's reduction from 20 to 18 teams for the 2023/24 season. BM refers to the lower bound of the benchmark range. < BM indicates a one-sided t-test assessing whether the mean is below the benchmark. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

regard to surprise, Fig. 2(b) and Panel B of Table B.1 in Appendix B show that mean values less frequently fall below the benchmark range. Manchester City again stands out as an exception, with values falling significantly below the benchmark range in five seasons during our observation window.

Remarkably, Panels A and B of Table B.1 show that comparatively low levels of suspense and/or surprise are generated not only by particularly strong teams, but also by particularly weak teams in a given season. Examples include Huddersfield in 2018/19 (finishing the season with 16 points), Norwich in 2019/20 and 2021/22 (21 and 22 points, respectively), and Sheffield United in 2023/24 (16 points). Since such teams are typically relegated on a regular basis, however, we do not present them in Fig. 2(a). Note also that Leicester City's Premier League title in the 2015/16 season, which has been characterized as an exceptionally unlikely sporting success (BBC Sport, 2016), is likewise reflected in our data. In that season, the mean values of suspense and surprise for Leicester City matches (suspense: 6.23; surprise: 1.51) were higher than those for all other Premier League teams excluding Leicester City (suspense: 5.99; surprise: 1.46).

To formally investigate the magnitude of time trends in suspense and surprise, we estimate linear regressions using the natural log of suspense and surprise as the dependent variable and season year as a continuous independent variable.⁵ Table 3 summarizes the results. Column (1) indicates a slight decline in suspense over time, while Column (2) reveals that this negative trend is driven entirely by matches involving Manchester City, with suspense in those matches decreasing by approximately 3.8% per season. Columns (3) and (4) show a similar pattern for surprise: matches involving Manchester City exhibit an additional decline of approximately 2.7% per season relative to the baseline trend. By contrast, matches involving Arsenal, Liverpool, or the remaining teams do not show a comparable decline.

Overall, these patterns align with Manchester City's dominance, having won seven league titles during our sample period. At the same time, however, suspense and surprise values in matches involving other Premier League teams remained relatively unchanged over time.

4.3. Suspense and surprise trends in the German Bundesliga

Fig. 3 presents box plots for the top three teams in the German Bundesliga—Bayern Munich, Borussia Dortmund, and Bayer Leverkusen—alongside the mean for all other teams.

⁵ Since our trend analysis is conducted at the match-level across multiple seasons, implementing a time series approach (e.g., Lee & Fort, 2012) is not feasible. To account for dependence within match-pair observations, we cluster standard errors at the home team-away team level.

Table 3

English Premier League time trends.

	Ln(suspense)		Ln(surprise)	
	(1)	(2)	(3)	(4)
Season	−0.005** (0.002)	−0.000 (0.002)	−0.003 (0.002)	0.001 (0.002)
Manchester City × season		−0.038*** (0.009)		−0.027*** (0.009)
Liverpool × season		−0.005 (0.006)		−0.006 (0.007)
Arsenal × season		−0.008 (0.008)		−0.006 (0.007)
Main effects		Yes		Yes
Observations	5320	5320	5320	5320
Adj-R ²	0.001	0.055	0.000	0.030

Notes: This table reports the results from OLS regressions with robust standard errors, clustered at the home team-away team level, shown in parentheses. Season is defined as a continuous variable. **** $p < 0.01$, ** $p < 0.05$.

Fig. 3(a) shows that mean suspense values for Bayern Munich matches are consistently the lowest in the Bundesliga and significantly below the benchmark range. Matches involving Dortmund exhibit the second-lowest suspense values, with many seasons also falling significantly below the lower bound. Thus, the Bundesliga is characterized by exceptionally low suspense in matches involving Bayern and Dortmund, while matches involving other teams remain on average closer to the lower benchmark bound associated with an otherwise balanced match with home advantage as defined in Section 3. However, Panel A of Table B.2 in Appendix B also shows that particularly weak teams occasionally generated comparably low levels of suspense, such as Paderborn 07 (20 points in 2019/20), Schalke 04 (16 points in 2020/21), Greuther Fürth (18 points in 2021/22), and Darmstadt 98 (17 points in 2023/24).

Interestingly, although the 2023/24 season saw a club other than Bayern win the title for the first time in 11 years, Bayern's mean value of suspense remained lower than that of the eventual league winner, Bayer Leverkusen. Moreover, while mean surprise values commonly fall well within the benchmark range, they are significantly below this range for matches involving Bayern Munich in 10 of 14 seasons (see Fig. 3(b)).

The linear regression results in Table 4 reveal an overall negative trend in both suspense and surprise in the Bundesliga. In the case of suspense, this trend is consistent with the greater number of team-seasons falling significantly below the benchmark range toward the end of our sample period (see Panel A of Table B.2 in Appendix B). However, the magnitudes of these effects appear modest (−0.7% and −0.5% per season, respectively) and do not appear to be driven by the

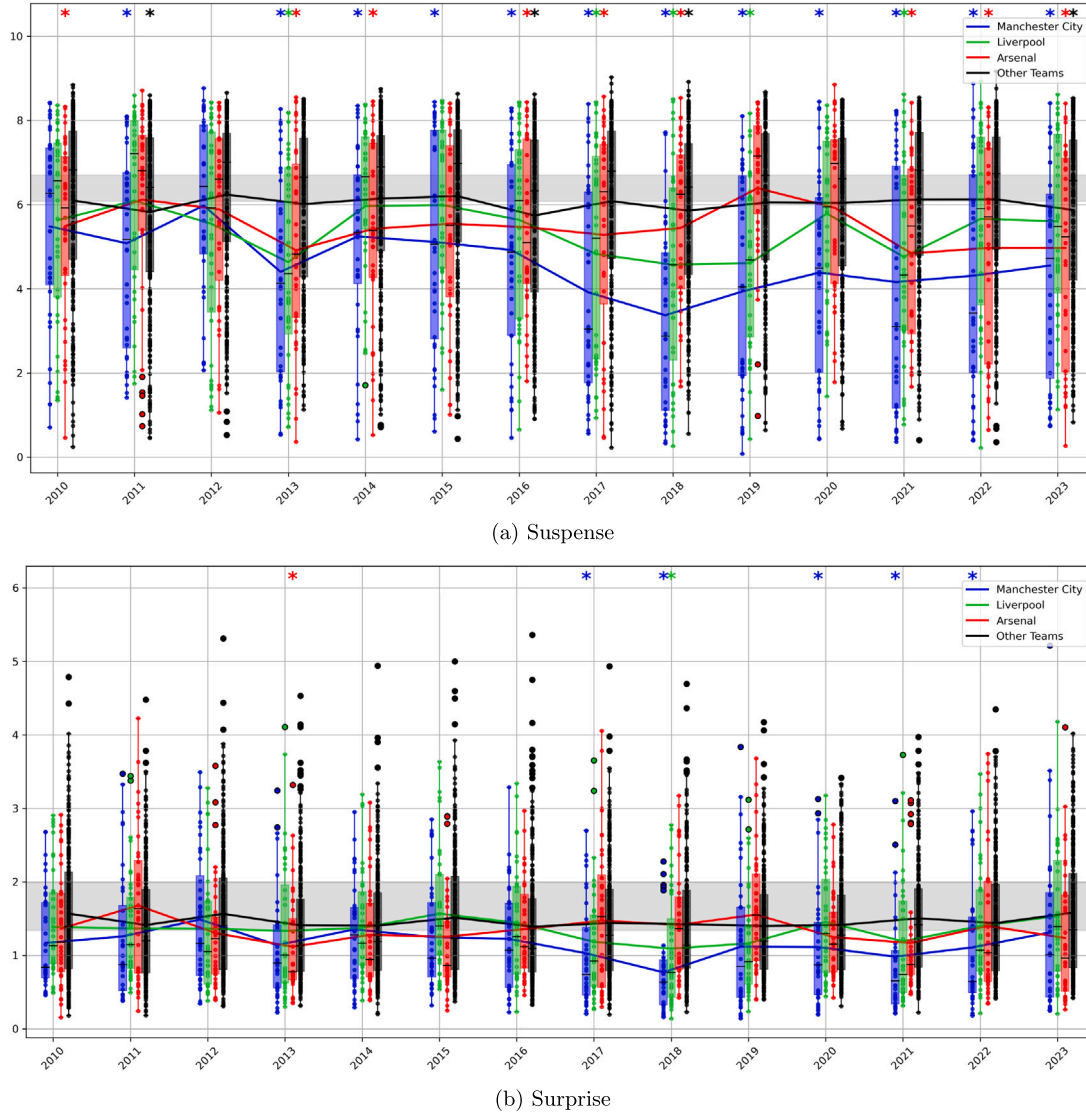


Fig. 2. Suspense and surprise in the English Premier League.

Notes: This figure displays box plots for mean suspense (Fig. 2(a)) and mean surprise (Fig. 2(b)) per game across teams and seasons in the English Premier League. The gray horizontal band represents the benchmark range as defined in Section 3. For suspense, the upper (lower) bound of the benchmark range corresponds to mean suspense of an otherwise balanced match with home advantage and low (high) scoring rates of $\lambda_H = 0.85$ and $\lambda_A = 0.5$ ($\lambda_H = 2.85$, $\lambda_A = 2.5$). For surprise, the upper (lower) bound of the benchmark range corresponds to mean surprise of an otherwise balanced match with home advantage and high (low) scoring rates of $\lambda_H = 2.85$ and $\lambda_A = 2.5$ ($\lambda_H = 0.85$, $\lambda_A = 0.5$). * indicates a significant difference ($p < 0.05$) between the mean value at the team-season level and the lower bound of the benchmark range, based on a one-sided t-test.

top teams; if anything, the estimated trend for Dortmund is slightly positive.

Overall, the Bundesliga's title concentration, with Bayern winning the championship 11 times and Dortmund twice during our 14-year observation period, is clearly reflected in the observed suspense and surprise patterns. Importantly, however, while the levels of suspense and surprise have slightly decreased over time, this trend is not driven by either Bayern or Dortmund.

4.4. Suspense and surprise trends in the Spanish La Liga

In Spain's La Liga, Barcelona, Real Madrid, and Atlético Madrid have accumulated the most points during our observation period and are thus classified as the top teams.

Fig. 4(a) shows that matches involving Barcelona or Real Madrid typically generate suspense values significantly below the benchmark

range, although this pattern becomes less pronounced in the second half of the sample period.

In the 2023/24 season, Barcelona's suspense values increased sharply and fell within the benchmark range; however, in 2021/22 they were already not significantly different from the lower bound of the benchmark range. For Atlético Madrid, suspense values tend to be higher compared to the other top clubs, but still fall significantly below the lower benchmark bound in most of the earlier years. The surprise box plots for La Liga, shown in Fig. 4(b), are broadly consistent with previous observations. While Barcelona's surprise values fall significantly below the benchmark range on several occasions, the values for all other teams, including Real Madrid and Atlético Madrid, mostly lie within the benchmark range. In the 2023/24 season, however, Barcelona's surprise values increased markedly, surpassing even the mean value of all other teams.

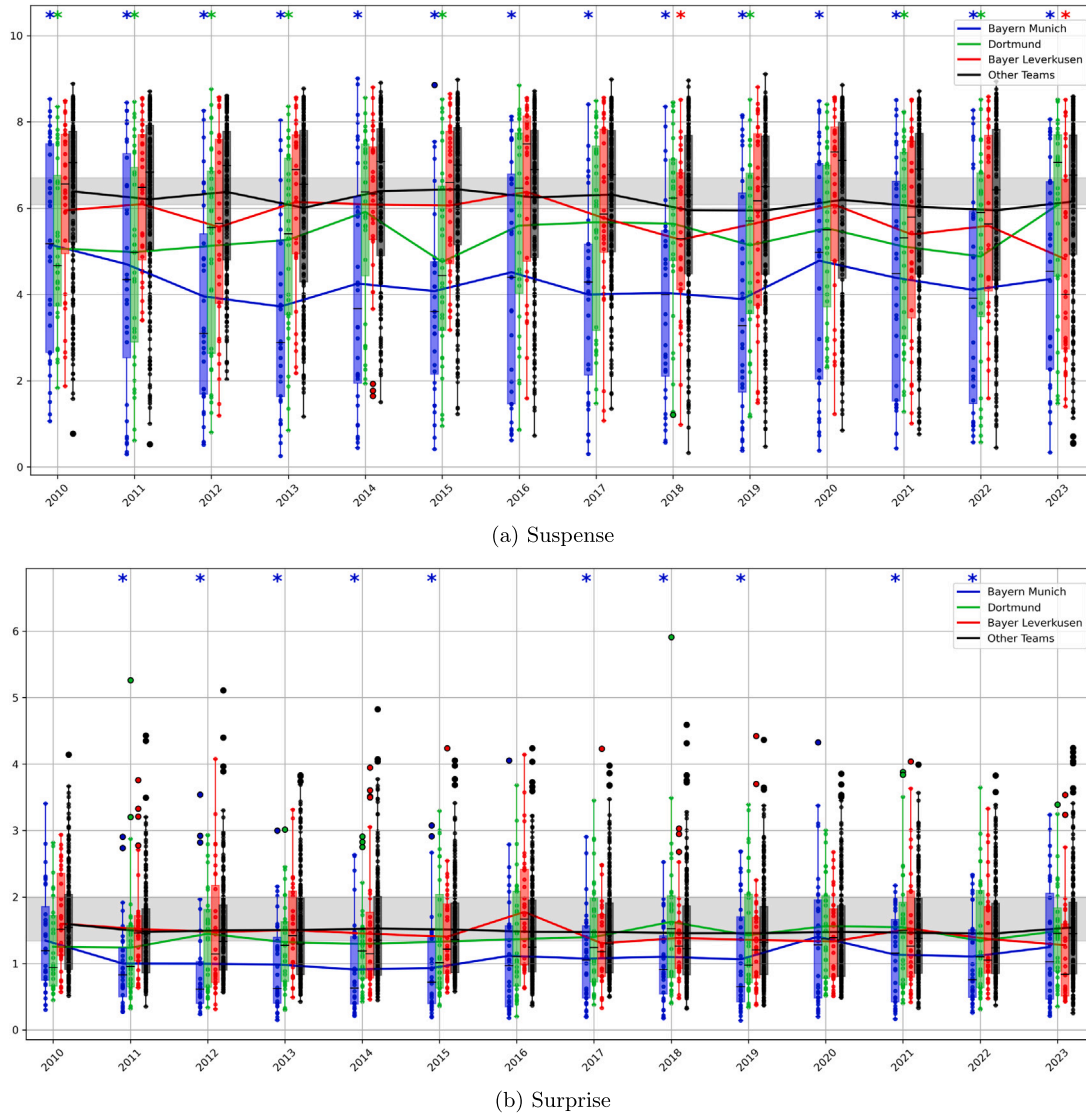


Fig. 3. Suspense and surprise in the German Bundesliga.

Notes: This figure displays box plots for mean suspense (Fig. 3(a)) and mean surprise (Fig. 3(b)) per game across teams and seasons in the German Bundesliga. The gray horizontal band represents the benchmark range as defined in Section 3. For suspense, the upper (lower) bound of the benchmark range corresponds to mean suspense of an otherwise balanced match with home advantage and low (high) scoring rates of $\lambda_H = 0.85$ and $\lambda_A = 0.5$ ($\lambda_H = 2.85$, $\lambda_A = 2.5$). For surprise, the upper (lower) bound of the benchmark range corresponds to mean surprise of an otherwise balanced match with home advantage and high (low) scoring rates of $\lambda_H = 2.85$ and $\lambda_A = 2.5$ ($\lambda_H = 0.85$, $\lambda_A = 0.5$). * indicates a significant difference ($p < 0.05$) between the mean value at the team-season level and the lower bound of the benchmark range, based on a one-sided t-test.

Remarkably, and in contrast to the Bundesliga, a greater number of team-seasons fall significantly below the benchmark range at the beginning rather than at the end of our sample period (see Panels A and B of Table B.3 in Appendix B). Consistent with this pattern, visual inspection of Fig. 4(a) suggests that mean suspense slightly increases over time.

This is confirmed by Table 5, which indicates a mild overall increase in suspense for non-top teams of approximately 0.5% per season (see Column 2). This positive trend is much more pronounced in matches involving Real Madrid or Barcelona, which exhibit additional increases in suspense of 4.0% and 4.9% per season, respectively, relative to the baseline trend. A similar upward pattern is observed for surprise. As shown in Column (4) of Table 5, matches involving Real Madrid and Barcelona exhibit additional increases in surprise of 2.3% and 3.8% per season, respectively, relative to the baseline increase of 0.6% per season.

Overall, suspense values, and to a lesser extent surprise values, were substantially below the benchmark range at the start of the sample period for La Liga matches, particularly those involving top teams. However, both measures have steadily increased over time, with the most pronounced growth observed for Real Madrid and Barcelona.

4.5. Suspense and surprise trends in the Italian Serie A

Fig. 5 presents box plots for the top teams, Juventus, Napoli, and Internazionale, alongside the mean values of all other teams in the Italian Serie A.

Fig. 5(a) shows that suspense values in the 2010/11 season were initially clustered closely together, just around the lower bound of the benchmark range. Over time, however, particularly in matches involving Juventus, suspense values regularly fell below the benchmark. Toward the end of the sample period, suspense values appear to

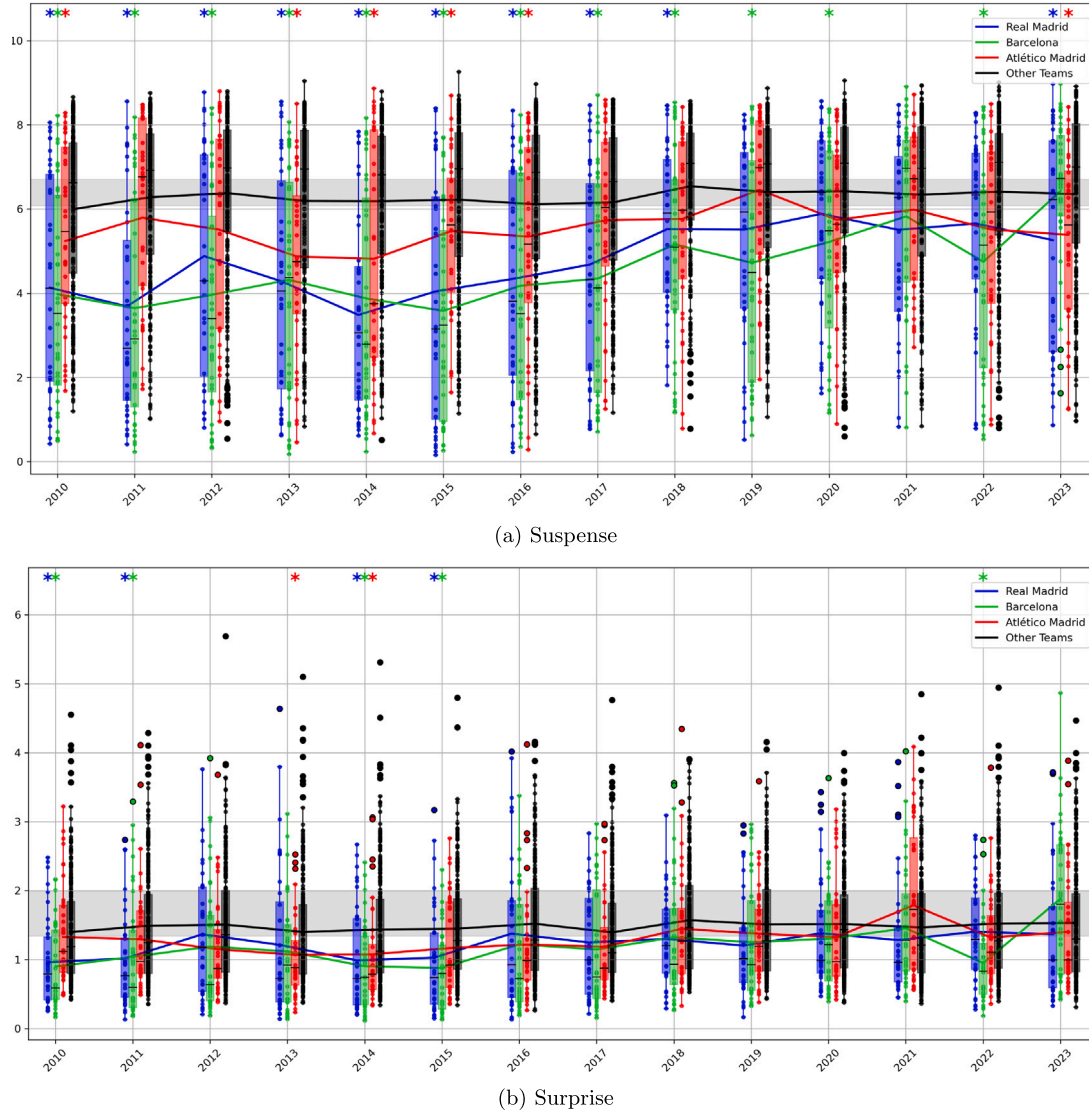


Fig. 4. Suspense and surprise in the Spanish La Liga.

Notes: This figure displays box plots for mean suspense (Fig. 4(a)) and mean surprise (Fig. 4(b)) per game across teams and seasons in the Spanish La Liga. The gray horizontal band represents the benchmark range as defined in Section 3. For suspense, the upper (lower) bound of the benchmark range corresponds to mean suspense of an otherwise balanced match with home advantage and low (high) scoring rates of $\lambda_H = 0.85$ and $\lambda_A = 0.5$ ($\lambda_H = 2.85$, $\lambda_A = 2.5$). For surprise, the upper (lower) bound of the benchmark range corresponds to mean surprise of an otherwise balanced match with home advantage and high (low) scoring rates of $\lambda_H = 2.85$ and $\lambda_A = 2.5$ ($\lambda_H = 0.85$, $\lambda_A = 0.5$). * indicates a significant difference ($p < 0.05$) between the mean value at the team-season level and the lower bound of the benchmark range, based on a one-sided t-test.

converge again, with most teams falling within the benchmark range, except for Internazionale, which won, for instance, the 2023/24 season by a margin of 19 points. Interestingly, in 2023/24, Juventus recorded the highest mean of suspense, which was even higher than the mean value of all other teams and well within the benchmark range. With regard to surprise, Fig. 5(b) shows that values most often remained within the benchmark range. However, several lower-ranked teams again recorded isolated team-seasons with low suspense and/or surprise values, including Pescara (2012/13 and 2016/17, with 22 and 18 points, respectively), Benevento (2017/18, with 21 points), and Hellas Verona (2017/18, with 25 points). For a full list of team-seasons with mean suspense and/or surprise values that fall significantly below the benchmark range, see Panels A and B of Table B.4 in Appendix B.

The linear regression results in Table 6 do not indicate any notable overall trends in Serie A. However, matches involving Juventus exhibit an additional increase in suspense of approximately 1.4% per

season relative to the baseline trend. By contrast, matches involving Internazionale show additional declines in suspense and surprise of approximately 2.1% and 2.4% per season, respectively.

4.6. Suspense and surprise trends in the French Ligue 1

Fig. 6 shows box plots for the top teams Paris Saint-Germain, Lyon, and Marseille, together with the mean values for all other teams in French Ligue 1.

In the French Ligue 1, only suspense values in matches involving Paris Saint-Germain frequently fall significantly below the lower bound of the benchmark range, as also confirmed by Table B.5 in Appendix B. Interestingly, the suspense and surprise values of all teams were initially clustered closely together during the first three seasons in our sample (2010/11 to 2012/13), before the mean values for Paris Saint-Germain began to decline substantially.

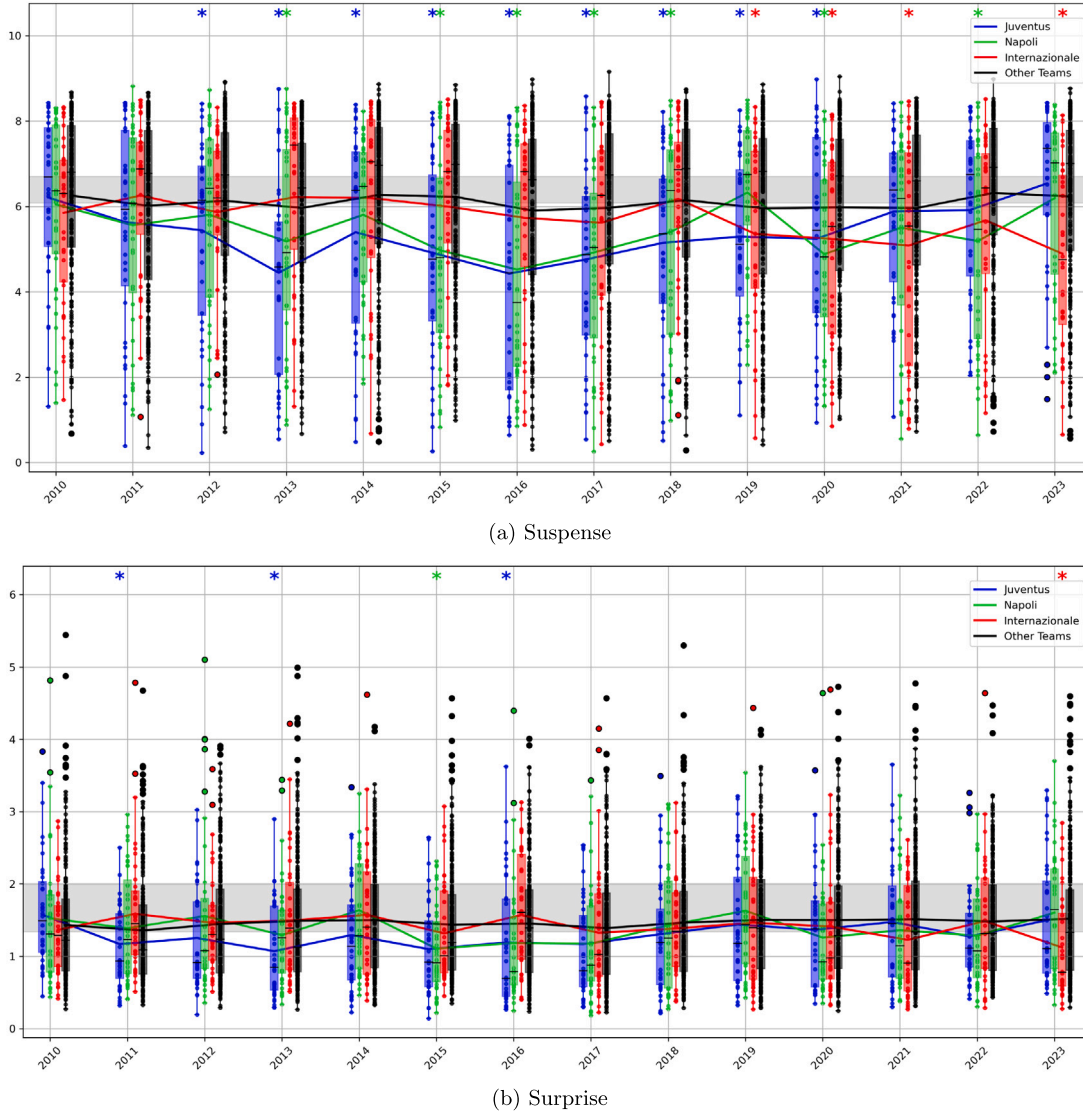


Fig. 5. Suspense and surprise in the Italian Serie A.

Notes: This figure displays box plots for mean suspense (Fig. 5(a)) and mean surprise 5(b)) per game across teams and seasons in the Italian Serie A. The gray horizontal band represents the benchmark range as defined in Section 3. For suspense, the upper (lower) bound of the benchmark range corresponds to mean suspense of an otherwise balanced match with home advantage and low (high) scoring rates of $\lambda_H = 0.85$ and $\lambda_A = 0.5$ ($\lambda_H = 2.85$, $\lambda_A = 2.5$). For surprise, the upper (lower) bound of the benchmark range corresponds to mean surprise of an otherwise balanced match with home advantage and high (low) scoring rates of $\lambda_H = 2.85$ and $\lambda_A = 2.5$ ($\lambda_H = 0.85$, $\lambda_A = 0.5$). * indicates a significant difference ($p < 0.05$) between the mean value at the team-season level and the lower bound of the benchmark range, based on a one-sided t-test.

The linear regressions in Table 7 confirm these visual patterns. While Column (1) indicates a mild negative overall trend in suspense, Column (2) shows that this trend is driven mainly by matches involving Paris Saint-Germain. These matches exhibit an additional decline in suspense of approximately 2.9% per season relative to the baseline trend. A similar pattern emerges for surprise: as shown in Column (4), matches involving Paris Saint-Germain exhibit an additional decline of approximately 2.5% per season relative to the baseline trend. By contrast, we do not observe systematic changes for matches involving Lyon, Marseille, or the remaining teams in Ligue 1.

4.7. Summary of empirical findings

Table 8 summarizes our empirical findings. Panel A reports the number of team-seasons in which mean suspense or mean surprise falls below the benchmark ranges defined in Section 3, while Panel B reports the corresponding time trends derived from the regression analyses presented above.

While the leagues differ little in the number of team-seasons falling below the benchmark for surprise, more pronounced differences emerge for suspense. For example, over our observation window, the Premier League accumulated more than three times as many such team-seasons as Ligue 1 (63 vs. 20). This difference is driven by both top teams (26 vs. 14) and other teams (37 vs. 6). Remarkably, the corresponding number for other teams in the Premier League (37) is also considerably higher than in the other three leagues: 15 in the Bundesliga, 20 in La Liga, and 29 in Serie A. Moreover, across all leagues, these counts for other teams are driven by both particularly strong teams outside the top 3 and particularly weak teams in a given season. This reflects the general nature of our measures: suspense and surprise are low both when the favorite wins comfortably and when the underdog loses clearly.

Our trend analyses reveal three distinct patterns across and within the leagues. First, we identify leagues in which both mean suspense and surprise decline markedly in matches involving a single top team, while

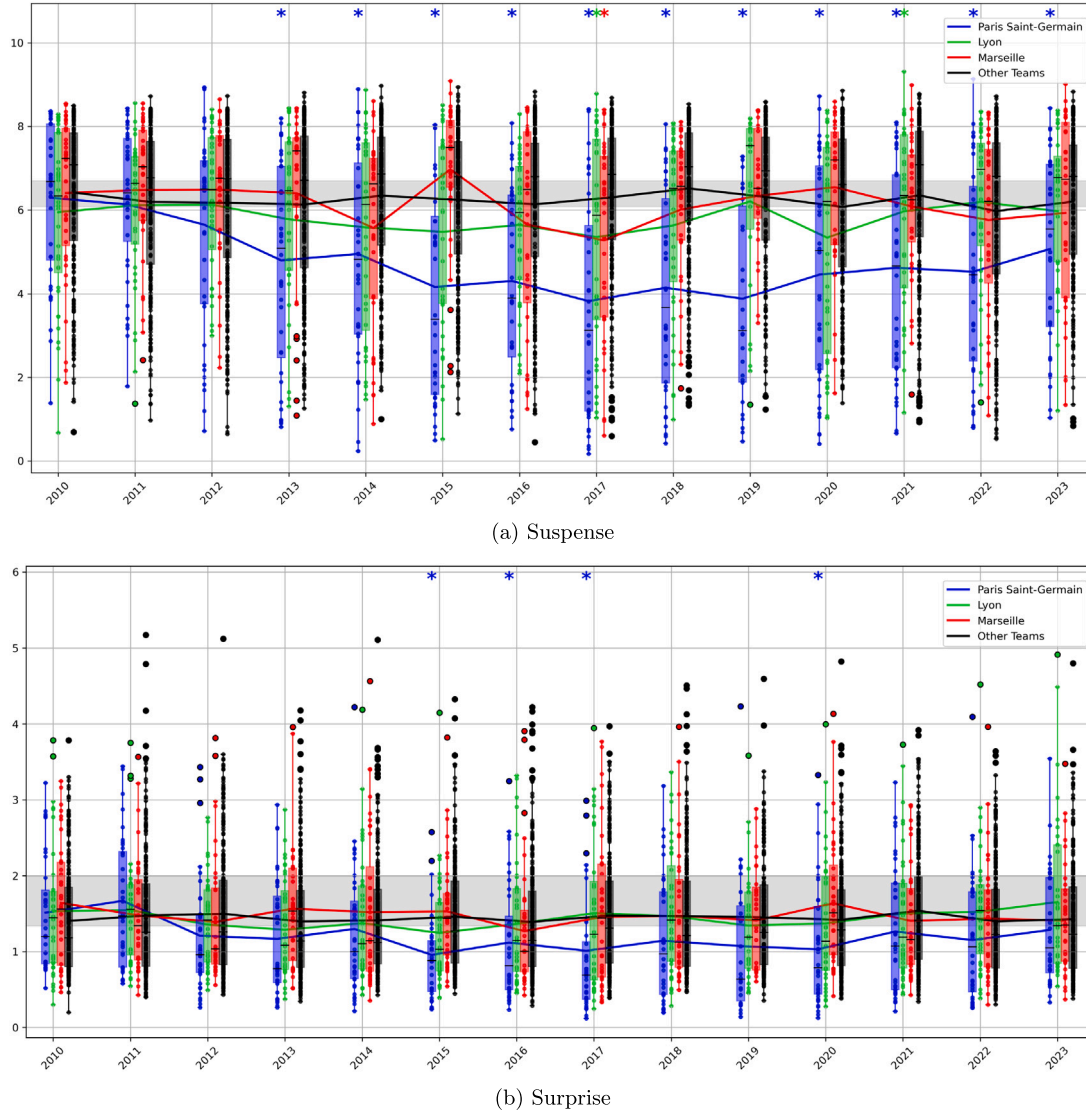


Fig. 6. Suspense and surprise in the French Ligue 1.

Notes: This figure displays box plots for mean suspense (Fig. 6(a)) and mean surprise (Fig. 6(b)) per game across teams and seasons in the French Ligue 1. The gray horizontal band represents the benchmark range as defined in Section 3. For suspense, the upper (lower) bound of the benchmark range corresponds to mean suspense of an otherwise balanced match with home advantage and low (high) scoring rates of $\lambda_H = 0.85$ and $\lambda_A = 0.5$ ($\lambda_H = 2.85$, $\lambda_A = 2.5$). For surprise, the upper (lower) bound of the benchmark range corresponds to mean surprise of an otherwise balanced match with home advantage and high (low) scoring rates of $\lambda_H = 2.85$ and $\lambda_A = 2.5$ ($\lambda_H = 0.85$, $\lambda_A = 0.5$). * indicates a significant difference ($p < 0.05$) between the mean value at the team-season level and the lower bound of the benchmark range, based on a one-sided t-test.

matches featuring other teams in the same league remain relatively stable. This pattern applies to Manchester City in the Premier League and Paris Saint-Germain in Ligue 1, and to a lesser extent to Internazionale in Serie A. Second, we observe a modest overall decline in both mean suspense and surprise in the German Bundesliga, which is not driven by top teams. Third, we identify a marked increase in mean suspense and surprise over time in Spain's La Liga, a trend that appears to be accentuated by matches involving Real Madrid and Barcelona.

5. Discussion and conclusion

We present match-level suspense and surprise as measures that capture the entertainment utility generated by competitive balance and outcome uncertainty for sports spectators, as they account for how outcome uncertainty unfolds throughout the course of a match. These measures seem promising because they offer an accurate understanding of both the current state and the dynamics of match attractiveness

associated with competitive balance across clubs and seasons. As such, our micro analysis complements exiting macro analyses which regularly focus on much more aggregated measures of competitive balance.

Through simulation analysis, we identify a trade-off between suspense and surprise even in perfectly balanced matches: suspense tends to be higher at lower scoring rates, while surprise increases with higher scoring rates. Building on this insight, we establish benchmark ranges for both metrics based on otherwise perfectly balanced matches with home advantage and varying scoring rates. Our analysis of the top five men's European football leagues indicates that mean suspense is commonly below the benchmark range, particularly for games involving top teams. In contrast, matches involving non-top teams tend to show mean suspense values that are close to the benchmark's lower bound or fall within the benchmark range. Meanwhile, mean surprise values mostly remain within the benchmark range.

This empirical pattern can be interpreted in light of further simulation results showing that suspense is substantially more sensitive

Table 4
German Bundesliga time trends.

	Ln(suspense)		Ln(surprise)	
	(1)	(2)	(3)	(4)
Season	−0.006*** (0.002)	−0.007*** (0.002)	−0.003 (0.002)	−0.005** (0.002)
Bayern Munich × season		−0.003 (0.010)		0.012 (0.009)
Borussia Dortmund × season		0.012** (0.006)		0.016** (0.007)
Bayer Leverkusen × season		−0.009 (0.006)		−0.012 (0.007)
Main effects		Yes		Yes
Observations	4284	4284	4284	4284
Adj-R ²	0.002	0.101	0.000	0.058

Notes: This table reports the results from OLS regressions with robust standard errors, clustered at the home team–away team level, shown in parentheses. Season is defined as a continuous variable. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5
Spanish La Liga time trends.

	Ln(suspense)		Ln(surprise)	
	(1)	(2)	(3)	(4)
Season	0.014*** (0.002)	0.005*** (0.002)	0.013*** (0.002)	0.006*** (0.002)
Real Madrid × season		0.040*** (0.009)		0.023*** (0.008)
Barcelona × season		0.049*** (0.010)		0.038*** (0.009)
Atlético Madrid × season		0.004 (0.007)		0.010 (0.008)
Main effects		Yes		Yes
Observations	5320	5320	5320	5320
Adj-R ²	0.010	0.122	0.008	0.061

Notes: This table reports the results from OLS regressions with robust standard errors, clustered at the home team–away team level, shown in parentheses. Season is defined as a continuous variable. *** $p < 0.01$.

Table 6
Italian Serie A time trends.

	Ln(suspense)		Ln(surprise)	
	(1)	(2)	(3)	(4)
Season	−0.002 (0.002)	−0.001 (0.002)	0.002 (0.002)	0.004* (0.002)
Juventus × season		0.014** (0.007)		0.006 (0.007)
Napoli × season		−0.001 (0.006)		−0.005 (0.007)
Internazionale × season		−0.021*** (0.006)		−0.024*** (0.007)
Main effects		Yes		Yes
Observations	5320	5320	5320	5320
Adj-R ²	0.000	0.017	0.000	0.010

Notes: This table reports the results from OLS regressions with robust standard errors, clustered at the home team–away team level, shown in parentheses. Season is defined as a continuous variable. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

to team-strength imbalance than surprise when holding the average scoring-rate level constant. Since matches involving top teams are likely to involve greater team-strength imbalances, such imbalances may reduce suspense more strongly than surprise. This provides a plausible explanation for why mean match suspense is often below the benchmark range, whereas mean match surprise more often remains within the benchmark range. However, this pattern should not be interpreted as implying that surprise is inherently more important to consumers than suspense. Rather, it indicates that suspense and surprise respond differently to scoring rates and competitive imbalance.

In contrast to other studies that report a general decline in competitive balance in European football over time (e.g., [Avila-Cano &](#)

Table 7
French Ligue 1 time trends.

	Ln(suspense)		Ln(surprise)	
	(1)	(2)	(3)	(4)
Season	−0.006*** (0.002)	−0.002 (0.002)	−0.002 (0.002)	0.001 (0.002)
Paris Saint-Germain × season		−0.029*** (0.007)		−0.025*** (0.009)
Lyon × season		0.002 (0.005)		0.002 (0.006)
Marseille × season		−0.004 (0.004)		−0.005 (0.007)
Main effects		Yes		Yes
Observations	5145	5145	5145	5145
Adj-R ²	0.002	0.068	0.000	0.027

Notes: This table reports the results from OLS regressions with robust standard errors, clustered at the home team–away team level, shown in parentheses. Season is defined as a continuous variable. *** $p < 0.01$.

Table 8
Summary table for levels and time trends.

Panel A: Number of team-seasons < BM						
	Suspense			Surprise		
	All	Top 3	Other	All	Top 3	Other
Premier League	63	26	37 (12)	13	7	6 (4)
Bundesliga	39	24	15 (6)	12	10	2 (0)
La Liga	48	28	20 (6)	15	11	4 (1)
Serie A	49	20	29 (9)	11	5	6 (2)
Ligue 1	20	14	6 (3)	9	4	5 (3)
Total	219	112	107 (36)	60	37	23 (10)
Panel B: Time trends						
	Suspense			Surprise		
	All	Top 3	Other	All	Top 3	Other
Premier League	↓	↓ –	–	–	↓ –	–
Bundesliga	↓	– ↑	↓	–	– ↑	↓
La Liga	↑	↑ ↑	↑	↑	↑ ↑	↑
Serie A	–	↑ – ↓	–	–	– – ↓	↑
Ligue 1	↓	↓ –	–	–	↓ –	–

Notes: “< BM” refers to the result of a one-sided t -test assessing whether the mean for a team in a season is below the benchmark (BM) of 6.08 for suspense and 1.34 for surprise. “All” refers to all teams in the league in a given season. “Top 3” refers to those teams that accumulated the most points during our observation period from 2010/11 to 2023/24. “Other” refers to all non-top 3 teams in a given season. The top 3 teams are the following (ordered by the 1st, 2nd, and 3rd best performing teams): Premier League: Manchester City, Liverpool, and Arsenal; Bundesliga: Bayern Munich, Borussia Dortmund, and Bayer Leverkusen; La Liga: Barcelona, Real Madrid, and Atlético Madrid; Serie A: Juventus, Napoli, and Internazionale; Ligue 1: Paris Saint-Germain, Lyon, and Marseille. Values in parentheses indicate the number of observations in the “Other” category involving teams relegated in the corresponding season. Time trends are derived from the regressions (see Sections 4.2–4.6) and coded as ↑ (upward), ↓ (downward), and – (no trend). For top 3 teams, the trends are presented by rank, i.e. (from left to right), the 1st (2nd) [3rd] trend refers to the 1st (2nd) [3rd] best performing team during our observation window.

[Triguero-Ruiz, 2023](#); [Basini et al., 2023](#); [Pawlowski et al., 2010](#); [Poli et al., 2018](#)), we do not find such overall decline when using suspense and surprise. Rather we observe considerable differences across leagues including downward, upward, or no trends at all. This is in line with [Csató and Petróczy \(2025\)](#) who did not find any evidence for declining competitive balance in the UEFA Champions League group stage using novel indicators of competitive balance. Moreover, some trends we observe for the whole league can be fully attributed to matches involving just one or two clubs within these leagues. However, it is important to note that lower levels of mean suspense and surprise in matches featuring top teams do not currently appear to reduce overall sporting interest. The negative impact may be offset by positive influences such as star appeal or the quality of play (e.g., [Buraimo et al., 2022](#)).

Overall, our paper provides a practical framework for assessing the state and evolution of suspense and surprise in European football. This approach not only advances the theoretical understanding of how competitive balance and outcome uncertainty translate into demand for sports, but also offers actionable insights. In particular, we outline three key practical implications. First, policymakers and league organizers should consider the trade-offs between suspense and surprise when designing interventions aimed at increasing the attractiveness of their competition. For example, efforts to equalize team strengths may increase suspense but reduce surprise, depending on the absolute level of scoring rates. Second, our findings highlight the importance of examining not only structural differences across leagues but also club-level variation over time. Mean values of these measures can differ substantially even within a single league, suggesting that league-wide trends may obscure important patterns at the level of individual clubs. Third, although few top clubs financially dominate their leagues, this dominance is only partially reflected in lower suspense and surprise values, which continue to exhibit substantial match-level variation. One possible explanation lies in the low-scoring nature of football, where chance plays a significant role (e.g., Brechot & Flepp, 2020). As a result, the current levels of suspense and surprise in men's football may not suggest an urgent need for regulatory intervention. Nevertheless, continued monitoring may be warranted given (i) downward trends in mean suspense and surprise for certain teams during our observation window from 2010/11 to 2023/24, for example, in matches involving Manchester City, Paris Saint-Germain, and Internazionale, as well as persistently low levels in matches involving Bayern Munich, and (ii) the possibility that these trends may change as additional seasons are taken into account (Csató & Petróczy, 2025).

We conclude by acknowledging several limitations of our study and highlighting promising directions for future research. One limitation lies in our focus on match-level suspense and surprise, which captures only short-term, match-specific dynamics. Extending this perspective to the medium term, for example, by calculating suspense and surprise with respect to beliefs about league outcomes or title races, could provide valuable insights into how season-long narratives shape sporting demand. Another limitation is that the benchmark ranges we develop are purely theory-based and have not been validated directly against consumer demand. Future research could therefore assess these benchmark ranges using behavioral data from fans to identify potential “sweet spots” of match-level suspense and surprise from the consumer perspective.

Methodologically, our in-play probability model relies on betting odds, which may be subject to various biases (e.g., Feddersen et al., 2017). However, a recent paper by Winkelmann et al. (2024) shows that, although informational inefficiencies in betting odds may occur in individual seasons, they are neither persistent nor systematic across the top five European football leagues. We therefore do not believe that our key results are driven by systematic biases in betting odds. Moreover, our in-play probability model incorporates only goals and red cards, omitting other potentially influential in-game events. Incorporating data on missed penalties, other scoring opportunities, corner kicks, possession changes and possession streaks, or defensive interventions could lead to more refined measures of suspense and surprise. In this context, recent advancements in modeling expected possession values (e.g., Fernández et al., 2021) represent a promising avenue for further development. A further limitation is that our analysis adopts a neutral perspective, without accounting for the emotional attachment that fans (or “haters”) may have toward different clubs. These emotional factors likely shape the perception of suspense and surprise, making fan loyalty an important consideration for future research, particularly in the context of league governance (e.g., Pawlowski et al., 2024).

Finally, extending the analysis beyond men's football appears to be an important avenue for future research. One natural step would be to examine women's football. This could also be revealing from a methodological perspective, as recent findings question whether women's football can be adequately modeled using univariate Poisson distributions

(Michels et al., 2025). Another promising extension would be to apply the analysis to sports other than football. The concepts of suspense and surprise are broadly applicable across sports, including non-invasive sports. For high-scoring sports such as basketball, for example, it may also be useful to examine complementary micro-level measures, such as the number of lead changes during a game. Overall, such comparative studies could offer valuable insights into how suspense and surprise function across diverse sporting environments, thereby enriching our broader understanding of professional sport as an entertainment product.

CRedit authorship contribution statement

Raphael Flepp: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Tim Pawlowski:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Travis Richardson:** Writing – review & editing, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.ejor.2026.07.017>.

References

- Avila-Cano, A., Owen, P. D., & Triguero-Ruiz, F. (2023). Measuring competitive balance in sports leagues that award bonus points, with an application to rugby union. *European Journal of Operational Research*, 309(2), 939–952.
- Avila-Cano, A., Ruiz-Sepulveda, A., & Triguero-Ruiz, F. (2021). Identifying the maximum concentration of results in bilateral sports competitions. *Mathematics*, 9(11), 1293.
- Avila-Cano, A., & Triguero-Ruiz, F. (2023). On the control of competitive balance in the major European football leagues. *Managerial and Decision Economics*, 44(2), 1254–1263.
- Baker, R., Chadwick, S., Parma, R., & Scarf, P. (2022). The binomial-match, outcome uncertainty, and the case of netball. *Journal of the Operational Research Society*, 73(8), 1856–1872.
- Baker, R., & McHale, I. G. (2018). Time-varying ratings for international football teams. *European Journal of Operational Research*, 267(2), 659–666.
- Basini, F., Tsouli, V., Ntzoufras, I., & Friel, N. (2023). Assessing competitive balance in the English Premier League for over forty seasons using a stochastic block model. *Journal of the Royal Statistical Society Series A: Statistics in Society*, 186(3), 530–556.
- BBC Sport (2016). Leicester City win Premier League title after Tottenham draw at Chelsea. <https://www.bbc.com/sport/football/35988673>. (Accessed 24 April 2026).
- Bizzozero, P., Flepp, R., & Franck, E. (2016). The importance of suspense and surprise in entertainment demand: Evidence from Wimbledon. *Journal of Economic Behavior and Organization*, 130, 47–63.
- Brechot, M., & Flepp, R. (2020). Dealing with randomness in match outcomes: How to rethink performance evaluation in European club football using expected goals. *Journal of Sports Economics*, 21(4), 335–362.
- Budzinski, O. (2012). The institutional framework for doing sports business: Principles of EU competition policy in sports markets. *International Journal of Sport Management and Marketing*, 11(1–2), 44–72.
- Buraimo, B., Forrest, D., McHale, I. G., & Tena, J. d. (2020). Unscripted drama: Soccer audience response to suspense, surprise, and shock. *Economic Inquiry*, 58(2), 881–896.
- Buraimo, B., Forrest, D., McHale, I. G., & Tena, J. d. D. (2022). Armchair fans: Modelling audience size for televised football matches. *European Journal of Operational Research*, 298(2), 644–655.
- Chater, M., Arrondel, L., Gayant, J.-P., & Laslier, J.-F. (2021). Fixing match-fixing: Optimal schedules to promote competitiveness. *European Journal of Operational Research*, 294(2), 673–683.

- Collins, C., & Humphreys, B. R. (2022). Contest outcome uncertainty and fan decisions: A meta-analysis. *Journal of Sports Economics*, 23(6), 789–807.
- Csató, L. (2022). Quantifying incentive (in)compatibility: A case study from sports. *European Journal of Operational Research*, 302(2), 717–726.
- Csató, L. (2023). How to avoid uncompetitive games? The importance of tie-breaking rules. *European Journal of Operational Research*, 307(3), 1260–1269.
- Csató, L., & Gyimesi, A. (2026). Increasing competitiveness by imbalanced groups: The example of the 48-team FIFA World Cup. *European Journal of Operational Research*, [ISSN: 0377-2217] 332(3), 868–879.
- Csató, L., & Petróczy, D. G. (2025). Competitive balance in the UEFA Champions League group stage: Novel measures show no evidence of decline. *Annals of Operations Research*, 352, 105–120.
- Depken, C. A. (1999). Free-agency and the competitiveness of major league baseball. *Review of Industrial Organization*, 14(3), 205–217.
- Devriesere, K., Csató, L., & Goossens, D. (2025). Tournament design: A review from an operational research perspective. *European Journal of Operational Research*, 324(1), 1–21.
- Di Mattia, A., & Krumer, A. (2023). Fewer teams, more games, larger attendance? Evidence from the structural change in basketball's EuroLeague. *European Journal of Operational Research*, 309(1), 359–370.
- Ely, J., Frankel, A., & Kamenica, E. (2015). Suspense and surprise. *Journal of Political Economy*, 123(1), 215–260.
- Feddersen, A., Humphreys, B. R., & Soebbing, B. P. (2017). Sentiment bias and asset prices: Evidence from sports betting markets and social media. *Economic Inquiry*, 55(2), 1119–1129.
- Fernández, J., Bornn, L., & Cervone, D. (2021). A framework for the fine-grained evaluation of the instantaneous expected value of soccer possessions. *Machine Learning*, 110(6), 1389–1427.
- Fort, R. (2022). Rottenberg at sixty-five: In honor of the 20th anniversary of the *Journal of Sports Economics*. *Journal of Sports Economics*, 23(6), 808–825.
- Fort, R., & Quirk, J. (1995). Cross-subsidization, incentives, and outcomes in professional team sports leagues. *Journal of Economic Literature*, 33(3), 1265–1299.
- Goller, D., & Krumer, A. (2020). Let's meet as usual: Do games played on non-frequent days differ? Evidence from top European soccer leagues. *European Journal of Operational Research*, 286(2), 740–754.
- Hvattum, L. M., & Arntzen, H. (2010). Using ELO ratings for match result prediction in association football. *International Journal of Forecasting*, 26(3), 460–470.
- Johnson, S., & Fort, R. (2022). Match outcome uncertainty and sports fan demand: An agnostic review and the standard economic theory of sports leagues. *International Journal of Empirical Economics*, 1(2), Article 2250007.
- Kaplan, S. (2021). *Entertainment utility from skill and thrill*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3888785.
- Lee, Y. H., & Fort, R. (2012). Competitive balance: Time series lessons from the english premier league. *Scottish Journal of Political Economy*, 59(3), 266–282.
- Maher, M. (1982). Modelling association football scores. *Statistica Neerlandica*, 36(3), 109–118.
- Mehra, S. K., & Zuercher, T. J. (2006). Striking out “competitive balance” in sports, antitrust, and intellectual property. *Berkeley Technology Law Journal*, 21(4), 1499–1545.
- Michels, R., Ötting, M., & Karlis, D. (2025). Extending the dixon and coles model: An application to women's football data. *Journal of the Royal Statistical Society. Series C. Applied Statistics*, 74(1), 167–186.
- Neale, W. C. (1964). The peculiar economics of professional sports. *The Quarterly Journal of Economics*, 78(1), 1–14.
- Owen, P. D., Ryan, M., & Weatherston, C. R. (2007). Measuring competitive balance in professional team sports using the Herfindahl-Hirschman index. *Review of Industrial Organization*, 31, 289–302.
- Pawlowski, T., Breuer, C., & Hovemann, A. (2010). Top clubs' performance and the competitive situation in European domestic football competitions. *Journal of Sports Economics*, 11(2), 186–202.
- Pawlowski, T., & Nalbantis, G. (2019). Competitive balance: Measurement and relevance. *The SAGE Handbook of Sports Economics*, 154–162.
- Pawlowski, T., Nalbantis, G., & Coates, D. (2018). Perceived game uncertainty, suspense and the demand for sport. *Economic Inquiry*, 56(1), 173–192.
- Pawlowski, T., Rambaccussing, D., Ramirez, P., Reade, J. J., & Rossi, G. (2024). Exploring entertainment utility from football games. *Journal of Economic Behavior and Organization*, 223, 185–198.
- Percy, D. F. (2009). A mathematical analysis of badminton scoring systems. *Journal of the Operational Research Society*, 60(1), 63–71.
- Poli, R., Ravenel, L., & Besson, R. (2018). *Competitive balance: A spatio-temporal comparison: CIES football observatory monthly report*, Retrieved from <https://football-observatory.com/Competitive-balance-a-spatio-temporal-comparison>.
- Richardson, T., Nalbantis, G., & Pawlowski, T. (2023). Emotional cues and the demand for televised sports: Evidence from the UEFA champions league. *Journal of Sports Economics*, 24(8), 993–1025.
- Rottenberg, S. (1956). The baseball players' labor market. *Journal of Political Economy*, 64(3), 242–258.
- Scarf, P., Khare, A., & Alotaibi, N. (2022). On skill and chance in sport. *IMA Journal of Management Mathematics*, 33(1), 53–73.
- Scarf, P., Parma, R., & McHale, I. (2019). On outcome uncertainty and scoring rates in sport: The case of international rugby union. *European Journal of Operational Research*, 273(2), 721–730.
- Scarf, P., Yusof, M. M., & Bilbao, M. (2009). A numerical study of designs for sporting contests. *European Journal of Operational Research*, 198(1), 190–198.
- Simonov, A., Ursu, R. M., & Zheng, C. (2023). Suspense and surprise in media product design: Evidence from Twitch. *Journal of Marketing Research*, 60(1), 1–24.
- Szymanski, S. (2003). The economic design of sporting contests. *Journal of Economic Literature*, 41(4), 1137–1187.
- van Eetvelde, H., & Ley, C. (2019). Ranking methods in soccer. In R. S. Kenett, T. N. Longford, W. Piegorisch, & F. Ruggeri (Eds.), *Wiley statsref: statistics reference online* (pp. 1–9). Hoboken, New Jersey, USA: Wiley.
- Vecer, J., Kopriva, F., & Ichiba, T. (2009). Estimating the effect of the red card in soccer: When to commit an offense in exchange for preventing a goal opportunity. *Journal of Quantitative Analysis in Sports*, 5(1).
- Winkelmann, D., Ötting, M., Deutscher, C., & Makarewicz, T. (2024). Are betting markets inefficient? Evidence from simulations and real data. *Journal of Sports Economics*, 25(1), 54–97.
- Wunderlich, F. (2025). Using the wisdom of crowds in sports: How performance analysis in football can benefit from the information enclosed in betting odds. *International Journal of Performance Analysis in Sport*, 25(4), 687–706.
- Wunderlich, F., & Memmert, D. (2018). The betting odds rating system: Using soccer forecasts to forecast soccer. *PLoS One*, 13(6), Article e0198668.

Online Appendix

Suspense and Surprise in European Football

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A TV Demand Analysis

We begin our validity check of suspense and surprise by merging our match-level measures for the Premier League with the original dataset used by Buraimo, Forrest, McHale, & Tena (2022). This dataset includes all matches broadcast in the UK market on Sky Sports and BT Sport between the second half of the 2013/14 season and the end of the 2018/19 season ($n = 790$). Relative to all other Premier League matches played between the 2013/14 and 2018/19 seasons, suspense values in this subsample are significantly lower ($t(2,278) = 3.26, p < 0.001$), whereas surprise values do not differ significantly ($t(2,278) = 0.33, p = 0.74$).

The match audience size is defined as the average per-minute audience size, measured from kick-off to 110 minutes later, accounting for half-time (15 minutes) and added extra time (5 minutes). In addition, the dataset includes match-level measures of player quality derived from an expected points plus-minus rating model, match significance measures based on match forecasting models, and a commonly used measure of outcome uncertainty based on the absolute difference in pre-match win probabilities for the two teams (e.g., Caruso, Addesa, & Di Domizio, 2019). Building on Buraimo et al. (2022), we estimate the following linear regression model of TV demand:

$$\begin{aligned} \ln(\text{audience size}) = f(\ln(\text{suspense}), \ln(\text{surprise}), \text{player quality}, \\ \text{outcome uncertainty, championship significance,} \\ \text{European significance, relegation significance, controls}) \end{aligned} \tag{A.1}$$

where the control variables include home- and away-team dummies, season dummies, month dummies, a derby-match indicator, a weekday indicator, a Christmas indicator, a BT Sport indicator, and BT Sport $\times$ season interaction terms. For a detailed description of the variable construction, we refer readers to Buraimo et al. (2022).

Table A.1 presents the results for the TV demand model. In Column (1), we first replicate the specification of Buraimo et al. (2022) using the natural log of audience size during the match as the dependent variable, and obtain almost identical results. Most importantly for our

study, the coefficient of outcome uncertainty, measured pre-match, is non-significant. In Column (2) of Table A.1, we add the natural log of suspense to the model. The coefficient is positive and statistically significant ($\beta = 0.046$, $p = 0.017$), indicating that a 1% increase in suspense is associated with a 0.046% increase in audience size.

In Column (3) of Table A.1, we add the natural log of surprise to the baseline model. The coefficient is positive and significant ($\beta = 0.052$, $p = 0.003$), indicating that a 1% increase in surprise is associated with a 0.052% increase in audience size. In Column (4), we include both $\ln(\text{suspense})$ and $\ln(\text{surprise})$ in the model. While both coefficients remain positive, the coefficient of $\ln(\text{suspense})$ is not estimated precisely enough to reach statistical significance at the conventional level, which may be due to the relatively low number of observations. As additional unreported robustness checks, we derive the first principal component of $\ln(\text{suspense})$ and $\ln(\text{surprise})$ to aggregate them into a single measure. The first principal component explains approximately 85% of the variance contained in $\ln(\text{suspense})$ and $\ln(\text{surprise})$ and loads positively on both variables. The results show that the first principal component has a positive and significant effect on the audience size. Finally, we include the standardized sum of $\ln(\text{suspense})$ and $\ln(\text{surprise})$ in the TV demand model, and the results remain consistent.

Overall, the results of this subsample analysis suggest that both suspense and surprise are positively associated with TV demand, whereas the most commonly used measure of outcome uncertainty, based on the absolute difference in pre-match win probabilities for either team, has no effect.

Table A.1: Regression Results TV Demand

	Ln(audience)			
	(1)	(2)	(3)	(4)
Ln(suspense)		0.046*** (0.017)		0.020 (0.020)
Ln(surprise)			0.052*** (0.017)	0.039* (0.021)
Average player rating	4.358*** (1.423)	4.546*** (1.432)	4.6646*** (1.432)	4.658*** (1.434)
Outcome uncertainty	-0.037 (0.054)	-0.002 (0.054)	-0.005 (0.053)	0.002 (0.054)
Derby match	0.053* (0.030)	0.049 (0.030)	0.057* (0.029)	0.054* (0.030)
Match significance (championship)	0.666*** (0.134)	0.643*** (0.135)	0.645*** (0.137)	0.640*** (0.137)
Match significance (European)	0.193* (0.111)	0.185* (0.111)	0.196* (0.111)	0.192* (0.111)
Match significance (relegation)	0.361*** (0.092)	0.364*** (0.093)	0.369*** (0.093)	0.368*** (0.093)
Christmas	0.090** (0.035)	0.095*** (0.036)	0.102*** (0.035)	0.101*** (0.036)
Weekday	0.015 (0.020)	0.014 (0.020)	0.015 (0.020)	0.015 (0.020)
BT	-0.790*** (0.049)	-0.775*** (0.050)	-0.782*** (0.049)	-0.778*** (0.050)
BT $\times$ season ending: 2015	0.140** (0.060)	0.127** (0.060)	0.126** (0.059)	0.124** (0.059)
BT $\times$ season ending: 2016	0.277*** (0.064)	0.265*** (0.064)	0.270*** (0.064)	0.266*** (0.064)
BT $\times$ season ending: 2017	0.299*** (0.063)	0.283*** (0.064)	0.288*** (0.063)	0.284*** (0.064)
BT $\times$ season ending: 2018	0.391*** (0.066)	0.387*** (0.067)	0.399*** (0.066)	0.396*** (0.067)
BT $\times$ season ending: 2019	0.282*** (0.066)	0.272*** (0.066)	0.273*** (0.065)	0.271*** (0.066)
Month FE	Yes	Yes	Yes	Yes
Season FE	Yes	Yes	Yes	Yes
Home team FE	Yes	Yes	Yes	Yes
Away team FE	Yes	Yes	Yes	Yes
Observations	790	790	790	790
Adj-R ²	0.714	0.716	0.717	0.717

Notes: This table reports the results from OLS regressions with robust standard errors in parentheses. The data for all variables except suspense and surprise were provided by Buraimo et al. (2022). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

B Team-Seasons Below the Benchmark

Table B.1: Premier League Team-Seasons Below Benchmark

Team	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Count
<i>Panel A: Suspense</i>															
Arsenal	5.49 ↑			4.92 ↑	5.42 ↑		5.47 ↑	5.28 ↑	5.45 ↑			4.84 ↑	4.97 ↑	4.97 ↑	9
Aston Villa														5.36	1
Bolton Wanderers		5.39 ↓													1
Bournemouth									5.20						1
Burnley									5.45						1
Cardiff City									5.25 ↓					5.17 ↓	2
Chelsea	5.24				5.10		4.70	5.30	5.23	5.14					6
Crystal Palace											5.39				1
Fulham				5.39 ↓										5.44	3
Huddersfield Town								5.37	5.25 ↓						2
Hull City							5.41 ↓								1
Leicester City							5.46								1
Liverpool				4.63 ↑				4.83 ↑	4.57 ↑	4.61 ↑		4.76 ↑			5
Manchester City		5.08 ↑		4.40 ↑	5.24 ↑	5.11 ↑	4.92 ↑	3.92 ↑	3.37 ↑	3.94 ↑	4.39 ↑	4.16 ↑	4.31 ↑	4.55 ↑	12
Manchester United		4.43	5.38	5.12				5.41	5.33						5
Newcastle United														5.35	1
Norwich City										5.31 ↓		4.99 ↓			2
Sheffield United														4.91 ↓	1
Sunderland							5.30 ↓								1
Tottenham Hotspur							5.12	5.05	5.35		5.40	5.29			5
Watford									5.48			5.42 ↓			2
League mean	5.94	5.79	6.10	5.62	5.97	6.01	5.60	5.70	5.45	5.78	5.84	5.67	5.79	5.59	
<i>Panel B: Surprise</i>															
Arsenal				1.12 ↑											1
Huddersfield Town								1.11							1
Liverpool									1.09 ↑						1
Manchester City								1.03 ↑	0.77 ↑		1.11 ↑	0.98 ↑	1.11 ↑		5
Manchester United		1.06													1
Norwich City				1.13 ↓						1.12 ↓		1.02 ↓			3
Sheffield United											1.16 ↓				1
League mean	1.50	1.42	1.51	1.34	1.38	1.46	1.37	1.38	1.33	1.37	1.37	1.38	1.39	1.52	

Notes: Entries report team-season mean values that are significantly below the benchmark. ↑ indicates top teams as defined in Section 4.2; ↓ indicates season-specific relegated teams. The league mean row reports the league-wide mean in each season. All team entries satisfy $p < 0.05$.

Table B.2: Bundesliga Team-Seasons Below Benchmark

Team	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Count
<i>Panel A: Suspense</i>															
Bayer Leverkusen									5.27 ↑					4.82 ↑	2
Bayern Munich	5.16 ↑	4.70 ↑	3.96 ↑	3.72 ↑	4.25 ↑	4.08 ↑	4.51 ↑	4.00 ↑	4.04 ↑	3.89 ↑	4.78 ↑	4.38 ↑	4.10 ↑	4.35 ↑	14
Bochum													5.00		1
Darmstadt 98														5.05 ↓	1
Dortmund	5.07 ↑	4.98 ↑	5.13 ↑	5.26 ↑		4.75 ↑				5.14 ↑		5.11 ↑	4.88 ↑		8
Düsseldorf									5.36						1
Greuther Fürth												5.23 ↓			1
Hertha BSC												5.41			1
Köln		5.31 ↓													2
Paderborn 07										4.94					1
RB Leipzig										5.40 ↓					1
Schalke 04										5.12		5.06	5.45		3
Stuttgart		5.13									4.94 ↓				2
League mean	6.09	5.88	5.87	5.68	6.06	5.96	6.02	5.98	5.65	5.61	5.95	5.69	5.62	5.80	
<i>Panel B: Surprise</i>															
Arminia											1.11				1
Augsburg			1.13												1
Bayern Munich		1.00 ↑	1.00 ↑	0.98 ↑	0.91 ↑	0.93 ↑		1.07 ↑	1.10 ↑	1.06 ↑		1.13 ↑	1.11 ↑		10
League mean	1.54	1.41	1.43	1.43	1.43	1.43	1.47	1.41	1.42	1.40	1.45	1.44	1.40	1.47	

Notes: Entries report team-season mean values that are significantly below the benchmark. ↑ indicates top teams as defined in Section 4.3; ↓ indicates season-specific relegated teams. The league mean row reports the league-wide mean in each season. All team entries satisfy $p < 0.05$.

Table B.3: La Liga Team-Seasons Below Benchmark

Team	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Count
<i>Panel A: Suspense</i>															
Alavés								5.36							1
Athletic Club	5.51					5.22								5.42	3
Atlético Madrid	5.24 ↑			4.87 ↑	4.81 ↑	5.47 ↑	5.34 ↑							5.39 ↑	6
Barcelona	3.98 ↑	3.64 ↑	3.96 ↑	4.32 ↑	3.88 ↑	3.58 ↑	4.18 ↑	4.35 ↑	5.16 ↑	4.72 ↑	5.22 ↑		4.74 ↑		12
Eibar						5.40									1
Elche					5.31 ↓										1
Getafe	5.20					5.22 ↓									2
Granada						5.46	5.27 ↓							5.33 ↓	3
Las Palmas							5.37								1
Levante					5.32										1
Mallorca										5.22 ↓					1
Málaga	5.21														1
Osasuna							5.16 ↓								1
Rayo Vallecano		5.29		4.71											2
Real Madrid	4.13 ↑	3.69 ↑	4.88 ↑	4.29 ↑	3.48 ↑	4.04 ↑	4.34 ↑	4.68 ↑	5.52 ↑					5.26 ↑	10
Real Sociedad							5.52								1
Sevilla					5.20										1
League mean	5.57	5.73	5.90	5.66	5.56	5.66	5.65	5.77	6.22	6.13	6.17	6.20	6.08	6.16	
<i>Panel B: Surprise</i>															
Alavés								1.14							1
Athletic Club						1.15									1
Atlético Madrid				1.07 ↑	1.08 ↑										2
Barcelona	0.90 ↑	1.04 ↑			0.90 ↑	0.88 ↑								0.95 ↑	5
Getafe											1.19				1
Osasuna				1.09 ↓											1
Real Madrid	0.96 ↑	1.02 ↑			0.99 ↑	1.03 ↑									4
League mean	1.31	1.38	1.42	1.32	1.30	1.32	1.44	1.34	1.51	1.44	1.47	1.49	1.43	1.53	

Notes: Entries report team-season mean values that are significantly below the benchmark. ↑ indicates top teams as defined in Section 4.4; ↓ indicates season-specific relegated teams. The league mean row reports the league-wide mean in each season. All team entries satisfy $p < 0.05$.

Table B.4: Serie A Team-Seasons Below Benchmark

Team	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Count
<i>Panel A: Suspense</i>															
Atalanta											4.74				1
Benevento								5.17 ↓							1
Bologna											5.46				1
Cagliari							4.86								1
Crotone								5.08 ↓			5.06 ↓				2
Fiorentina			5.48												1
Frosinone									5.28 ↓						1
Hellas Verona				5.39				4.67 ↓							2
Internazionale										5.36 ↑	5.24 ↑	5.08 ↑		4.89 ↑	4
Juventus			5.44 ↑	4.45 ↑	5.39 ↑	4.91 ↑	4.43 ↑	4.76 ↑	5.15 ↑	5.29 ↑	5.24 ↑				9
Lazio			5.30			5.49	5.41				5.44	5.22			5
Lecce										5.37 ↓					1
Livorno				5.09 ↓											1
Milan		5.28										5.33			2
Napoli				5.18 ↑		4.97 ↑	4.52 ↑	4.92 ↑	5.40 ↑		4.88 ↑		5.19 ↑		7
Pescara			4.79 ↓				5.14 ↓								2
Roma				5.11			4.91				5.40				3
Salernitana												5.33			1
Sampdoria				5.44		5.31						5.05			3
Udinese								5.48							1
League mean	6.19	5.96	6.01	5.77	6.11	5.95	5.60	5.68	5.97	5.87	5.71	5.80	6.10	6.12	
<i>Panel B: Surprise</i>															
Atalanta											1.16				1
Cagliari		1.07													1
Hellas Verona								1.12 ↓							1
Internazionale														1.12 ↑	1
Juventus		1.17 ↑		1.07 ↑		1.10 ↑									3
Napoli						1.11 ↑									1
Pescara			1.09 ↓												1
Roma				1.12				1.06							2
League mean	1.45	1.36	1.44	1.43	1.48	1.36	1.41	1.34	1.44	1.50	1.45	1.46	1.44	1.49	

Notes: Entries report team-season mean values that are significantly below the benchmark. ↑ indicates top teams as defined in Section 4.5; ↓ indicates season-specific relegated teams. The league mean row reports the league-wide mean in each season. All team entries satisfy $p < 0.05$.

Table B.5: Ligue 1 Team-Seasons Below Benchmark

Team	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	Count
<i>Panel A: Suspense</i>															
Ajaccio													5.31 ↓		1
Angers													5.33 ↓		1
Dijon											5.42 ↓				1
Lyon								5.35 ↑			5.34 ↑				2
Marseille								5.27 ↑							1
Monaco							4.38	5.12							2
Paris Saint-Germain				4.80 ↑	4.95 ↑	4.16 ↑	4.31 ↑	3.82 ↑	4.14 ↑	3.88 ↑	4.46 ↑	4.62 ↑	4.53 ↑	5.07 ↑	11
Rennes												5.23			1
League mean	6.35	6.22	6.15	6.01	6.04	6.03	5.86	5.87	6.17	6.09	5.89	6.10	5.83	6.08	
<i>Panel B: Surprise</i>															
Arles-Avignon	1.15 ↓														1
Dijon											1.12 ↓				1
Nancy							1.13 ↓								1
Nice				1.14					1.17						2
Paris Saint-Germain						0.96 ↑	1.12 ↑	1.01 ↑			1.03 ↑				4
League mean	1.44	1.50	1.45	1.38	1.41	1.39	1.35	1.42	1.44	1.41	1.40	1.49	1.40	1.45	

Notes: Entries report team-season mean values that are significantly below the benchmark. ↑ indicates top teams as defined in Section 4.6; ↓ indicates season-specific relegated teams. The league mean row reports the league-wide mean in each season. All team entries satisfy $p < 0.05$.

4.3 Study 3: Emotional Driving — Reference-Dependent Emotions and Risky Driving Behavior after Sporting Events

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Emotional driving: Reference-dependent emotions and risky driving behavior after sporting events*

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Abstract

Using average vehicle speed data in 10-minute increments at the Traffic Message Channel (TMC) location level, along with precise crash timing and location information, we analyze driving behavior around five Florida stadiums before and after NFL and NBA regular season games from 2015 to 2019. We find no evidence of emotional driving following NBA games, but strong and consistent effects following NFL games, concentrated in predicted-close games that end in disappointing home-team losses — combining high pre-game suspense with negative outcome valence. These games are associated with significant increases in average vehicle speed within 3 km of stadiums during the first post-game hour, dissipating with increasing time and distance from the stadium. Average vehicle speed increases by up to 3 mph relative to predicted-close games that ended in a win — an effect several times larger than the typical game day versus non-game day speed differential. Overall, our results highlight how the combination of sustained suspense and negative outcome valence in close sporting contests can spill over into risky post-game driving behavior, underscoring the behavioral and public safety implications of affective cues in large-scale sporting events.

JEL Codes: C23, D12, D91, L82, L83, R40, Z20.

Keywords: Emotional driving, affective spillovers, reference-dependent emotions, suspense, surprise, outcome valence, disappointment, professional sports, stadium proximity, point spread, vehicle speed, traffic behavior, road safety.

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*Data was kindly provided by HERE - Road Traffic Analytics Location Intelligence. HERE had no role in the study design, further data collection and analysis, or the preparation of the manuscript. The authors do not have a financial interest in the topic of this paper and there are no conflicts of interest. The authors made use of AI-assisted tools (Claude, Anthropic) for coding assistance in data processing and regression analysis, as well as for language and text editing support during manuscript preparation. All substantive intellectual contributions, analytical decisions, and conclusions remain those of the authors. All errors are our own.

1 Introduction

A central insight from models of reference-dependent preferences is that outcomes are evaluated not only in absolute terms, but relative to expectations (Kahneman & Tversky, 1979). When realized outcomes deviate from an expectations-based reference point, individuals may experience elation when outcomes exceed expectations, or disappointment, anger, and frustration when outcomes fall short (Bell, 1985; Loomes & Sugden, 1986; van Dijk & Van der Pligt, 1997), and these affective responses may shape subsequent behavior.

According to the gain-loss utility framework by Kőszegi and Rabin (2006), such deviations from the expectations-based reference point might generate rapid and strong behavioral responses. Moreover, emotions generated by economic and social experiences can spill over into decisions that are seemingly unrelated to the original source of affect. Sporting events provide a uniquely clean natural setting for observing such behavior in the field: fans enter games with well-defined expectations and hopes about the likely or preferred outcome, and their emotional reactions to deviations from that set point, whether positive or negative, can spill over into behaviors beyond the game itself. Recent evidence has documented such emotional spillovers in a variety of contexts, including stock market returns (Edmans, Garcia, & Norli, 2007), voter turnout (Potoski & Urbatsch, 2017), judicial sentencing (Eren & Mocan, 2018), consumer spending (Q. Cai & Li, 2026), and intimate partner violence (Card & Dahl, 2011; Cardazzi, McCannon, Humphreys, & Rodriguez, 2024).

This paper investigates whether and how emotionally charged game outcomes might affect post-game driving behavior using fine-grained spatiotemporal data on vehicle speed in Florida. Driving behavior is a particularly valuable outcome for studying emotional spillovers for several reasons. First, post-game travel by car is the dominant mode of transportation to and from stadium events, meaning a large share of emotionally affected sports fans transition directly from the stadium into real-world traffic (Humphreys & Pyun, 2018). Second, unlike outcomes such as domestic violence or consumer spending, vehicle speed is observable at high temporal and spatial resolution, allowing for measurable minute-by-minute and kilometer-by-kilometer (mile-by-mile) emotional responses as fans disperse from the venue (Hwang, Humphreys, & Pyun, 2025). Third, even small deviations in vehicle speed carry meaningful public safety consequences; according to the World Health Organization (2023), each 1% increase in average speed results in a 4% increase in the likelihood of a fatal crash, making driving a particularly high-stakes domain in which to study emotional spillovers.

The growing field of affective automotive user interfaces recognizes that a driver’s emotional state profoundly influences road safety (Braun, Weber, & Alt, 2021). Literature extensively reviewed by Braun et al. (2021) highlights how medium arousal and positive valence typically support optimal driving. This is in line with the Yerkes-Dodson law (Yerkes & Dodson, 1908), which holds that performance peaks at moderate levels of arousal, but declines when arousal becomes too low or too high. Negative emotions have clear adverse effects, but even positive emotions can impair performance under high arousal (H. Cai & Lin, 2011; Russell, 1980), as elevated arousal can disrupt attentional focus and impair the cognitive control mechanisms that support safe driving.¹ In a naturalistic study of taxi drivers in Japan, Kadoya, Watanapongvanich, and Khan (2021) find that negative emotional states, anger and sadness, significantly increase driving speed in real traffic conditions, while happy and relaxed states show no such effect. Crucially, Dingus et al. (2016) show that emotional drivers, whether angry or sad, are nearly 10 times more likely to crash compared to baseline driving conditions. In summary, driving appears particularly sensitive to emotional states because emotional arousal can impair risk perception and increase risky behavior. However, large-scale field evidence about the effects of emotional cues, like emotionally salient game outcomes, on driving patterns is largely missing.

One prime exception is the study by Wood, McInnes, and Norton (2011), who analyze major college and professional football and basketball games and show that close, competitive contests are associated with significantly higher traffic fatalities near the winning team’s location. They interpret this as evidence that physiological arousal, potentially driven by the excitement and hormonal effects of a narrow win, translates into aggressive driving behavior. Their findings emphasize the importance of emotional intensity, not just outcome valence, in shaping traffic risk. Crucially, however, Wood et al. focus on winning fans and celebratory arousal. Whether the frustration and disappointment experienced by fans of the losing team generate similarly elevated driving risk remains an open question; one that aggregate, event-level crash data are ill-suited to answer. Building on this insight, our study focuses on the behavioral mechanism underlying such effects by examining how emotional cues from sporting outcomes influence post-game vehicle speed in real-world traffic. Because emotional arousal is transient by nature, peaking immediately after the game and dissipating over time and distance, identifying its

¹Anger is consistently linked to aggressive and reckless driving and worsens performance by increasing reaction times and impairing risk perception (Deffenbacher, Deffenbacher, Lynch, & Richards, 2003; Jeon, Walker, & Yim, 2014; Mesken, Hagenzieker, Rothengatter, & De Waard, 2007; Precht, Keinath, & Krems, 2017; Roidl, Frehse, & Höger, 2014; Steinhauser et al., 2018; Underwood, Chapman, Wright, & Crundall, 1999; T. Zhang, Chan, Ba, & Zhang, 2016; Zimasa, Jamson, & Henson, 2019). Even high-arousal happiness can increase risky behavior (Taubman-Ben-Ari, 2012). Q. Zhang, Qu, Ge, Sun, and Zhang (2020) find that both angry and happy drivers leave less space between vehicles and brake more slowly, while Q. Zhang, Qu, and Ge (2022) show that anger increases speed and risk near pedestrians.

behavioral imprint requires data that are disaggregated both temporally and spatially. Using fine-grained speed data measured at 10-minute intervals across distance bands of 1 km, we provide direct evidence of how emotional arousal after emotionally salient contests manifests in driving behavior, and how quickly and how far those effects travel from the stadium.²

We test what we refer to as *emotional driving*, i.e., observable changes in driving behavior that occur when individuals transition from emotionally intense settings, such as witnessing unexpected or unwanted game outcomes, into real-world traffic environments. Close, tightly contested games are especially relevant, as they heighten emotional arousal and amplify reactions to final outcomes. Specifically, we explore whether and how predicted close games that ended in a loss, as well as upset wins and losses by the home team of professional National Basketball Association (NBA) and National Football League (NFL) games, might lead to measurable changes in post-game driving speed of vehicles in close geographic proximity to the stadiums where the matches are played.

For our analysis, we link Global Positioning System (GPS)-based traffic data surrounding five stadiums and arenas in Florida with information about the corresponding NFL and NBA home teams as well as their regular season games—including pre-game betting spreads to construct ex-ante expectations about the likely game outcome—from 2015 to 2019, a period unaffected by the COVID-19 pandemic.³ Our fixed-effects regression models are disaggregated by time (60/120 minutes before/after the games, 10-minute increments) and distance (0–5 kilometers around the stadium, 1-km increment).⁴

Overall, our analysis reveals no evidence of emotional driving following NBA games. This could be attributed to comparably small attendance numbers or arenas being located downtown in metropolitan areas with dense traffic (hence, there could be less opportunity/environmental affordance to speed). Another plausible explanation could be the high-scoring nature of basketball making any upsets less likely and outcome-related emotions less intense.⁵ For the NFL, however, we find that the strongest and most consistent effects occur after predicted close games

²Redelmeier and Stewart (2003) observe a 41% spike in traffic fatalities after the Super Bowl, while Jakar, Gordon, and He (2023) report a significant increase in vehicular crashes with reported damage in Cleveland, Ohio, particularly after highly attended NFL games. In contrast to these event-level studies focused on aggregate crash outcomes, our primary focus is put on minute-level vehicle speed as a behavioral mechanism that underlies elevated post-game risk. Our main analysis, however, will be complemented with a crash analysis (see Section 4.3).

³We focus on the 2015–2019 period to ensure a consistent, pre-pandemic sample. The COVID-19 pandemic beginning in 2020 fundamentally disrupted stadium attendance, fan behavior, and traffic patterns, making post-2019 seasons ill-suited for comparison.

⁴Technically, only the lower bound of each distance band is an integer; for example, a radius labeled “1–2 km” corresponds to distances from 1.0 km up to but not including 2.0 km. For ease of reading, we retain integer values for both bounds throughout the text, tables, and figures.

⁵We further elaborate on these possible explanations in the discussion section.

that end in disappointing home-team losses. These contests, which combine high suspense with emotional frustration, are associated with significant increases in average vehicle speed. These effects are concentrated in the first hour after the game and decline with increasing time and distance to the stadium. This pattern is robust across different specifications, alternative spread thresholds, sample restrictions, controls for belief updating, and is not replicated when game outcome labels are randomly reassigned or when real game labels are applied to non-game Sundays.

This paper contributes to three strands of literature. First, it contributes to behavioral economics by providing field evidence that expectations-based emotional cues can spill over into immediate real-world behavior, complementing laboratory and survey evidence on reference-dependent preferences (Bell, 1985; Köszegi & Rabin, 2006; Loomes & Sugden, 1986). Second, it contributes to research on sports outcomes and social behavior by identifying a high-frequency behavioral mechanism, minute-level vehicle speed, that may help explain why emotionally intense games are associated with elevated public safety risks (Card & Dahl, 2011; Cardazzi et al., 2024; Wood et al., 2011). Third, it contributes to research on transportation and road safety by showing that risky driving behavior can be shaped not only by road conditions and enforcement, but also by predictable affective states generated by collective events (Dingus et al., 2016; Kadoya et al., 2021).

Taken together, these findings emphasize that high-arousal sporting results in the NFL, specifically close, disappointing contests, can translate into tangible risks on the road which should be considered for traffic management and public safety near stadiums. Simple policy interventions, such as targeted speed enforcement, improved signage, increased public transportation, or post-game crowd management, might reduce the likelihood of emotionally driven vehicle speed increases in these high-risk windows.

The remainder of this paper is structured as follows: Section 2 develops a conceptual framework distinguishing surprise, suspense, valence, and behavioral response; Section 3 describes the data—including traffic, weather, and sports game information—and outlines the empirical strategy; Section 4 presents the main findings and several robustness checks; Section 5 offers a discussion of the limitations and implications of our study; Section 6 concludes.

2 Conceptual framework

Our analysis is motivated by the distinction between surprise, suspense, and outcome valence. Upsets represent deviations from pre-game expectations: the home team surprisingly wins when a loss was expected, or loses when a win was expected. Close games, by contrast, may generate

high suspense even when the final outcome is not statistically surprising, since either team had a plausible chance of winning before the game. In our empirical setting, betting-market point spreads provide a useful proxy for pre-game expectations, with games classified as predicted wins, predicted close contests, or predicted losses from the perspective of the home team (see Section 3.2 for formal definitions).

To clarify the behavioral mechanism, we distinguish three related but conceptually separate emotional dimensions — surprise, suspense, and valence — and one behavioral dimension: behavioral response. All three emotional dimensions are grounded in pre-game expectations, which form the reference point against which outcomes are evaluated (Kőszegi & Rabin, 2009; Kőszegi & Rabin, 2006). When outcomes fall short of expectations, fans may experience disappointment, frustration, or anger; when outcomes exceed expectations, fans may experience elation or relief (Bell, 1985; Loomes & Sugden, 1986).

Surprise refers to the deviation between the expected and the realized outcome: a game ends in a surprise when the home team wins despite being predicted to lose, or loses despite being predicted to win (Kőszegi & Rabin, 2006). An upset loss combines negative valence with surprise; an upset win combines positive valence with surprise.

Surprise is not the same as suspense, however, a distinction between the two is important to note (Ely, Frankel, & Kamenica, 2015): a game can be highly surprising without having been suspenseful (e.g., a heavily favored team losing a lopsided contest), or highly suspenseful without being surprising (e.g., a predicted-close game decided narrowly). A predicted-close loss may therefore not be highly surprising in a probabilistic sense, yet it combines sustained emotional arousal throughout the contest with a negative final resolution — so the behavioral response may be driven not only by the deviation from expectations, but also by the intensity of suspense experienced during the game.

Suspense refers to the emotional intensity generated while the outcome remains unresolved (Ely et al., 2015). A game expected to be close may sustain attention and arousal throughout the contest, since fans remain uncertain about the final result until late in the game. In our empirical setting, we proxy for sustained suspense using the pre-game point spread, under the assumption that games predicted to be close are more likely to remain competitive throughout. We partially test this assumption in Section 4.2.5, where we examine whether halftime score differentials alter the main findings.

Valence refers to whether the final outcome is emotionally positive or negative for the home-team fan base (Russell, 1980): a home-team win is likely to generate happiness, while a home-team loss is likely to generate disappointment, frustration, or anger.

Behavioral response refers to the observable post-game driving behavior that may follow from these emotional states. The relationship between valence and behavioral response is not simply positive versus negative, however. In a judgment and decision-making context, Lerner and Keltner (2001) show that anger and fear, though both negative emotions, have opposing effects on risk-taking, with angry individuals’ risk assessments more closely resembling those of happy individuals than fearful individuals. In a simulated driving context, however, Jeon et al. (2014) find that while both anger and happiness degrade driving performance overall, only anger significantly affects aggressive driving, including speed, infractions, and collisions, whereas happiness does not. Because anger intensifies with the degree of frustration experienced, a home-team loss, especially a close loss, which combines frustration and negative arousal, may therefore produce more aggressive behavioral responses than a lopsided loss, which generates less sustained arousal prior to the outcome. Emotional arousal can affect attention, risk perception, self-control, and aggressiveness behind the wheel (Dingus et al., 2016; Kadoya et al., 2021). In our setting, these responses are measured through changes in average vehicle speed near stadiums after games. Because the traffic data are aggregated, we do not observe individual fans’ emotions or driving choices directly. The analysis therefore estimates reduced-form changes in local driving behavior around emotionally salient events.

Table 1 summarizes the emotional profiles of each outcome type, combining pre-game expectations, actual results, and the resulting surprise–suspense–valence profiles.

Table 1
Emotional profiles of game outcome types

Expectation	Outcome	Emotional profile	Interpretation
Predicted win	Home loss	Surprise and negative valence	Upset loss; disappointment
Predicted close	Home loss	Suspense and negative valence	High-suspense, negative resolution
Predicted loss	Home win	Surprise and positive valence	Upset win; elation
Predicted close	Home win	Suspense and positive valence	High-suspense, positive resolution
Predicted win	Home win	Expected positive outcome	Confirmation of favorable expectations
Predicted loss	Home loss	Expected negative outcome	Confirmation of unfavorable expectations

Notes: The table classifies each game outcome type by its pre-game expectation category, actual result, and the resulting emotional profile experienced by home-team fans. Predicted win, predicted close, and predicted loss are defined using pre-game betting-market point spreads as described in Section 3.2. Suspense refers to sustained uncertainty during the contest; surprise refers to the deviation of the realized outcome from the pre-game reference point; valence refers to whether the final outcome is emotionally positive or negative from the perspective of the home team.

While both predicted-close wins and losses involve the same level of pre-game suspense, they differ fundamentally in how that suspense resolves. A predicted-close win resolves with positive affect — relief or celebration — whereas a predicted-close loss resolves with frustration, disappointment, and anger, the emotions most strongly linked to aggressive driving above. The behavioral response may therefore be strongest when sustained suspense is resolved negatively.

3 Data and methods

3.1 Vehicle and weather data

Our primary dataset for vehicle speed, crash, and location was obtained from HERE Technologies.⁶ HERE Probe Data is a location-based dataset that captures the movement of vehicles through anonymized and aggregated GPS signals collected from connected vehicles and mobile devices. The data provides a detailed, real-time and historical view of traffic patterns and vehicular mobility. By leveraging a large volume of spatial and temporal observations, HERE Probe Data enables analysis of congestion dynamics, travel speeds, and roadway usage. It is commonly used in applications such as traffic flow modeling, safety assessments, transportation infrastructure planning, and the enhancement of driver assistance systems. Using Global Navigation Satellite System (GNSS) or GPS, the position of each vehicle is established using satellite-based positioning reliable enough to indicate precisely which road a vehicle is on.

For our analysis, we use historical traffic flow (HERE Traffic API, Flow Resource) and incident (HERE Traffic API, Incidents Resource) data aggregated to Traffic Message Channel (TMC) level by the day of week and the time of day (10-minute increments) for all road links/corridors within a 5-kilometer radius around Florida’s professional football stadiums and basketball arenas for the period 2015 to 2019.⁷ Each observation in our dataset corresponds to a unique TMC road segment and 10-minute time interval. These facilities include the Raymond James Stadium (Tampa Bay Buccaneers), the Hard Rock Stadium (Miami Dolphins), the EverBank Field (Jacksonville Jaguars), the American Airlines Arena (Miami Heat), and the Kia Center (Orlando Magic).⁸

Vehicle speed data originally consisted of billions of observations across the five selected stadium regions. To focus on periods most relevant to emotional responses following professional sports events, we restricted the dataset to specific temporal windows aligned with game schedules. For NFL games, we include Sundays during the 2015–2019 regular seasons, limited to one hour before the earliest kickoff and up to two hours after the latest game ending, while excluding late-night games as differing travel conditions, lighting, and crowd demographics at

⁶HERE Technologies is a location data and technology company, best known in the automotive sector. It helps users and automated driving applications navigate with complete, accurate maps of real-world places.

⁷TMC coverage is limited to major roads: “TMCs are generally longer [comprising multiple links] and available only for important roads” (HERE Technologies, 2024). Smaller residential streets and low-volume roads are therefore typically not represented in the data, as they do not generate enough continuous probe data to produce reliable speed profiles.

⁸To visualize the corresponding road network coverage, ArcGIS-based maps with concentric 1 km rings (from 0–1 km through 4–5 km) centered around the arena and stadium location are presented in Appendix Figures A.1–A.5.

those times introduce confounds unrelated to emotional state. For NBA games, we focus on the 2015/16 to 2018/19 regular seasons, including games with start times of 6:00 PM or later, and retained observations account for pre- and post-game periods of 1 hour pre-game and 2 hours post-game. We adopt a one-hour pre-game and two-hour post-game window to capture behavioral buildup and aftermath effects while minimizing unrelated temporal noise. The pre-game hour reflects the typical onset of fan and media activity, whereas the two-hour post-game window accounts for extended audience or mobility responses following game completion.

While our analysis is not primarily focused on vehicular crashes, it is important to consider crashes for isolating emotionally driven behavioral responses from physical traffic disruptions. Moreover, exploring the probability of crashes on gamedays may further add some credibility to the findings we observe in our speed analysis. We obtained statewide crash data for Florida covering the full period from January 1, 2015 to December 31, 2019. These records were filtered to match the temporal scope of the speed data and were spatially merged to corresponding TMC location segments using precise latitude and longitude coordinates, along with exact crash timestamps, enabling integration at the level of individual road segments and time intervals.

Finally, weather data were obtained from WorldWeatherData.com at 15-minute intervals for the geographic areas surrounding each of the five primary stadiums analyzed in this study. These observations were matched temporally and spatially to the corresponding traffic speed data, which were recorded in 10-minute increments. To control for environmental conditions that may affect driving behavior, we constructed binary indicator variables for adverse weather conditions: hot, cold, windy, precipitation, and low visibility. Each indicator represents values approximately one standard deviation above or below the local mean (e.g., for temperature or wind speed), with the exception of precipitation, which is coded as a binary variable indicating any recorded rainfall. Visibility is measured on a 1–10 scale, with values at or below 3—representing moderate to dense fog—classified as low visibility. These weather controls are included to isolate emotional effects on driving from physical or environmental factors.

Table 2 reports descriptive statistics for average vehicle speed by sport, distance band, and day type. Baseline speeds range from approximately 23–29 mph for the NFL and 21–28 mph for the NBA depending on distance band, reflecting the mix of road types and traffic conditions surrounding each venue. On average, game day speeds are slightly lower than non-game day speeds across most distance bands, consistent with standard pre- and post-game congestion effects. Notably, the average difference between game day and non-game day speeds is less than 1 mph across all distance bands and both sports, providing a useful baseline against which to assess the magnitude of any emotionally induced speed changes identified in our analysis.

Table 2

Descriptive statistics: average vehicle speed by sport, distance band, and day type

Sport	Distance band	Game Day			Non-Game Day		
		Mean	SD	N	Mean	SD	N
NFL	0–1 km	23.56	15.15	192,462	24.44	15.60	310,442
	1–2 km	22.42	14.24	366,808	22.99	14.43	597,631
	2–3 km	25.59	15.94	608,661	25.86	16.05	988,050
	3–4 km	28.69	16.06	822,410	28.71	16.09	1,342,588
	4–5 km	29.31	17.28	1,076,313	29.20	17.35	1,743,316
NBA	0–1 km	20.64	16.74	1,019,476	21.06	16.99	3,557,765
	1–2 km	23.00	14.83	1,580,465	23.19	15.00	5,522,594
	2–3 km	25.47	13.88	1,380,502	25.64	14.02	4,828,122
	3–4 km	27.65	14.39	1,438,816	27.85	14.53	5,024,329
	4–5 km	27.97	12.98	1,201,460	28.11	13.08	4,212,559

Notes: Average vehicle speed is measured in miles per hour (mph). Each observation corresponds to a unique TMC road segment and 10-minute time interval. Game day observations are limited to the temporal windows aligned with game schedules as described in Section 3.1. Non-game day observations are matched to the same time of day and day of week as game day observations. Distance bands reflect straight-line distance from the stadium or arena. NFL statistics are based on Sunday regular-season home games for the Miami Dolphins, Tampa Bay Buccaneers, and Jacksonville Jaguars across the 2015–2019 seasons, excluding the 2018 and 2019 Miami Dolphins seasons. NBA statistics are based on regular-season home games for the Miami Heat and Orlando Magic across the 2015/16–2018/19 seasons, with tip-off times of 6:00 PM or later. The larger ratio of non-game day to game day observations for the NBA reflects the fact that NBA games occur across all days of the week, expanding the pool of matched non-game day observations relative to the NFL, where games are restricted to Sundays.

3.2 Sports data and sample selection

Our sample includes all regular-season home games for Florida-based teams in the NFL and the NBA during the period 2015 to 2019, comprising five NFL seasons and four NBA seasons.⁹ Specifically, we include three NFL franchises: Tampa Bay Buccaneers, Miami Dolphins, and Jacksonville Jaguars, as well as two NBA franchises: Miami Heat and Orlando Magic; yielding data for 84 NFL Sunday home games¹⁰ (with kickoff times between 1:00 PM and 4:25 PM) and 308 NBA home games (with start times of 6:00 PM or later).¹¹ For each game, we record the geographic coordinates of the stadium, halftime scores, final scores, and pre-game betting lines.

We closely follow Card and Dahl (2011) for the NFL and Cardazzi et al. (2024) for the NBA and use the point spread—widely viewed as an unbiased and informationally efficient predictor of game results (see Gandar, Zuber, O’Brien, & Russo, 1988; Pankoff, 1968)—as our primary

⁹The sample is restricted to regular-season games for two reasons. First, playoff games generate atypical levels of emotional intensity, fan travel patterns, and media attention that are not directly comparable to regular-season contests, potentially confounding identification. Second, across the three NFL franchises and two NBA franchises over the sample period, only two teams qualified for the playoffs, yielding just one usable NFL home playoff game and seven usable NBA home playoff games.

¹⁰Due to missing HERE data, we exclude the Miami Dolphins 2018 and 2019 seasons, resulting in two seasons not being included.

¹¹Based on the *NFL Follower Map*, which analyzes data from nearly 60 million Twitter followers of NFL teams and displays the most-followed team per county, we assume the local NFL team represents the dominant fan base in each region (see Appendix Figures A.6 and A.7; Source: Sorenson (2022)). Likewise, based on the *NBA Fan Map*, which analyzes data from over 70 million Twitter followers of NBA teams and displays the most-followed team per U.S. county and Canadian census division, we assume the local NBA team represents the dominant fan base in each region (see Appendix Figures A.8 and A.9; Source: Sorenson (2024)).

measure of pre-game expectations. Accordingly, NFL games are classified based on the Las Vegas point spread as:

- Predicted win: Home team favored by more than 4 points (spread ≤ -4),
- Predicted close: $-4 < \text{point spread} < +4$,
- Predicted loss: Home team expected to lose by more than 4 points (spread $\geq +4$).¹²

For NBA games, we follow the classification proposed by Cardazzi et al. (2024), who argue that the NFL’s ± 4 threshold does not account for the higher scoring volatility and tighter margins in professional basketball. Instead, they propose using asymmetric thresholds derived from the empirical distribution of NBA point spreads:

- Predicted win: Home team favored by more than 6.75 points (spread ≤ -6.75),
- Predicted close: $-6.75 < \text{point spread} < +4.75$,
- Predicted loss: Home team expected to lose by more than 4.75 points (spread $\geq +4.75$).¹³

These classifications not only define pregame expectations but also provide a natural measure of the emotional profiles described in Section 2. In particular, predicted close games are likely to produce the strongest affective responses, as sustained uncertainty about the outcome keeps fan arousal high until the final moments, generating the high-suspense conditions that, when resolved positively or negatively, may spill over into post-game driving behavior. Predicted wins and losses that end in upsets, by contrast, combine surprise with either positive or negative valence, generating a distinct emotional profile. Tables 3 and 4 provide a detailed description of all games for both NFL and NBA.¹⁴

3.3 Empirical strategy

Our main dependent variable is the average vehicle speed, Speed_{it} , measured on road segment i at time t (measured in 10-minute increments), within a 5-kilometer radius (stratified by distance from stadium in 1 km increments) of a home NFL or NBA stadium.¹⁵ To estimate how

¹²Card and Dahl (2011) justify these cutoffs by showing that a -4 point spread corresponds to a 63% home win probability, while a +4 point spread corresponds to 37%, making them reasonable thresholds for differentiating expectations.

¹³These cutoffs correspond to approximate home win probabilities of 70% and 35%, respectively, and more accurately reflect the emotional expectations embedded in basketball betting lines.

¹⁴To facilitate scalable and reliable data management, we stored and processed all data in Apache Parquet format. Parquet is a columnar, compressed storage format which offers substantial performance advantages compared to CSV reducing the computational overhead associated with parsing, casting, and reformatting raw data, which is particularly valuable for high-frequency panel data across multiple road segments. The use of Parquet ensured not only improved processing speed during iterative filtering, merging, and regression modeling, but also preserved data integrity, particularly for date-time formatting and road segment identifiers. As a result, the Parquet format played a key infrastructural role in making our empirical pipeline reproducible, memory-efficient, and suitable for large-scale traffic behavior analysis.

¹⁵While speed is reported in miles per hour (mph), we use kilometers for spatial measurement because the smaller unit size allows for finer-grained distance bins and clearer delineation of stadium proximity effects.

Table 3
NFL games

Team	Total # of games	Predicted win	Predicted close	Predicted loss	Predicted win × lose	Predicted close × lose	Predicted loss × win
Tampa Bay Buccaneers	33	4	26	3	2	13	1
Miami Dolphins	19	3	13	3	0	5	2
Jacksonville Jaguars	32	9	19	4	3	16	3
Total NFL	84	16	58	10	5	34	6

Notes: Data include regular-season home games for the Miami Dolphins, Tampa Bay Buccaneers, and Jacksonville Jaguars played on Sundays with kickoff times between 1:00 PM and 4:25 PM Eastern Time. No primetime or late games are included. Seasons 2018 and 2019 for the Miami Dolphins are excluded due to missing traffic data. In addition, two games are omitted: one New Year’s Eve game for the Tampa Bay Buccaneers and one for the Miami Dolphins.

Table 4
NBA games

Team	Total # of games	Predicted win	Predicted close	Predicted loss	Predicted win × lose	Predicted close × lose	Predicted loss × win
Miami Heat	153	42	101	10	13	43	3
Orlando Magic	155	20	97	38	5	50	13
Total NBA	308	62	198	48	18	93	16

Notes: Data include regular-season home games for the Miami Heat and Orlando Magic from the 2015/16 through 2018/19 NBA seasons. Games with scheduled tip-off times before 6:00 PM are excluded (17 games in total). The sample therefore consists only of games beginning between 6:00 PM and 8:00 PM Eastern Time.

game outcomes shape driving behavior across different suspense–valence profiles, we employ a fixed-effects linear regression model that accounts for both spatial and temporal heterogeneity. Specifically, we estimate the following specification:

$$\text{Speed}_{it} = \alpha_i + f(p_{it}, y_{it}; \lambda) + \theta_{it} + \delta_{it} + \varepsilon_{it} \quad (1)$$

In this framework, α_i denotes TMC-level fixed effects to control for time-invariant characteristics of each road segment, absorbing stable differences in baseline speed across road segments such as road type, speed limit, and location. θ_{it} denotes a binary indicator for crash presence on segment i at time t , which we include in some model specifications to distinguish behavioral changes from physical disruptions in traffic flow. We note that crashes may themselves be a downstream consequence of emotionally induced speeding rather than an independent confounder; we therefore present results both with and without this control to assess its influence. δ_{it} includes a set of time-varying control variables such as weather conditions (e.g., temperature extremes, precipitation, visibility), holiday indicators, and (for NBA games) day-of-week and month or (for NFL games) week-of-season fixed effects and season dummies. Standard errors

are clustered at the TMC-code level to account for serial correlation within road segments over time.

The term $f(p_{it}, y_{it}; \lambda)$ represents a function of pre-game expectations and actual game outcomes. The pre-game expectation p_{it} is defined using the point spread from betting markets. Based on these spreads, we classify each game into one of three mutually exclusive pre-game expectation categories (with the home team as the unit of observation/point of reference): predicted win, predicted close game, and predicted loss. These thresholds vary by sport as described in Section 3.2, with symmetric ± 4 -point cutoffs applied to NFL games (following Card and Dahl (2011)) and asymmetric cutoffs of -6.75 and $+4.75$ for NBA games (following Cardazzi et al. (2024)). The realized outcome of the game, y_{it} , is coded as a win or loss for the home team. Following Card and Dahl (2011), interactions between the pre-game expectation p_{it} and the actual game outcome y_{it} allow us to isolate the behavioral effects of different expectation–outcome combinations, corresponding to the suspense–valence profiles described in Section 2. As such, we can rewrite $f(\cdot)$ as:

$$\begin{aligned} f(\cdot) = & \lambda_1 \text{predicted win}_{it} + \lambda_2 (\text{predicted win}_{it} \times \text{lose}_{it}) \\ & + \lambda_3 \text{predicted close}_{it} + \lambda_4 (\text{predicted close}_{it} \times \text{lose}_{it}) \\ & + \lambda_5 \text{predicted loss}_{it} + \lambda_6 (\text{predicted loss}_{it} \times \text{win}_{it}) \end{aligned} \quad (2)$$

The coefficients λ_1 , λ_3 , and λ_5 capture the average speed difference on game days relative to matched non-game-day observations for each pre-game expectation category. These coefficients are potentially interesting but less directly interpretable, since variation in the point spread may be correlated with other factors that independently affect traffic conditions (Card & Dahl, 2011). The main coefficients of interest are λ_2 , λ_4 , and λ_6 , which measure the differential effect of the actual outcome within each expectation category. Specifically, λ_2 captures the effect of an upset loss (surprise combined with negative valence), λ_4 captures the effect of a predicted-close loss (sustained suspense combined with negative valence), and λ_6 captures the effect of an upset win (surprise combined with positive valence). Note that within each expectation category, the interaction term compares the two possible outcomes directly: λ_4 , for example, captures the speed difference between predicted-close losses and predicted-close wins, with the latter serving as the implicit reference outcome. This within-category comparison isolates the effect of outcome valence while holding the level of pre-game suspense constant.

For each 10-minute event-time window, we estimate a separate regression on the subset of observations corresponding to that window on game days and matched non-game-day observations occurring at the same time of day and day of week. Non-game-day control observations

are identified via pre-constructed matching indicators in the data, which flag non-game-day observations at the same time of day and day of week as each game-day window, restricted to dates falling within the regular season window defined by the first and last home game of each season. This ensures that non-game-day control observations reflect comparable seasonal traffic conditions rather than off-season patterns. Our regressions are stratified by distance from the stadium in 1 km increments (0–5 km), and we estimate separate models for each of the 18×10 -minute intervals (6 pre-game and 12 post-game), resulting in 90 separate models across time and space, whose coefficients are plotted in Figures 1 and 2 to trace how effects evolve over time and distance from the stadium.

In summary, by estimating separate models for each event-time window, matching game-day observations to non-game-day observations within the regular season window, and conditioning on both environmental and temporal factors, our design provides credible within-road-segment comparisons to identify the traffic patterns that follow emotionally salient sporting events with distinct suspense–valence profiles. The identifying assumption is that, conditional on the pre-game point spread, the actual game outcome is as good as random (Card & Dahl, 2011), so that the interaction coefficients λ_2 , λ_4 , and λ_6 capture the causal effects of each expectation–outcome profile on post-game driving speed. A positive estimate on these terms reflects higher post-game speeds following that outcome profile relative to the base effect of the pre-game expectation category.

To complement our speed analysis, we also estimate models using crash counts as the dependent variable to assess whether emotional effects on driving speed translate into observable differences in collision frequency. Because crashes are sparse count data, we estimate Poisson fixed-effects regressions analogous to the main specification, using the same temporal windows (60 minutes pre-game, 60 and 120 minutes post-game) but aggregated across the full 0–5 km radius rather than disaggregated by distance bands. Formally, we estimate:

$$\log(\text{Crash}_{it}) = \alpha_i + f(p_{it}, y_{it}; \lambda) + \delta_{it} + \varepsilon_{it} \quad (3)$$

where Crash_{it} denotes the number of reported crashes on segment i at time t . The functional form $f(\cdot)$ mirrors Equation 2, and the fixed effects and control variables are identical. The detailed estimates are presented in Appendix Tables A.1 and A.2.

4 Empirical findings

4.1 Baseline results

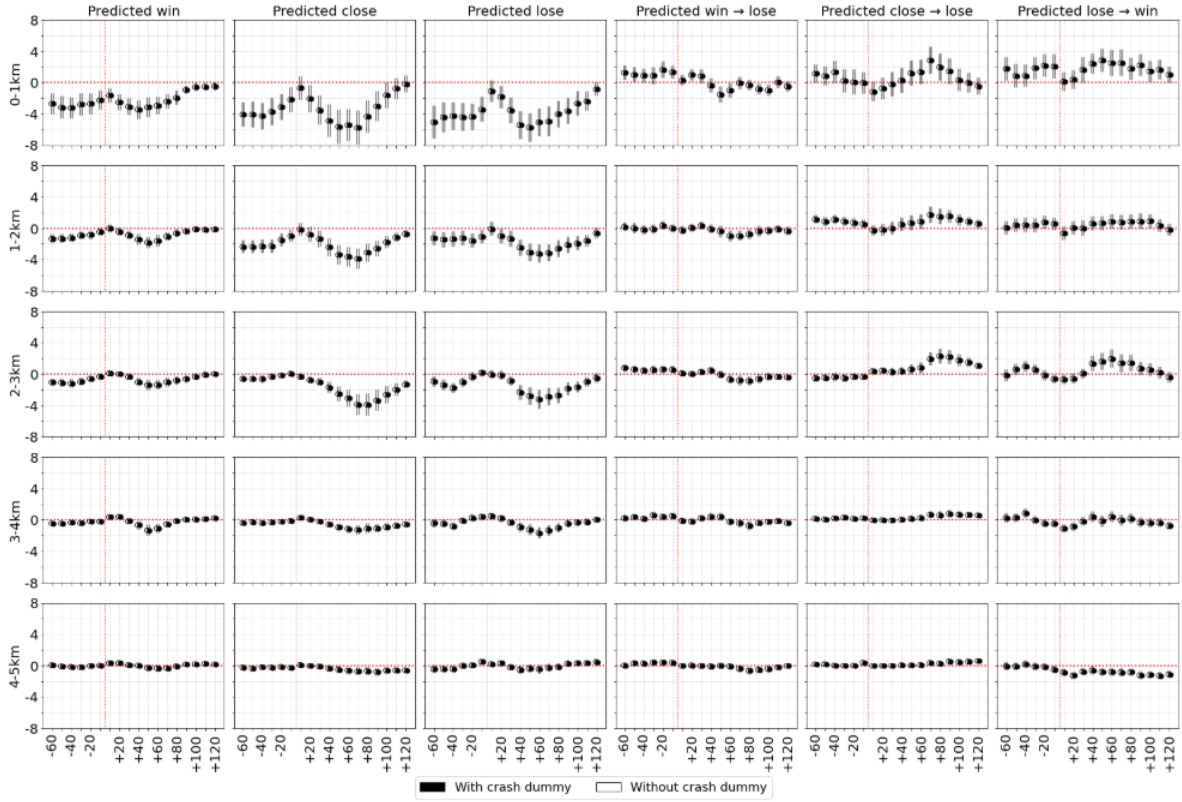
Figure 1 presents the estimated effects of NFL game outcomes on average vehicle speed across 18×10 -minute intervals (6 pre-game and 12 post-game). Each of the 30 subplots corresponds to a unique combination of spatial proximity to the stadium (5 radii) as well as pre-game expectations and actual game outcomes (6 variables). For each distance-time cell, we estimate a fixed-effects panel regression with entity-clustered standard errors as specified in Section 3.3. We acknowledge that residuals may exhibit both temporal dependence within road segments and spatial dependence across nearby segments; the robustness of our inference to alternative clustering approaches is assessed in Section 4.2.1. Each regression is estimated twice, once including a crash control dummy and once without it, yielding a total of 180 regressions (5 radii $\times$ 18 time intervals $\times$ 2 (crash/no crash), see Table A.3 for concrete numbers).

The red vertical line in each subplot denotes the scheduled start/end of the game, anchoring all observations in event time. The x-axis spans 60 minutes prior to the game start through 120 minutes after the game end. The y-axis reflects the estimated change in speed (miles/hour) either relative to matched non-game-day observations occurring at the same clock time and same day of the week (columns 1–3) or games with alternative outcomes within the same expectation category (columns 4–6). In other words: while all subplots in columns 1–3 reflect common traffic patterns on game days (compared to non-game days), the subplots in columns 4–6 reflect traffic patterns following the suspense–valence profiles described in Section 2, i.e., a loss (compared to a win) when a win was predicted, a loss (compared to a win) when the game was predicted to be close, or a win (compared to a loss) when a loss was predicted. The minimal difference between estimates with (filled black circles) and without crash controls (hollow circles) suggests that crash-induced congestion does not drive any of the patterns we observe. We note, however, that the crash control is measured at the TMC-segment level and may not fully capture spillover effects to adjacent segments; we treat this as a limitation of the crash control approach. Moreover, average speed reflects aggregate traffic behavior and cannot directly distinguish individual aggressive driving from changes in traffic composition, such as a shift toward faster vehicle types or a thinning of slower vehicles after the game.

To start with, the subplots in columns 1–3 in Figure 1 reveal clear and consistent traffic slowdowns before and after the NFL games. Average speed declines before the game starts and begins declining within 10 minutes after the game ends, reaches a minimum roughly 40 to 70 minutes post-game, and then gradually recovers. This pattern is most evident in the

Figure 1

Effects of expected and unexpected NFL game outcomes on vehicle speed near stadiums



Notes: Predicted win indicates a point spread of -4 or less (negative spreads indicate the number of points a team is expected to win by); predicted close indicates a point spread between -4 and $+4$ exclusive; and predicted loss indicates a spread of $+4$ or more. The sample is limited to Sundays during the regular-season home games for Florida's three NFL teams—the Miami Dolphins, Tampa Bay Buccaneers, and Jacksonville Jaguars—across the 2015–2019 seasons. Due to missing traffic data, the 2018 and 2019 Miami Dolphins seasons are excluded, resulting in a total of 84 Sunday home games with start times between 1:00 PM and 4:25 PM Eastern Time. Regressions include TMC-code fixed effects, as well as week-of-season time fixed effects and season dummies to control for temporal variation. Standard errors are clustered at the TMC-code level. Average vehicle speed represents observed speed across road links within 5 km of each stadium, broken up into 1-km distance bands, measured in 10-minute intervals spanning 60 minutes before to 120 minutes after each game. Average attendance across the three Florida NFL teams during the sample period was approximately 60,847 per game (Jacksonville Jaguars: 62,702; Miami Dolphins: 65,168; Tampa Bay Buccaneers: 56,560).

0–1 km range but diminishes with distance and is hardly visible anymore in the 4–5 km range. Importantly, even though this pattern seems to be more pronounced for predicted losses and predicted close games, it is generally evident and consistent across all three predictions.

Figure 1 further reveals some interesting patterns following different expectation–outcome combinations. The clearest and most robust effect emerges for predicted-close games that ended in a loss (column 5) — the high-suspense, negative-valence profile identified in Section 2 as theoretically most likely to generate post-game behavioral spillovers. These games exhibit significant post-game increases in vehicle speed within the 0–3 km range, with the largest changes observed during the first hour after the game ends. Average speed following predicted-close losses increases by up to 3 mph relative to predicted-close wins — a difference several

times larger than the average game day versus non-game day speed differential reported in Table 2, underscoring the behavioral and economic significance of this effect. This combination of sustained suspense and negative valence appears to translate into measurably higher post-game vehicle speeds, which is suggestive of more aggressive driving behavior, though we cannot test this directly. The spatial decay we see between 4–5 km suggests that these emotional spillovers are highly localized and likely tied to the immediate post-game context, rather than generalized driving behavior across the city.

While we do observe some smaller though less precise positive effects for upset wins, consistent with the surprise–positive valence profile (column 6), the coefficients for upset losses, which combine surprise with negative valence, (column 4) mainly oscillate around zero. In the robustness checks we try to explore whether this can be traced back to real differences in observed driving behavior after different suspense–valence profiles or whether this is just an artifact caused by the small number of observations.¹⁶

Figure 2 shows the results for NBA games (see Table A.4 for full results), estimating changes in average vehicle speed around home games played by Florida teams. Starting with columns 1–3, we observe a consistent—though compared to NFL games much smaller—decline in traffic speed beginning approximately 10 minutes after the game ends, bottoming out between 40 and 70 minutes post-game, and then gradually returning toward baseline. This pattern is consistent with standard post-game traffic congestion and is most pronounced in the 0–1 km range, attenuating with distance from the arena. In contrast to our findings for the NFL, however, all estimates for the suspense–valence profiles from NBA games (columns 4–6) mainly oscillate around zero and lack any systematic post-game movement. Again, the inclusion or exclusion of crash controls does not materially alter this finding. As such, and in contrast to our findings for the NFL games, we find no evidence that any of the expectation–outcome profiles in NBA games affect driving behavior as measured by average vehicle speed. While post-game traffic slowdowns are visible and local in nature, neither the high-suspense negative-valence profile nor the surprise–positive or surprise–negative valence profiles appear to generate measurable behavioral spillovers into the driving environment.

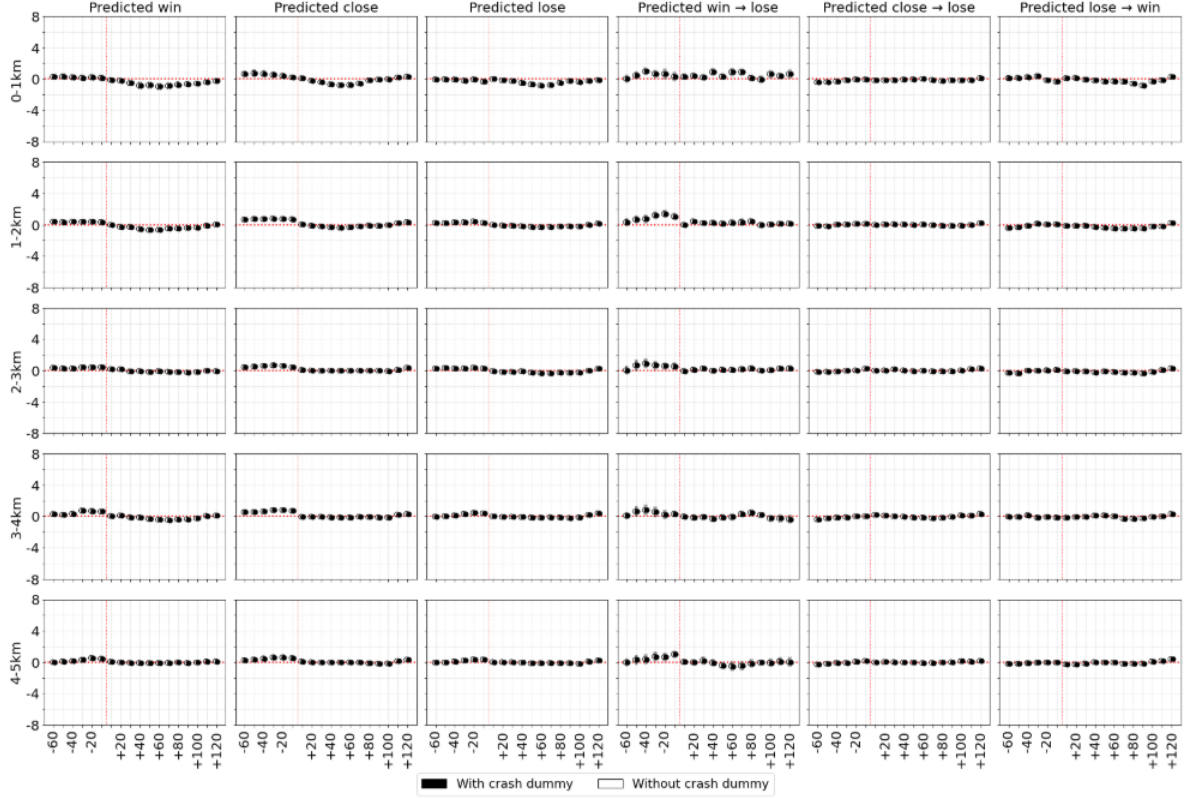
4.2 Robustness checks

To assess the stability of our findings for the NFL, we conduct a series of tests confirming that the observed post-game speed increases are not driven by specific game start times, incomplete

¹⁶Recall, while we observe 58 games that were predicted to be close, we only observe 16 (10) games that were predicted wins (losses) out of which just 5 (6) ended in an upset loss (win).

Figure 2

Effects of expected and unexpected NBA game outcomes on vehicle speed near arenas



Notes: Predicted win indicates a point spread of -6.75 or less (negative spreads indicate the number of points a team is expected to win by); predicted close indicates a point spread between -6.75 and $+4.75$ exclusive; and predicted loss indicates a spread of $+4.75$ or more. The sample is limited to regular-season NBA games between the 2015/16 and 2018/19 seasons, encompassing four total seasons. The analysis includes home games played by Florida's two NBA teams—the Miami Heat and the Orlando Magic—with scheduled tip-off times of 6:00 PM or later. Regressions include TMC-code fixed effects, as well as month time fixed effects, season dummies, and day-of-week dummies to control for temporal variation. Standard errors are clustered at the TMC-code level. Average vehicle speed represents observed speed across road links within 5 km of each arena, broken up into 1-km distance bands, measured in 10-minute intervals spanning 60 minutes before to 120 minutes after each game. Average attendance across the two Florida NBA teams during the sample period was approximately 18,651 per game (Miami Heat: 19,665; Orlando Magic: 17,651).

team coverage, or different modeling choices. We first examine the sensitivity of our inference to alternative standard error specifications, including two-way clustering and a wild cluster bootstrap procedure. We then assess robustness to kickoff time restrictions, team coverage, alternative spread thresholds, and controls for belief updating. We close this section by providing some counterfactual (during game) evidence, followed by two placebo tests: a randomization placebo in which win/loss outcome labels are randomly reassigned within each spread category, and a pseudo game-day placebo where real game labels are assigned to non-game Sundays. Together, these exercises demonstrate that the documented emotional-driving effects are robust across specifications and samples.

4.2.1 Alternative standard error specifications

Our baseline specification uses entity-clustered standard errors at the TMC-code level, which account for serial correlation within road segments over time. To assess whether inference is sensitive to this choice, we consider two additional clustering approaches, as well as a wild cluster bootstrap procedure.

First, we adopt two-way clustered standard errors that cluster simultaneously at the TMC-code (entity) level and the season-week (time) level, following Cameron, Gelbach, and Miller (2011). We implement this under two fixed-effects structures: (i) the baseline week-of-season and season fixed effects, and (ii) a more demanding specification using season-week fixed effects (84 unique time periods). Appendix Figures A.10 and A.11 present the results. Under both specifications, the core finding of elevated post-game speed following predicted-close losses remains robust, with significant effects concentrated in the 2–3 km distance band during the 70–110 minutes post-game window. The upset win effect remains significant under two-way clustering with the baseline fixed effects, though it becomes imprecise under the more demanding season-week fixed-effects specification, suggesting that this effect is more sensitive to the time fixed-effects structure than the predicted-close loss effect.

Second, we implement a wild cluster bootstrap (Cameron & Miller, 2015) to address potential finite-sample concerns with cluster-robust inference. Following the recommendation of Roodman, Nielsen, MacKinnon, and Webb (2019), we use Rademacher weights with the null imposed (WCR bootstrap, type “11”). The bootstrap p-values, presented in Appendix Table A.5, confirm the significance of the predicted-close loss effect at the 1% level across the key post-game windows (+70 to +100 minutes) and the 2–3 km distance band. Bootstrap p-values for the upset win coefficient are at or below 0.001 across most post-game windows, providing strong confirmation that the surprise-positive valence effect on driving speed is statistically robust under finite-sample inference.

Together, these exercises confirm that the main findings are not an artifact of the standard error specification. The predicted close $\times$ loss effect, combining sustained suspense with negative valence, is consistently significant under all three alternative inference procedures. The upset win effect holds under entity clustering and wild bootstrap but is less stable under the more conservative two-way clustering with season-week fixed effects.

4.2.2 Kickoff time

We also test whether game start time influences the results we find. Restricting the sample to NFL games with 1:00 PM kickoffs eliminates variation arising from later start times (4:05 PM

or 4:25 PM), which could be affected by differing travel conditions, lighting, or crowd dispersal patterns. The resulting estimates, presented in Appendix Figure A.12, are nearly identical to those in the baseline model (Figure 1). Overall, our main findings remain: average post-game speed increases significantly following predicted-close losses, the high-suspense, negative-valence profile, with similar magnitudes and timing across all distance bands as in our main specification. Moreover, the effects for upset wins, combining surprise with positive valence, even become more pronounced.

4.2.3 Team coverage

Next, we evaluate whether incomplete traffic data for the Miami Dolphins during the 2018 and 2019 seasons influence the results. We re-estimate the regressions excluding all Dolphins home games, leaving only Tampa Bay Buccaneers and Jacksonville Jaguars games in the sample. Appendix Figure A.13 shows that the estimated patterns remain virtually unchanged relative to the full-sample results. Post-game speeds still rise significantly following predicted-close losses and upset wins, with no notable changes in magnitude or timing across distance bands. Overall, these results confirm that incomplete data for the Miami Dolphins do not drive the baseline findings for the NFL.

4.2.4 Spread thresholds

To assess whether our findings depend on the definition of pre-game expectations, we replicate our analysis using alternative point-spread cutoffs of ± 3 and ± 5 points (instead of ± 4). Table 5 provides an overview of how the distribution of games changes under different thresholds highlighting how narrower (wider) cutoffs identify fewer (more) close games and more (fewer) wins and losses respectively. Importantly, there is some asymmetry here, i.e., while decreasing the threshold from ± 4 to ± 3 causes 26 games to be classified differently, increasing the threshold from ± 4 to ± 5 causes only 5 games to be classified differently.

Overall, we still observe positive effects on average speed following predicted-close losses using a cut-off at ± 3 , though these are smaller than in the baseline. The upset win effect—combining surprise with positive valence—however vanishes under this narrower threshold (if anything, there is even a small but negative effect within the 1–3 km range, see Figure A.14). This is consistent with the narrower threshold reclassifying many games previously identified as predicted wins or losses into the predicted-close category, diluting the suspense–valence contrast. In contrast, using a cut-off at ± 5 we find very similar results to our main specification with

Table 5
Game counts by spread threshold and outcome category

Version	Predicted win	Predicted close	Predicted loss	Predicted win × lose	Predicted close × lose	Predicted loss × win
Spread ± 2	40	17	27	18	10	12
Spread ± 3	31	32	21	12	18	8
Baseline ± 4	16	58	10	5	34	6
Spread ± 5	13	63	8	3	37	5
Spread ± 6	10	69	5	2	39	3

Notes: Counts reflect the number of NFL home games in each predicted outcome and interaction category under alternative spread thresholds. Narrower cutoffs (e.g., ± 2 , ± 3) reduce the number of close games and increase predicted wins and losses; wider cutoffs (e.g., ± 5 , ± 6) do the opposite. For example, under the ± 6 threshold, any game with a point spread at or below -6 is classified as a predicted win, any at or above $+6$ as a predicted loss, and those between -6 and $+6$ (exclusive) as predicted close contests. The sample is limited to Sundays during the regular-season home games for Florida’s three NFL teams—the Miami Dolphins, Tampa Bay Buccaneers, and Jacksonville Jaguars—across the 2015–2019 seasons. Due to missing traffic data, the 2018 and 2019 Miami Dolphins seasons are excluded, resulting in a total of 84 Sunday home games with start times between 1:00 PM and 4:25 PM Eastern Time.

both the predicted-close loss effect and the upset win effect being even more pronounced (see Figure A.15).

4.2.5 Updating beliefs

In order to test whether updating beliefs is relevant in our setting, we consider score differentials at halftime as proposed by Card and Dahl (2011). More precisely, we include halftime status as a control variable to isolate its influence relative to pregame expectations. A second specification focuses directly on halftime (instead of before the game) predictions, examining how post-game traffic varies considering the home team’s position at halftime and the final result. As discussed in Section 2, we proxy for sustained suspense using the pre-game point spread under the assumption that games predicted to be close are more likely to remain competitive throughout. The halftime specifications below partially test this assumption by examining whether within-game score dynamics alter the main findings.

In line with Card and Dahl (2011), we find little evidence of systematic belief updating based on halftime information affecting our results. In the control specification (Figure A.16), the patterns for predicted-close losses—the high-suspense, negative-valence profile—and upset wins largely mirror the results in Figure 1, though the effects are slightly less precise. In the halftime prediction specification (Figure A.17), the coefficients for games predicted to be close at halftime but that ultimately ended in a loss show no consistent pattern, and any negative deviations in post-game speeds are small and confined to the immediate stadium area (0–1 km). Similarly, games in which the home team was predicted to lose at halftime but ultimately won show at most a minor and imprecise positive response within the 0–1 km range. Together, these results suggest that even though fans are likely to adjust their expectations as games

unfold, such belief updating during games plays only a minor role in shaping post-game driving speeds. This is consistent with our conceptual framework, which emphasizes pre-game suspense and final outcome valence as the primary drivers of post-game behavioral responses, rather than within-game dynamics. We also examined whether games featuring a fourth-quarter lead change — for instance, teams winning going into the fourth quarter but ultimately losing, or vice versa — generate distinct post-game driving patterns. However, with only 9 such heartbreak losses and 6 late comeback wins among our 84 games, the sample is too small to support reliable inference for these categories. We therefore flag more granular within-game belief updating, including quarter-by-quarter score dynamics and late lead changes, as a promising avenue for future research, particularly in settings with larger game samples.

4.2.6 Counterfactual analysis

To relax the possible concern that any traffic patterns we observe are simply game-day related rather than driven by the suspense–valence profiles described in Section 2, we test during-game patterns in a counterfactual setup. More precisely, we construct a panel of 10-minute bins beginning at game start and extending to 170 minutes post-kickoff, corresponding to the duration of the shortest game in the sample. Figure A.18 displays the estimated changes in speed by expectation–outcome combination and distance band. The interpretation mirrors our pre/post-game specification since each time bin is compared to a matched non-gameday bin of the same time-of-day and day of week (columns 1–3) or to games with alternative outcomes within the same expectation category (columns 4–6).

As can be seen in Figure A.18, traffic speed remains rather stable during games. Whether the home team was predicted to win, lose, or play in a close contest, and regardless of the final outcome, we observe no meaningful change in driving speed relative to non-gamedays (or alternative outcomes). The only exception concerns upset wins, the surprise–positive valence profile, for which we observe mildly reduced average speed. Overall, however, these results reinforce our central claim that the emotional context generated by the final outcome and the pre-game expectation of a close contest, rather than the mere occurrence of a game, may drive the changes in traffic behavior we observe.

4.2.7 Randomization placebo

To verify that our main findings are not an artifact of the data structure or estimation procedure, we implement a randomization placebo test. We run our full regression model 150 times, each time randomly shuffling the win/loss outcome labels within each spread category before

estimation — keeping spread category assignments fixed but randomizing the actual outcome within each category. Everything else remains identical: the same games, same dates, same stadiums, same traffic data, same weather controls, and same fixed effects.

Appendix Figure A.19 presents the average coefficient across the 150 draws for each time window and distance band, along with the 2.5 and 97.5 percentile range of the placebo coefficients — reflecting what we would expect to find by chance under random outcome assignment. For all three interaction terms the placebo mean is essentially zero across all time windows and distance bands, with no systematic post-game pattern. The percentile bands for the predicted loss $\times$ win interaction are somewhat wider, reflecting the small number of predicted loss games in the sample (only 10), though the mean remains close to zero throughout. The real coefficient for predicted-close losses at the key post-game windows sits well outside the 97.5 percentile of the placebo coefficients, confirming that the main finding cannot be replicated by random outcome assignment.

4.2.8 Pseudo game-day placebo

As a further placebo test, we examine whether the post-game speed patterns we observe could be driven by normal Sunday afternoon traffic patterns, rather than by the actual occurrence of an NFL game and accompanying emotions. We restrict the sample to non-game Sundays only and construct a set of pseudo game days by randomly assigning each of the 84 real games to a non-game Sunday from the same team’s stadium area, without replacement. Each assigned date inherits the real game’s spread category and outcome label, and the existing matched time-window indicators, which flag observations occurring at the same time of day as a real game’s pre- and post-game windows, are used as event-time dummies for the pseudo game days. The remaining non-game Sundays serve as the control group. The same regression specification as the main model is then estimated on this pseudo game-day dataset. As with the randomization placebo in Section 4.2.7, we repeat this procedure 150 times, each time with a new random assignment of real games to non-game Sundays.

Across the three teams, a total of 135 non-game Sundays are available for assignment: 52 for the Jacksonville Jaguars, 32 for the Miami Dolphins, and 51 for the Tampa Bay Buccaneers. After assigning one non-game Sunday to each of the 84 real games, 51 non-game Sundays remain as control observations (Jacksonville: 20, Miami: 13, Tampa Bay: 18).

As shown in Appendix Figure A.20, the average coefficient across the 150 draws is, across all six outcome profiles, all five distance bands, and all 18 time windows, essentially zero, with no systematic pre- or post-game pattern, and the 2.5th to 97.5th percentile range of the placebo

coefficients remains narrow and centered around zero throughout. This confirms that the post-game speed increases documented in the main analysis are not driven by normal Sunday traffic dynamics, time-of-day effects, or the event-time window construction, but are instead tied to the actual occurrence of an NFL game and its emotional outcome.

4.3 Crash analysis

Due to crash events being quite rare, we estimate Poisson fixed-effects regressions using crash counts as the dependent variable on the aggregated 0–5 km sample as well as split only into three intervals (60 minutes pre-game, 60 and 120 minutes post-game). Table 6 presents the results for the NFL, for gamedays as well as splitting gamedays into wins and losses. Before discussing the results, we note that crash counts in our sample are low — 17 crashes in the pre-game window and 40 in the post-game 60-minute window across all gamedays in the 2015–2019 sample — so the Poisson coefficients, which are expressed as log changes, should be interpreted with appropriate caution. We report percentage changes derived from the exponentiated coefficients as indicative of the direction and approximate magnitude of effects, rather than as precise estimates.

Turning to the results, Table 6 reveals two notable patterns. First, pre-game crash counts are already elevated on gamedays relative to matched non-gamedays. The gameday coefficient in the Pregame_60 window is positive and statistically significant (estimate = 0.933, $p = 0.008$), corresponding to approximately 154% more crashes on gamedays relative to non-gamedays in the hour before kickoff. This likely reflects elevated pre-game travel and fan activity around stadiums rather than emotional driving, and represents a new finding relative to earlier versions of this analysis.

Second, our estimates reveal a clear post-game increase in crashes for both time windows. In the Postgame_60 window, gameday crashes are approximately 404% more frequent relative to matched non-gamedays (estimate = 1.618, $p = 0.000$). This increase is somewhat larger following losses (approximately 505% more crashes, estimate = 1.798, $p = 0.000$) than following wins (approximately 408% more crashes, estimate = 1.624, $p = 0.000$). In the Postgame_120 window, the pattern persists: gameday crashes remain significantly elevated (approximately 243% more frequent, estimate = 1.232, $p = 0.000$), again with a larger effect following losses (approximately 353% more crashes, estimate = 1.510, $p = 0.000$) than wins (approximately 181% more crashes, estimate = 1.032, $p = 0.015$). While these percentage increases are large in relative terms, they should be interpreted in the context of the low absolute crash counts involved.

Table 6
Poisson fixed-effects regressions of NFL crash counts by win/loss outcome

Period	Number of crashes	Estimate	<i>p</i> -value	95% CI Low	95% CI High
Pregame_60					
Gamedays (non-gamedays)	17 (33)	0.933	0.008	0.249	1.616
Postgame_60					
Gamedays (non-gamedays)	40 (52)	1.618	0.000	1.159	2.077
Wins	18	1.624	0.000	0.972	2.275
Losses	22	1.798	0.000	1.284	2.313
Postgame_120					
Gamedays (non-gamedays)	21 (41)	1.232	0.000	0.662	1.803
Wins	9	1.032	0.015	0.196	1.867
Losses	12	1.510	0.000	0.776	2.243

Notes: The dependent variable is the crash count per TMC segment and 60-minute time interval. Crash counts reported in this table reflect the total number of unique crash events aggregated across all observation windows in the 2015–2019 sample (i.e., all gamedays and all corresponding matched non-gameday control periods), rather than averages per gameday or per non-gameday. Estimates are from Poisson fixed-effects regressions on the aggregated 0–5 km sample. The sample is limited to Sundays during the regular-season home games for Florida’s three NFL teams—the Miami Dolphins, Tampa Bay Buccaneers, and Jacksonville Jaguars—across the 2015–2019 seasons. Due to missing traffic data, the 2018 and 2019 Miami Dolphins seasons are excluded, resulting in a total of 84 Sunday home games with start times between 1:00 PM and 4:25 PM Eastern Time. Poisson regressions include TMC-code fixed effects, as well as week-of-season time fixed effects and season dummies to control for temporal variation. Standard errors are clustered at the TMC-code level. Coefficients are reported as log changes; positive values indicate higher crash frequencies relative to matched non-gameday periods.

Due to the very limited number of crash observations, further splitting the sample does not yield any consistent patterns (see Table A.1 in the Appendix). Still, it is worth noting that elevated post-game speeds around NFL stadiums coincide with higher crash counts on gamedays relative to non-gamedays, particularly after losses. This pattern is consistent with the speed analysis: the high-suspense, negative-valence profile of predicted-close losses generates the largest post-game speed increases, and the crash analysis suggests that these speed increases may translate into elevated collision risk. Together, the speed and crash findings paint a coherent picture of emotionally induced behavioral spillovers from NFL games into post-game traffic.¹⁷

5 Discussion

Our analysis provides robust evidence of emotional driving after NFL games, concentrated in the high-suspense, negative-valence profile: games predicted to be close that ended in disappointing home-team losses. Average vehicle speed rises by up to 3 mph relative to predicted-close games that ended in a win in the first post-game hour. As shown in Table 2, the average difference between game day and non-game day speeds is less than 1 mph across all distance bands, meaning the 3 mph effect following predicted-close losses is several times larger than the typical game day deviation — underscoring the behavioral and economic significance of this finding.

¹⁷Crash count regressions for the NBA do not indicate any significant effects (see Table A.2 in the Appendix).

The spatial decay we see between 4–5 km suggests that these emotional spillovers are highly localized and likely tied to the immediate post-game context, rather than generalized driving behavior across the city. We also find some smaller—though less precise—positive effects on average speed following upset wins — the surprise–positive valence profile — while we do not observe any consistent patterns following upset losses — the surprise–negative valence profile. Importantly, however, sample size restrictions limit the extent of our investigation for both upset wins and upset losses. As such, despite our non-findings here, we refrain from concluding that upset losses in the NFL generally do not unfold any such effects on average vehicle speed.

In contrast to these findings for the NFL, NBA games—for which we also observe a considerable number of upset wins and losses in our data—show no systematic relationship between expectation–outcome profiles and post-game traffic behavior. While modest traffic slowdowns occur near arenas, these reflect standard congestion patterns rather than emotional responses. One may speculate that the NBA’s higher game frequency (41 home games in the NBA compared to 8 in the NFL) and scoring volatility may attenuate the emotional salience of any single game outcome. By contrast, each NFL game carries greater weight in the season, and the sport’s high-impact, stop-start rhythm fosters more intense emotional investment and sharper post-game emotions. For our setting, however, the most notable difference between NFL and NBA games certainly relates to the number of spectators. Average attendance is much smaller in the NBA (approximately 18,651 per game across the two Florida teams) compared to the NFL (approximately 60,847 per game across the three Florida teams), reducing overall crowd-related traffic pressure and the probability to observe a sufficiently large portion of spectators among the drivers in a 5-kilometer radius after the games. Moreover, NBA games in Florida take place in denser urban environments with limited road capacity and lower average vehicle speeds, which may dampen opportunities for speeding. In summary, we caution against interpreting this contrast as evidence that NBA games generate weaker emotional responses among fans *per se*. The absence of detectable effects in the NBA likely reflects structural differences in attendance, venue location, and traffic environment rather than differences in the emotional intensity experienced by individual fans.

Overall, the spatial and temporal concentration of the observed effects for NFL games supports an interpretation of transient emotional responses. Speed increases are largest within 1 km of the stadium, concentrated in the first hour after games, and dissipate beyond 3 km—consistent with the short-lived nature of emotional arousal and its immediate influence on cognition and risk perception. Within the expectations-based reference framework (Kőszegi & Rabin, 2006), predicted-close contests generate strong pre-game expectations on both sides

of the reference point, and a narrow home-team loss represents the negative resolution of a high-suspense event — combining sustained arousal with disappointing valence in a way that lopsided losses do not. The Yerkes and Dodson (1908) law, which suggests that performance deteriorates at high arousal levels, might help explain why we observe the largest behavioral response in these close, disappointing losses rather than in more lopsided contests. Moreover, this pattern aligns with experimental evidence that heightened emotional states—especially anger, frustration, or stress—reduce reaction times and increase risk-taking tendencies (e.g., Deffenbacher et al., 2003; Jeon et al., 2014; Q. Zhang et al., 2022, 2020). Close losses, in particular, can provoke these responses by combining high physiological activation with negative valence, thereby increasing the likelihood of aggressive or inattentive driving after the event. The timing, spatial decay, robustness checks, and absence of during-game effects are all consistent with an affective interpretation of the post-game speed increases. However, we acknowledge that the data cannot directly observe individual emotional states, and we cannot rule out all event-management and crowd-dispersal mechanisms as contributing factors; this will be discussed more in depth in Section 5.1.

Notably, Wood et al. (2011) find that close, competitive games increase traffic fatalities near the winning team’s location, likely reflecting celebratory arousal and risk-taking among fans of the winning team. Our results highlight a contrasting yet complementary pattern: while Wood et al. (2011) document elevated driving risk among winning fans, we find that losing fans of close, high-suspense games also exhibit measurably riskier driving behavior through frustration and negative arousal. Together, these findings suggest that high emotional intensity in close sporting events can affect post-game driving behavior through both positive and negative affective channels, regardless of which side of the outcome fans are on.

The effect we find is a behaviorally meaningful increase given the density of post-game traffic and the safety risks of even small deviations from speed limits. In many jurisdictions, a 3 mph deviation is enough to exceed posted speed limits and trigger enforcement, with potential implications for safety, especially near stadium exits and pedestrian crossings.¹⁸ Taken together with our crash analysis, which shows elevated post-game crash counts on gamedays relative to

¹⁸A 3 mph deviation aligns closely with the 5 km/h increase referenced in empirical studies, which show that the risk of involvement in a casualty crash can double for every 5 km/h increase in traveling speed above the limit in urban zones (Kloeden, McLean, & Glonek, 2002; Kloeden, McLean, Moore, & Ponte, 1997). Such low-level speeding (1–10 km/h over the limit) is highly prevalent and is collectively estimated to be attributable to up to 19.2% of all casualty crashes in urban 40 km/h zones due to its high frequency (Soole et al., 2023). Wang, Zhou, Quddus, Fan, and Fang (2018) further corroborate this relationship for urban arterials specifically, finding that a 1% increase in mean speed is associated with a 0.7% increase in total crashes.

matched non-gamedays, especially after losses, these findings suggest that emotional speeding is not merely cosmetic but may translate into higher collision risk.

5.1 Limitations

Several limitations of our analysis deserve acknowledgment. First, the data do not observe individual drivers, whether a driver attended the game, whether the driver supported the home team, or the driver’s emotional state. The estimated effects therefore capture changes in local traffic behavior around emotionally salient events, not direct individual-level emotional responses. In addition, average speed can change for reasons other than intentional speeding. Crowd-dispersal patterns, pedestrian flows, police traffic management, ride-share activity, parking-lot exits, and post-game celebrations may all affect observed speeds. A close win may encourage fans to linger, celebrate, or move more slowly through congested areas, while a close loss may produce faster and more synchronized departures. These mechanisms are not mutually exclusive with emotional driving, but they imply that the estimated effects should be understood as reduced-form behavioral spillovers around stadiums rather than a clean measure of individual emotional driving behavior.

Second, there may be a selection or composition issue in the surrounding traffic. On game days, some ordinary drivers may avoid the area or shift travel times, while attendees disproportionately enter the local network. As a result, non-game-day controls may not represent exactly the same underlying traffic composition. However, our pseudo game-day placebo test (Section 4.2.8) is suggestive of this not being a major concern: if non-game-day controls differed systematically in composition from game-day periods, we might expect to observe some spurious pattern even when real game labels are assigned to non-game Sundays, yet the placebo coefficients remain centered around zero with no systematic pattern. In any case, this would not invalidate the findings, but it does reinforce the idea that the estimates capture reduced-form local traffic responses to emotionally salient events, rather than a pure treatment effect on an otherwise unchanged traffic stream.

Third, some interaction cells in our NFL sample are small. While we observe 58 predicted-close games, we only observe 5 upset losses and 6 upset wins, making inference for these categories more exploratory than confirmatory. The predicted-close loss finding rests on 34 games — a more reliable base — but the upset win and upset loss findings should be interpreted with additional caution given the limited number of observations.

Fourth, our findings are specific to Florida NFL and NBA teams during the 2015–2019 regular seasons. Florida’s climate, road network, public transportation availability, and fan

culture may differ from other NFL markets. The absence of playoff games and the restriction to regular-season contests means that our findings may not generalize to higher-stakes postseason environments, where emotional intensity and attendance patterns may differ substantially.

5.2 Policy implications

Importantly, increased average vehicular speeds are predictable in time and space: they are largest within 0–3 km of stadiums and during the first post-game hour, especially following games that were expected to be close. This predictability suggests that targeted, time-bound interventions could substantially improve safety outcomes. Visible, short-term speed enforcement in the hour following close, disappointing games—through mobile radar units, automated enforcement cameras, or clearly marked police presence—could help deter impulsive speeding in these emotionally heightened periods. Municipalities might also increase pedestrian protection by deploying temporary barriers or expanding sidewalk space around stadium exits to separate walking fans from vehicle flow. Electronic roadside messaging systems — similar to those used to alert fatigued drivers — could be deployed near stadium exits in the post-game window, reminding drivers to slow down and exercise caution. Dynamic traffic signal systems that adjust to post-game congestion levels could further reduce stop-and-go frustration, which compounds emotional agitation behind the wheel.

Eventually, public communication and behavioral nudges can also play a preventive role. Messaging campaigns that encourage caution and remind drivers to anticipate congestion, particularly after close or high-stakes games, may reduce risky driving behavior among emotionally aroused fans. Providing post-game activities or designated waiting areas near stadiums — such as fan zones, entertainment, or food and beverage areas — could give emotionally aroused fans time to dissipate their emotional state before getting behind the wheel, reducing the number of emotionally affected drivers on the road immediately after games. Event organizers and local governments could coordinate these campaigns with post-game public announcements or digital signage near stadium exits. More broadly, aligning traffic management policies with the emotional salience of events may yield public safety benefits. Deploying additional traffic personnel or designating ride-share pickup zones for high-attendance or high-stakes games could reduce emotional exposure at the wheel. In the longer term, expanding or subsidizing public and shared transportation options for game days—such as discounted transit fares, dedicated shuttle routes, or ride-share vouchers—could reduce the number of emotionally affected drivers on the road. Overall, even modest shifts in driver behavior or mode choice during these predictable high-risk windows could generate meaningful safety gains for both fans and surrounding communities.

6 Conclusions

Using detailed traffic speed and crash data around professional sport venues in Florida, we show that NFL games predicted to be close before kickoff, generating sustained pre-game suspense, but that ultimately ended in a disappointing home-team loss produce localized increases in post-game vehicle speed. The resulting combination of sustained suspense and negative outcome valence appears to manifest as short-lived increases in risky driving behavior within 3 km of stadiums during the first post-game hour. Against the baseline of less than 1 mph average difference between game days and non-game days, the estimated 3 mph post-game speed increase following predicted-close losses is several times larger than the typical game day deviation, underscoring the behavioral significance of this effect. Further analysis suggests that the emotional context generated by the final outcome and the suspense experienced during the game, rather than congestion, environmental factors, or normal Sunday traffic patterns, drives the observed speeding.

These findings contribute to three strands of literature. They provide field evidence that expectations-based emotional cues generate behavioral spillovers into immediate real-world decisions, extending the reference-dependent preferences literature beyond laboratory settings. They identify a high-frequency behavioral mechanism, minute-level vehicle speed, linking emotionally intense sporting events to elevated public safety risks, complementing event-level crash studies. And they show that risky driving behavior can be shaped by predictable affective states generated by collective experiences, with implications for transportation policy and road safety management.

Beyond documenting this phenomenon, our findings carry important implications for public safety and event management. Because the timing and location of these high-risk emotional episodes are predictable, targeted interventions, such as visible post-game speed enforcement, dynamic traffic control, and improved pedestrian management, could effectively mitigate risk. More broadly, recognizing that emotions from collective experiences like sports can shape immediate real-world behavior underscores the value of integrating psychological and behavioral insights into traffic policy. Future research could examine whether these patterns hold in other jurisdictions, sports leagues, or playoff settings, or how specific interventions affect post-game collision rates.

Games predicted to be close before kickoff appear to create the emotional conditions most conducive to post-game speeding when the final outcome is unfavorable, combining the sustained arousal of a high-suspense contest with the frustration of a negative resolution. Anticipating

and managing these predictable, emotionally charged moments offers a promising, behaviorally informed avenue for improving public safety in the aftermath of major sporting events.

References

- Bell, D. E. (1985). Disappointment in decision making under uncertainty. *Operations Research*, 33(1), 1–27.
- Braun, M., Weber, F., & Alt, F. (2021). Affective automotive user interfaces—reviewing the state of driver affect research and emotion regulation in the car. *ACM Computing Surveys (CSUR)*, 54(7), 1–26.
- Cai, H., & Lin, Y. (2011). Modeling of operators’ emotion and task performance in a virtual driving environment. *International Journal of Human-Computer Studies*, 69(9), 571–586.
- Cai, Q., & Li, Q. (2026). Emotional shocks and consumer spending. *Journal of Economic Behavior & Organization*, 241, 107357.
- Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business & Economic Statistics*, 29(2), 238–249.
- Cameron, A. C., & Miller, D. L. (2015). A practitioner’s guide to cluster-robust inference. *Journal of Human Resources*, 50(2), 317–372.
- Card, D., & Dahl, G. B. (2011). Family violence and football: The effect of unexpected emotional cues on violent behavior. *The Quarterly Journal of Economics*, 126(1), 103–143.
- Cardazzi, A. J., McCannon, B. C., Humphreys, B. R., & Rodriguez, Z. (2024). Emotional cues and violent behavior: Unexpected basketball losses increase incidents of family violence. *The Journal of Law, Economics, and Organization*, 40(2), 267–288.
- Deffenbacher, J. L., Deffenbacher, D. M., Lynch, R. S., & Richards, T. L. (2003). Anger, aggression, and risky behavior: a comparison of high and low anger drivers. *Behaviour Research and Therapy*, 41(6), 701–718.
- Dingus, T. A., Guo, F., Lee, S., Antin, J. F., Perez, M., Buchanan-King, M., & Hankey, J. (2016). Driver crash risk factors and prevalence evaluation using naturalistic driving data. *Proceedings of the National Academy of Sciences*, 113(10), 2636–2641.
- Edmans, A., Garcia, D., & Norli, (2007). Sports sentiment and stock returns. *The Journal of Finance*, 62(4), 1967–1998.
- Ely, J. C., Frankel, A., & Kamenica, E. (2015). Suspense and surprise. *Journal of Political Economy*, 123(1), 215–260.
- Eren, O., & Mocan, N. (2018). Emotional judges and unlucky juveniles. *American Economic Journal: Applied Economics*, 10(3), 171–205.
- Gandar, J., Zuber, R., O’Brien, T., & Russo, B. (1988). Testing rationality in the point spread betting market. *The Journal of Finance*, 43(4), 995–1008.
- HERE Technologies. (2024). *Traffic api v7 — flow data*. Retrieved from <https://www.here.com/docs/bundle/traffic-api-v7-developer-guide/page/topics/flow-data.html> (Accessed: 2026)
- Humphreys, B. R., & Pyun, H. (2018). Professional sporting events and traffic: Evidence from U.S. cities. *Journal of Regional Science*, 58(5), 869–886.
- Hwang, H., Humphreys, B. R., & Pyun, H. (2025). Game day traffic and sports: Evidence from Yankee Stadium in the Bronx. *Journal of Sports Economics*, 26(3), 219–239.
- Jakar, G., Gordon, K., & He, Q. (2023). The temporal and spatial relationships between professional sport events and reported vehicular crashes: An analysis of cleveland, ohio. *Sport Management Review*, 26(4), 628–648.
- Jeon, M., Walker, B. N., & Yim, J. B. (2014). Effects of specific emotions on subjective judgment, driving performance, and perceived workload. *Transportation Research Part*

- F: Traffic Psychology and Behaviour*, 24, 197–209.
- Kadoya, Y., Watanapongvanich, S., & Khan, M. S. R. (2021). How is emotion associated with driving speed? A study on taxi drivers in Japan. *Transportation Research Part F: Traffic Psychology and Behaviour*, 79, 205–216.
- Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), 263–291.
- Kloeden, C. N., McLean, A. J., & Glonek, G. (2002). *Reanalysis of travelling speed and the rate of crash involvement in adelaide, south australia* (Tech. Rep. No. CR 207). Australian Transport Safety Bureau (ATSB).
- Kloeden, C. N., McLean, A. J., Moore, V. M., & Ponte, G. (1997). *Travelling speed and the rate of crash involvement. volume 1: Findings* (Tech. Rep. No. CR 172). Federal Office of Road Safety (FORS).
- Kőszegi, B., & Rabin, M. (2009). Reference-dependent consumption plans. *American Economic Review*, 99(3), 909–936.
- Kőszegi, B., & Rabin, M. (2006). A model of reference-dependent preferences. *The Quarterly Journal of Economics*, 121(4), 1133–1165.
- Lerner, J. S., & Keltner, D. (2001). Fear, anger, and risk. *Journal of Personality and Social Psychology*, 81(1), 146–159.
- Loomes, G., & Sugden, R. (1986). Disappointment and dynamic consistency in choice under uncertainty. *The Review of Economic Studies*, 53(2), 271–282.
- Mesken, J., Hagenzieker, M. P., Rothengatter, T., & De Waard, D. (2007). Frequency, determinants, and consequences of different drivers’ emotions: An on-the-road study using self-reports, observed behaviour, and physiology. *Transportation Research Part F: Traffic Psychology and Behaviour*, 10(6), 458–475.
- Pankoff, L. D. (1968). Market efficiency and football betting. *The Journal of Business*, 41(2), 203–214.
- Potoski, M., & Urbatsch, R. (2017). Entertainment and the opportunity cost of civic participation: Monday night football game quality suppresses turnout in us elections. *The Journal of Politics*, 79(2), 424–438.
- Precht, L., Keinath, A., & Krems, J. F. (2017). Effects of driving anger on driver behavior—results from naturalistic driving data. *Transportation Research Part F: Traffic Psychology and Behaviour*, 45, 75–92.
- Redelmeier, D. A., & Stewart, C. L. (2003). Driving fatalities on super bowl sunday. *The New England Journal of Medicine*, 348, 368–369.
- Roidl, E., Frehse, B., & Höger, R. (2014). Emotional states of drivers and the impact on speed, acceleration and traffic violations—a simulator study. *Accident Analysis & Prevention*, 70, 282–292.
- Roodman, D., Nielsen, M. Ø., MacKinnon, J. G., & Webb, M. D. (2019). Fast and wild: Bootstrap inference in Stata using `boottest`. *Stata Journal*, 19(1), 4–60.
- Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, 39(6), 1161–1178.
- Soole, D. W., O’Hern, S., Cameron, M., Peiris, S., Newstead, S., Anderson, W., & Smith, T. (2023). Using gps probe speed data to estimate the attribution of speeding on casualty crashes: A case study in queensland. *Journal of Road Safety*, 34(1), 39–48.
- Sorenson, M. (2022). *Nfl follower map*. <https://public.tableau.com/app/profile/matt.sorenson/viz/NFLFollowerMap/NFLMap>. (Last updated December 7, 2022. Accessed August 5, 2025.)
- Sorenson, M. (2024). *Nba fan map*. <https://public.tableau.com/app/profile/matt.sorenson/viz/NBAFollowerMap/NBAMap>. (Last updated January 30, 2024. Accessed August 5, 2025.)
- Steinhauser, K., Leist, F., Maier, K., Michel, V., Pärsch, N., Rigley, P., ... Steinhauser, M.

- (2018). Effects of emotions on driving behavior. *Transportation Research Part F: Traffic Psychology and Behaviour*, 59, 150–163.
- Taubman-Ben-Ari, O. (2012). The effects of positive emotion priming on self-reported reckless driving. *Accident Analysis & Prevention*, 45, 718–725.
- Underwood, G., Chapman, P., Wright, S., & Crundall, D. (1999). Anger while driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, 2(1), 55–68.
- van Dijk, W. W., & Van der Pligt, J. (1997). The impact of probability and magnitude of outcome on disappointment and elation. *Organizational Behavior and Human Decision Processes*, 69(3), 277–284.
- Wang, X., Zhou, Q., Quddus, M., Fan, T., & Fang, S. (2018). Speed, speed variation and crash relationships for urban arterials. *Accident Analysis & Prevention*, 113, 236–243.
- Wood, S., McInnes, M. M., & Norton, D. A. (2011). The bad thing about good games: The relationship between close sporting events and game-day traffic fatalities. *Journal of Consumer Research*, 38(4), 611–621.
- World Health Organization. (2023). Road traffic injuries. *Fact Sheets*. (Retrieved December 13, 2023, from <https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries>)
- Yerkes, R. M., & Dodson, J. D. (1908). The relation of strength of stimulus to rapidity of habit-formation. *Journal of Comparative Neurology and Psychology*, 18(5), 459–482.
- Zhang, Q., Qu, W., & Ge, Y. (2022). The effect of anger on pedestrian avoidance in a simulated driving task. *Accident Analysis & Prevention*, 171, 106664.
- Zhang, Q., Qu, W., Ge, Y., Sun, X., & Zhang, K. (2020). The effect of the emotional state on driving performance in a simulated car-following task. *Transportation Research Part F: Traffic Psychology and Behaviour*, 69, 349–361.
- Zhang, T., Chan, A. H., Ba, Y., & Zhang, W. (2016). Situational driving anger, driving performance and allocation of visual attention. *Transportation Research Part F: Traffic Psychology and Behaviour*, 42, 376–388.
- Zimasa, T., Jamson, S., & Henson, B. (2019). The influence of driver’s mood on car following and glance behaviour: Using cognitive load as an intervention. *Transportation Research Part F: Traffic Psychology and Behaviour*, 66, 87–100.

Appendix

Figure A.1

0–5 km Radius Map for the Raymond James Stadium (Tampa Bay Buccaneers)

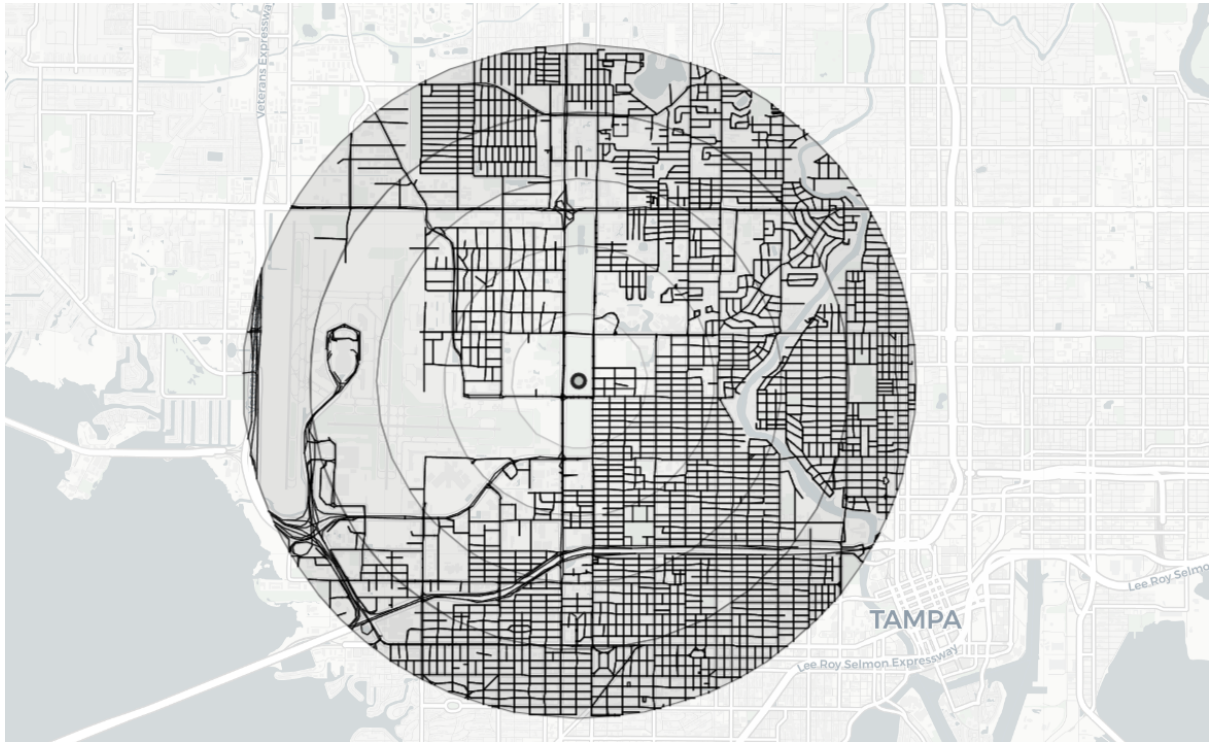


Figure A.2

0–5 km Radius Map for the Hard Rock Stadium (Miami Dolphins)

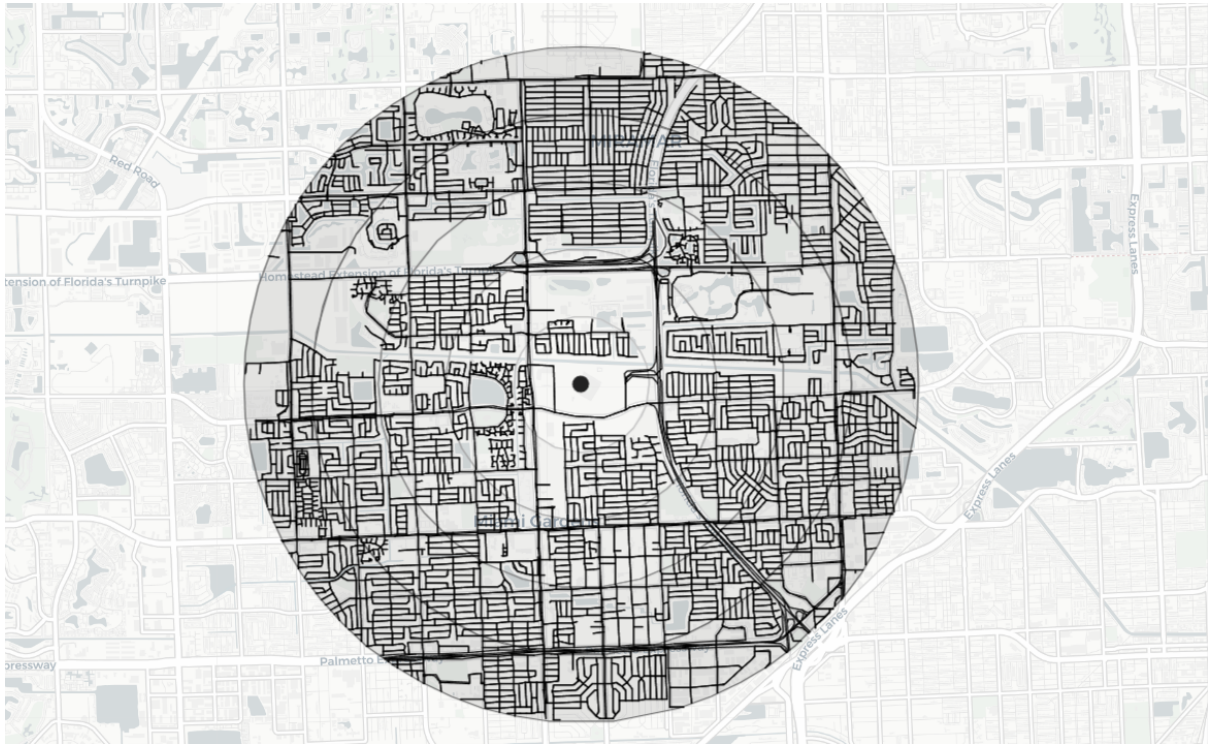


Figure A.3

0–5 km Radius Map for the EverBank Stadium (Jacksonville Jaguars)



Figure A.4

0-5 km Radius Map for the Kaseya Center (Miami Heat)

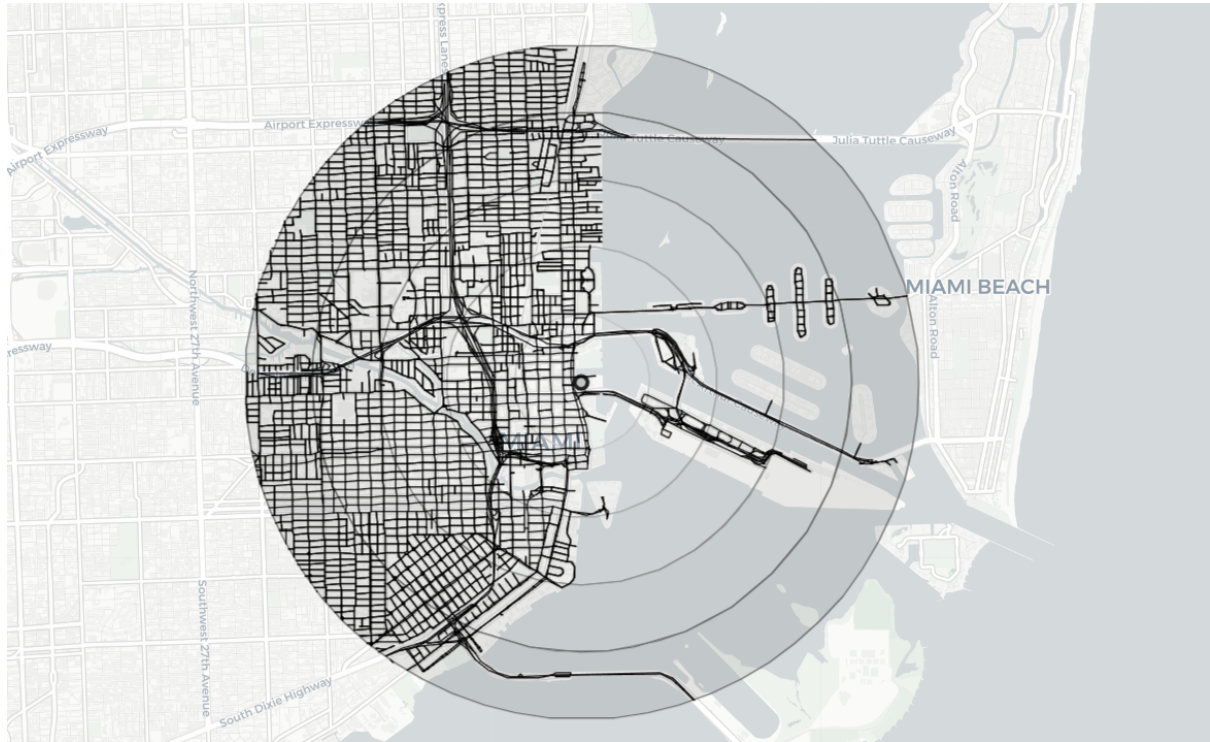


Figure A.5

0-5 km Radius Map for the Amway Center (Orlando Magic)

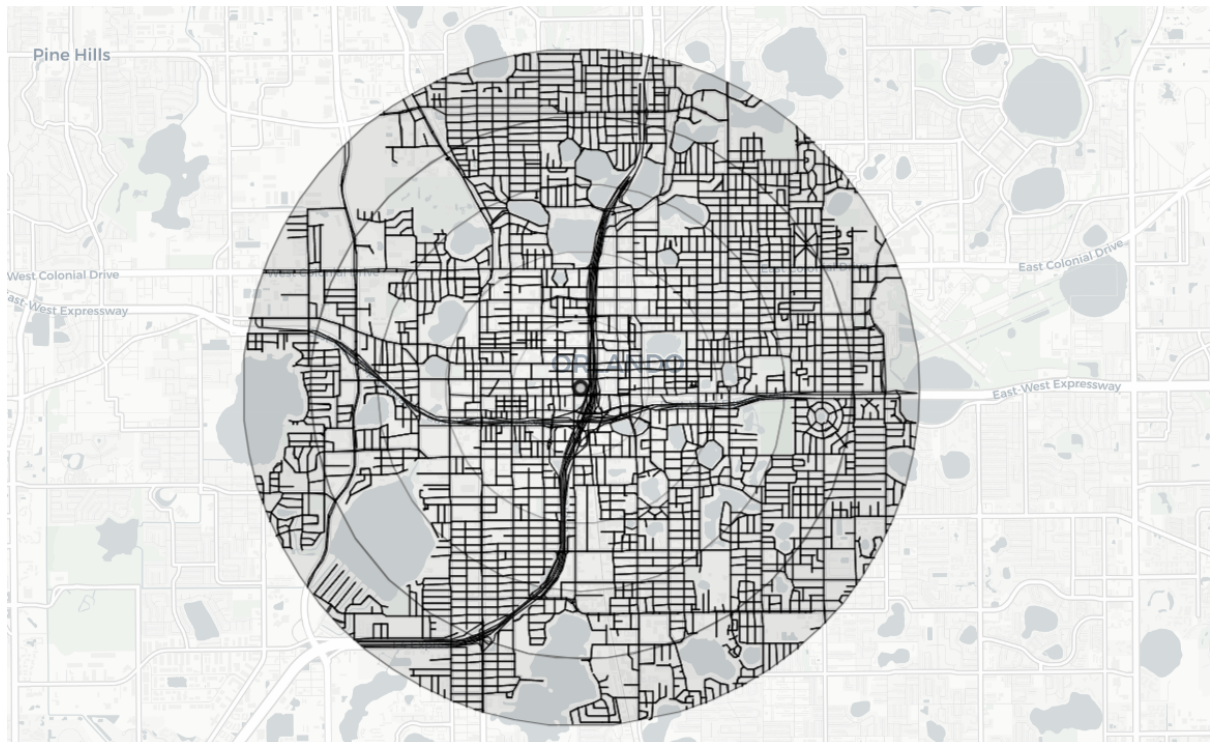
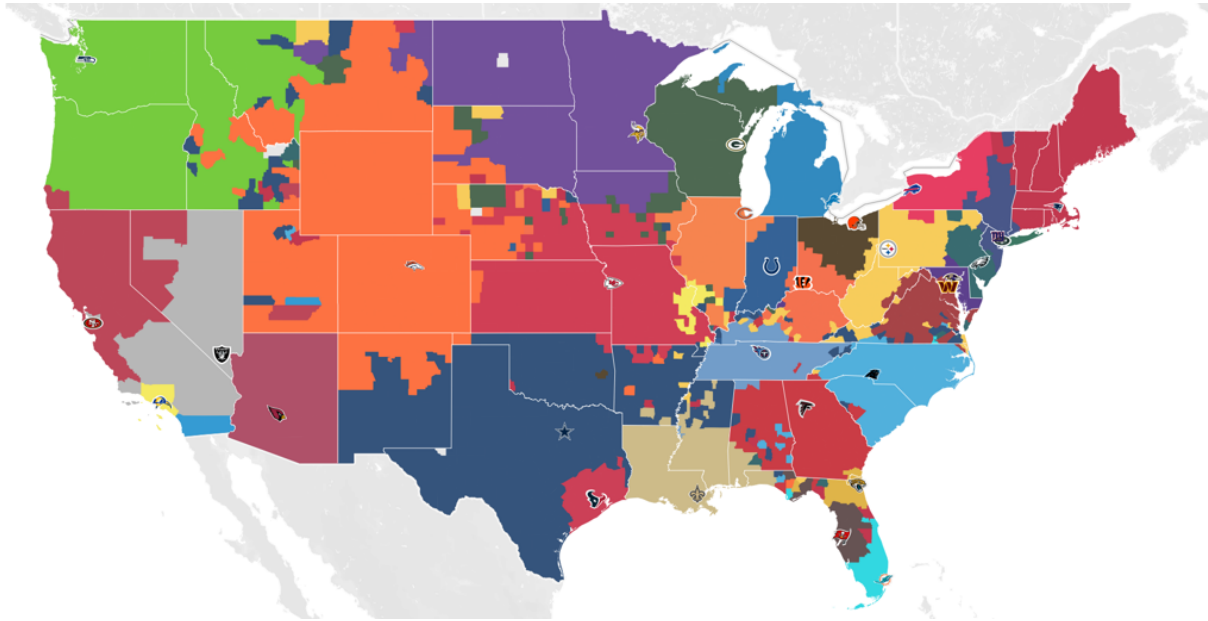
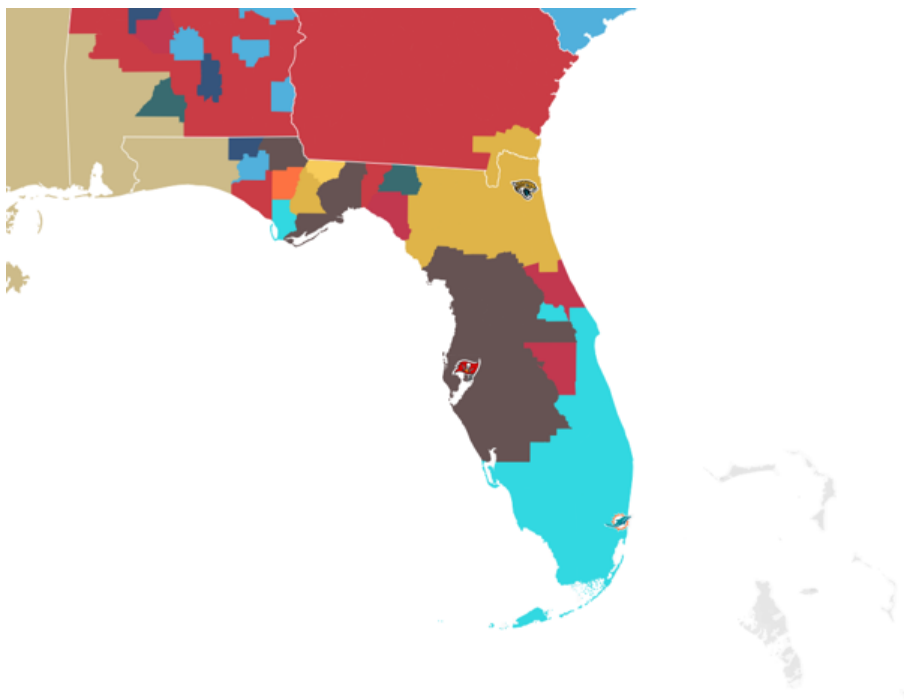


Figure A.6
Most-followed NFL teams per U.S. county



Notes: Source: Sorenson (2022).

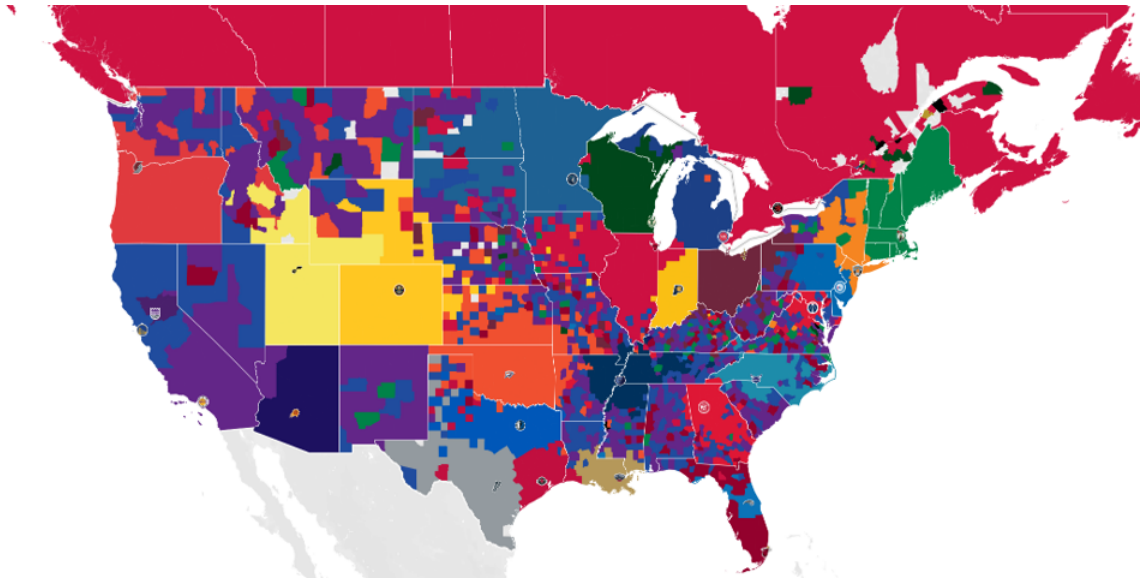
Figure A.7
Most-followed NFL teams by county in Florida



Notes: Source: Sorenson (2022). Brown: Tampa Bay Buccaneers; turquoise: Miami Dolphins; beige: Jacksonville Jaguars.

Figure A.8

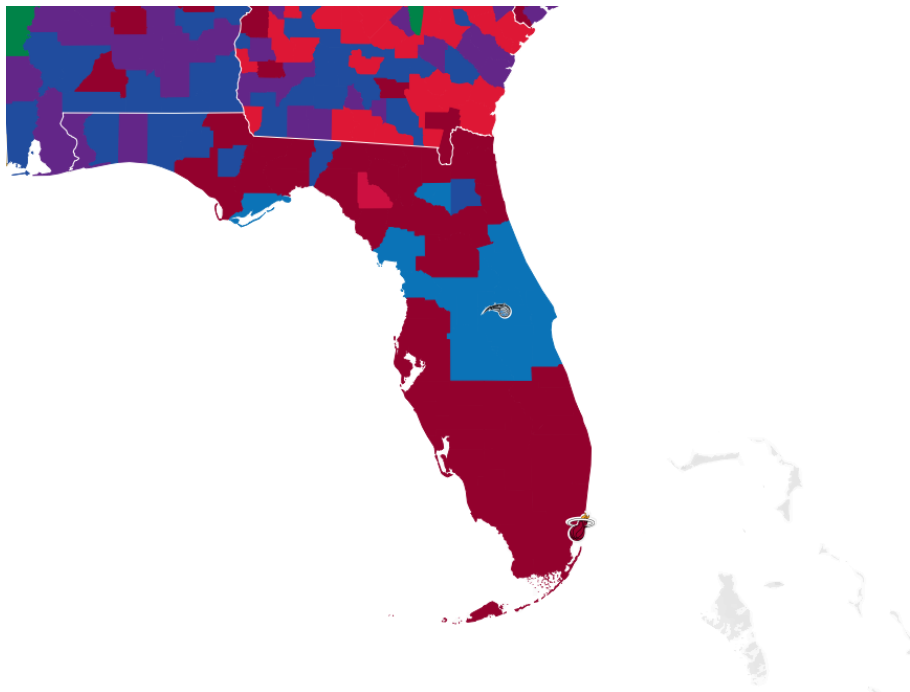
Most-followed NBA teams per U.S. county and Canadian census division



Notes: Source: Sorenson (2024).

Figure A.9

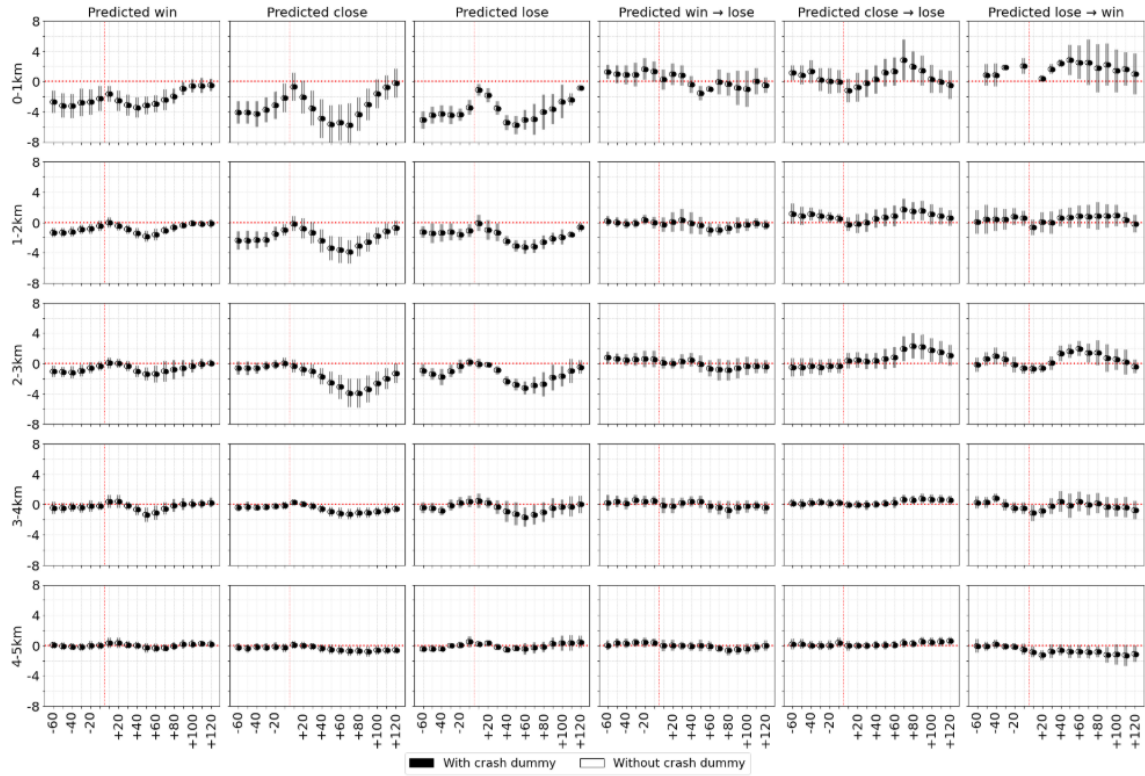
Most-followed NBA teams by county in Florida



Notes: Source: Sorenson (2024). Dark red: Miami Heat; light blue: Orlando Magic.

Figure A.10

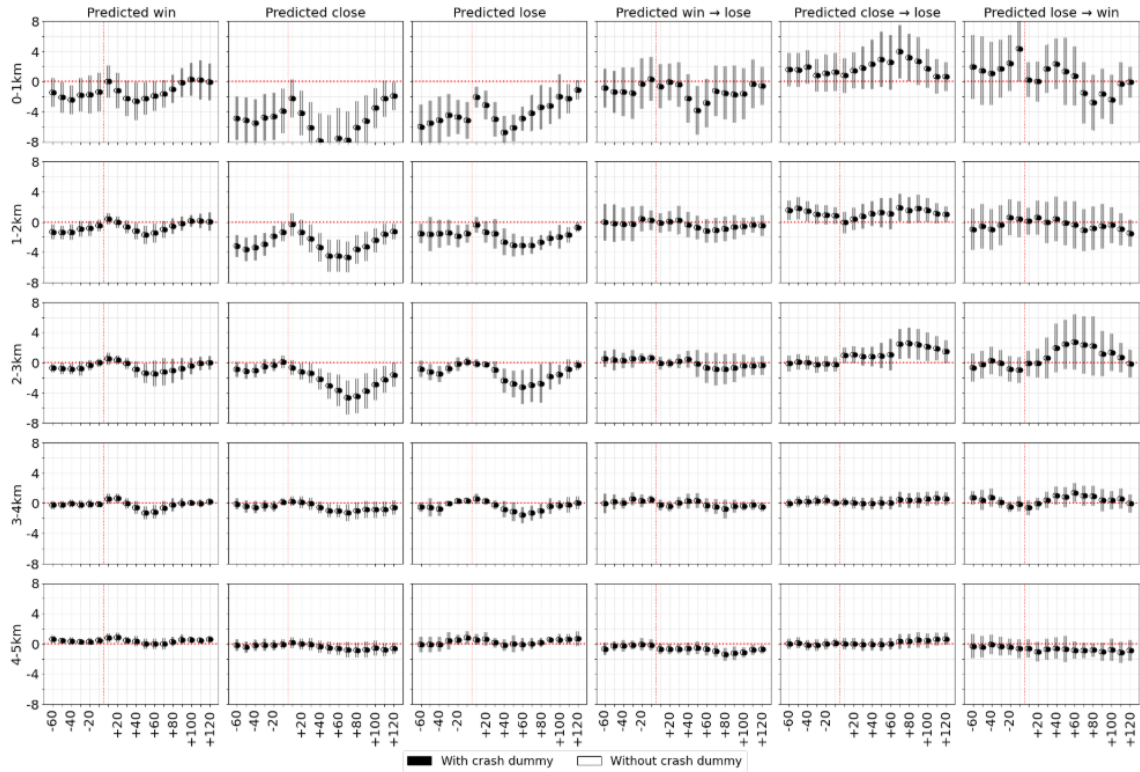
Effects of NFL game outcomes on vehicle speed near stadiums: two-way clustered standard errors



Notes: Predicted win indicates a point spread of -4 or less (negative spreads indicate the number of points a team is expected to win by); predicted close indicates a point spread between -4 and $+4$ exclusive; and predicted loss indicates a spread of $+4$ or more. This figure replicates the main specification using two-way clustered standard errors, clustering simultaneously at the TMC-code (entity) level and the season-week (time) level, following Cameron et al. (2011). Fixed effects follow the baseline specification: week-of-season time fixed effects and season dummies. The sample is limited to Sundays during the regular-season home games for Florida's three NFL teams—the Miami Dolphins, Tampa Bay Buccaneers, and Jacksonville Jaguars—across the 2015–2019 seasons. Due to missing traffic data, the 2018 and 2019 Miami Dolphins seasons are excluded, resulting in a total of 84 Sunday home games with start times between 1:00 PM and 4:25 PM Eastern Time. Average vehicle speed represents observed speed across road links within 5 km of each stadium, broken up into 1-km distance bands, measured in 10-minute intervals spanning 60 minutes before to 120 minutes after each game.

Figure A.11

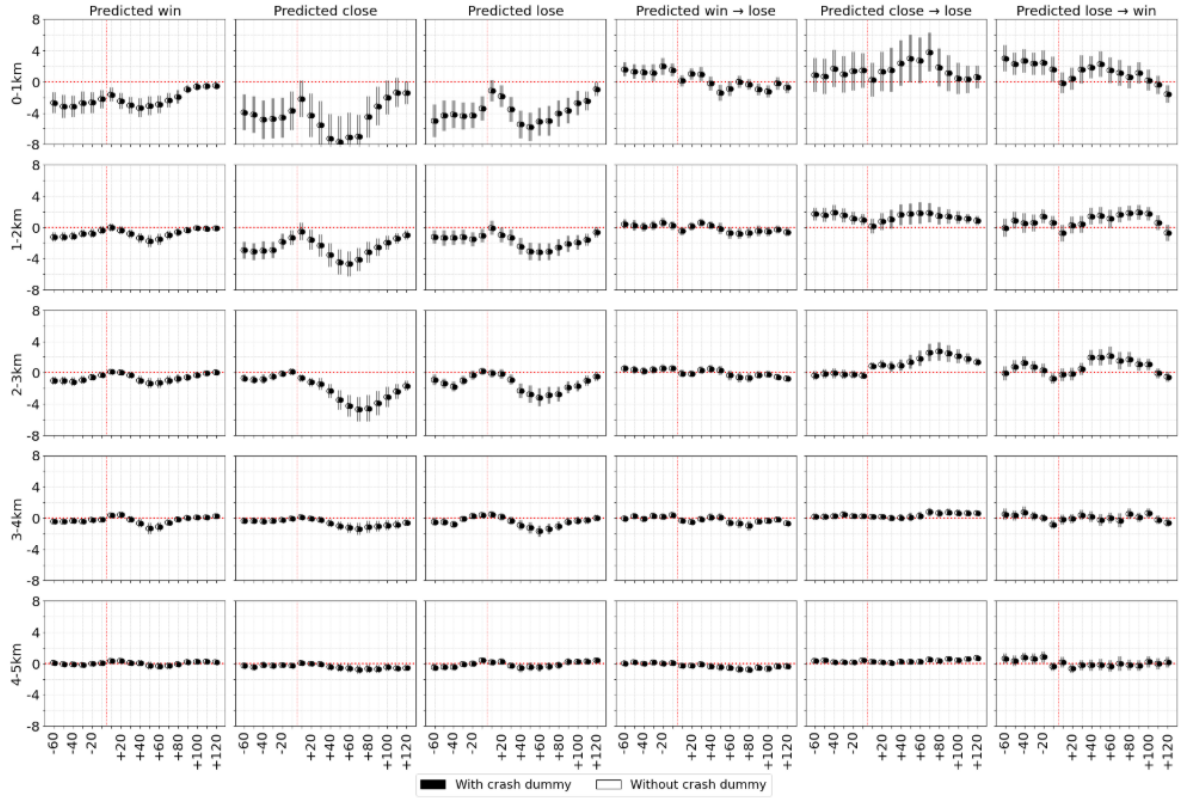
Effects of NFL game outcomes on vehicle speed near stadiums: two-way clustered standard errors with season-week fixed effects



Notes: Predicted win indicates a point spread of -4 or less (negative spreads indicate the number of points a team is expected to win by); predicted close indicates a point spread between -4 and $+4$ exclusive; and predicted loss indicates a spread of $+4$ or more. This figure replicates the main specification using two-way clustered standard errors, clustering simultaneously at the TMC-code (entity) level and the season-week (time) level, following Cameron et al. (2011). In contrast to Figure A.10, fixed effects use a more demanding season-week specification comprising 84 unique time periods, with season dummies absorbed by the fixed effects. The sample is limited to Sundays during the regular-season home games for Florida's three NFL teams—the Miami Dolphins, Tampa Bay Buccaneers, and Jacksonville Jaguars—across the 2015–2019 seasons. Due to missing traffic data, the 2018 and 2019 Miami Dolphins seasons are excluded, resulting in a total of 84 Sunday home games with start times between 1:00 PM and 4:25 PM Eastern Time. Average vehicle speed represents observed speed across road links within 5 km of each stadium, broken up into 1-km distance bands, measured in 10-minute intervals spanning 60 minutes before to 120 minutes after each game.

Figure A.12

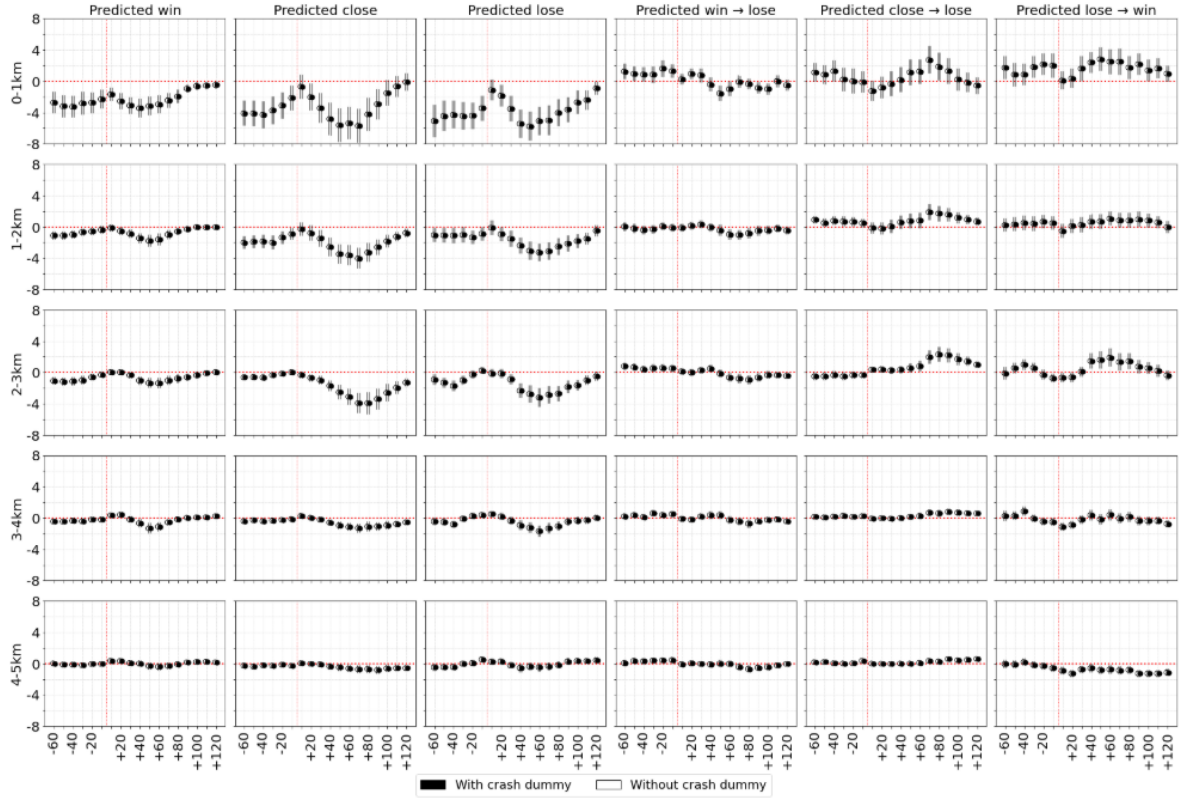
Effects of NFL game outcomes on vehicle speed near stadiums: 1:00 PM-games sample



Notes: Predicted win indicates a point spread of -4 or less (negative spreads indicate the number of points a team is expected to win by); predicted close indicates a point spread between -4 and $+4$ exclusive; and predicted loss indicates a spread of $+4$ or more. The sample is restricted to 1:00 PM kickoff games only, and is otherwise limited to Sundays during the regular-season home games for Florida's three NFL teams—the Miami Dolphins, Tampa Bay Buccaneers, and Jacksonville Jaguars—across the 2015–2019 seasons. Due to missing traffic data, the 2018 and 2019 Miami Dolphins seasons are excluded, resulting in a total of 68 Sunday home games with a 1:00 PM start time. Regressions include TMC-code fixed effects, as well as week-of-season time fixed effects and season dummies to control for temporal variation. Standard errors are clustered at the TMC-code level. Average vehicle speed represents observed speed across road links within 5 km of each stadium, broken up into 1-km distance bands, measured in 10-minute intervals spanning 60 minutes before to 120 minutes after each game.

Figure A.13

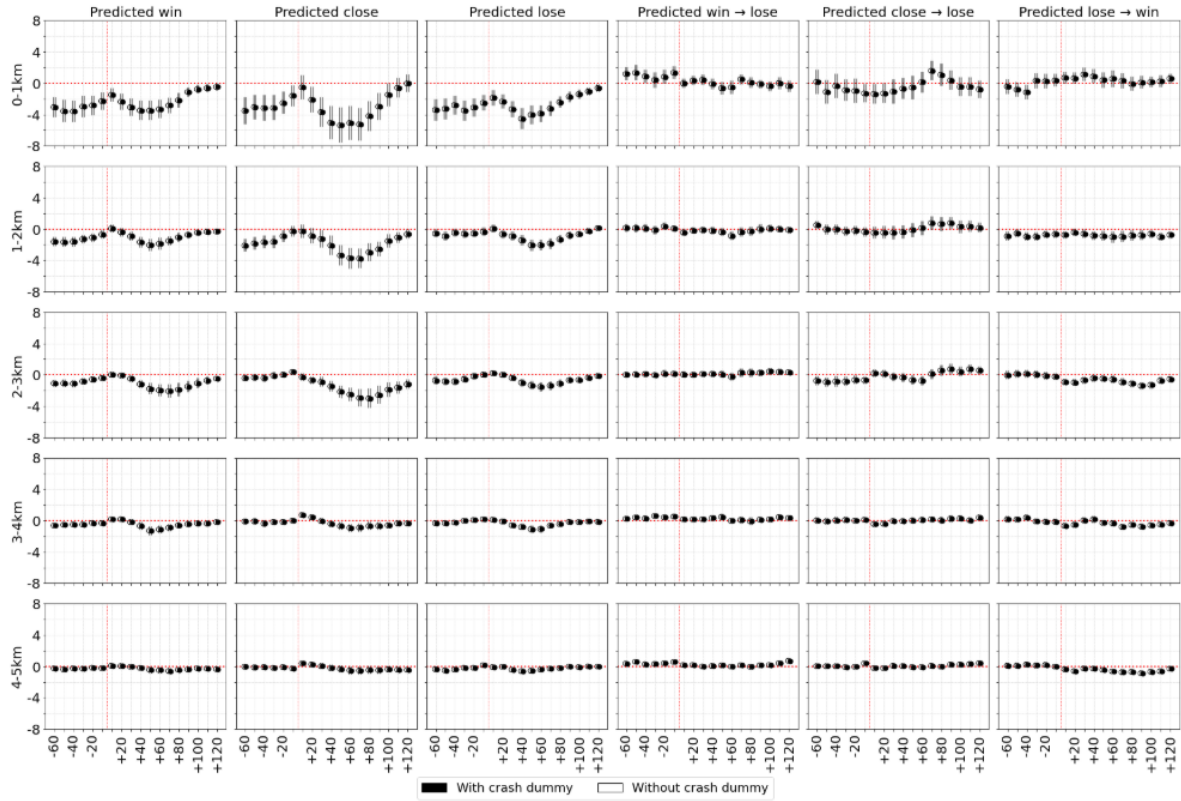
Effects of NFL game outcomes on vehicle speed near stadiums: excluding Miami Dolphins games



Notes: Predicted win indicates a point spread of -4 or less (negative spreads indicate the number of points a team is expected to win by); predicted close indicates a point spread between -4 and $+4$ exclusive; and predicted loss indicates a spread of $+4$ or more. The sample is limited to Sundays during the regular-season home games for Florida's three NFL teams across the 2015–2019 seasons, excluding all Miami Dolphins games due to missing traffic data in the Miami area. This results in 65 Sunday home games played by the Tampa Bay Buccaneers and Jacksonville Jaguars, with start times between 1:00 PM and 4:25 PM Eastern Time. Regressions include TMC-code fixed effects, as well as week-of-season time fixed effects and season dummies to control for temporal variation. Standard errors are clustered at the TMC-code level. Average vehicle speed represents observed speed across road links within 5 km of each stadium, broken up into 1-km distance bands, measured in 10-minute intervals spanning 60 minutes before to 120 minutes after each game.

Figure A.14

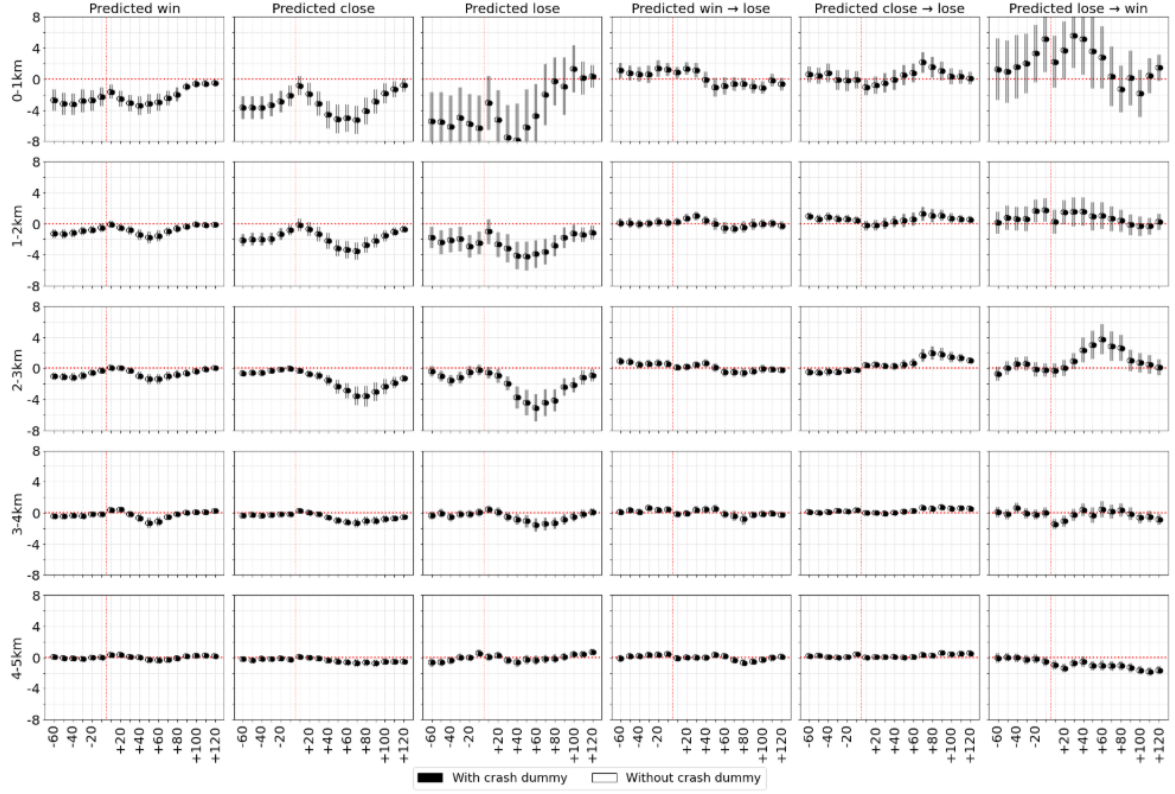
Effects of NFL game outcomes on vehicle speed near stadiums: ± 3 spread threshold



Notes: Predicted win indicates a point spread of -3 or less (negative spreads indicate the number of points a team is expected to win by); predicted close indicates a point spread between -3 and $+3$ exclusive; and predicted loss indicates a spread of $+3$ or more. This robustness check uses a narrower spread threshold of ± 3 points relative to the baseline specification of ± 4 . The sample is limited to Sundays during the regular-season home games for Florida's three NFL teams—the Miami Dolphins, Tampa Bay Buccaneers, and Jacksonville Jaguars—across the 2015–2019 seasons. Due to missing traffic data, the 2018 and 2019 Miami Dolphins seasons are excluded, resulting in a total of 84 Sunday home games with start times between 1:00 PM and 4:25 PM Eastern Time. Regressions include TMC-code fixed effects, as well as week-of-season time fixed effects and season dummies to control for temporal variation. Standard errors are clustered at the TMC-code level. Average vehicle speed represents observed speed across road links within 5 km of each stadium, broken up into 1-km distance bands, measured in 10-minute intervals spanning 60 minutes before to 120 minutes after each game.

Figure A.15

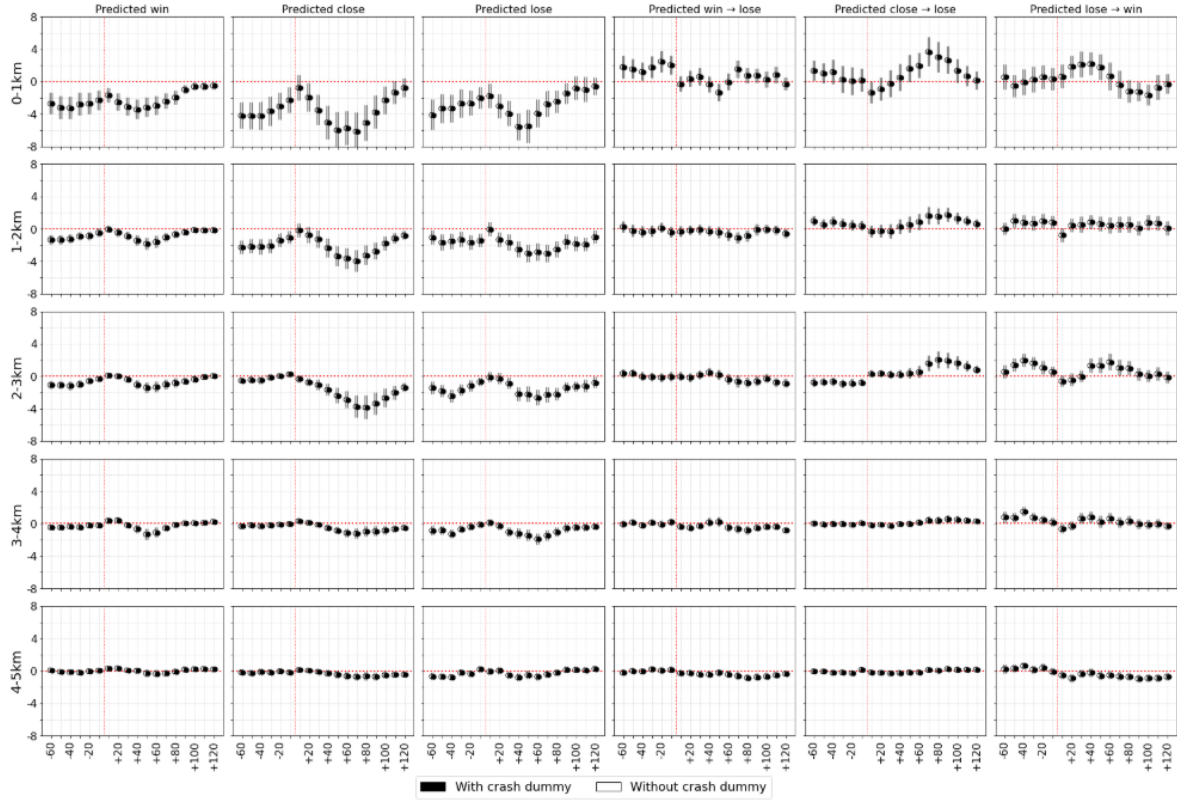
Effects of NFL game outcomes on vehicle speed near stadiums: ± 5 spread threshold



Notes: Predicted win indicates a point spread of -5 or less (negative spreads indicate the number of points a team is expected to win by); predicted close indicates a point spread between -5 and $+5$ exclusive; and predicted loss indicates a spread of $+5$ or more. This robustness check uses a wider spread threshold of ± 5 points relative to the baseline specification of ± 4 . The sample is limited to Sundays during the regular-season home games for Florida's three NFL teams—the Miami Dolphins, Tampa Bay Buccaneers, and Jacksonville Jaguars—across the 2015–2019 seasons. Due to missing traffic data, the 2018 and 2019 Miami Dolphins seasons are excluded, resulting in a total of 84 Sunday home games with start times between 1:00 PM and 4:25 PM Eastern Time. Regressions include TMC-code fixed effects, as well as week-of-season time fixed effects and season dummies to control for temporal variation. Standard errors are clustered at the TMC-code level. Average vehicle speed represents observed speed across road links within 5 km of each stadium, broken up into 1-km distance bands, measured in 10-minute intervals spanning 60 minutes before to 120 minutes after each game.

Figure A.16

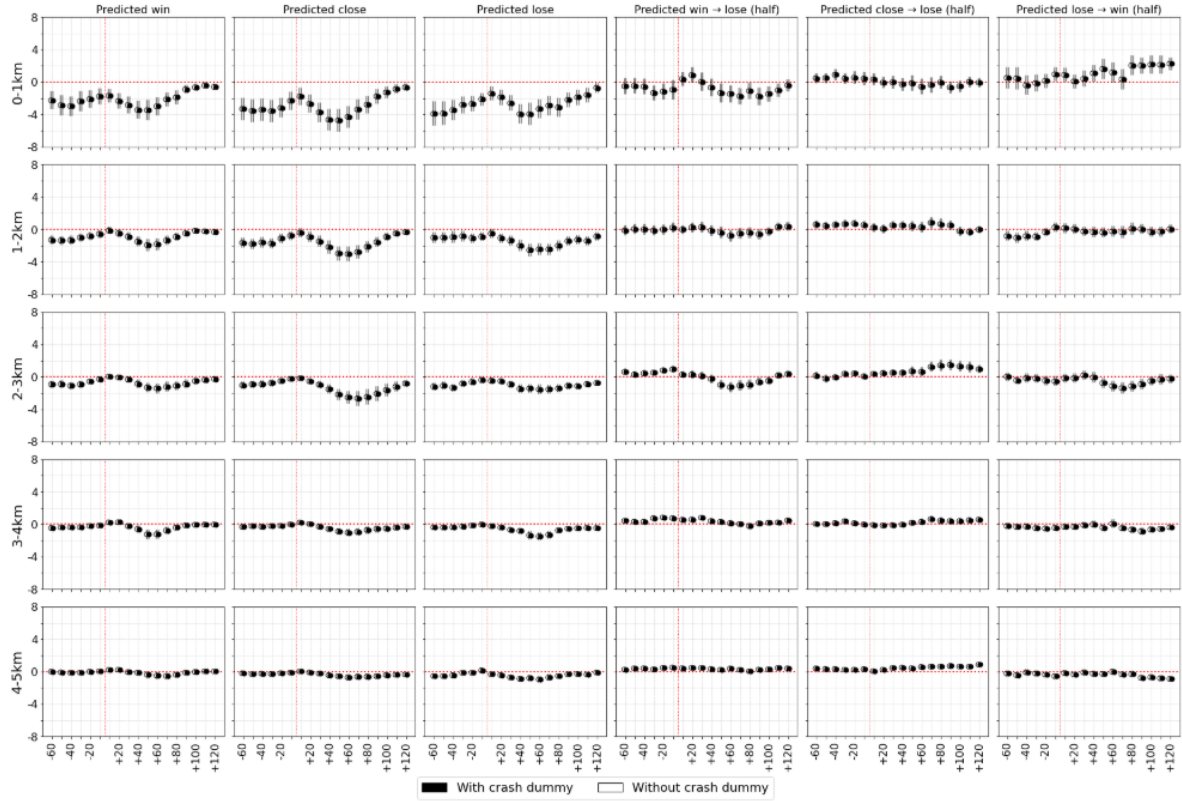
Effects of NFL game outcomes on vehicle speed near stadiums: including halftime controls



Notes: Predicted win indicates a point spread of -4 or less (negative spreads indicate the number of points a team is expected to win by); predicted close indicates a point spread between -4 and $+4$ exclusive; and predicted loss indicates a spread of $+4$ or more. In contrast to the baseline specification, this robustness check additionally controls for halftime status by including indicators for whether the home team was predicted to win, predicted close, or predicted to lose based on the halftime point differential, following Card and Dahl (2011). The sample is limited to Sundays during the regular-season home games for Florida's three NFL teams—the Miami Dolphins, Tampa Bay Buccaneers, and Jacksonville Jaguars—across the 2015–2019 seasons. Due to missing traffic data, the 2018 and 2019 Miami Dolphins seasons are excluded, resulting in a total of 84 Sunday home games with start times between 1:00 PM and 4:25 PM Eastern Time. Regressions include TMC-code fixed effects, as well as week-of-season time fixed effects and season dummies to control for temporal variation. Standard errors are clustered at the TMC-code level. Average vehicle speed represents observed speed across road links within 5 km of each stadium, broken up into 1-km distance bands, measured in 10-minute intervals spanning 60 minutes before to 120 minutes after each game.

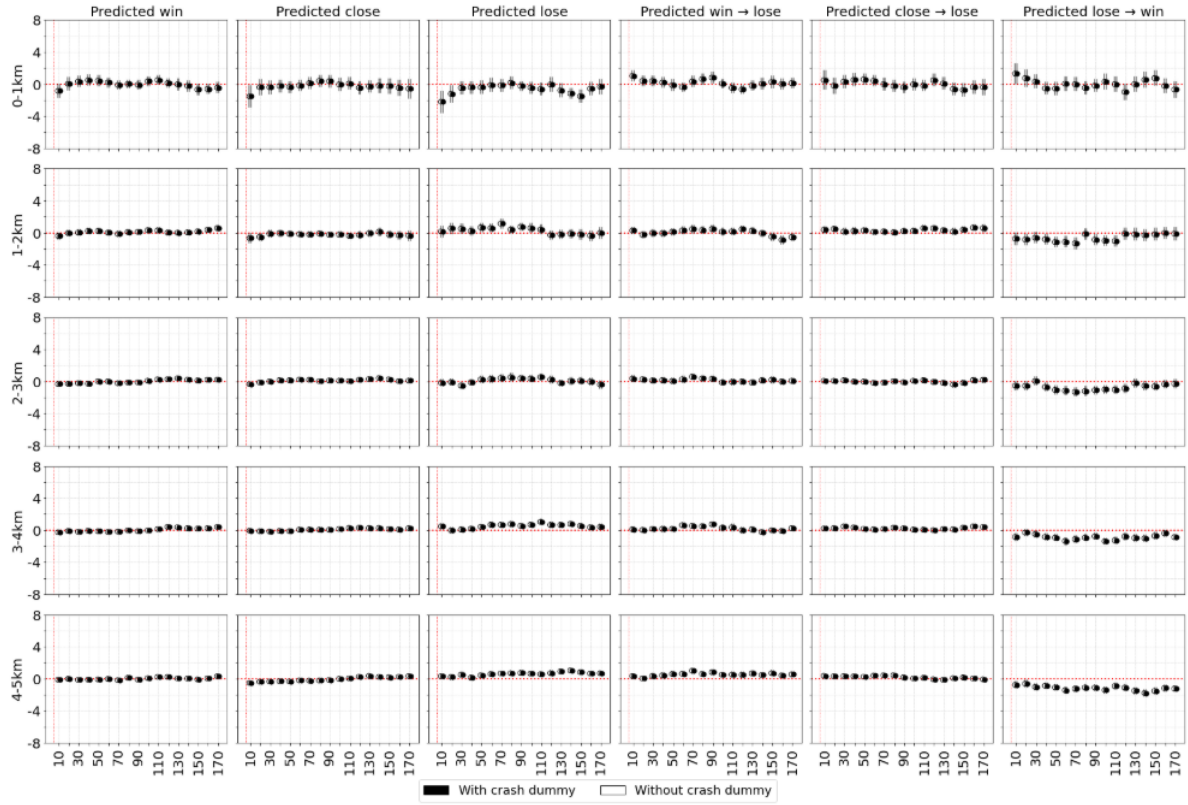
Figure A.17

Effects of NFL game outcomes on vehicle speed near stadiums: halftime predictions



Notes: This figure shows how post-game traffic speed varies based on the halftime prediction rather than the pregame spread expectation, following Card and Dahl (2011). Pregame predicted win, predicted close, and predicted loss are defined as in the baseline specification using a ± 4 point spread threshold. Halftime predicted win, halftime predicted close, and halftime predicted loss are defined based on the observed point differential at halftime, applying the same ± 4 threshold, where a negative halftime spread indicates the number of points the home team is actually leading by at halftime. The sample is limited to Sundays during the regular-season home games for Florida's three NFL teams—the Miami Dolphins, Tampa Bay Buccaneers, and Jacksonville Jaguars—across the 2015–2019 seasons. Due to missing traffic data, the 2018 and 2019 Miami Dolphins seasons are excluded, resulting in a total of 84 Sunday home games with start times between 1:00 PM and 4:25 PM Eastern Time. Regressions include TMC-code fixed effects, as well as week-of-season time fixed effects and season dummies to control for temporal variation. Standard errors are clustered at the TMC-code level. Average vehicle speed represents observed speed across road links within 5 km of each stadium, broken up into 1-km distance bands, measured in 10-minute intervals spanning 60 minutes before to 120 minutes after each game.

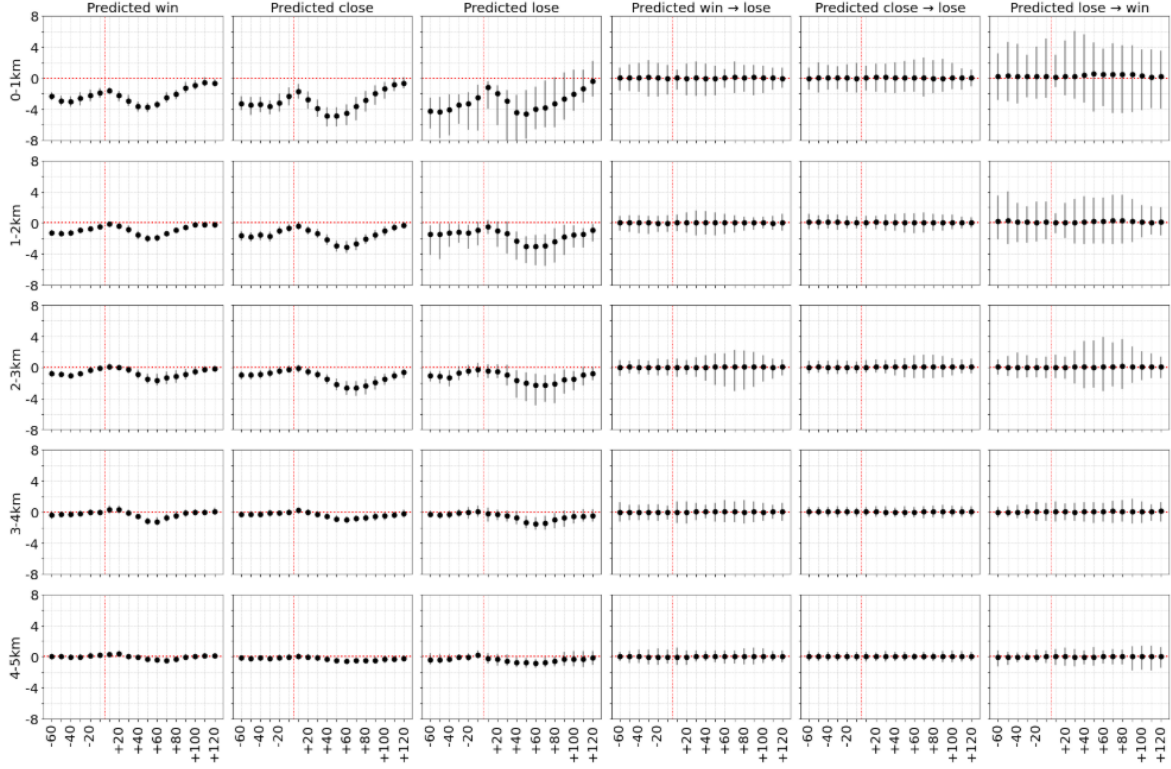
Figure A.18
Traffic speed effects *during* active NFL games



Notes: This figure shows how traffic speed varies during active NFL gameplay, comparing 10-minute intervals within games to matched non-gameday bins at the same time of day. Predicted win indicates a point spread of -4 or less (negative spreads indicate the number of points a team is expected to win by); predicted close indicates a point spread between -4 and $+4$ exclusive; and predicted loss indicates a spread of $+4$ or more. The sample is limited to Sundays during the regular-season home games for Florida's three NFL teams—the Miami Dolphins, Tampa Bay Buccaneers, and Jacksonville Jaguars—across the 2015–2019 seasons. Due to missing traffic data, the 2018 and 2019 Miami Dolphins seasons are excluded, resulting in a total of 84 Sunday home games with start times between 1:00 PM and 4:25 PM Eastern Time. Regressions include TMC-code fixed effects, as well as week-of-season time fixed effects and season dummies to control for temporal variation. Standard errors are clustered at the TMC-code level. Average vehicle speed represents observed speed across road links within 5 km of each stadium, broken up into 1-km distance bands, measured in 10-minute intervals spanning the first 170 minutes of gameplay—corresponding to the duration of the shortest game in the sample, ensuring all time intervals reflect strictly in-game periods and exclude any post-game traffic effects.

Figure A.19

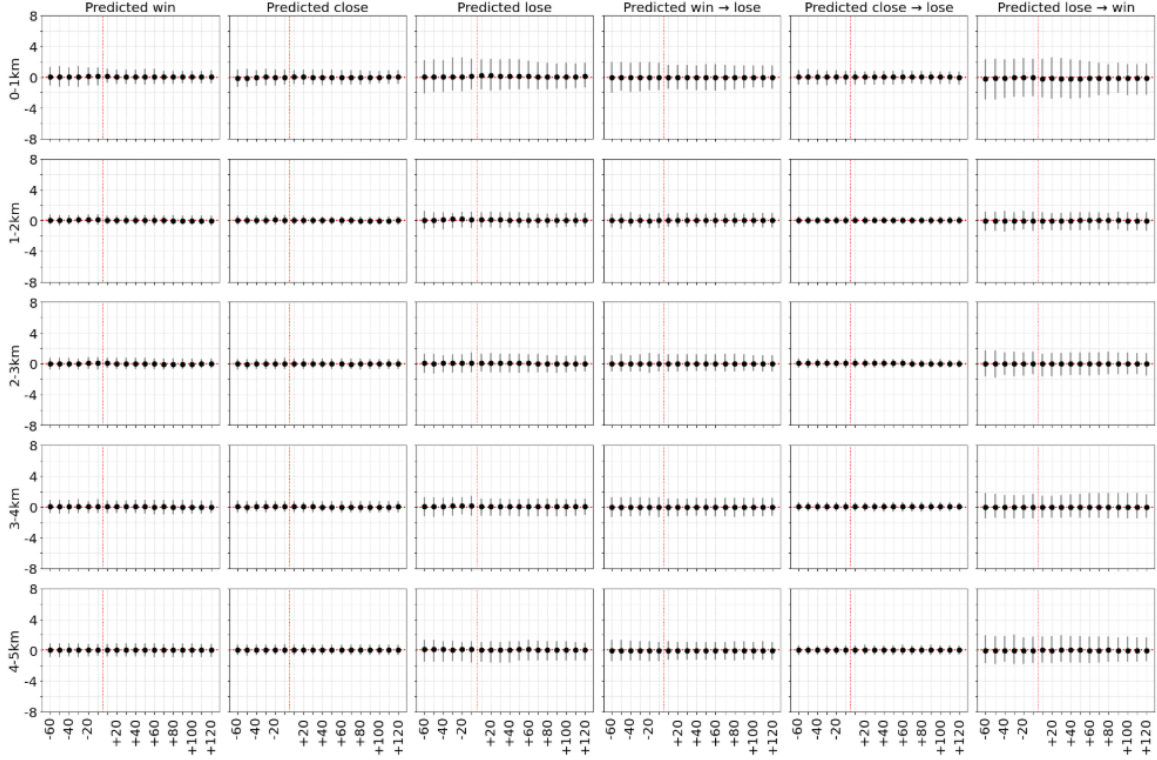
Randomization placebo: average coefficients across 150 draws with randomly reassigned game outcomes



Notes: This figure presents the results of a randomization placebo test. The full regression model is run 150 times, each time randomly reassigning win/loss outcome labels within each spread category — keeping spread category assignments fixed but randomizing the actual outcome within each category. All other aspects of the estimation remain identical to the baseline specification. Each subplot shows the average placebo coefficient across the 150 draws for each time window and distance band, with vertical lines representing the 2.5 and 97.5 percentile range of the 150 placebo coefficients, reflecting what would be expected by chance under random outcome assignment. Predicted win indicates a point spread of -4 or less; predicted close indicates a point spread between -4 and $+4$ exclusive; and predicted loss indicates a spread of $+4$ or more. The sample is limited to Sundays during the regular-season home games for Florida's three NFL teams—the Miami Dolphins, Tampa Bay Buccaneers, and Jacksonville Jaguars—across the 2015–2019 seasons. Due to missing traffic data, the 2018 and 2019 Miami Dolphins seasons are excluded, resulting in a total of 84 Sunday home games with start times between 1:00 PM and 4:25 PM Eastern Time. Regressions include TMC-code fixed effects, as well as week-of-season time fixed effects and season dummies to control for temporal variation. Standard errors are clustered at the TMC-code level. Average vehicle speed represents observed speed across road links within 5 km of each stadium, broken up into 1-km distance bands, measured in 10-minute intervals spanning 60 minutes before to 120 minutes after each game.

Figure A.20

Pseudo game-day placebo: average coefficients across 150 draws with real game labels assigned to non-game Sundays



Notes: This figure presents the results of a pseudo game-day placebo test. The sample is restricted to non-game Sundays only. Each of the 84 real games is randomly assigned to a non-game Sunday from the same team's stadium area, without replacement, and the assigned date inherits the real game's spread category and outcome label. The existing matched time-window indicators, which flag observations occurring at the same time of day as a real game's pre- and post-game windows, are used as event-time dummies for the pseudo game days. The remaining non-game Sundays serve as the control group. This procedure is repeated 150 times, each time with a new random assignment of real games to non-game Sundays. The figure presents the average coefficient across the 150 draws for each time window and distance band, along with the 2.5th and 97.5th percentile range of the placebo coefficients. The same regression specification as the main model is estimated on this pseudo game-day dataset using only non-game Sunday speed data throughout. Predicted win indicates a point spread of -4 or less; predicted close indicates a point spread between -4 and $+4$ exclusive; and predicted loss indicates a spread of $+4$ or more. The sample is limited to Sundays during the regular-season home games for Florida's three NFL teams—the Miami Dolphins, Tampa Bay Buccaneers, and Jacksonville Jaguars—across the 2015–2019 seasons. Due to missing traffic data, the 2018 and 2019 Miami Dolphins seasons are excluded, resulting in a total of 84 Sunday home games with start times between 1:00 PM and 4:25 PM Eastern Time. Regressions include TMC-code fixed effects, as well as week-of-season time fixed effects and season dummies to control for temporal variation. Standard errors are clustered at the TMC-code level. Average vehicle speed represents observed speed across road links within 5 km of each stadium, broken up into 1-km distance bands, measured in 10-minute intervals spanning 60 minutes before to 120 minutes after each game.

Table A.1

Poisson fixed-effects regressions of NFL crash counts by predicted outcome and actual result

Parameter	Number of crashes	Estimate	<i>p</i> -value	95% CI Low	95% CI High
Pregame.60					
Gameday	17	0.933	0.008	0.249	1.616
Predicted win	4	0.417	0.545	-0.934	1.768
Predicted close	9	0.169	0.826	-1.341	1.679
Predicted lose	4	2.337	0.010	0.551	4.123
Predicted win → lose	1	0.528	0.680	-1.978	3.034
Predicted close → lose	7	0.920	0.281	-0.752	2.593
Predicted lose → win	1	-0.810	0.581	-3.689	2.069
Postgame.60					
Gameday	40	1.618	0.000	1.159	2.077
Predicted win	13	1.480	0.001	0.613	2.348
Predicted close	25	1.745	0.000	0.884	2.606
Predicted lose	2	0.927	0.458	-1.522	3.376
Predicted win → lose	8	0.951	0.138	-0.305	2.207
Predicted close → lose	13	-0.248	0.565	-1.091	0.596
Predicted lose → win	1	-0.353	0.831	-3.590	2.883
Postgame.120					
Gameday	21	1.232	0.000	0.662	1.803
Predicted win	5	1.452	0.040	0.066	2.838
Predicted close	13	0.467	0.458	-0.766	1.700
Predicted lose	3	0.879	0.420	-1.256	3.015
Predicted win → lose	1	-0.663	0.590	-3.075	1.749
Predicted close → lose	10	0.967	0.173	-0.424	2.358
Predicted lose → win	2	1.003	0.479	-1.776	3.783

Notes: Poisson fixed-effects regressions of crash counts on predicted outcome categories and interaction terms, estimated on the aggregated 0–5 km sample. Crash counts reported in this table reflect the total number of unique crash events aggregated across all observation windows in the 2015–2019 sample (i.e., all gamedays and all corresponding matched non-gameday control periods), rather than averages per gameday or per non-gameday. Predicted win indicates a point spread of –4 or less (negative spreads indicate the number of points a team is expected to win by); predicted close indicates a point spread between –4 and +4 exclusive; and predicted loss indicates a spread of +4 or more. The sample is limited to Sundays during the regular-season home games for Florida’s three NFL teams—the Miami Dolphins, Tampa Bay Buccaneers, and Jacksonville Jaguars—across the 2015–2019 seasons. Due to missing traffic data, the 2018 and 2019 Miami Dolphins seasons are excluded, resulting in a total of 84 Sunday home games with start times between 1:00 PM and 4:25 PM Eastern Time. Poisson regressions include TMC-code fixed effects, as well as week-of-season time fixed effects and season dummies to control for temporal variation. Standard errors are clustered at the TMC-code level. Coefficients are reported as log changes; positive values indicate higher crash frequencies relative to matched non-gameday periods (or alternative outcomes).

Table A.2

Poisson fixed-effects regressions of NBA crash counts by predicted outcome and actual result

Parameter	Number of crashes	Estimate	p-value	95% CI Low	95% CI High
Pregame.60					
Gameday	89	0.003	0.978	-0.240	0.247
Predicted win	9	-0.309	0.406	-1.039	0.421
Predicted close	60	0.217	0.189	-0.107	0.540
Predicted lose	20	-0.116	0.727	-0.764	0.533
Predicted win → lose	2	-0.491	0.648	-2.601	1.618
Predicted close → lose	26	-0.308	0.148	-0.726	0.109
Predicted lose → win	9	0.439	0.383	-0.548	1.426
Postgame.60					
Gameday	40	0.233	0.228	-0.145	0.611
Predicted win	5	0.185	0.693	-0.733	1.103
Predicted close	31	0.340	0.280	-0.277	0.958
Predicted lose	4	-1.641	0.103	-3.612	0.330
Predicted win → lose	0			No crash occurred	
Predicted close → lose	18	0.313	0.408	-0.427	1.052
Predicted lose → win	3	1.850	0.141	-0.613	4.314
Postgame.120					
Gameday	29	-0.095	0.703	-0.584	0.394
Predicted win	7	0.072	0.876	-0.830	0.974
Predicted close	17	-0.113	0.765	-0.852	0.627
Predicted lose	5	-0.506	0.369	-1.609	0.598
Predicted win → lose	2	0.577	0.503	-1.112	2.266
Predicted close → lose	9	0.040	0.931	-0.858	0.937
Predicted lose → win	2	0.261	0.778	-1.555	2.076

Notes: Poisson fixed-effects regressions of crash counts on predicted outcome categories and interaction terms, estimated on the aggregated 0–5 km sample. Crash counts reported in this table reflect the total number of unique crash events aggregated across all observation windows in the 2015/16–2018/19 sample (i.e., all gamedays and all corresponding matched non-gameday control periods), rather than averages per gameday or per non-gameday. Predicted win indicates a point spread of –6.75 or less (negative spreads indicate the number of points a team is expected to win by); predicted close indicates a point spread between –6.75 and +4.75 exclusive; and predicted loss indicates a spread of +4.75 or more. The sample is limited to regular-season NBA games between the 2015/16 and 2018/19 seasons, encompassing four total seasons. The analysis includes home games played by Florida’s two NBA teams—the Miami Heat and the Orlando Magic—with scheduled tip-off times of 6:00 PM or later. Regressions include TMC-code fixed effects, as well as month time fixed effects, season dummies, and day-of-week dummies to control for temporal variation. Standard errors are clustered at the TMC-code level. Coefficients are reported as log changes; positive values indicate higher crash frequencies relative to matched non-gameday periods (or alternative outcomes).

Table A.3
NFL Regression results by time and distance

Time	Distance	Variable	With Crash	With Crash SE	No Crash	No Crash SE
Pregame 60						
0–1 km		Predicted Win	-2.7250	0.6613	-2.7250	0.6613
		Predicted Close	-4.1019	0.7760	-4.1024	0.7760
		Predicted Lose	-5.0876	1.0321	-5.0875	1.0321
		Predicted Win Lose	1.2369	0.4517	1.2368	0.4517
		Predicted Close Lose	1.1157	0.5589	1.1162	0.5590
		Predicted Lose Win	1.7266	0.7203	1.7263	0.7203
1–2 km		Predicted Win	-1.3441	0.2520	-1.3433	0.2520
		Predicted Close	-2.3719	0.3877	-2.3717	0.3876
		Predicted Lose	-1.2818	0.4205	-1.2821	0.4205
		Predicted Win Lose	0.1844	0.2592	0.1836	0.2591
		Predicted Close Lose	1.1244	0.2451	1.1243	0.2451
		Predicted Lose Win	0.0632	0.4024	0.0633	0.4023
2–3 km		Predicted Win	-1.0735	0.2111	-1.0737	0.2111
		Predicted Close	-0.6255	0.1645	-0.6257	0.1645
		Predicted Lose	-0.9234	0.3147	-0.9234	0.3147
		Predicted Win Lose	0.7640	0.2033	0.7637	0.2033
		Predicted Close Lose	-0.5258	0.2126	-0.5256	0.2126
		Predicted Lose Win	-0.1515	0.3615	-0.1515	0.3615
3–4 km		Predicted Win	-0.4545	0.1269	-0.4577	0.1271
		Predicted Close	-0.4079	0.1444	-0.4084	0.1444
		Predicted Lose	-0.4434	0.2370	-0.4523	0.2372
		Predicted Win Lose	0.1988	0.1709	0.2017	0.1711
		Predicted Close Lose	0.1553	0.1317	0.1556	0.1316
		Predicted Lose Win	0.2492	0.2973	0.2579	0.2974
4–5 km		Predicted Win	0.0562	0.1019	0.0575	0.1020
		Predicted Close	-0.2443	0.1465	-0.2437	0.1466
		Predicted Lose	-0.4616	0.2088	-0.4617	0.2088
		Predicted Win Lose	0.0192	0.1683	0.0178	0.1683
		Predicted Close Lose	0.1691	0.0948	0.1677	0.0950
		Predicted Lose Win	-0.0760	0.2490	-0.0756	0.2490
Pregame 50						
0–1 km		Predicted Win	-3.2036	0.6859	-3.2038	0.6860
		Predicted Close	-4.1103	0.7880	-4.1102	0.7879
		Predicted Lose	-4.4435	0.9537	-4.4433	0.9536
		Predicted Win Lose	0.9502	0.4523	0.9507	0.4522
		Predicted Close Lose	0.8233	0.5826	0.8248	0.5824
		Predicted Lose Win	0.8314	0.7331	0.8315	0.7331
1–2 km		Predicted Win	-1.3276	0.2534	-1.3276	0.2534
		Predicted Close	-2.3614	0.3990	-2.3616	0.3990
		Predicted Lose	-1.4429	0.4695	-1.4431	0.4695
		Predicted Win Lose	0.0079	0.3005	0.0079	0.3005
		Predicted Close Lose	0.8460	0.2712	0.8456	0.2712
		Predicted Lose Win	0.4105	0.4189	0.4106	0.4189
2–3 km		Predicted Win	-1.1013	0.2231	-1.1013	0.2231
		Predicted Close	-0.6325	0.1764	-0.6325	0.1764
		Predicted Lose	-1.4084	0.3030	-1.4084	0.3030
		Predicted Win Lose	0.6033	0.2061	0.6033	0.2061
		Predicted Close Lose	-0.4852	0.2058	-0.4852	0.2058
		Predicted Lose Win	0.5816	0.3243	0.5816	0.3243
3–4 km		Predicted Win	-0.4705	0.1243	-0.4706	0.1244
		Predicted Close	-0.2807	0.1531	-0.2808	0.1531
		Predicted Lose	-0.5182	0.2244	-0.5181	0.2244
		Predicted Win Lose	0.3557	0.1547	0.3559	0.1547
		Predicted Close Lose	0.0603	0.1318	0.0604	0.1318
		Predicted Lose Win	0.2621	0.2444	0.2621	0.2444
4–5 km		Predicted Win	-0.1069	0.0964	-0.1069	0.0964
		Predicted Close	-0.3697	0.1441	-0.3698	0.1441
		Predicted Lose	-0.4229	0.1851	-0.4228	0.1851
		Predicted Win Lose	0.2990	0.1452	0.2991	0.1452
		Predicted Close Lose	0.1971	0.0930	0.1972	0.0930
		Predicted Lose Win	-0.1216	0.2227	-0.1215	0.2227
Pregame 40						
0–1 km		Predicted Win	-3.2598	0.6595	-3.2595	0.6595
		Predicted Close	-4.2974	0.8291	-4.2996	0.8292
		Predicted Lose	-4.2928	0.8703	-4.2939	0.8702
		Predicted Win Lose	0.8594	0.4414	0.8583	0.4415
		Predicted Close Lose	1.2984	0.6777	1.3014	0.6782
		Predicted Lose Win	0.8481	0.6812	0.8491	0.6812
1–2 km		Predicted Win	-1.2305	0.2390	-1.2300	0.2390

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Time	Distance	Variable	With Crash	With Crash SE	No Crash	No Crash SE
Pregame 30	2–3 km	Predicted Close	-2.3108	0.4211	-2.3106	0.4211
		Predicted Lose	-1.3840	0.4590	-1.3842	0.4590
		Predicted Win Lose	-0.1842	0.2707	-0.1847	0.2706
		Predicted Close Lose	1.1005	0.2785	1.1003	0.2785
		Predicted Lose Win	0.4233	0.4473	0.4234	0.4473
	3–4 km	Predicted Win	-1.1896	0.2347	-1.1896	0.2347
		Predicted Close	-0.6389	0.1990	-0.6389	0.1990
		Predicted Lose	-1.7880	0.3072	-1.7880	0.3072
		Predicted Win Lose	0.4473	0.2036	0.4473	0.2036
		Predicted Close Lose	-0.3812	0.2302	-0.3812	0.2302
	4–5 km	Predicted Lose Win	0.9723	0.3191	0.9723	0.3191
		Predicted Win	-0.3579	0.1218	-0.3579	0.1218
		Predicted Close	-0.4130	0.1575	-0.4130	0.1575
		Predicted Lose	-0.8191	0.2153	-0.8191	0.2153
		Predicted Win Lose	0.1211	0.1613	0.1211	0.1613
	0–1 km	Predicted Close Lose	0.1904	0.1377	0.1904	0.1377
		Predicted Lose Win	0.8437	0.2615	0.8437	0.2615
		Predicted Win	-0.1502	0.1019	-0.1493	0.1020
		Predicted Close	-0.1875	0.1516	-0.1872	0.1517
		Predicted Lose	-0.4296	0.1778	-0.4294	0.1778
	1–2 km	Predicted Win Lose	0.2872	0.1512	0.2876	0.1512
		Predicted Close Lose	0.0220	0.0979	0.0224	0.0980
		Predicted Lose Win	0.1676	0.2114	0.1677	0.2114
		Predicted Win	-2.8169	0.7007	-2.8170	0.7006
	2–3 km	Predicted Close	-3.7352	0.8495	-3.7355	0.8495
		Predicted Lose	-4.4295	0.8641	-4.4296	0.8640
		Predicted Win Lose	0.8551	0.5169	0.8553	0.5168
		Predicted Close Lose	0.2132	0.7095	0.2138	0.7094
		Predicted Lose Win	1.8236	0.6758	1.8235	0.6757
Pregame 20	1–2 km	Predicted Win	-0.9266	0.2328	-0.9264	0.2327
		Predicted Close	-2.2742	0.4000	-2.2743	0.4001
		Predicted Lose	-1.2769	0.4572	-1.2773	0.4573
		Predicted Win Lose	-0.1085	0.2657	-0.1091	0.2658
		Predicted Close Lose	0.8694	0.2722	0.8666	0.2711
	2–3 km	Predicted Lose Win	0.3710	0.4328	0.3708	0.4328
		Predicted Win	-0.9906	0.2261	-0.9907	0.2261
		Predicted Close	-0.3345	0.1698	-0.3337	0.1696
		Predicted Lose	-1.0098	0.2687	-1.0141	0.2689
		Predicted Win Lose	0.5379	0.2127	0.5380	0.2127
	3–4 km	Predicted Close Lose	-0.4985	0.2184	-0.5005	0.2180
		Predicted Lose Win	0.5581	0.2790	0.5623	0.2789
		Predicted Win	-0.4223	0.1480	-0.4223	0.1480
		Predicted Close	-0.3338	0.1403	-0.3335	0.1403
		Predicted Lose	-0.0990	0.1632	-0.0984	0.1633
	4–5 km	Predicted Win Lose	0.5926	0.1752	0.5924	0.1753
		Predicted Close Lose	0.2836	0.1369	0.2833	0.1369
		Predicted Lose Win	-0.0609	0.2066	-0.0614	0.2067
		Predicted Win	-0.2066	0.1273	-0.2064	0.1273
		Predicted Close	-0.2364	0.1374	-0.2364	0.1374
Pregame 20	0–1 km	Predicted Lose	-0.0179	0.1675	-0.0179	0.1675
		Predicted Win Lose	0.3843	0.1578	0.3842	0.1578
		Predicted Close Lose	-0.0100	0.0954	-0.0099	0.0954
		Predicted Lose Win	-0.1360	0.2188	-0.1360	0.2188
	1–2 km	Predicted Win	-2.7400	0.6510	-2.7397	0.6510
		Predicted Close	-3.1446	0.8044	-3.1470	0.8045
		Predicted Lose	-4.3979	0.8252	-4.3991	0.8251
		Predicted Win Lose	1.6096	0.5066	1.6085	0.5065
		Predicted Close Lose	0.0358	0.7795	0.0390	0.7799
	2–3 km	Predicted Lose Win	2.1545	0.6777	2.1555	0.6777
		Predicted Win	-0.8620	0.2347	-0.8593	0.2340
		Predicted Close	-1.4819	0.3762	-1.4787	0.3743
		Predicted Lose	-1.5924	0.4240	-1.5924	0.4240
		Predicted Win Lose	0.3507	0.2519	0.3473	0.2523
	3–4 km	Predicted Close Lose	0.6806	0.2661	0.6800	0.2658
		Predicted Lose Win	0.7523	0.3951	0.7572	0.3965
		Predicted Win	-0.5949	0.1757	-0.5949	0.1757
		Predicted Close	-0.1702	0.1354	-0.1702	0.1354
		Predicted Lose	-0.3563	0.2588	-0.3563	0.2588
Pregame 20	0–1 km	Predicted Win Lose	0.5775	0.2045	0.5775	0.2045
		Predicted Close Lose	-0.3448	0.1928	-0.3448	0.1928
		Predicted Lose Win	-0.1714	0.2987	-0.1714	0.2987
	1–2 km	Predicted Win	-0.2150	0.1295	-0.2154	0.1295
		Predicted Close	-0.2430	0.1052	-0.2413	0.1053
		Predicted Lose	0.2502	0.1832	0.2495	0.1832

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Time	Distance	Variable	With Crash	With Crash SE	No Crash	No Crash SE
Pregame 10	4–5 km	Predicted Win Lose	0.3898	0.1641	0.3901	0.1641
		Predicted Close Lose	0.1487	0.1094	0.1466	0.1095
		Predicted Lose Win	-0.4682	0.2146	-0.4672	0.2146
		Predicted Win	-0.0453	0.1083	-0.0451	0.1082
		Predicted Close	-0.1531	0.1219	-0.1530	0.1218
		Predicted Lose	0.0347	0.1634	0.0346	0.1634
	0–1 km	Predicted Win Lose	0.3869	0.1481	0.3867	0.1480
		Predicted Close Lose	0.0174	0.0832	0.0174	0.0832
		Predicted Lose Win	-0.1485	0.2094	-0.1483	0.2094
		Predicted Win	-2.2940	0.5785	-2.2941	0.5785
		Predicted Close	-2.2044	0.7701	-2.2046	0.7701
		Predicted Lose	-3.4577	0.7861	-3.4579	0.7861
	1–2 km	Predicted Win Lose	1.3007	0.3950	1.3009	0.3950
		Predicted Close Lose	-0.0479	0.6682	-0.0476	0.6682
		Predicted Lose Win	2.0205	0.7458	2.0204	0.7457
		Predicted Win	-0.4656	0.2277	-0.4656	0.2277
		Predicted Close	-1.0102	0.3422	-1.0102	0.3421
		Predicted Lose	-1.1090	0.4024	-1.1090	0.4023
	2–3 km	Predicted Win Lose	-0.0035	0.2174	-0.0035	0.2174
		Predicted Close Lose	0.5208	0.2338	0.5208	0.2338
		Predicted Lose Win	0.5546	0.3814	0.5546	0.3814
		Predicted Win	-0.3309	0.1502	-0.3309	0.1502
		Predicted Close	0.0437	0.1403	0.0443	0.1405
		Predicted Lose	0.1338	0.2043	0.1369	0.2043
	3–4 km	Predicted Win Lose	0.5690	0.1968	0.5691	0.1968
		Predicted Close Lose	-0.3744	0.1602	-0.3750	0.1602
		Predicted Lose Win	-0.6529	0.2432	-0.6564	0.2432
		Predicted Win	-0.2072	0.1292	-0.2102	0.1293
		Predicted Close	-0.1448	0.1017	-0.1448	0.1017
		Predicted Lose	0.3853	0.1728	0.3859	0.1728
	4–5 km	Predicted Win Lose	0.4852	0.1540	0.4879	0.1544
		Predicted Close Lose	0.2275	0.1095	0.2272	0.1095
		Predicted Lose Win	-0.5066	0.2192	-0.5104	0.2191
		Predicted Win	0.0142	0.1084	0.0143	0.1084
		Predicted Close	-0.2895	0.1111	-0.2896	0.1111
		Predicted Lose	0.4814	0.1552	0.4815	0.1552
Postgame 10	0–1 km	Predicted Win Lose	0.3781	0.1444	0.3766	0.1443
		Predicted Close Lose	0.3783	0.0898	0.3782	0.0898
		Predicted Lose Win	-0.5143	0.2052	-0.5145	0.2051
		Predicted Win	-1.6735	0.4203	-1.6735	0.4203
		Predicted Close	-0.7249	0.7483	-0.7249	0.7483
		Predicted Lose	-1.1245	0.6593	-1.1245	0.6593
	1–2 km	Predicted Win Lose	0.2492	0.3091	0.2492	0.3091
		Predicted Close Lose	-1.1994	0.6051	-1.1994	0.6051
		Predicted Lose Win	0.1122	0.5730	0.1122	0.5730
		Predicted Win	-0.0472	0.2081	-0.0470	0.2081
		Predicted Close	-0.1687	0.3989	-0.1685	0.3989
		Predicted Lose	-0.0990	0.4327	-0.0987	0.4327
	2–3 km	Predicted Win Lose	-0.2624	0.2367	-0.2620	0.2367
		Predicted Close Lose	-0.2691	0.3160	-0.2719	0.3159
		Predicted Lose Win	-0.6564	0.4163	-0.6570	0.4163
		Predicted Win	0.0771	0.1412	0.0771	0.1412
		Predicted Close	-0.3473	0.1732	-0.3474	0.1733
		Predicted Lose	-0.0620	0.2423	-0.0621	0.2424
	3–4 km	Predicted Win Lose	0.0872	0.1810	0.0872	0.1810
		Predicted Close Lose	0.3613	0.1655	0.3614	0.1655
		Predicted Lose Win	-0.6862	0.2763	-0.6862	0.2763
		Predicted Win	0.3524	0.1293	0.3523	0.1292
		Predicted Close	0.2575	0.0973	0.2575	0.0973
		Predicted Lose	0.4801	0.1671	0.4801	0.1671
	4–5 km	Predicted Win Lose	-0.1205	0.1664	-0.1204	0.1664
		Predicted Close Lose	-0.0582	0.1089	-0.0582	0.1089
		Predicted Lose Win	-1.1285	0.2159	-1.1285	0.2159
		Predicted Win	0.3001	0.1016	0.3004	0.1016
		Predicted Close	0.0824	0.0744	0.0826	0.0744
		Predicted Lose	0.1968	0.1725	0.1969	0.1725
Postgame 20	0–1 km	Predicted Win Lose	-0.0250	0.1458	-0.0294	0.1459
		Predicted Close Lose	-0.0318	0.0720	-0.0327	0.0720
		Predicted Lose Win	-0.8570	0.2210	-0.8567	0.2210
		Predicted Win	-2.5478	0.5007	-2.5478	0.5007
		Predicted Close	-2.0854	0.8441	-2.0854	0.8441
		Predicted Lose	-1.8463	0.6833	-1.8463	0.6833
	0–1 km	Predicted Win Lose	0.9438	0.3275	0.9438	0.3275

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Time	Distance	Variable	With Crash	With Crash SE	No Crash	No Crash SE
	1–2 km	Predicted Close Lose	-0.7592	0.6580	-0.7592	0.6580
		Predicted Lose Win	0.3666	0.5945	0.3666	0.5945
		Predicted Win	-0.4543	0.2242	-0.4544	0.2242
		Predicted Close	-0.7952	0.4552	-0.7953	0.4552
		Predicted Lose	-0.9998	0.4400	-0.9999	0.4400
		Predicted Win Lose	0.0720	0.2326	0.0720	0.2326
	2–3 km	Predicted Close Lose	-0.1721	0.3572	-0.1731	0.3572
		Predicted Lose Win	0.0376	0.3963	0.0376	0.3963
		Predicted Win	-0.0047	0.1472	-0.0049	0.1472
		Predicted Close	-0.7582	0.2001	-0.7581	0.2001
		Predicted Lose	-0.1616	0.2746	-0.1616	0.2746
		Predicted Win Lose	0.0147	0.1838	0.0148	0.1837
	3–4 km	Predicted Close Lose	0.4445	0.1786	0.4445	0.1786
		Predicted Lose Win	-0.5770	0.3030	-0.5770	0.3030
		Predicted Win	0.4028	0.1355	0.4027	0.1355
		Predicted Close	0.0375	0.1032	0.0375	0.1032
		Predicted Lose	0.1927	0.1995	0.1926	0.1995
		Predicted Win Lose	-0.2147	0.1672	-0.2147	0.1672
	4–5 km	Predicted Close Lose	-0.0256	0.1110	-0.0256	0.1110
		Predicted Lose Win	-0.8818	0.2280	-0.8818	0.2280
		Predicted Win	0.3272	0.1082	0.3243	0.1083
		Predicted Close	-0.0297	0.0977	-0.0294	0.0976
		Predicted Lose	0.2910	0.1640	0.2912	0.1640
		Predicted Win Lose	0.0246	0.1461	0.0280	0.1461
Postgame 30	0–1 km	Predicted Close Lose	-0.0160	0.0756	-0.0161	0.0756
		Predicted Lose Win	-1.2762	0.2012	-1.2760	0.2012
		Predicted Win	-3.1070	0.5251	-3.1070	0.5251
		Predicted Close	-3.5584	0.9208	-3.5584	0.9208
		Predicted Lose	-3.5395	0.8021	-3.5397	0.8021
		Predicted Win Lose	0.7714	0.4234	0.7713	0.4234
	1–2 km	Predicted Close Lose	-0.2316	0.7647	-0.2316	0.7647
		Predicted Lose Win	1.6094	0.7953	1.6096	0.7952
		Predicted Win	-0.8924	0.2462	-0.8926	0.2462
		Predicted Close	-1.3551	0.5017	-1.3700	0.5074
		Predicted Lose	-1.3328	0.4814	-1.3333	0.4816
		Predicted Win Lose	0.3102	0.2202	0.3001	0.2208
	2–3 km	Predicted Close Lose	-0.0201	0.3840	-0.0054	0.3882
		Predicted Lose Win	-0.0153	0.4688	-0.0150	0.4689
		Predicted Win	-0.3754	0.1752	-0.3754	0.1752
		Predicted Close	-1.0209	0.2610	-1.0208	0.2610
		Predicted Lose	-0.8853	0.2829	-0.8853	0.2829
		Predicted Win Lose	0.2742	0.1889	0.2732	0.1888
	3–4 km	Predicted Close Lose	0.2644	0.2039	0.2644	0.2039
		Predicted Lose Win	0.0469	0.3000	0.0469	0.3000
		Predicted Win	-0.1805	0.1670	-0.1805	0.1670
		Predicted Close	-0.2092	0.1226	-0.2093	0.1226
		Predicted Lose	-0.3524	0.2155	-0.3525	0.2155
		Predicted Win Lose	0.1967	0.1673	0.1967	0.1673
	4–5 km	Predicted Close Lose	-0.0881	0.1346	-0.0882	0.1346
		Predicted Lose Win	-0.2040	0.2472	-0.2040	0.2472
		Predicted Win	0.0624	0.1272	0.0623	0.1272
		Predicted Close	-0.1206	0.1262	-0.1214	0.1266
		Predicted Lose	-0.2127	0.1754	-0.2178	0.1767
		Predicted Win Lose	-0.0374	0.1564	-0.0371	0.1564
Postgame 40	0–1 km	Predicted Close Lose	-0.0161	0.0933	-0.0166	0.0934
		Predicted Lose Win	-0.7679	0.2006	-0.7622	0.2018
		Predicted Win	-3.4531	0.5798	-3.4532	0.5798
		Predicted Close	-4.9071	1.0332	-4.8965	1.0326
		Predicted Lose	-5.4415	0.8842	-5.4427	0.8843
		Predicted Win Lose	-0.4179	0.4243	-0.4180	0.4243
	1–2 km	Predicted Close Lose	0.2616	0.7845	0.2573	0.7847
		Predicted Lose Win	2.3998	0.6311	2.4013	0.6312
		Predicted Win	-1.4476	0.2968	-1.4477	0.2968
		Predicted Close	-2.4299	0.5557	-2.4298	0.5557
		Predicted Lose	-2.4702	0.5023	-2.4702	0.5023
		Predicted Win Lose	-0.0980	0.2395	-0.0978	0.2395
	2–3 km	Predicted Close Lose	0.4794	0.3974	0.4793	0.3974
		Predicted Lose Win	0.5988	0.4262	0.5946	0.4264
		Predicted Win	-1.0401	0.2501	-1.0402	0.2501
		Predicted Close	-1.7092	0.3206	-1.7080	0.3205
		Predicted Lose	-2.3321	0.4445	-2.3323	0.4445
		Predicted Win Lose	0.4791	0.2022	0.4791	0.2022
		Predicted Close Lose	0.3597	0.2073	0.3584	0.2072
		Predicted Lose Win	1.3401	0.4591	1.3402	0.4591

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Time	Distance	Variable	With Crash	With Crash SE	No Crash	No Crash SE
Postgame 50	3–4 km	Predicted Win	-0.6752	0.2446	-0.6751	0.2446
		Predicted Close	-0.5875	0.1583	-0.5896	0.1597
		Predicted Lose	-0.9219	0.2754	-0.9218	0.2754
		Predicted Win Lose	0.3731	0.2177	0.3730	0.2177
		Predicted Close Lose	0.0082	0.1331	0.0098	0.1337
		Predicted Lose Win	0.3654	0.3024	0.3655	0.3025
	4–5 km	Predicted Win	0.0051	0.1650	0.0052	0.1650
		Predicted Close	-0.3846	0.1680	-0.3844	0.1679
		Predicted Lose	-0.5319	0.2395	-0.5318	0.2395
		Predicted Win Lose	-0.0948	0.1729	-0.0982	0.1730
		Predicted Close Lose	0.0545	0.0999	0.0544	0.0999
		Predicted Lose Win	-0.5929	0.2483	-0.5928	0.2483
	0–1 km	Predicted Win	-3.1761	0.5914	-3.1761	0.5914
		Predicted Close	-5.6458	1.0673	-5.6458	1.0673
		Predicted Lose	-5.7616	0.9060	-5.7616	0.9060
		Predicted Win Lose	-1.5538	0.4858	-1.5538	0.4858
		Predicted Close Lose	1.1846	0.7936	1.1846	0.7936
		Predicted Lose Win	2.8205	0.7283	2.8205	0.7283
	1–2 km	Predicted Win	-1.8321	0.3434	-1.8321	0.3434
		Predicted Close	-3.4023	0.5881	-3.4022	0.5881
		Predicted Lose	-3.1223	0.5398	-3.1222	0.5398
		Predicted Win Lose	-0.4071	0.3265	-0.4065	0.3265
		Predicted Close Lose	0.6674	0.4368	0.6673	0.4368
		Predicted Lose Win	0.6263	0.4450	0.6262	0.4450
	2–3 km	Predicted Win	-1.4045	0.2924	-1.4045	0.2925
		Predicted Close	-2.5550	0.4386	-2.5541	0.4382
		Predicted Lose	-2.7989	0.5228	-2.7989	0.5228
		Predicted Win Lose	-0.0825	0.2310	-0.0825	0.2311
		Predicted Close Lose	0.5795	0.2730	0.5789	0.2728
		Predicted Lose Win	1.5968	0.5180	1.5967	0.5180
	3–4 km	Predicted Win	-1.3356	0.3202	-1.3361	0.3202
		Predicted Close	-0.9588	0.2039	-0.9592	0.2043
		Predicted Lose	-1.2555	0.3169	-1.2554	0.3169
		Predicted Win Lose	0.3775	0.2205	0.3769	0.2207
		Predicted Close Lose	0.1386	0.1563	0.1388	0.1565
		Predicted Lose Win	-0.1622	0.3255	-0.1622	0.3255
	4–5 km	Predicted Win	-0.3125	0.2149	-0.3125	0.2149
		Predicted Close	-0.5129	0.1913	-0.5128	0.1912
		Predicted Lose	-0.3639	0.2321	-0.3638	0.2320
		Predicted Win Lose	-0.0157	0.1933	-0.0156	0.1933
		Predicted Close Lose	0.0368	0.1112	0.0367	0.1112
		Predicted Lose Win	-0.8169	0.2339	-0.8169	0.2339
Postgame 60	0–1 km	Predicted Win	-2.9601	0.5517	-2.9600	0.5517
		Predicted Close	-5.4563	1.0181	-5.4563	1.0181
		Predicted Lose	-5.0828	0.8745	-5.0830	0.8744
		Predicted Win Lose	-1.0098	0.4457	-1.0099	0.4457
		Predicted Close Lose	1.3251	0.7498	1.3252	0.7498
		Predicted Lose Win	2.4810	0.7883	2.4813	0.7883
	1–2 km	Predicted Win	-1.6097	0.3383	-1.6097	0.3382
		Predicted Close	-3.6377	0.5984	-3.6377	0.5984
		Predicted Lose	-3.2399	0.5415	-3.2399	0.5415
		Predicted Win Lose	-0.9558	0.3154	-0.9587	0.3150
		Predicted Close Lose	0.8459	0.4549	0.8460	0.4549
		Predicted Lose Win	0.8193	0.4527	0.8193	0.4527
	2–3 km	Predicted Win	-1.3679	0.2971	-1.3679	0.2970
		Predicted Close	-3.1082	0.4963	-3.1078	0.4963
		Predicted Lose	-3.2407	0.5613	-3.2407	0.5613
		Predicted Win Lose	-0.6682	0.2532	-0.6669	0.2531
		Predicted Close Lose	0.7945	0.3065	0.7943	0.3065
		Predicted Lose Win	1.9435	0.5597	1.9436	0.5597
	3–4 km	Predicted Win	-1.1085	0.2609	-1.1104	0.2610
		Predicted Close	-1.1485	0.2236	-1.1485	0.2236
		Predicted Lose	-1.6882	0.3337	-1.6881	0.3337
		Predicted Win Lose	-0.2588	0.2037	-0.2608	0.2038
		Predicted Close Lose	0.2524	0.1637	0.2518	0.1632
		Predicted Lose Win	0.3922	0.3140	0.3921	0.3140
	4–5 km	Predicted Win	-0.3504	0.1997	-0.3503	0.1997
		Predicted Close	-0.6382	0.2000	-0.6380	0.1999
		Predicted Lose	-0.4744	0.2373	-0.4743	0.2373
		Predicted Win Lose	-0.1038	0.1737	-0.1035	0.1736
		Predicted Close Lose	0.0837	0.1112	0.0836	0.1112
		Predicted Lose Win	-0.7943	0.2346	-0.7941	0.2346
Postgame 70	0–1 km					

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Time	Distance	Variable	With Crash	With Crash SE	No Crash	No Crash SE	
Postgame 80	1–2 km	Predicted Win	-2.4422	0.4524	-2.4414	0.4524	
		Predicted Close	-5.7966	1.0716	-5.7973	1.0716	
		Predicted Lose	-4.9977	0.9412	-4.9998	0.9408	
		Predicted Win Lose	-0.0947	0.3687	-0.0751	0.3703	
		Predicted Close Lose	2.8108	0.8484	2.8116	0.8484	
		Predicted Lose Win	2.4811	0.8242	2.4833	0.8237	
	2–3 km	Predicted Win	-1.0437	0.2472	-1.0437	0.2472	
		Predicted Close	-3.9084	0.6149	-3.9084	0.6149	
		Predicted Lose	-3.1518	0.5226	-3.1518	0.5226	
		Predicted Win Lose	-0.9731	0.2901	-0.9731	0.2901	
		Predicted Close Lose	1.7035	0.4943	1.7034	0.4944	
		Predicted Lose Win	0.7640	0.4393	0.7640	0.4393	
	3–4 km	Predicted Win	-1.0176	0.2725	-1.0176	0.2725	
		Predicted Close	-3.9046	0.6293	-3.9045	0.6293	
		Predicted Lose	-2.9015	0.5327	-2.9015	0.5327	
		Predicted Win Lose	-0.8271	0.2729	-0.8270	0.2729	
		Predicted Close Lose	1.9178	0.4139	1.9178	0.4139	
		Predicted Lose Win	1.3610	0.5411	1.3610	0.5411	
	4–5 km	Predicted Win	-0.5677	0.1646	-0.5676	0.1646	
		Predicted Close	-1.2872	0.2755	-1.2871	0.2755	
		Predicted Lose	-1.3485	0.3151	-1.3484	0.3151	
		Predicted Win Lose	-0.4409	0.2270	-0.4409	0.2270	
		Predicted Close Lose	0.6536	0.1837	0.6536	0.1837	
		Predicted Lose Win	-0.0556	0.3068	-0.0570	0.3071	
	Postgame 90	0–1 km	Predicted Win	-0.3249	0.1721	-0.3250	0.1721
			Predicted Close	-0.7485	0.2212	-0.7474	0.2212
			Predicted Lose	-0.2926	0.2246	-0.2931	0.2246
			Predicted Win Lose	-0.4051	0.1979	-0.4052	0.1979
			Predicted Close Lose	0.3602	0.1345	0.3589	0.1345
			Predicted Lose Win	-0.8591	0.2397	-0.8552	0.2399
1–2 km		Predicted Win	-1.9579	0.4142	-1.9579	0.4142	
		Predicted Close	-4.3502	1.0236	-4.3502	1.0236	
		Predicted Lose	-4.0498	0.8327	-4.0497	0.8327	
		Predicted Win Lose	-0.3506	0.3133	-0.3506	0.3133	
		Predicted Close Lose	1.9536	0.8619	1.9535	0.8619	
		Predicted Lose Win	1.7433	0.6996	1.7432	0.6996	
2–3 km		Predicted Win	-0.6619	0.2125	-0.6616	0.2125	
		Predicted Close	-3.1123	0.5643	-3.1123	0.5643	
		Predicted Lose	-2.6179	0.4968	-2.6182	0.4968	
		Predicted Win Lose	-0.7670	0.3035	-0.7669	0.3035	
		Predicted Close Lose	1.4938	0.4650	1.4885	0.4629	
		Predicted Lose Win	0.8528	0.4474	0.8528	0.4474	
3–4 km		Predicted Win	-0.8249	0.2470	-0.8248	0.2470	
		Predicted Close	-3.9197	0.6933	-3.9196	0.6933	
		Predicted Lose	-2.7557	0.4619	-2.7557	0.4619	
		Predicted Win Lose	-0.8978	0.2577	-0.8979	0.2577	
		Predicted Close Lose	2.2921	0.4560	2.2921	0.4560	
		Predicted Lose Win	1.4037	0.4827	1.4037	0.4827	
4–5 km		Predicted Win	-0.1733	0.1371	-0.1733	0.1371	
		Predicted Close	-1.1007	0.2916	-1.1008	0.2916	
		Predicted Lose	-1.0429	0.2704	-1.0429	0.2704	
		Predicted Win Lose	-0.7337	0.2588	-0.7336	0.2588	
		Predicted Close Lose	0.5913	0.1942	0.5914	0.1942	
		Predicted Lose Win	0.1649	0.2870	0.1649	0.2870	
0–1 km	Predicted Win	-0.0966	0.1440	-0.0965	0.1439		
	Predicted Close	-0.6970	0.2155	-0.6973	0.2156		
	Predicted Lose	-0.1669	0.2007	-0.1669	0.2007		
	Predicted Win Lose	-0.6643	0.1950	-0.6644	0.1951		
	Predicted Close Lose	0.2785	0.1292	0.2786	0.1291		
	Predicted Lose Win	-0.8483	0.2171	-0.8483	0.2171		
1–2 km	Predicted Win	-0.9592	0.2223	-0.9588	0.2223		
	Predicted Close	-3.0451	0.9400	-3.0453	0.9401		
	Predicted Lose	-3.6399	0.7997	-3.6400	0.7997		
	Predicted Win Lose	-0.8566	0.3320	-0.8570	0.3321		
	Predicted Close Lose	1.4169	0.7894	1.4171	0.7894		
	Predicted Lose Win	2.1833	0.6743	2.1834	0.6743		
2–3 km	Predicted Win	-0.4014	0.1667	-0.4014	0.1667		
	Predicted Close	-2.6077	0.4658	-2.6077	0.4658		
	Predicted Lose	-2.1372	0.4815	-2.1372	0.4815		
	Predicted Win Lose	-0.4086	0.3037	-0.4086	0.3037		
	Predicted Close Lose	1.5280	0.3856	1.5280	0.3856		
	Predicted Lose Win	0.8750	0.4561	0.8750	0.4561		
3–4 km	Predicted Win	-0.6347	0.2040	-0.6355	0.2041		
	Predicted Close	-3.3771	0.6414	-3.3770	0.6414		

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Time	Distance	Variable	With Crash	With Crash SE	No Crash	No Crash SE
Postgame 100	3–4 km	Predicted Lose	-1.8709	0.3662	-1.8709	0.3662
		Predicted Win Lose	-0.6344	0.2580	-0.6335	0.2578
		Predicted Close Lose	2.1562	0.4293	2.1559	0.4292
		Predicted Lose Win	0.7006	0.4030	0.7006	0.4030
		Predicted Win	0.0304	0.1316	0.0304	0.1316
		Predicted Close	-1.0781	0.2558	-1.0781	0.2558
	4–5 km	Predicted Lose	-0.4804	0.2397	-0.4804	0.2397
		Predicted Win Lose	-0.3972	0.1720	-0.3972	0.1720
		Predicted Close Lose	0.7762	0.1822	0.7762	0.1822
		Predicted Lose Win	-0.3525	0.2682	-0.3525	0.2682
		Predicted Win	0.1618	0.1504	0.1618	0.1504
		Predicted Close	-0.8035	0.2067	-0.8035	0.2067
	0–1 km	Predicted Lose	0.2613	0.1921	0.2613	0.1921
		Predicted Win Lose	-0.5233	0.1761	-0.5233	0.1761
		Predicted Close Lose	0.5490	0.1342	0.5491	0.1342
		Predicted Lose Win	-1.2370	0.2127	-1.2370	0.2127
		Predicted Win	-0.6034	0.2179	-0.6034	0.2179
		Predicted Close	-1.6277	0.7939	-1.6277	0.7939
	1–2 km	Predicted Lose	-2.6887	0.7507	-2.6887	0.7507
		Predicted Win Lose	-1.0062	0.3410	-1.0062	0.3410
		Predicted Close Lose	0.3118	0.6920	0.3118	0.6920
		Predicted Lose Win	1.3804	0.6546	1.3804	0.6546
		Predicted Win	-0.1369	0.1496	-0.1369	0.1496
		Predicted Close	-1.7858	0.3696	-1.7858	0.3696
	2–3 km	Predicted Lose	-1.9463	0.4310	-1.9463	0.4310
		Predicted Win Lose	-0.3341	0.2584	-0.3341	0.2584
		Predicted Close Lose	1.0624	0.3266	1.0624	0.3266
		Predicted Lose Win	0.8924	0.4299	0.8924	0.4299
		Predicted Win	-0.3715	0.1870	-0.3714	0.1870
		Predicted Close	-2.6389	0.5223	-2.6387	0.5223
	3–4 km	Predicted Lose	-1.7009	0.3154	-1.7007	0.3154
		Predicted Win Lose	-0.3465	0.2270	-0.3464	0.2270
		Predicted Close Lose	1.7324	0.3574	1.7323	0.3574
		Predicted Lose Win	0.5540	0.3766	0.5538	0.3766
		Predicted Win	0.0653	0.1160	0.0650	0.1161
		Predicted Close	-0.9325	0.2415	-0.9325	0.2415
	4–5 km	Predicted Lose	-0.3438	0.2149	-0.3438	0.2149
		Predicted Win Lose	-0.2535	0.1594	-0.2531	0.1596
		Predicted Close Lose	0.6705	0.1781	0.6705	0.1781
		Predicted Lose Win	-0.3901	0.2533	-0.3901	0.2533
		Predicted Win	0.1968	0.1303	0.1969	0.1303
		Predicted Close	-0.6108	0.1883	-0.6107	0.1883
Postgame 110	0–1 km	Predicted Lose	0.2949	0.1565	0.2950	0.1565
		Predicted Win Lose	-0.4279	0.1926	-0.4279	0.1926
		Predicted Close Lose	0.4501	0.1424	0.4500	0.1424
		Predicted Lose Win	-1.1931	0.2035	-1.1930	0.2035
		Predicted Win	-0.5587	0.2084	-0.5587	0.2084
		Predicted Close	-0.7843	0.6422	-0.7843	0.6422
	1–2 km	Predicted Lose	-2.4065	0.5890	-2.4065	0.5890
		Predicted Win Lose	-0.0023	0.3646	-0.0023	0.3646
		Predicted Close Lose	-0.0426	0.5984	-0.0426	0.5984
		Predicted Lose Win	1.6328	0.6141	1.6328	0.6141
		Predicted Win	-0.1848	0.1571	-0.1848	0.1571
		Predicted Close	-1.1775	0.2847	-1.1775	0.2847
	2–3 km	Predicted Lose	-1.5914	0.3533	-1.5914	0.3533
		Predicted Win Lose	-0.1056	0.2197	-0.1055	0.2197
		Predicted Close Lose	0.8365	0.2620	0.8365	0.2620
		Predicted Lose Win	0.3506	0.3680	0.3505	0.3680
		Predicted Win	-0.0934	0.1550	-0.0934	0.1550
		Predicted Close	-1.9943	0.3724	-1.9942	0.3724
	3–4 km	Predicted Lose	-1.0065	0.2945	-1.0064	0.2945
		Predicted Win Lose	-0.3663	0.1591	-0.3662	0.1591
		Predicted Close Lose	1.4728	0.2802	1.4728	0.2802
		Predicted Lose Win	0.1786	0.3637	0.1785	0.3637
		Predicted Win	0.0807	0.1105	0.0807	0.1105
		Predicted Close	-0.7623	0.1861	-0.7623	0.1861
	4–5 km	Predicted Lose	-0.2728	0.1989	-0.2727	0.1989
		Predicted Win Lose	-0.1704	0.1457	-0.1703	0.1458
		Predicted Close Lose	0.6139	0.1477	0.6138	0.1477
		Predicted Lose Win	-0.3640	0.2341	-0.3640	0.2341
		Predicted Win	0.2332	0.1055	0.2332	0.1055
		Predicted Close	-0.6116	0.1546	-0.6115	0.1546
		Predicted Lose	0.3227	0.1431	0.3209	0.1428
		Predicted Win Lose	-0.2020	0.1556	-0.2020	0.1556

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Time	Distance	Variable	With Crash	With Crash SE	No Crash	No Crash SE
Postgame 120		Predicted Close Lose	0.5111	0.1235	0.5110	0.1235
		Predicted Lose Win	-1.2977	0.2015	-1.2959	0.2014
	0–1 km	Predicted Win	-0.4829	0.2173	-0.4829	0.2173
		Predicted Close	-0.2173	0.5249	-0.2173	0.5249
		Predicted Lose	-0.8857	0.4082	-0.8857	0.4082
		Predicted Win Lose	-0.5086	0.3322	-0.5086	0.3322
		Predicted Close Lose	-0.4658	0.5172	-0.4658	0.5172
		Predicted Lose Win	0.9698	0.4828	0.9698	0.4828
	1–2 km	Predicted Win	-0.1579	0.1562	-0.1579	0.1562
		Predicted Close	-0.7265	0.2263	-0.7265	0.2263
		Predicted Lose	-0.6390	0.3265	-0.6390	0.3265
		Predicted Win Lose	-0.3582	0.2341	-0.3582	0.2341
		Predicted Close Lose	0.5480	0.2303	0.5481	0.2303
		Predicted Lose Win	-0.2014	0.3681	-0.2014	0.3681
	2–3 km	Predicted Win	0.0249	0.1292	0.0255	0.1291
		Predicted Close	-1.3441	0.2196	-1.3434	0.2196
		Predicted Lose	-0.4943	0.2621	-0.4938	0.2621
		Predicted Win Lose	-0.4361	0.1599	-0.4368	0.1600
		Predicted Close Lose	1.0402	0.1867	1.0351	0.1861
		Predicted Lose Win	-0.4052	0.3107	-0.4059	0.3106
	3–4 km	Predicted Win	0.2242	0.0953	0.2242	0.0953
		Predicted Close	-0.5618	0.1275	-0.5618	0.1275
		Predicted Lose	0.0200	0.1646	0.0200	0.1646
		Predicted Win Lose	-0.4267	0.1379	-0.4267	0.1379
		Predicted Close Lose	0.5802	0.1171	0.5801	0.1171
		Predicted Lose Win	-0.7631	0.2079	-0.7631	0.2079
	4–5 km	Predicted Win	0.1660	0.0942	0.1657	0.0941
		Predicted Close	-0.5856	0.1130	-0.5855	0.1130
		Predicted Lose	0.4593	0.1525	0.4593	0.1525
		Predicted Win Lose	-0.0387	0.1426	-0.0384	0.1426
		Predicted Close Lose	0.5981	0.1029	0.5981	0.1029
		Predicted Lose Win	-1.1214	0.2018	-1.1214	0.2018

Notes: This table reports the coefficients corresponding to Figure 1. For brevity, coefficients for crash, weather, holiday, and season dummy indicators are omitted; this amounts to 1,980 omitted coefficients across the 180 regressions reported in the table. Predicted win indicates a point spread of -4 or less (negative spreads indicate the number of points a team is expected to win by); predicted close indicates a point spread between -4 and $+4$ exclusive; and predicted loss indicates a spread of $+4$ or more. The sample is limited to Sundays during the regular-season home games for Florida’s three NFL teams—the Miami Dolphins, Tampa Bay Buccaneers, and Jacksonville Jaguars—across the 2015–2019 seasons. Due to missing traffic data, the 2018 and 2019 Miami Dolphins seasons are excluded, resulting in a total of 84 Sunday home games with start times between 1:00 PM and 4:25 PM Eastern Time. Regressions include TMC-code fixed effects, as well as week-of-season time fixed effects and season dummies to control for temporal variation. Standard errors are clustered at the TMC-code level. Average vehicle speed represents observed speed across road links within 5 km of each stadium, broken up into 1-km distance bands, measured in 10-minute intervals from 60 minutes before to 120 minutes after each game.

Table A.4
NBA Regression results by time and distance

Time	Distance	Variable	With Crash	With Crash SE	No Crash	No Crash SE
Pregame 60						
	0–1 km	Predicted Win	0.2638	0.1256	0.2641	0.1256
		Predicted Close	0.6235	0.1829	0.6232	0.1829
		Predicted Lose	-0.0653	0.0833	-0.0646	0.0835
		Predicted Win Lose	0.0170	0.2218	0.0173	0.2219
		Predicted Close Lose	-0.4269	0.0784	-0.4273	0.0786
		Predicted Lose Win	0.1018	0.1148	0.1017	0.1148
	1–2 km	Predicted Win	0.3928	0.1075	0.3931	0.1076
		Predicted Close	0.6574	0.1286	0.6576	0.1286
		Predicted Lose	0.2488	0.0710	0.2492	0.0710
		Predicted Win Lose	0.3214	0.2079	0.3216	0.2079
		Predicted Close Lose	-0.1619	0.0642	-0.1618	0.0642
		Predicted Lose Win	-0.4229	0.1073	-0.4239	0.1074
	2–3 km	Predicted Win	0.3540	0.1396	0.3532	0.1396
		Predicted Close	0.4305	0.1296	0.4308	0.1296
		Predicted Lose	0.2477	0.0771	0.2480	0.0771
		Predicted Win Lose	0.0430	0.2561	0.0442	0.2561
		Predicted Close Lose	-0.1512	0.0811	-0.1520	0.0812
		Predicted Lose Win	-0.2947	0.1180	-0.2978	0.1178
	3–4 km	Predicted Win	0.2831	0.1275	0.2837	0.1276
		Predicted Close	0.5250	0.1375	0.5250	0.1376
		Predicted Lose	-0.0215	0.1041	-0.0218	0.1041
		Predicted Win Lose	0.0882	0.2000	0.0887	0.2000
		Predicted Close Lose	-0.3906	0.0787	-0.3910	0.0788
		Predicted Lose Win	-0.0284	0.1348	-0.0291	0.1347
	4–5 km	Predicted Win	0.0122	0.1258	0.0122	0.1258
		Predicted Close	0.2536	0.1388	0.2536	0.1388
		Predicted Lose	-0.0541	0.1047	-0.0540	0.1048
		Predicted Win Lose	-0.0254	0.2089	-0.0253	0.2101
		Predicted Close Lose	-0.3018	0.0828	-0.3018	0.0828
		Predicted Lose Win	-0.2148	0.1338	-0.2148	0.1338
Pregame 50						
	0–1 km	Predicted Win	0.3043	0.1567	0.3041	0.1567
		Predicted Close	0.7186	0.2055	0.7185	0.2054
		Predicted Lose	-0.0545	0.1070	-0.0540	0.1070
		Predicted Win Lose	0.4428	0.2334	0.4427	0.2334
		Predicted Close Lose	-0.4005	0.0720	-0.4002	0.0720
		Predicted Lose Win	0.1470	0.1102	0.1462	0.1102
	1–2 km	Predicted Win	0.3518	0.1058	0.3514	0.1057
		Predicted Close	0.7310	0.1234	0.7309	0.1234
		Predicted Lose	0.2127	0.0757	0.2128	0.0757
		Predicted Win Lose	0.6705	0.2364	0.6710	0.2364
		Predicted Close Lose	-0.1889	0.0622	-0.1888	0.0622
		Predicted Lose Win	-0.3400	0.1086	-0.3407	0.1086
	2–3 km	Predicted Win	0.2868	0.1020	0.2874	0.1021
		Predicted Close	0.5014	0.1329	0.5017	0.1330
		Predicted Lose	0.3192	0.0849	0.3197	0.0849
		Predicted Win Lose	0.6640	0.3339	0.6640	0.3339
		Predicted Close Lose	-0.1361	0.0756	-0.1365	0.0757
		Predicted Lose Win	-0.3531	0.1139	-0.3532	0.1139
	3–4 km	Predicted Win	0.2156	0.1297	0.2158	0.1297
		Predicted Close	0.5371	0.1437	0.5372	0.1437
		Predicted Lose	0.0293	0.1058	0.0296	0.1057
		Predicted Win Lose	0.6299	0.3079	0.6300	0.3079
		Predicted Close Lose	-0.2611	0.0793	-0.2612	0.0793
		Predicted Lose Win	-0.0690	0.1302	-0.0690	0.1302
	4–5 km	Predicted Win	0.1055	0.1150	0.1059	0.1150
		Predicted Close	0.3467	0.1454	0.3463	0.1454
		Predicted Lose	-0.0492	0.1050	-0.0490	0.1050
		Predicted Win Lose	0.2994	0.3017	0.2994	0.3017
		Predicted Close Lose	-0.1901	0.0837	-0.1896	0.0836
		Predicted Lose Win	-0.1869	0.1288	-0.1869	0.1288
Pregame 40						
	0–1 km	Predicted Win	0.1996	0.1606	0.1998	0.1607
		Predicted Close	0.6603	0.1950	0.6595	0.1947
		Predicted Lose	-0.0817	0.1101	-0.0825	0.1096
		Predicted Win Lose	0.9408	0.2217	0.9413	0.2217
		Predicted Close Lose	-0.3127	0.0631	-0.3116	0.0630
		Predicted Lose Win	0.2290	0.1543	0.2277	0.1542
	1–2 km	Predicted Win	0.3906	0.1165	0.3899	0.1163

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Time	Distance	Variable	With Crash	With Crash SE	No Crash	No Crash SE
Pregame 30	2–3 km	Predicted Close	0.7149	0.1094	0.7139	0.1090
		Predicted Lose	0.3043	0.0781	0.3047	0.0782
		Predicted Win Lose	0.7289	0.2397	0.7300	0.2398
		Predicted Close Lose	0.0131	0.0558	0.0142	0.0558
		Predicted Lose Win	-0.1444	0.1200	-0.1444	0.1200
	3–4 km	Predicted Win	0.2713	0.1348	0.2717	0.1349
		Predicted Close	0.5999	0.1255	0.6003	0.1255
		Predicted Lose	0.2695	0.0817	0.2699	0.0817
		Predicted Win Lose	0.9026	0.2842	0.9029	0.2842
		Predicted Close Lose	-0.1252	0.0665	-0.1252	0.0665
	4–5 km	Predicted Lose Win	-0.0012	0.1225	-0.0012	0.1225
		Predicted Win	0.3269	0.1573	0.3267	0.1572
		Predicted Close	0.6291	0.1289	0.6285	0.1289
		Predicted Lose	0.1168	0.1036	0.1167	0.1035
		Predicted Win Lose	0.7977	0.3059	0.7986	0.3062
	0–1 km	Predicted Close Lose	-0.1469	0.0685	-0.1463	0.0686
		Predicted Lose Win	0.1384	0.1588	0.1390	0.1588
		Predicted Win	0.1392	0.1227	0.1391	0.1227
		Predicted Close	0.4652	0.1490	0.4656	0.1491
		Predicted Lose	0.0956	0.1149	0.0955	0.1150
	1–2 km	Predicted Win Lose	0.3630	0.2876	0.3689	0.2902
		Predicted Close Lose	-0.0697	0.0812	-0.0703	0.0811
		Predicted Lose Win	-0.1145	0.1563	-0.1144	0.1563
		Predicted Win	0.1486	0.1649	0.1483	0.1648
		Predicted Close	0.5052	0.1778	0.5054	0.1778
	2–3 km	Predicted Lose	-0.2175	0.1443	-0.2178	0.1441
		Predicted Win Lose	0.6613	0.2237	0.6613	0.2237
		Predicted Close Lose	-0.1437	0.0653	-0.1442	0.0652
		Predicted Lose Win	0.3390	0.1588	0.3390	0.1587
		Predicted Win	0.3598	0.1047	0.3597	0.1047
	3–4 km	Predicted Close	0.7976	0.1133	0.7977	0.1133
		Predicted Lose	0.3227	0.0948	0.3227	0.0948
		Predicted Win Lose	1.2000	0.2198	1.1999	0.2198
		Predicted Close Lose	0.0474	0.0566	0.0474	0.0566
		Predicted Lose Win	0.1380	0.1214	0.1381	0.1214
	4–5 km	Predicted Win	0.4151	0.1594	0.4139	0.1591
		Predicted Close	0.6590	0.1382	0.6577	0.1377
		Predicted Lose	0.2829	0.0875	0.2838	0.0875
		Predicted Win Lose	0.6727	0.2584	0.6752	0.2588
		Predicted Close Lose	-0.0306	0.0683	-0.0292	0.0680
	0–1 km	Predicted Lose Win	-0.0177	0.1132	-0.0179	0.1132
		Predicted Win	0.7195	0.1723	0.7191	0.1723
		Predicted Close	0.7994	0.1455	0.8002	0.1455
		Predicted Lose	0.3250	0.1090	0.3248	0.1090
		Predicted Win Lose	0.5639	0.3023	0.5653	0.3024
	1–2 km	Predicted Close Lose	-0.0982	0.0669	-0.0983	0.0669
		Predicted Lose Win	-0.1556	0.1351	-0.1547	0.1352
		Predicted Win	0.2921	0.1526	0.2923	0.1525
		Predicted Close	0.6142	0.1708	0.6143	0.1707
		Predicted Lose	0.2195	0.1250	0.2195	0.1250
	2–3 km	Predicted Win Lose	0.7215	0.2884	0.7216	0.2885
		Predicted Close Lose	-0.0638	0.0715	-0.0640	0.0714
		Predicted Lose Win	-0.0572	0.1412	-0.0571	0.1412
		Predicted Win	0.2170	0.1844	0.2173	0.1844
		Predicted Close	0.3776	0.1541	0.3768	0.1541
	3–4 km	Predicted Lose	-0.0731	0.1323	-0.0744	0.1322
		Predicted Win Lose	0.6458	0.2983	0.6457	0.2983
		Predicted Close Lose	-0.0633	0.0869	-0.0625	0.0869
		Predicted Lose Win	-0.1647	0.1080	-0.1632	0.1080
		Predicted Win	0.3757	0.1269	0.3759	0.1269
Pregame 20	0–1 km	Predicted Close	0.7286	0.0987	0.7284	0.0986
		Predicted Lose	0.4414	0.0876	0.4416	0.0876
		Predicted Win Lose	1.3896	0.2281	1.3896	0.2281
		Predicted Close Lose	0.1071	0.0608	0.1071	0.0608
		Predicted Lose Win	0.0432	0.0991	0.0426	0.0991
	1–2 km	Predicted Win	0.3994	0.1539	0.3998	0.1539
		Predicted Close	0.5911	0.1376	0.5914	0.1377
		Predicted Lose	0.3840	0.0870	0.3842	0.0870
		Predicted Win Lose	0.5738	0.2098	0.5738	0.2098
		Predicted Close Lose	0.0332	0.0700	0.0333	0.0700
	2–3 km	Predicted Lose Win	0.0407	0.1406	0.0407	0.1406
		Predicted Win	0.6838	0.1780	0.6841	0.1780
		Predicted Close	0.7901	0.1378	0.7900	0.1378
		Predicted Lose	0.4493	0.1016	0.4491	0.1016

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Time	Distance	Variable	With Crash	With Crash SE	No Crash	No Crash SE
Pregame 10	4–5 km	Predicted Win Lose	0.2336	0.2673	0.2337	0.2673
		Predicted Close Lose	0.0103	0.0590	0.0107	0.0590
		Predicted Lose Win	-0.0919	0.1266	-0.0915	0.1266
		Predicted Win	0.5366	0.1674	0.5367	0.1674
		Predicted Close	0.6064	0.1665	0.6065	0.1665
		Predicted Lose	0.3717	0.1218	0.3718	0.1219
	0–1 km	Predicted Win Lose	0.6544	0.2370	0.6544	0.2370
		Predicted Close Lose	0.0694	0.0719	0.0694	0.0719
		Predicted Lose Win	-0.0290	0.1346	-0.0290	0.1346
		Predicted Win	0.1336	0.1518	0.1337	0.1518
		Predicted Close	0.1803	0.1339	0.1806	0.1340
		Predicted Lose	-0.3544	0.1241	-0.3541	0.1242
	1–2 km	Predicted Win Lose	0.2812	0.2466	0.2815	0.2467
		Predicted Close Lose	-0.0737	0.0825	-0.0744	0.0820
		Predicted Lose Win	-0.3614	0.1180	-0.3614	0.1180
		Predicted Win	0.3355	0.1090	0.3358	0.1090
		Predicted Close	0.7093	0.1006	0.7091	0.1007
		Predicted Lose	0.2544	0.0858	0.2542	0.0859
	2–3 km	Predicted Win Lose	1.0567	0.1912	1.0568	0.1912
		Predicted Close Lose	0.0999	0.0739	0.1004	0.0740
		Predicted Lose Win	0.0727	0.1000	0.0722	0.1000
		Predicted Win	0.4306	0.1357	0.4310	0.1358
		Predicted Close	0.4169	0.1153	0.4172	0.1153
		Predicted Lose	0.2715	0.0808	0.2711	0.0808
	3–4 km	Predicted Win Lose	0.5335	0.2181	0.5336	0.2181
		Predicted Close Lose	0.2377	0.0725	0.2373	0.0725
		Predicted Lose Win	0.0868	0.1116	0.0876	0.1114
		Predicted Win	0.6083	0.1550	0.6080	0.1551
		Predicted Close	0.7026	0.1262	0.7028	0.1262
		Predicted Lose	0.3942	0.1050	0.3947	0.1049
	4–5 km	Predicted Win Lose	0.3063	0.1835	0.3073	0.1835
		Predicted Close Lose	0.0185	0.0743	0.0182	0.0743
		Predicted Lose Win	-0.1404	0.1102	-0.1404	0.1101
		Predicted Win	0.4403	0.1600	0.4397	0.1600
		Predicted Close	0.5179	0.1528	0.5176	0.1528
		Predicted Lose	0.3473	0.1245	0.3470	0.1245
Postgame 10	0–1 km	Predicted Win Lose	1.0043	0.2046	1.0044	0.2046
		Predicted Close Lose	0.1738	0.0734	0.1738	0.0734
		Predicted Lose Win	-0.0437	0.1169	-0.0436	0.1169
		Predicted Win	-0.1375	0.1036	-0.1374	0.1036
		Predicted Close	0.0809	0.0475	0.0810	0.0475
		Predicted Lose	-0.0212	0.0456	-0.0212	0.0456
	1–2 km	Predicted Win Lose	0.2637	0.1686	0.2637	0.1686
		Predicted Close Lose	-0.1852	0.0565	-0.1852	0.0565
		Predicted Lose Win	0.0871	0.0700	0.0871	0.0700
		Predicted Win	-0.0207	0.0566	-0.0205	0.0566
		Predicted Close	0.0467	0.0407	0.0468	0.0407
		Predicted Lose	-0.0046	0.0413	-0.0048	0.0413
	2–3 km	Predicted Win Lose	-0.0218	0.1135	-0.0218	0.1135
		Predicted Close Lose	-0.0146	0.0544	-0.0146	0.0544
		Predicted Lose Win	-0.1449	0.0734	-0.1446	0.0735
		Predicted Win	0.1832	0.0666	0.1832	0.0665
		Predicted Close	0.0768	0.0421	0.0769	0.0421
		Predicted Lose	-0.0581	0.0379	-0.0581	0.0379
	3–4 km	Predicted Win Lose	-0.0620	0.1115	-0.0620	0.1115
		Predicted Close Lose	-0.0016	0.0510	-0.0016	0.0510
		Predicted Lose Win	-0.1054	0.0768	-0.1059	0.0767
		Predicted Win	0.0595	0.0784	0.0595	0.0784
		Predicted Close	-0.0697	0.0432	-0.0697	0.0432
		Predicted Lose	-0.0075	0.0489	-0.0075	0.0489
	4–5 km	Predicted Win Lose	-0.0144	0.1447	-0.0144	0.1447
		Predicted Close Lose	0.1955	0.0511	0.1955	0.0511
		Predicted Lose Win	-0.1703	0.0820	-0.1703	0.0820
		Predicted Win	0.0554	0.0704	0.0554	0.0704
		Predicted Close	0.0951	0.0423	0.0951	0.0423
		Predicted Lose	0.0259	0.0584	0.0258	0.0584
Postgame 20	0–1 km	Predicted Win Lose	0.0342	0.1507	0.0342	0.1507
		Predicted Close Lose	-0.0091	0.0612	-0.0091	0.0612
		Predicted Lose Win	-0.2748	0.0841	-0.2748	0.0841
		Predicted Win	-0.2132	0.1211	-0.2131	0.1211
		Predicted Close	-0.2188	0.0727	-0.2187	0.0727
		Predicted Lose	-0.1939	0.0547	-0.1939	0.0547
	0–1 km	Predicted Win Lose	0.4047	0.1704	0.4047	0.1704

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Time	Distance	Variable	With Crash	With Crash SE	No Crash	No Crash SE
	1–2 km	Predicted Close Lose	-0.1544	0.0597	-0.1544	0.0597
		Predicted Lose Win	0.1313	0.0857	0.1312	0.0857
		Predicted Win	-0.2710	0.0739	-0.2709	0.0739
		Predicted Close	-0.1127	0.0422	-0.1126	0.0422
		Predicted Lose	-0.0830	0.0410	-0.0829	0.0410
		Predicted Win Lose	0.4470	0.1072	0.4470	0.1072
	2–3 km	Predicted Close Lose	0.0635	0.0562	0.0631	0.0561
		Predicted Lose Win	-0.1395	0.0742	-0.1402	0.0741
		Predicted Win	0.1604	0.0753	0.1603	0.0753
		Predicted Close	0.0193	0.0423	0.0193	0.0423
		Predicted Lose	-0.1720	0.0442	-0.1720	0.0442
		Predicted Win Lose	0.1106	0.1353	0.1106	0.1353
	3–4 km	Predicted Close Lose	0.0393	0.0513	0.0393	0.0513
		Predicted Lose Win	-0.0457	0.0705	-0.0457	0.0705
		Predicted Win	0.1072	0.0657	0.1073	0.0657
		Predicted Close	-0.0581	0.0418	-0.0580	0.0418
		Predicted Lose	-0.0761	0.0539	-0.0760	0.0539
		Predicted Win Lose	-0.1477	0.1645	-0.1477	0.1645
	4–5 km	Predicted Close Lose	0.0891	0.0489	0.0891	0.0489
		Predicted Lose Win	-0.0862	0.0825	-0.0863	0.0825
		Predicted Win	-0.0191	0.0750	-0.0191	0.0750
		Predicted Close	0.0193	0.0407	0.0193	0.0406
		Predicted Lose	0.0258	0.0612	0.0258	0.0612
		Predicted Win Lose	-0.0086	0.1626	-0.0086	0.1626
Postgame 30	0–1 km	Predicted Close Lose	0.0305	0.0528	0.0304	0.0528
		Predicted Lose Win	-0.2873	0.0897	-0.2874	0.0897
		Predicted Win	-0.5361	0.1602	-0.5360	0.1602
		Predicted Close	-0.4141	0.0937	-0.4140	0.0937
		Predicted Lose	-0.2760	0.0708	-0.2759	0.0708
		Predicted Win Lose	0.1911	0.1642	0.1911	0.1642
	1–2 km	Predicted Close Lose	-0.1525	0.0513	-0.1525	0.0513
		Predicted Lose Win	-0.1037	0.1100	-0.1038	0.1100
		Predicted Win	-0.2802	0.0830	-0.2801	0.0830
		Predicted Close	-0.2190	0.0521	-0.2192	0.0520
		Predicted Lose	-0.1096	0.0591	-0.1095	0.0591
		Predicted Win Lose	0.2250	0.1321	0.2250	0.1321
	2–3 km	Predicted Close Lose	0.0836	0.0570	0.0837	0.0570
		Predicted Lose Win	-0.1174	0.0916	-0.1174	0.0916
		Predicted Win	-0.1131	0.0859	-0.1137	0.0860
		Predicted Close	-0.0274	0.0452	-0.0273	0.0452
		Predicted Lose	-0.1399	0.0460	-0.1399	0.0460
		Predicted Win Lose	0.2591	0.1447	0.2598	0.1446
	3–4 km	Predicted Close Lose	0.1528	0.0490	0.1524	0.0490
		Predicted Lose Win	-0.1149	0.0764	-0.1149	0.0764
		Predicted Win	-0.1016	0.0745	-0.1017	0.0745
		Predicted Close	-0.0425	0.0505	-0.0425	0.0505
		Predicted Lose	-0.0530	0.0584	-0.0530	0.0584
		Predicted Win Lose	-0.0887	0.1518	-0.0887	0.1518
	4–5 km	Predicted Close Lose	-0.0043	0.0597	-0.0043	0.0597
		Predicted Lose Win	-0.0509	0.0865	-0.0509	0.0865
		Predicted Win	-0.0620	0.0691	-0.0618	0.0691
		Predicted Close	-0.0294	0.0440	-0.0296	0.0440
		Predicted Lose	0.0250	0.0609	0.0250	0.0609
		Predicted Win Lose	0.1992	0.2345	0.1992	0.2346
Postgame 40	0–1 km	Predicted Close Lose	0.0249	0.0622	0.0252	0.0622
		Predicted Lose Win	-0.1584	0.0960	-0.1584	0.0960
		Predicted Win	-0.8501	0.2219	-0.8499	0.2219
		Predicted Close	-0.7002	0.1421	-0.7002	0.1421
		Predicted Lose	-0.5114	0.1185	-0.5114	0.1185
		Predicted Win Lose	0.8771	0.2230	0.8769	0.2230
	1–2 km	Predicted Close Lose	-0.0864	0.0514	-0.0864	0.0514
		Predicted Lose Win	-0.2007	0.0989	-0.2007	0.0989
		Predicted Win	-0.5325	0.1282	-0.5323	0.1282
		Predicted Close	-0.3399	0.0800	-0.3398	0.0800
		Predicted Lose	-0.1718	0.0861	-0.1716	0.0861
		Predicted Win Lose	0.2564	0.1475	0.2564	0.1475
	2–3 km	Predicted Close Lose	0.0432	0.0548	0.0432	0.0548
		Predicted Lose Win	-0.2619	0.0923	-0.2619	0.0923
		Predicted Win	-0.0511	0.0735	-0.0512	0.0735
		Predicted Close	-0.0056	0.0643	-0.0056	0.0643
		Predicted Lose	-0.0885	0.0649	-0.0885	0.0649
		Predicted Win Lose	-0.0093	0.1568	-0.0092	0.1568
		Predicted Close Lose	0.0422	0.0562	0.0422	0.0562
		Predicted Lose Win	-0.2211	0.0808	-0.2212	0.0807

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Time	Distance	Variable	With Crash	With Crash SE	No Crash	No Crash SE
Postgame 50	3–4 km	Predicted Win	-0.1279	0.0792	-0.1279	0.0792
		Predicted Close	-0.1001	0.0668	-0.1001	0.0668
		Predicted Lose	-0.0937	0.0674	-0.0937	0.0674
		Predicted Win Lose	-0.3027	0.1706	-0.3027	0.1706
		Predicted Close Lose	-0.0095	0.0595	-0.0093	0.0595
		Predicted Lose Win	0.1011	0.0946	0.1011	0.0945
	4–5 km	Predicted Win	-0.0926	0.0823	-0.0926	0.0824
		Predicted Close	-0.0309	0.0551	-0.0305	0.0551
		Predicted Lose	-0.0582	0.0660	-0.0583	0.0660
		Predicted Win Lose	-0.0736	0.1985	-0.0736	0.1985
		Predicted Close Lose	-0.0284	0.0501	-0.0286	0.0501
		Predicted Lose Win	0.0244	0.0803	0.0244	0.0803
	0–1 km	Predicted Win	-0.7988	0.1981	-0.7988	0.1981
		Predicted Close	-0.8089	0.1641	-0.8090	0.1641
		Predicted Lose	-0.7030	0.1350	-0.7031	0.1350
		Predicted Win Lose	0.2930	0.1941	0.2931	0.1941
		Predicted Close Lose	-0.0445	0.0487	-0.0445	0.0487
		Predicted Lose Win	-0.3215	0.1296	-0.3215	0.1296
	1–2 km	Predicted Win	-0.6843	0.1344	-0.6842	0.1344
		Predicted Close	-0.3893	0.1000	-0.3893	0.1000
		Predicted Lose	-0.2585	0.1034	-0.2584	0.1034
		Predicted Win Lose	0.1421	0.1574	0.1421	0.1574
		Predicted Close Lose	-0.0158	0.0539	-0.0159	0.0539
		Predicted Lose Win	-0.3754	0.1029	-0.3754	0.1029
	2–3 km	Predicted Win	-0.1652	0.0905	-0.1657	0.0905
		Predicted Close	-0.0323	0.0776	-0.0324	0.0776
		Predicted Lose	-0.2590	0.0876	-0.2589	0.0876
		Predicted Win Lose	0.1081	0.1301	0.1086	0.1299
		Predicted Close Lose	-0.0584	0.0606	-0.0584	0.0606
		Predicted Lose Win	-0.1095	0.0933	-0.1095	0.0933
	3–4 km	Predicted Win	-0.3433	0.1073	-0.3433	0.1073
		Predicted Close	-0.1237	0.0856	-0.1237	0.0856
		Predicted Lose	-0.1425	0.0764	-0.1424	0.0764
		Predicted Win Lose	-0.1193	0.1508	-0.1192	0.1508
		Predicted Close Lose	-0.1225	0.0653	-0.1225	0.0653
		Predicted Lose Win	0.1278	0.0916	0.1278	0.0916
	4–5 km	Predicted Win	-0.1143	0.0980	-0.1144	0.0980
		Predicted Close	-0.0333	0.0786	-0.0333	0.0786
		Predicted Lose	-0.1428	0.0666	-0.1428	0.0666
		Predicted Win Lose	-0.4241	0.1885	-0.4241	0.1885
		Predicted Close Lose	-0.0424	0.0524	-0.0424	0.0524
		Predicted Lose Win	-0.0357	0.0906	-0.0357	0.0906
Postgame 60	0–1 km	Predicted Win	-0.9740	0.2095	-0.9740	0.2095
		Predicted Close	-0.7737	0.1698	-0.7737	0.1698
		Predicted Lose	-0.8462	0.1435	-0.8462	0.1435
		Predicted Win Lose	0.8651	0.2565	0.8651	0.2565
		Predicted Close Lose	0.0150	0.0513	0.0150	0.0513
		Predicted Lose Win	-0.2996	0.1422	-0.2996	0.1422
	1–2 km	Predicted Win	-0.6628	0.1240	-0.6627	0.1240
		Predicted Close	-0.3324	0.1078	-0.3325	0.1078
		Predicted Lose	-0.3135	0.0936	-0.3134	0.0936
		Predicted Win Lose	0.2717	0.2139	0.2717	0.2139
		Predicted Close Lose	0.0383	0.0602	0.0385	0.0602
		Predicted Lose Win	-0.4565	0.0899	-0.4565	0.0899
	2–3 km	Predicted Win	-0.0803	0.0875	-0.0803	0.0875
		Predicted Close	-0.0288	0.0766	-0.0288	0.0766
		Predicted Lose	-0.3088	0.0852	-0.3088	0.0852
		Predicted Win Lose	0.0942	0.1383	0.0942	0.1383
		Predicted Close Lose	-0.0157	0.0539	-0.0159	0.0540
		Predicted Lose Win	-0.1646	0.0968	-0.1646	0.0968
	3–4 km	Predicted Win	-0.4280	0.1258	-0.4280	0.1258
		Predicted Close	-0.1266	0.0903	-0.1267	0.0903
		Predicted Lose	-0.1621	0.0776	-0.1622	0.0776
		Predicted Win Lose	-0.0871	0.1854	-0.0871	0.1854
		Predicted Close Lose	-0.1464	0.0595	-0.1463	0.0595
		Predicted Lose Win	0.0004	0.0942	0.0004	0.0942
	4–5 km	Predicted Win	-0.1120	0.1185	-0.1119	0.1185
		Predicted Close	-0.0041	0.0898	-0.0043	0.0898
		Predicted Lose	-0.1306	0.0777	-0.1306	0.0777
		Predicted Win Lose	-0.5094	0.2825	-0.5094	0.2825
		Predicted Close Lose	-0.1060	0.0603	-0.1060	0.0603
		Predicted Lose Win	-0.0425	0.0887	-0.0425	0.0887
Postgame 70	0–1 km					

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Time	Distance	Variable	With Crash	With Crash SE	No Crash	No Crash SE
Postgame 80	1–2 km	Predicted Win	-0.8973	0.2026	-0.8973	0.2026
		Predicted Close	-0.5741	0.1276	-0.5741	0.1276
		Predicted Lose	-0.7831	0.1245	-0.7831	0.1245
		Predicted Win Lose	0.8679	0.2034	0.8679	0.2034
		Predicted Close Lose	-0.1210	0.0508	-0.1210	0.0508
		Predicted Lose Win	-0.3517	0.1500	-0.3517	0.1500
	2–3 km	Predicted Win	-0.4839	0.1183	-0.4838	0.1183
		Predicted Close	-0.2070	0.0949	-0.2069	0.0949
		Predicted Lose	-0.2780	0.0825	-0.2779	0.0825
		Predicted Win Lose	0.3298	0.2345	0.3298	0.2344
		Predicted Close Lose	-0.0599	0.0618	-0.0599	0.0618
		Predicted Lose Win	-0.4956	0.0982	-0.4956	0.0982
	3–4 km	Predicted Win	-0.1473	0.1059	-0.1472	0.1059
		Predicted Close	-0.0025	0.0646	-0.0024	0.0646
		Predicted Lose	-0.3389	0.0722	-0.3389	0.0722
		Predicted Win Lose	0.1636	0.1700	0.1636	0.1700
		Predicted Close Lose	-0.0969	0.0547	-0.0973	0.0547
		Predicted Lose Win	-0.2655	0.1104	-0.2655	0.1104
	4–5 km	Predicted Win	-0.4515	0.1182	-0.4515	0.1182
		Predicted Close	-0.0451	0.0924	-0.0451	0.0924
		Predicted Lose	-0.0995	0.0713	-0.0995	0.0713
		Predicted Win Lose	0.3129	0.1806	0.3129	0.1806
		Predicted Close Lose	-0.2334	0.0551	-0.2334	0.0551
		Predicted Lose Win	-0.2944	0.0935	-0.2944	0.0935
		Predicted Win	-0.0857	0.1134	-0.0857	0.1134
		Predicted Close	-0.0251	0.1068	-0.0251	0.1068
		Predicted Lose	-0.1012	0.0722	-0.1012	0.0722
		Predicted Win Lose	-0.4692	0.2622	-0.4692	0.2622
		Predicted Close Lose	-0.0894	0.0725	-0.0894	0.0725
		Predicted Lose Win	-0.2028	0.0922	-0.2028	0.0922
Postgame 90	0–1 km	Predicted Win	-0.7388	0.1887	-0.7388	0.1887
		Predicted Close	-0.1809	0.0736	-0.1808	0.0736
		Predicted Lose	-0.4795	0.0695	-0.4794	0.0695
		Predicted Win Lose	0.1336	0.1711	0.1336	0.1711
		Predicted Close Lose	-0.2631	0.0583	-0.2631	0.0583
		Predicted Lose Win	-0.6031	0.1376	-0.6031	0.1376
	1–2 km	Predicted Win	-0.4769	0.1142	-0.4767	0.1142
		Predicted Close	-0.0857	0.0644	-0.0855	0.0644
		Predicted Lose	-0.2309	0.0637	-0.2308	0.0636
		Predicted Win Lose	0.4423	0.1596	0.4424	0.1596
		Predicted Close Lose	-0.1277	0.0512	-0.1280	0.0511
		Predicted Lose Win	-0.4507	0.0956	-0.4506	0.0956
	2–3 km	Predicted Win	-0.2077	0.0884	-0.2085	0.0887
		Predicted Close	-0.0055	0.0563	-0.0054	0.0563
		Predicted Lose	-0.2532	0.0631	-0.2532	0.0631
		Predicted Win Lose	0.2575	0.1718	0.2549	0.1713
		Predicted Close Lose	-0.0935	0.0483	-0.0935	0.0483
		Predicted Lose Win	-0.2785	0.0967	-0.2798	0.0969
	3–4 km	Predicted Win	-0.3910	0.1207	-0.3909	0.1207
		Predicted Close	-0.0902	0.0888	-0.0901	0.0888
		Predicted Lose	-0.1296	0.0680	-0.1294	0.0680
		Predicted Win Lose	0.4540	0.1986	0.4540	0.1986
		Predicted Close Lose	-0.1796	0.0582	-0.1796	0.0582
		Predicted Lose Win	-0.2795	0.0947	-0.2794	0.0947
	4–5 km	Predicted Win	-0.0063	0.1135	-0.0063	0.1135
		Predicted Close	-0.1467	0.0968	-0.1467	0.0968
		Predicted Lose	-0.1322	0.0740	-0.1322	0.0740
		Predicted Win Lose	-0.1610	0.2557	-0.1610	0.2557
		Predicted Close Lose	-0.0234	0.0788	-0.0233	0.0789
		Predicted Lose Win	-0.1634	0.0969	-0.1634	0.0969
	0–1 km	Predicted Win	-0.6591	0.1670	-0.6590	0.1670
		Predicted Close	-0.0920	0.0558	-0.0920	0.0558
		Predicted Lose	-0.2771	0.0556	-0.2771	0.0556
		Predicted Win Lose	-0.0732	0.2064	-0.0732	0.2064
		Predicted Close Lose	-0.1838	0.0588	-0.1838	0.0588
		Predicted Lose Win	-0.8416	0.1452	-0.8416	0.1452
	1–2 km	Predicted Win	-0.4184	0.1050	-0.4185	0.1050
		Predicted Close	-0.1405	0.0530	-0.1406	0.0530
		Predicted Lose	-0.1882	0.0587	-0.1882	0.0587
		Predicted Win Lose	-0.0512	0.1770	-0.0512	0.1770
		Predicted Close Lose	-0.1474	0.0534	-0.1474	0.0534
		Predicted Lose Win	-0.4300	0.0899	-0.4300	0.0899
	2–3 km	Predicted Win	-0.2475	0.0845	-0.2474	0.0845
		Predicted Close	-0.0095	0.0481	-0.0099	0.0481

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Time	Distance	Variable	With Crash	With Crash SE	No Crash	No Crash SE
Postgame 100	3–4 km	Predicted Lose	-0.2941	0.0573	-0.2939	0.0573
		Predicted Win Lose	0.0176	0.1446	0.0176	0.1446
		Predicted Close Lose	-0.0853	0.0576	-0.0846	0.0577
		Predicted Lose Win	-0.3501	0.0928	-0.3524	0.0928
		Predicted Win	-0.3598	0.1104	-0.3597	0.1104
		Predicted Close	-0.1178	0.0678	-0.1179	0.0678
	4–5 km	Predicted Lose	-0.1865	0.0581	-0.1864	0.0581
		Predicted Win Lose	0.1810	0.1613	0.1793	0.1611
		Predicted Close Lose	-0.0543	0.0660	-0.0541	0.0660
		Predicted Lose Win	-0.2353	0.1021	-0.2353	0.1021
		Predicted Win	-0.1066	0.0951	-0.1067	0.0951
		Predicted Close	-0.1759	0.0787	-0.1756	0.0786
	0–1 km	Predicted Lose	-0.1262	0.0561	-0.1263	0.0561
		Predicted Win Lose	-0.0548	0.1671	-0.0548	0.1671
		Predicted Close Lose	0.0173	0.0705	0.0170	0.0704
		Predicted Lose Win	-0.1573	0.0809	-0.1573	0.0809
		Predicted Win	-0.5918	0.1435	-0.5915	0.1434
		Predicted Close	-0.0292	0.0421	-0.0293	0.0421
	1–2 km	Predicted Lose	-0.3788	0.0551	-0.3786	0.0551
		Predicted Win Lose	0.6144	0.2402	0.6140	0.2402
		Predicted Close Lose	-0.2005	0.0736	-0.2004	0.0736
		Predicted Lose Win	-0.3086	0.0908	-0.3088	0.0908
		Predicted Win	-0.3623	0.0876	-0.3622	0.0876
		Predicted Close	-0.0611	0.0515	-0.0611	0.0515
	2–3 km	Predicted Lose	-0.2348	0.0611	-0.2347	0.0612
		Predicted Win Lose	0.0370	0.1441	0.0370	0.1441
		Predicted Close Lose	-0.1056	0.0465	-0.1057	0.0465
		Predicted Lose Win	-0.2427	0.0729	-0.2427	0.0729
		Predicted Win	-0.1894	0.0824	-0.1892	0.0824
		Predicted Close	-0.0697	0.0445	-0.0707	0.0445
	3–4 km	Predicted Lose	-0.2451	0.0578	-0.2449	0.0578
		Predicted Win Lose	0.0447	0.1380	0.0447	0.1380
		Predicted Close Lose	0.0434	0.0517	0.0435	0.0517
		Predicted Lose Win	-0.1443	0.0875	-0.1443	0.0875
		Predicted Win	-0.2701	0.0940	-0.2701	0.0940
		Predicted Close	-0.1318	0.0590	-0.1317	0.0590
	4–5 km	Predicted Lose	-0.1322	0.0583	-0.1322	0.0583
		Predicted Win Lose	-0.2579	0.2093	-0.2578	0.2093
		Predicted Close Lose	0.1415	0.0693	0.1415	0.0693
		Predicted Lose Win	-0.0619	0.1015	-0.0618	0.1015
		Predicted Win	-0.0283	0.1016	-0.0284	0.1016
		Predicted Close	-0.1523	0.0622	-0.1523	0.0622
Postgame 110	0–1 km	Predicted Lose	-0.2014	0.0567	-0.2008	0.0567
		Predicted Win Lose	-0.0714	0.2448	-0.0715	0.2448
		Predicted Close Lose	0.1243	0.0725	0.1243	0.0725
		Predicted Lose Win	0.1018	0.0943	0.1012	0.0944
		Predicted Win	-0.4326	0.1490	-0.4326	0.1490
		Predicted Close	0.1681	0.0472	0.1681	0.0472
	1–2 km	Predicted Lose	-0.2569	0.0659	-0.2569	0.0659
		Predicted Win Lose	0.3865	0.1782	0.3865	0.1782
		Predicted Close Lose	-0.1467	0.0537	-0.1467	0.0537
		Predicted Lose Win	-0.1549	0.1263	-0.1549	0.1263
		Predicted Win	-0.1091	0.0880	-0.1095	0.0881
		Predicted Close	0.2051	0.0551	0.2050	0.0551
	2–3 km	Predicted Lose	0.0054	0.0685	0.0054	0.0685
		Predicted Win Lose	0.1112	0.1312	0.1117	0.1312
		Predicted Close Lose	-0.0322	0.0511	-0.0321	0.0511
		Predicted Lose Win	-0.2109	0.0883	-0.2109	0.0883
		Predicted Win	-0.0341	0.0937	-0.0340	0.0937
		Predicted Close	0.0816	0.0602	0.0817	0.0601
	3–4 km	Predicted Lose	-0.0177	0.0646	-0.0196	0.0651
		Predicted Win Lose	0.2599	0.1491	0.2598	0.1491
		Predicted Close Lose	0.2011	0.0795	0.2010	0.0795
		Predicted Lose Win	0.0681	0.0781	0.0702	0.0780
		Predicted Win	0.0772	0.0976	0.0773	0.0976
		Predicted Close	0.2311	0.0502	0.2312	0.0502
	4–5 km	Predicted Lose	0.1916	0.0607	0.1917	0.0607
		Predicted Win Lose	-0.2480	0.2397	-0.2480	0.2397
		Predicted Close Lose	0.0846	0.0640	0.0846	0.0640
		Predicted Lose Win	-0.0048	0.0860	-0.0048	0.0860
		Predicted Win	0.0905	0.1043	0.0906	0.1043
		Predicted Close	0.1360	0.0605	0.1360	0.0605
		Predicted Lose	0.0994	0.0597	0.0994	0.0597
		Predicted Win Lose	0.1051	0.2517	0.1051	0.2517

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Time	Distance	Variable	With Crash	With Crash SE	No Crash	No Crash SE
Postgame 120		Predicted Close Lose	0.0932	0.0661	0.0932	0.0661
		Predicted Lose Win	0.1604	0.0949	0.1604	0.0949
	0–1 km	Predicted Win	-0.2770	0.1373	-0.2770	0.1373
		Predicted Close	0.2945	0.0465	0.2945	0.0465
		Predicted Lose	-0.1321	0.0787	-0.1321	0.0787
		Predicted Win Lose	0.6209	0.2623	0.6209	0.2623
		Predicted Close Lose	0.1057	0.0661	0.1057	0.0661
		Predicted Lose Win	0.2636	0.1058	0.2636	0.1058
	1–2 km	Predicted Win	0.0270	0.0820	0.0269	0.0821
		Predicted Close	0.3405	0.0572	0.3405	0.0572
		Predicted Lose	0.1747	0.0682	0.1747	0.0681
		Predicted Win Lose	0.1550	0.1324	0.1552	0.1324
		Predicted Close Lose	0.2050	0.0510	0.2049	0.0511
		Predicted Lose Win	0.2351	0.0831	0.2351	0.0831
	2–3 km	Predicted Win	-0.0785	0.0811	-0.0783	0.0811
		Predicted Close	0.3606	0.0521	0.3600	0.0524
		Predicted Lose	0.2293	0.0632	0.2294	0.0632
		Predicted Win Lose	0.2665	0.1557	0.2666	0.1557
		Predicted Close Lose	0.2810	0.0562	0.2816	0.0566
		Predicted Lose Win	0.2970	0.0798	0.2970	0.0798
	3–4 km	Predicted Win	0.0995	0.0668	0.0996	0.0668
		Predicted Close	0.3103	0.0568	0.3102	0.0568
		Predicted Lose	0.4063	0.0735	0.4064	0.0735
		Predicted Win Lose	-0.3671	0.2508	-0.3671	0.2508
		Predicted Close Lose	0.3332	0.0539	0.3333	0.0539
		Predicted Lose Win	0.3207	0.0904	0.3206	0.0904
	4–5 km	Predicted Win	0.1083	0.0723	0.1084	0.0723
		Predicted Close	0.3241	0.0663	0.3241	0.0663
		Predicted Lose	0.2320	0.0725	0.2321	0.0725
		Predicted Win Lose	0.0225	0.2727	0.0225	0.2727
		Predicted Close Lose	0.1813	0.0699	0.1808	0.0698
		Predicted Lose Win	0.3969	0.0864	0.3968	0.0864

Notes: This table reports the coefficients corresponding to Figure 2. For brevity, coefficients for crash, weather, holiday, season dummy, and day-of-week dummy indicators are omitted; this amounts to 1,980 omitted coefficients across the 180 regressions reported in the table. Predicted win indicates a point spread of –6.75 or less (negative spreads indicate the number of points a team is expected to win by); predicted close indicates a point spread between –6.75 and +4.75 exclusive; and predicted loss indicates a spread of +4.75 or more. The sample is limited to regular-season NBA games between the 2015/16 and 2018/19 seasons, encompassing four total seasons. The analysis includes home games played by Florida’s two NBA teams—the Miami Heat and the Orlando Magic—with scheduled tip-off times of 6:00 PM or later. Regressions include TMC-code fixed effects, as well as month time fixed effects, season dummies, and day-of-week dummies to control for temporal variation. Standard errors are clustered at the TMC-code level. Average vehicle speed represents observed speed across road links within 5 km of each arena, broken up into 1-km distance bands, measured in 10-minute intervals from 60 minutes before to 120 minutes after each game.

Table A.5

Wild cluster bootstrap p-values for key parameters at 2–3 km distance band

Post-game window	Predicted close $\times$ lose		Predicted lose $\times$ win		Predicted win $\times$ lose	
	p (entity)	p (boot)	p (entity)	p (boot)	p (entity)	p (boot)
+10 min	0.029	0.246	0.013	0.005	0.000	0.000
+20 min	0.013	0.100	0.057	0.006	0.000	0.000
+30 min	0.195	0.135	0.876	0.000	0.000	0.000
+40 min	0.083	0.073	0.004	0.000	0.000	0.000
+50 min	0.034	0.022	0.002	0.000	0.000	0.000
+60 min	0.010	0.010	0.001	0.000	0.000	0.000
+70 min	0.000	0.000	0.012	0.000	0.000	0.000
+80 min	0.000	0.000	0.004	0.000	0.000	0.000
+90 min	0.000	0.000	0.082	0.000	0.000	0.000
+100 min	0.000	0.006	0.141	0.000	0.000	0.000
+110 min	0.000	0.068	0.623	0.000	0.000	0.000
+120 min	0.000	0.340	0.192	0.000	0.000	0.000

Notes: The table reports entity-clustered p-values and wild cluster bootstrap p-values for the three key outcome interaction parameters at the 2–3 km distance band across all post-game time windows. Bootstrap p-values are based on 999 replications using Rademacher weights, bootstrap type ‘11’ (CRV1), with the null imposed, clustered at the TMC-code level. The main model specification is used throughout: entity fixed effects (TMC-code), week-of-season time fixed effects, season dummies, and entity-clustered standard errors. The sample is limited to Sundays during the regular-season home games for Florida’s three NFL teams across the 2015–2019 seasons, excluding the 2018 and 2019 Miami Dolphins seasons, resulting in 84 Sunday home games. With crash dummy included.

5 Discussion

The three empirical studies presented in Chapter 4 provide new evidence on how belief dynamics in sport, through suspense, surprise, and expectation violations, shape consumer demand and behavior. In the following section, the empirical findings and their theoretical implications are summarized and discussed (Section 5.1). This is followed by a discussion of the practical implications for broadcasters, league organizers, and public safety policy (Section 5.2), and finally by an account of the limitations of the studies and the directions for possible future research (Section 5.3).

5.1 Central findings and theoretical contributions

Study 1 and Study 2 examine the entertainment utility generated by belief dynamics within and across football competitions, drawing on minute-by-minute television audience data for the UEFA Champions League and on match-level suspense and surprise computed for more than 25,000 matches across Europe's top five leagues. Study 3 turns to the behavioral consequences of belief dynamics beyond the stadium, using fine-grained vehicle speed data around professional sports venues in Florida. Overall, the studies show that belief dynamics in sport generate consequences at every level of the chain this dissertation has traced: within the live event, across competitions and seasons, and into everyday behavior. These findings, and their theoretical implications, are discussed in turn in the following sections (5.1.1–5.1.4).

5.1.1 Suspense and surprise as drivers of real-time demand

Study 1 examines whether suspense, surprise, and shock drive minute-by-minute television demand for UEFA Champions League matches, and whether these effects differ across the contrasting TV markets of the United Kingdom and Spain. The results show that suspense and surprise are significant drivers of TV audience viewership size in both markets, while shock plays only a marginal role, reaching significance only in the Spanish market. An increase of one standard deviation in suspense raises audience size by

approximately 1.4% in the United Kingdom and 2.9% in Spain, whereas the corresponding effect of surprise is considerably smaller in both markets. Study 1 thus confirms, in a supranational competition and across two distinct national audiences, the central empirical regularity established in earlier single-market settings: that the belief dynamics generated within a match, rather than static pre-match uncertainty, drive real-time consumer demand.

Beyond confirming the framework in a new setting, the cross-market comparison reveals that the magnitude of these effects depends on market context. The effect of suspense in both markets is larger than that estimated for Wimbledon tennis, while the effect of surprise is smaller (Bizzozero et al., 2016). When the joint effect of suspense and surprise is considered, the estimate for the Spanish market is close to that reported for Wimbledon, whereas the estimate for the United Kingdom is similar to that reported for the English Premier League (Buraimo et al., 2020). The relative weight of the two emotions is therefore not fixed but varies with the audience and the competition, a finding that the comparison across two markets watching the same matches was uniquely able to surface. To convey the economic magnitude of these effects, scenario simulations show that a match ending in an underdog win can attract on the order of 89,500 more viewers per minute than one ending in a dominant favorite-team win, underscoring that belief dynamics carry consequences of real commercial significance for broadcasters.

The marginal role of shock is, itself, informative. Shock captures the deviation of current outcome probabilities from pre-match expectations, whereas suspense and surprise capture, respectively, the anticipation of the next moment and the revision of beliefs from one moment to the next. That suspense and surprise drive demand while shock does not points to the moment-to-moment evolution of beliefs during a contest, rather than the cumulative departure from pre-match expectations, as the potential source of the effect. This distinction reinforces the central argument of this dissertation: that what matters is not how far a contest has strayed from its pre-match script, but how beliefs move as the contest is experienced.

5.1.2 Suspense and surprise as policy diagnostics for competition attractiveness

Study 2 develops match-level suspense and surprise into diagnostic tools for evaluating the attractiveness of competitions, and applies them to more than 25,000 matches across Europe's top five leagues. The simulation analysis at the heart of the study reveals a trade-off between the two measures even in perfectly balanced matches: suspense tends to be higher at lower scoring rates, while surprise increases with higher scoring rates. A further simulation result is central to interpreting the empirical findings, namely that suspense is substantially more sensitive to team-strength imbalance than surprise. This explains the headline empirical pattern: across the five leagues, mean suspense is commonly below the benchmark range, particularly in matches involving top teams, whereas mean surprise most often remains within the benchmark. The asymmetry should not be read as evidence that surprise matters more to consumers than suspense; rather, the two respond differently to scoring rates and to competitive imbalance.

The trend analysis yields the study's most policy-relevant contribution. In contrast to studies reporting a general decline in competitive balance in European football, Study 2 finds no such uniform decline when measured through suspense and surprise. Instead, the trends differ markedly across leagues and, in several cases, are attributable to matches involving only one or two clubs. The clearest case is the English Premier League, where the overall decline in suspense is driven entirely by matches involving Manchester City, an additional decline of roughly 3.8% per season relative to the baseline, while matches involving other clubs show little change. Other leagues diverge sharply: France's Ligue 1 follows the same single-club pattern around Paris Saint-Germain, whereas Spain's La Liga runs in the opposite direction, with a rising trend most pronounced in matches involving Real Madrid and Barcelona; the Bundesliga and Serie A show only modest or mutually offsetting movements, not traceable to their dominant clubs. The full club- and league-level estimates are reported in Study 2; what matters for the present argument is the shape of the picture — heterogeneous, frequently single-club-driven, and inconsistent with a uniform decline — rather than any individual coefficient.

These patterns carry a clear methodological lesson. A single league-level index would have reported only the aggregate trend and obscured the fact that it is frequently the product of one or two clubs, whereas the bottom-up construction of suspense and surprise allows the source of a trend to be located rather than merely observed. This is the sense in which the measures function as more informative diagnostics than the traditional measures computed from final standings. At the same time, Study 2 is careful about the policy conclusion it draws. The persistently lower suspense and surprise generated by dominant clubs do not currently appear to reduce overall sporting interest, an effect that may be offset by influences such as star appeal or the quality of play. Moreover, dominance is only partially reflected in the measures, which continue to exhibit substantial match-level variation, plausibly because of the low-scoring nature of football, in which chance plays a significant role. The study therefore concludes that the current levels of suspense and surprise in men's football do not suggest an urgent need for regulatory intervention, while noting that continued monitoring may be warranted given the downward trends for certain clubs and the persistently low levels in matches involving others.

5.1.3 Expectation violations and behavioral spillovers beyond sport

Study 3 moves beyond the sporting event itself to ask whether the emotions generated by game outcomes spill over into real-world behavior, using vehicle speed data around five Florida stadiums. The strongest and most consistent effect occurs after NFL games that were predicted to be close but ended in a disappointing home-team loss, the profile combining sustained pre-game suspense with negative outcome valence. In the first hour after the game and within 3 km of the stadium, average speeds following predicted-close losses exceed those following predicted-close wins by as much as 3 mph, an effect that fades as time passes and distance from the venue grows. Against a baseline difference of less than 1 mph between game days and non-game days, this 3 mph increase is several times larger than the typical game-day deviation. A smaller and less precise positive effect appears following upset wins, the surprise and positive-valence profile, while no consistent pattern emerges for upset losses; given the small number of upset games in the sample, however, the study refrains from concluding that upset losses produce no such effect.

No emotional driving effect is found for NBA games across any expectation-outcome profile. The study is careful not to interpret this as evidence that NBA games generate weaker emotions among fans. Rather, the absence of a detectable effect is attributed to structural differences between the two settings: NBA attendance is far lower than NFL attendance, the arenas sit in denser urban environments with limited road capacity and lower average speeds, and the higher game frequency may reduce the emotional weight of any single result.

The interpretation of the NFL result rests on the same belief-dynamics logic that runs through the dissertation. Within the expectations-based reference framework of Kőszegi and Rabin (2006), a predicted-close contest generates strong expectations on both sides of the reference point, and a narrow home-team loss represents the negative resolution of a high-suspense event, combining sustained arousal with a disappointing outcome in a way that lopsided losses do not. The Yerkes and Dodson (1908) law, under which performance deteriorates at high levels of arousal, offers a reason why the largest behavioral response appears in these close, disappointing losses rather than in less competitive contests. The findings also broaden the interpretation of earlier traffic-safety evidence. Wood et al. (2011) associate closely contested games with adverse outcomes around winning markets, whereas the present results indicate that unfavorable resolutions may matter as well. Read together, the studies imply that post-event traffic risk cannot be reduced to celebration following victory; intense contests may produce different forms of affective carryover depending on how they conclude.

A complementary crash analysis reinforces the speed findings. Post-game crash counts on game days are elevated relative to matched non-game days, and the increase is larger following losses than wins, consistent with the interpretation that the speed increases documented for disappointing losses carry a genuine safety cost. Taken together, Study 3 provides the first fine-grained behavioral evidence that the belief dynamics of sport spill over past the stadium: the same combination of sustained suspense and outcome valence that, in Studies 1 and 2, shaped what spectators watch and how attractive competitions are, here shapes how people drive once the game is over.

5.1.4 The cumulative argument

Taken individually, each of the three studies answers a self-contained question. Taken together, they make a single argument: that the belief dynamics generated by sporting contests, through suspense, surprise, and expectation violations, produce measurable consequences at every level from the individual viewer to society at large. This is the central claim of the dissertation, and it is the joint achievement of the three studies rather than of any one of them.

The argument unfolds across three levels of consequence. At the level of the live event, Study 1 shows that suspense and surprise drive demand minute by minute, as viewers respond in real time to how the outcome of a match evolves. At the level of the competition, Study 2 shows that the same constructs, aggregated across thousands of matches and many seasons, capture how much entertainment value a league actually delivers and how that value is changing over time, turning a measure of individual experience into a diagnostic for competition policy. At the level of behavior beyond the stadium, Study 3 shows that when the belief dynamics of a contest resolve into a disappointing outcome, their emotional residue does not end at the final whistle but follows the spectator into the world, measurably altering how people drive in the minutes and kilometers after the game.

What unifies the three is not merely a shared vocabulary but a shared mechanism: in each study, it is the movement and resolution of beliefs about an uncertain outcome, rather than any static property of the contest fixed before it begins, that does the explanatory work. How these beliefs are measured shifts across the studies: Studies 1 and 2 use formal, minute-level suspense and surprise, while Study 3, lacking such measures, captures the resolution of a pre-game expectation through the betting spread. The object being measured, however, is the same throughout: those beliefs, and the utility and behavior they generate as they are held, revised, and resolved. Suspense, the anticipation of an unresolved outcome, and surprise, the revision of beliefs as events unfold, drive what spectators watch and how attractive competitions are; and when a high-suspense contest ends in disappointment, the same family of belief dynamics spills over into risky behavior on the road. The progression from Study 1 to Study 3 traces these dynamics outward

from the screen, to the league, to everyday life, and shows that they remain consequential at each step.

5.2 Practical implications

The findings of the three studies carry practical implications for three sets of decision-makers: broadcasters and advertisers, league organizers and policymakers, and public safety authorities.

For broadcasters and advertisers, Study 1 shows that audiences respond to suspense and surprise as a match unfolds, which bears directly on the timing of advertising and sponsorship. Advertisers may benefit from the heightened viewership that follows surprising moments and accompanies suspenseful passages of play, and broadcasters need not avoid scheduling matches with a clear favorite, since the possibility of an upset still generates demand. The relevant signal for programming and ad placement is not the pre-match expectation of a close contest, but the belief dynamics that develop during the game itself.

For league organizers and policymakers, Study 2 reframes suspense and surprise as monitoring tools for the attractiveness of competitions. Three implications follow. First, interventions intended to improve attractiveness should account for the trade-off between the two measures, since equalizing team strengths may raise suspense but reduce surprise depending on the level of scoring. Second, league-wide trends can obscure club-level patterns, so monitoring should examine individual clubs and not only aggregate competitions, given that an observed league trend is often the product of one or two clubs. Third, because dominance is only partially reflected in suspense and surprise, and because current levels do not appear to be reducing overall sporting interest, the evidence does not support an urgent case for regulatory intervention in men's football, though continued monitoring of specific clubs is warranted.

For public safety authorities, Study 3 shows that the elevated driving risk following emotionally intense games is predictable in both time and space, concentrated within three kilometers of the stadium and in the first post-game hour, and especially after games

expected to be close. This predictability is what makes intervention feasible. For public-safety authorities, the principal implication of Study 3 is that any additional traffic risk associated with emotionally intense games appears to be geographically and temporally concentrated. This makes event-specific prevention more plausible than broad, permanent intervention. Local authorities could consider whether existing post-event traffic-management plans should be intensified after contests expected to generate strong crowd reactions, while future research should test which interventions actually change driver behavior before specific measures are recommended. Measures that give emotionally aroused fans time to settle before driving, such as designated waiting areas or expanded public and shared transport on game days, could reduce the number of affected drivers on the road immediately after a game.

Across all three, the practical lesson is the same: because belief dynamics in sport are measurable and, in their consequences, predictable in time and place, the parties affected by them, from broadcasters to league regulators to traffic authorities, can anticipate and respond to them rather than treat them as noise.

5.3 Limitations and future research

Each of the three studies has limitations that qualify its conclusions and point toward future research.

Study 1 draws on television audience data from two markets and a single competition, the UEFA Champions League, and its findings reflect the structure and audience of that competition. The analysis observes aggregate audience size rather than individual viewers, so it identifies how belief dynamics move demand without observing the responses of individual consumers.

Study 2 measures suspense and surprise only at the match level, capturing short-term dynamics rather than the medium-term tension of a title or relegation race; extending the measures to beliefs about league outcomes is a natural next step. The benchmark ranges it derives are theory-based and have not been validated directly against consumer demand, leaving open whether the levels fans most value coincide with the benchmark.

The in-play model also rests on betting odds and incorporates only goals and red cards, omitting other in-game events that could refine the measures, and it adopts a neutral perspective that does not account for the emotional attachment of fans to particular clubs.

Study 3 does not observe individual drivers, their attendance at the game, or their emotional state, so its estimates capture reduced-form changes in local traffic behavior rather than individual emotional responses, and average speed can move for reasons other than intentional speeding. Some of its interaction cells are small, with only five upset losses and six upset wins, making inference for those profiles exploratory rather than confirmatory, while the predicted-close loss finding rests on a firmer base of games. Its findings are also specific to Florida teams in the 2015 to 2019 regular seasons and may not extend to other markets or to higher-stakes postseason settings.

As set out in Section 1.2, the dissertation measures belief dynamics with deliberately different precision across its three levels: Studies 1 and 2 compute suspense and surprise formally from in-play outcome probabilities, whereas Study 3, operating in a setting without minute-by-minute measures, proxies anticipated suspense with the pre-game betting spread. Bringing formal, minute-level suspense and surprise measures to behavioral settings beyond the screen is therefore a promising direction for future work, as is extending the framework to women's football, to other sports, and to the medium-term dynamics of season-long competition.

6 Conclusion

This dissertation set out to show that belief dynamics in sport, through suspense, surprise, and expectation violations, generate measurable consequences at multiple levels, from the moment-by-moment behavior of individual television viewers, to the attractiveness of league competitions over time, to behavioral spillovers into everyday life beyond the stadium. Three empirical studies make this case across distinct settings, methods, and outcomes.

Study 1 establishes suspense and surprise as the primary drivers of real-time television demand in the UEFA Champions League, and shows that their relative weight varies across viewer markets. Study 2 develops the same constructs into diagnostics for competition attractiveness, revealing trends across European football that are heterogeneous and often driven by a small number of clubs, which traditional CB measures cannot detect. Study 3 shows that when sustained pre-game suspense resolves into a disappointing loss, the emotional residue spills over into riskier post-game driving, with direct implications for public safety.

The central contribution is to demonstrate that belief dynamics operate across all three levels: within contests, across competitions, and beyond the sporting context entirely. In doing so, the dissertation connects a formal account of the utility generated by the movement of beliefs to the behavioral economics of expectation, disappointment, and arousal, and offers broadcasters, league organizers, and public safety authorities a set of empirically grounded tools for anticipating and responding to the consequences of belief dynamics in sport.

Sporting contests generate belief dynamics that matter — for how we watch, for how leagues are designed, and for what happens when the game is over.

References

- Antony, J. W., Hartshorne, T. H., Pomeroy, K., Gureckis, T. M., Hasson, U., McDougle, S. D., & Norman, K. A. (2021). Behavioral, physiological, and neural signatures of surprise during naturalistic sports viewing. *Neuron*, 109(2), 377–390.
- Avila-Cano, A., & Triguero-Ruiz, F. (2023). On the control of competitive balance in the major european football leagues. *Managerial and Decision Economics*, 44(2), 1254–1263.
- Basini, F., Tsouli, V., Ntzoufras, I., & Friel, N. (2023). Assessing competitive balance in the english premier league for over forty seasons using a stochastic block model. *Journal of the Royal Statistical Society Series A*, 186(3), 530–556.
- Bee, C. C., & Madrigal, R. (2012). It's not whether you win or lose; it's how the game is played. *Journal of Advertising*, 41(1), 47–58.
- Bizzozero, P., Flepp, R., & Franck, E. (2016). The importance of suspense and surprise in entertainment demand: Evidence from wimbledon. *Journal of Economic Behavior & Organization*, 130, 47–63.
- Borland, J., & MacDonald, R. (2003). Demand for sport. *Oxford Review of Economic Policy*, 19(4), 478–502.
- Braun, M., Weber, F., & Alt, F. (2021). Affective automotive user interfaces: Reviewing the state of driver affect research and emotion regulation in the car. *ACM Computing Surveys*, 54(7), 1–26.
- Breuer, C., Rumpf, C., & Boronczyk, F. (2020). Sponsor message processing in live broadcasts: A pilot study on the role of game outcome uncertainty and emotions. *Psychology & Marketing*, 38(5), 896–907.
- Bromberg-Martin, E. S., & Hikosaka, O. (2009). Midbrain dopamine neurons signal preference for advance information about upcoming rewards. *Neuron*, 63(1), 119–126.
- Budzinski, O. (2012). The institutional framework for doing sports business: Principles of eu competition policy in sports markets. *International Journal of Sport Management and Marketing*, 11(1–2), 44–72.
- Buraimo, B., Forrest, D., McHale, I. G., & Tena, J. D. (2020). Unscripted drama: Soccer audience response to suspense, surprise, and shock. *Economic Inquiry*, 58(2), 881–

896.

- Buraimo, B., & Simmons, R. (2008). Do sports fans really value uncertainty of outcome? evidence from the english premier league. *International Journal of Sport Finance*, 3(3), 146–155.
- Buraimo, B., & Simmons, R. (2009). A tale of two audiences: Spectators, television viewers and outcome uncertainty in spanish football. *Journal of Economics and Business*, 61(4), 326–338.
- Buraimo, B., & Simmons, R. (2015). Uncertainty of outcome or star quality? television audience demand for english premier league football. *International Journal of the Economics of Business*, 22(3), 449–469.
- Cairns, J., Jennett, N., & Sloane, P. J. (1986). The economics of professional team sports: A survey of theory and evidence. *Journal of Economic Studies*, 13, 3–80.
- Card, D., & Dahl, G. B. (2011). Family violence and football: The effect of unexpected emotional cues on violent behavior. *The Quarterly Journal of Economics*, 126(1), 103–143.
- Cardazzi, A. J., McCannon, B. C., Humphreys, B. R., & Rodriguez, Z. (2024). Emotional cues and violent behavior: Unexpected basketball losses increase incidents of family violence. *Journal of Law, Economics, and Organization*, 40(2), 267–288.
- Coates, D., Humphreys, B. R., & Zhou, L. (2014). Reference-dependent preferences, loss aversion, and live game attendance. *Economic Inquiry*, 52(3), 959–973.
- Collins, C., & Humphreys, B. R. (2022). Contest outcome uncertainty and fan decisions: A meta-analysis. *Journal of Sports Economics*, 23(6), 789–807.
- Csató, L., & Petróczy, D. G. (2025). Competitive balance in the uefa champions league group stage: Novel measures show no evidence of decline. *Annals of Operations Research*, 352, 105–120.
- Deffenbacher, J. L., Deffenbacher, D. M., Lynch, R. S., & Richards, T. L. (2003). Anger, aggression, and risky behavior: A comparison of high and low anger drivers. *Behaviour Research and Therapy*, 41(6), 701–718.
- Depken, C. A. (1999). Free-agency and the competitiveness of major league baseball. *Review of Industrial Organization*, 14(3), 205–217.
- Devriesere, K., Csató, L., & Goossens, D. (2025). Tournament design: A review from an operational research perspective. *European Journal of Operational Research*,

- 324(1), 1–21.
- Dingus, T. A., Guo, F., Lee, S., Antin, J. F., Perez, M., Buchanan-King, M., & Hankey, J. (2016). Driver crash risk factors and prevalence evaluation using naturalistic driving data. *Proceedings of the National Academy of Sciences*, 113(10), 2636–2641.
- Edmans, A., García, D., & Norli, Ø. (2007). Sports sentiment and stock returns. *The Journal of Finance*, 62(4), 1967–1998.
- Ely, J., Frankel, A., & Kamenica, E. (2015). Suspense and surprise. *Journal of Political Economy*, 123(1), 215–260.
- Eren, O., & Mocan, N. (2018). Emotional judges and unlucky juveniles. *American Economic Journal: Applied Economics*, 10(3), 171–205.
- Forrest, D., Simmons, R., & Buraimo, B. (2005). Outcome uncertainty and the couch potato audience. *Scottish Journal of Political Economy*, 52(4), 641–661.
- Fort, R. (2022). Rottenberg at sixty-five: In honor of the 20th anniversary of the journal of sports economics. *Journal of Sports Economics*, 23(6), 808–825.
- Fort, R., & Quirk, J. (1995). Cross-subsidization, incentives, and outcomes in professional team sports leagues. *Journal of Economic Literature*, 33(3), 1265–1299.
- Gold, B. P., Mas-Herrero, E., Zeighami, Y., Benovoy, M., Dagher, A., & Zatorre, R. J. (2019). Musical reward prediction errors engage the nucleus accumbens and motivate learning. *Proceedings of the National Academy of Sciences*, 116(8), 3310–3315.
- Hall, A. E. (2015). Entertainment-oriented gratifications of sports media: Contributors to suspense, hedonic enjoyment, and appreciation. *Journal of Broadcasting & Electronic Media*, 59(2), 259–277.
- Humphreys, B. R., & Perez, L. (2019). Loss aversion, upset preference, and sports television viewing audience size. *Journal of Behavioral and Experimental Economics*, 78, 61–67.
- Jakar, G., Gordon, K., & He, Q. (2023). The temporal and spatial relationships between professional sport events and vehicular crashes. *Sport Management Review*, 26(4), 628–648.
- Jennett, N. (1984). Attendances, uncertainty of outcome and policy in scottish league football. *Scottish Journal of Political Economy*, 31(2), 176–198.
- Johnson, S., & Fort, R. (2022). Match outcome uncertainty and sports fan demand: An agnostic review. *International Journal of Empirical Economics*, 1(2), 2250007.

- Kadoya, Y., Watanapongvanich, S., & Khan, M. S. R. (2021). How is emotion associated with driving speed? a study on taxi drivers in japan. *Transportation Research Part F: Traffic Psychology and Behaviour*, 79, 205–216.
- Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), 263–291.
- Kaplan, S. (2021). *Entertainment utility from skill and thrill*. (Working Paper)
- Kőszegi, B., & Rabin, M. (2006). A model of reference-dependent preferences. *The Quarterly Journal of Economics*, 121(4), 1133–1165.
- Lee, Y. H., & Fort, R. (2012). Competitive balance: Time series lessons from the english premier league. *Scottish Journal of Political Economy*, 59(3), 266–282.
- Li, Z. W., Bramley, N. R., & Gureckis, T. M. (2021). Expectations about future learning influence moment-to-moment feelings of suspense. *Cognition and Emotion*, 35(6), 1099–1120.
- Madrigal, R., Bee, C., & Chen, J. (2022). Hope and fear in the experience of suspense. *Cognition and Emotion*, 36(6), 1074–1092.
- Madrigal, R., Bee, C., & Chen, J. (2023). When the stakes are low: How key features of momentary suspense contribute to a global evaluation of enjoyment. *Communication Research*, 50(3), 287–311.
- Maher, M. (1982). Modelling association football scores. *Statistica Neerlandica*, 36(3), 109–118.
- Mesken, J., Hagenzieker, M. P., Rothengatter, T., & De Waard, D. (2007). Frequency, determinants, and consequences of different drivers' emotions. *Transportation Research Part F*, 10(6), 458–475.
- Neale, W. C. (1964). The peculiar economics of professional sports. *The Quarterly Journal of Economics*, 78(1), 1–14.
- Owen, P. D., Ryan, M., & Weatherston, C. R. (2007). Measuring competitive balance in professional team sports using the herfindahl-hirschman index. *Review of Industrial Organization*, 31, 289–302.
- Pawlowski, T., Breuer, C., & Hovemann, A. (2010). Top clubs' performance and the competitive situation in european domestic football competitions. *Journal of Sports Economics*, 11(2), 186–202.
- Pawlowski, T., & Nalbantis, G. (2019). Competitive balance: Measurement and rele-

- vance. In P. Downward, B. Frick, B. R. Humphreys, T. Pawlowski, J. E. Ruseski, & B. P. Soebbing (Eds.), *The sage handbook of sports economics* (pp. 154–162). Sage.
- Pawlowski, T., Nalbantis, G., & Coates, D. (2018). Perceived game uncertainty, suspense and the demand for sport. *Economic Inquiry*, 56(1), 173–192.
- Pawlowski, T., Rambaccussing, D., Ramirez, P., Reade, J. J., & Rossi, G. (2024). Exploring entertainment utility from football games. *Journal of Economic Behavior & Organization*, 223, 185–198.
- Poli, R., Ravenel, L., & Besson, R. (2018). Competitive balance: A spatio-temporal comparison. *CIES Football Observatory Monthly Report*.
- Potoski, M., & Urbatsch, R. (2017). Entertainment and the opportunity cost of civic participation: Monday night football game quality suppresses turnout in us elections. *Journal of Politics*, 79(2), 424–438.
- Redelmeier, D. A., & Stewart, C. L. (2003). Driving fatalities on super bowl sunday. *New England Journal of Medicine*, 348, 368–369.
- Richardson, T., Chesbro, G., De Stefano, L., Larson, R., Wenger, M., & Larson, D. J. (2026). Neural effects of suspense and surprise in sports media. *Communication & Sport*. (Advance online publication)
- Roidl, E., Frehse, B., & Höger, R. (2014). Emotional states of drivers and the impact on speed, acceleration and traffic violations: A simulator study. *Accident Analysis & Prevention*, 70, 282–292.
- Rottenberg, S. (1956). The baseball players' labor market. *Journal of Political Economy*, 64(3), 242–258.
- Scarf, P., Parma, R., & McHale, I. (2019). On outcome uncertainty and scoring rates in sport: The case of international rugby union. *European Journal of Operational Research*, 273(2), 721–730.
- Scarf, P., Yusof, M. M., & Bilbao, M. (2009). A numerical study of designs for sporting contests. *European Journal of Operational Research*, 198(1), 190–198.
- Simonov, A., Ursu, R. M., & Zheng, C. (2023). Suspense and surprise in media product design: Evidence from twitch. *Journal of Marketing Research*, 60(1), 1–24.
- Steinhauser, K., Leist, F., Maier, K., Michel, V., Parsch, N., Rigley, P., & Steinhauser, M. (2018). Effects of emotions on driving behavior. *Transportation Research Part*

- F*, 59, 150–163.
- Szymanski, S. (2003). The economic design of sporting contests. *Journal of Economic Literature*, 41(4), 1137–1187.
- Vecer, J., Kopriva, F., & Ichiba, T. (2009). Estimating the effect of the red card in soccer: When to commit an offense in exchange for preventing a goal opportunity. *Journal of Quantitative Analysis in Sports*, 5(1).
- Wood, S., McInnes, M. M., & Norton, D. A. (2011). The bad thing about good games: The relationship between close sporting events and game-day traffic fatalities. *Journal of Consumer Research*, 38(4), 611–621.
- Yerkes, R. M., & Dodson, J. D. (1908). The relation of strength of stimulus to rapidity of habit-formation. *Journal of Comparative Neurology and Psychology*, 18(5), 459–482.

Declaration of Academic Integrity

I hereby declare that I have written this work myself and have not used any sources or resources other than those stated. I have identified texts, ideas, concepts, graphics, and other material taken directly or indirectly from external sources as such, and have provided complete references to the respective sources.

Regarding the use of generative artificial intelligence, I confirm that I have used such tools as an aid only and that my own creative and intellectual contribution predominates throughout this work. In the empirical studies included in this dissertation, AI-assisted tools (Claude, Anthropic) were used to support coding in data processing and analysis. In preparing the dissertation itself, such tools were used to help structure and refine the framing of overarching ideas, to support language and text editing, and to assist in organizing and formatting the document. All substantive intellectual contributions, analytical decisions, and conclusions remain my own, as do any errors. I am aware that I bear responsibility for the content of this work, and that the use of such tools does not in itself guarantee the correctness of the material produced.

This work has not been submitted in the same or a similar form to any other examination authority in Germany or abroad.

I am aware that a violation of the above points may have consequences under examination law, and in particular may result in the work being graded as “fail,” and, in the event of repeated or serious attempts at deception, may result in termination of enrollment or the initiation of proceedings for the withdrawal of any academic title awarded.

Tübingen, _____

Travis William Richardson