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“Do Football Fans' Emotions Drive Accident Rates? An Analysis of Championship Match Outcomes and Traffic Accidents in the UK”

Master Thesis

MSc Business Economics, Strategy Economics

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Date final version: 13/08/2024

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ABSTRACT

I investigate how emotions affect the dynamics of traffic accident rates after football matches in the United Kingdom. I combine two different datasets of traffic accident data from the UK Department for Transport's Road Accident with the analytical list of the timing and details of football matches from the period 2004 to 2014 to estimate the effect of these football matches on traffic accident rates. I find that the highest number of traffic accidents occurs two hours before the kick off. There is a significant reduction in road accidents during the game, and a reduction in intensity and severity after the game. Furthermore, when examining the additional effect of different results on the number of accidents, I find that an away win contributes to fewer traffic accidents in the area of the winning team's supporters. Finally, I find that home football matches that start early (before 19:00) are associated with a significant increase in traffic accidents in the home area, compared to matches that start later in the day.

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1. INTRODUCTION

Traffic accidents are one of the leading causes of mortality globally. Their occurrence is influenced by a variety of factors, including road design, traffic control, and driver behavior (Vorko et. al, 2006). Emotional states also play a significant role, often leading to aggressive or careless driving (Hu et al., 2013). These emotional states can be triggered by various events, including football games. For instance, Munyo and Rossi (2013) found that the outcomes of football matches significantly impact emotional states, which in turn can influence driving behavior. However, it is still unknown how football-related emotions influence road accidents, particularly in terms of timing and whether these accidents occur before, during, or after the game. Understanding the specific time pattern of this relationship is critical for creating effective public safety policies to prevent traffic accidents, such as determining the optimal time to increase police control or deciding when to schedule football games to minimize the risk of traffic accidents.

In this thesis I aim to investigate the topic of how a major football event, specifically a Championship game, impacts the frequency and the timing of traffic accidents in the participating teams' cities. Additionally, I investigate whether the final result of the match, a win, draw, or loss, affects this relationship. I look at games played both at home and away to understand if playing close to home has a separate effect compared to playing away. In addition, I examine if the early games might have different effect than the late games on the total number of traffic accidents. These research questions provide important insights into the determinants of traffic accidents, and how emotional shocks generated by football may influence car crashes.

The 2022 Annual Report on Road Casualties from Great Britain shows that 135,480 road accidents took place and of these 1711 people lost their lives while 29,742 suffered some degree of serious injury, while the main category of these victims were young males between the ages of 17 and 29. (Department for Transport, 2023)[1]. All these traffic accidents have serious consequences, not only for the public health of the population, but also for the economy. According to the report by SWOV[2] (the Institute for Road Safety Research), the estimated social cost of road accidents in

[1] https://www.gov.uk/government/statistics/reported-road-casualties-great-britain-annual-report-2022/reported-road-casualties-great-britain-annual-report-2022
[2] https://swov.nl/en

2020 is €27 billion, with an annual range of €15-36 billion. This corresponds to 3.3% of gross domestic product (1.9-4.5%). Approximately €6.5 million is spent on each fatality and €0.7 million on each serious injury.

Furthermore, in the United Kingdom alone, which is the subject of my thesis, the 2021 Road Safety Report[3] suggests that 1.5% of the UK's GDP is spent on road traffic crashes in that year. In addition, major sporting events have been associated with increases in domestic and urban violence (Montolio & Struse, 2016), as well as with economic benefits and disadvantages (Dobson et al, 2001). Given the social and economic costs associated with traffic accidents, and the ambiguous roles of major sports events, I am interested to examine the effect of a major sport event in the number of traffic accidents in the United Kingdom and its determinants.

Football Games from the English Championship, the second tier of English football, are selected for this study because football is the most popular sport in Great Britain and the Championship fans are concentrated locally, making it easier to examine the accidents per area. These games bring lots of fans into cities, causing different traffic patterns and a variety of different moods.

Although the effect of football matches and the intense emotions they provoke on behavior has been studied, the specific timing of these emotional impacts on driving behavior remains unclear. On the first part of my thesis I am to clarify this, by examining whether accidents are more likely to occur before, during, or after the game. Understanding the time pattern and how these events contribute to making roads more dangerous on match days is crucial for developing effective traffic management strategies and enhancing public safety.

The second part of my research focuses on whether the outcome of the game has an additional effect on the number of traffic accidents. Looking at road accidents before, during and after the games and seeing how they can be related to the outcome of the game, has important policy implications. Increasing police presence after emotionally charged games could be important, especially if the games involve rival teams or surprise results. Implementing stricter traffic regulations and conducting more roadside tests for drunk driving depending on the game's result,

[3] https://www.gov.uk/government/statistics/reported-road-casualties-great-britain-annual-report-2021

especially after an emotional one, can help reduce the risk of accidents, encouraging safer driving behavior.

Finally, the third part of my thesis examines whether the timing of a football match, for example early matches or late matches, has an additional effect on the total number of accidents in that area. This has important policy implications, as for early matches, temporary closures of roads can be used to control traffic, avoiding queues and reducing the number of accidents during period of high traffic. In addition, for late games, extending public transport options and services, to ensure that supporters have safe alternatives to driving late at night, can be crucial in reducing the accidents caused by alcohol or increased fatigue.

This thesis finds that the highest number of traffic accidents occurs two hours before kick-off, with a decrease during and after the match. While the additional effect of distinct match results on accidents is limited, some away wins are associated with fewer accidents in the area of the winning team. Additionally, early home matches (before 19:00) result in more accidents compared to later matches These findings highlight the need to improve public transport options before and after home matches and other major events, and to delay kick-off times to avoid early drinking and reduce the risk of accidents. Managing drivers' emotional states through public awareness campaigns and stricter alcohol regulations could further reduce these risks, while these policies can be applied beyond just football events.

The remainder of the thesis is organized as follows: The first section reviews previous literature and formulates hypotheses based on theoretical and empirical insights. The next section provides the data sources and their analysis. The third section describes the research design, including the estimation model and regression equations employed. The fourth section presents the results of the analysis. Finally, the last section offers the conclusion, including a discussion of the findings and their implications for future research and policy.

2. LITERATURE & HYPOTHESIS GENERATION

Football Games and Emotional Responses

Football is the most popular sport in the world, and it is able to create a wide range of emotions to its fans. These feelings can vary many times depending on the outcome of the matches, including wins, losses and draws. The intensity of these emotions can have a high impact on fans' behavior, and influence them in many aspects of everyday lives.

Munyo and Rossi (2013) found that football games results have a significant impact on emotional states. According to their findings, fans' negative emotions increased significantly following an unexpected loss. In contrast, happiness after an unexpected win led to a decrease in negative emotions. This dual nature shows the significant changes in emotions that football fans experience as a result of match results.

Card and Dahl (2011) investigated the emotional impact of American football outcomes in the setting of family dynamics. Their findings found that unexpected losses caused a 10% rise in the rate of domestic violence by men against their wives. This research emphasizes the high impact of unexpected negative outcomes on emotions, which can lead to aggressive behavior. Notably, close losses did not have such strong effects, showing that the element of surprise is critical in the strength of emotional responses.

Depetris-Chauvin et al (2020) investigated the wider social impact of football match results, beyond the impact on individuals or families. Their research looked at the impact of national football team success and the shared emotions it generates on violence and war. Interestingly, they found that national team success reduces violence. Countries that qualify for the African Cup of Nations experience less conflict in the following months than those that do not. This reduction in violence may be linked to the strong positive emotional responses that national team victories generate, which create a sense of unity and shared happiness among the population.

Kerr et al. (2005) also examined the emotional responses of fans to winning and losing teams during two professional football matches. The study showed that losing fans had significantly higher levels of negative emotions such as boredom, anger, sullenness, embarrassment and resentment after the match than winning fans, who reported higher levels of relaxation. This study also showed how negative emotions are significantly higher for fans of losing teams after the match.

Emotions and driving behavior

Some interesting findings on the relationship between emotions and driving behavior can be found in the published literature. Both positive and negative impacts of emotions on driving behavior have been shown by Steinhauser et al. (2018). They noticed that while some emotions could lead to greater focus and cautiousness, others can cause people to take more risks and make worse decisions.

In a 100 km/h road area, Mesken et al. (2007) found a correlation between anger and higher speeds. This finding emphasizes the role that emotions play in influencing actions that are risky. They found that angry drivers often drove faster and made more aggressive moves, which raised the risk of an accident.

Hu et al. (2013) discussed the detailed connection between driving behavior and emotions or moods. Their research showed that though negative feelings and moods might make people notice danger better, they might also encourage more aggressive driving behavior. This dual effect increases the possibility that, despite being aware of the risks, drivers tend to drive riskier of the impact of their psychological state.

Given that football matches tend to make people feel strong emotions, and these feelings can affect the way they drive, it's reasonable to think that having a big Championship game could significantly affect the number of traffic accidents in the cities where the teams are from. Furthermore, Ivandić et al. (2024) highlight the importance of analyzing the temporal dynamics surrounding events. Their approach of using multiple leads and lags to capture pre and post event effects provides a comprehensive understanding of how events influence behavior over time. Applying this to football matches, it is crucial to examine in this thesis, how traffic accidents change before, during, and after the games. This first idea leads me to the shaping of the first hypothesis that:

“The presence of a Championship football game significantly influences the number of traffic accidents in the cities of the teams involved, particularly before, during and after the game.”

The studies mentioned above, support the idea that unexpected outcomes influence emotions. For example, Card and Dahl (2011) highlight that unexpected losses significantly increase negative emotions and aggressive behavior. Mesken et al. (2007) and Hu et al. (2013) show that such negative emotions can lead to more aggressive and risky driving behaviors. Therefore, the outcome of the game, especially unexpected losses, is likely to affect the number of traffic accidents due to the more intense negative emotions experienced by fans. This forms the basis of the second hypothesis:

"The different outcomes of the game, a win, a draw or a loss, have a different impact on the number of road accidents, with losses leading to a higher number of accidents due to increased negative emotions, especially after the game."

Timing of Games and Public Safety

The kick off time of the football games can significantly influence driving behavior and subsequently, traffic accidents. Early games, which typically start before 19:00, are usually associated with higher daytime traffic volumes, leading to an increased risk of accidents due to higher traffic. Late games, starting after 19:00, are associated with a variety of safety issues, such as reduced visibility, higher alcohol consumption, and exhaustion.

Ivandić et al. (2024) show that early football matches lead to prolonged periods of aggressive behavior, such as increased domestic violence, due to prolonged drinking. In addition, the study by Card and Dahl (2011) highlighted how the timing of sporting events can change public behavior. This can lead to increased incidents of violence and accidents after the event. Early games often lead to longer drinking sessions, which can lead to more significant public safety problems. This logic suggests that early games lead to longer drinking sessions, which increases risky behavior, including road accidents, later in the day. Longer periods of drinking after early matches lead to more chances of bad driving and accidents compared to late matches. This is the basis of the third hypothesis:

"Early football games (starting before 19:00) result in a higher number of traffic accidents compared to late games (starting after 19:00)."

Literature Gaps

There has been some research on the effect of football matches on car accidents. Wood et al (2011), in their analysis of major sporting events (2001-8), found that close matches, or matches between evenly matched opponents, were associated with an increase in competitive testosterone, which tends to result in aggressive driving. This led to an increase in road deaths, particularly in the regions of the winning supporters. In contrast, they suggested that fans whose team lost were more likely to return home safely. Another paper by Yam et al. (2020) examined the relationship between high profile football matches in Europe and car accidents in Taiwan and Singapore. Interestingly, they found that there were more traffic accidents on days with important matches than on days without. The reason for this increase in accidents is the lack of sleep suffered by spectators who watch the matches in the early hours of the morning.

Previous literature by Wood et al. (2011) focused more on the effect of derby matches compared to non-derby matches. The overall effect of football matches as a whole on accidents was not examined. Also, the paper by Yam et al. (2020) concentrated more on the effects due to fatigue and tiredness rather than the emotions derived from a football match. As the accidents were in Asia and the football matches were in the UK, the results did not really influence the driving behavior of Asian people. They also only included high-profile matches in their research, and not all the matches played by weaker European teams with huge fan bases.

Finally, a thesis research by Oostdijk (2022) examined the precise effect of emotion after English Championship football matches on traffic accidents, but found no significant relationship, contrary to previous literature.

Literature Contribution

My contribution to the literature is to examine the specific timing patterns of road accident reports, focusing on the periods just before, during and just after football matches. Following a similar approach to Ivandić et al. (2024), but for road crashes rather than violence, allows me to observe the specific timing that temporary emotions, which are typically more intense around these events, might affect road safety. By analyzing data before, during and after matches, I aim to investigate both the immediate and the post effects of football matches on the frequency of road accidents. This method, examining 'leads and lags" helps to provide a more complete picture of the true impact of the football games on English roads. Unlike previous studies, such as those by Oostdijk (2022), which mainly looked at whether a football game was happening, my thesis takes a closer look at what happens before, during, and after the game. This way, I can separate the effects of the game itself from what goes on in traffic safety at different times. The goal of my research is to explain how the emotions from these games can lead to risky driving behaviors, especially by examining when these crashes typically happen.

3. DATA

Traffic Accidents Data.

In this paper, I use two different datasets. The first data source is the road traffic accident data from the UK Department for Transport's Road Accident Statistics Branch. The information is derived from the UK Data Archive at the University of Essex in Colchester and covers the years 2004 to 2014. The dataset contains variables like accident severity (fatal, serious, or slight), the number of vehicles involved, weather conditions, road type, lighting conditions, and more. This covers a range of accident types, including those involving cars, motorbikes, bicycles, buses, coaches, and pedestrians. It also includes information on accidents where people were injured while boarding and departing from buses and coaches, and on accidents involving cyclists and pedestrians that did not involve a motor vehicle. The dataset contains accidents occurring within 30 days of the event and reported to the police. I concentrate on key characteristics, such as the year of the accident, the day and month of the accident, the hour and minute of the accident, and the east and north coordinates of the accident location. These variables are the most important for merging accident data with the timing of football matches to analyze my research question.

The traffic accident dataset has information about the total number of traffic accidents that happened in the UK from January 2004 to December 2014. During this period, 1,684,453 traffic accidents are recorded. I attribute each accident to a different football team's area of support using specific criteria. The exact criteria by which this Area of Support (AoS) is determined is explained in more detail below. Accidents are kept in the dataset only if their location (easting and northing coordinates) can be attributed to a football team's AoS. This transformation results in a dataset of 324,639 accidents for analysis. I assign each accident a unique accident ID to facilitate matching with the football teams' AoS.

To examine the impact of football games, I collapse the dataset into a two-hourly time series format. This choice is based on that, on average, a football game lasts approximately two hours. Therefore, each observation in my final dataset corresponds to a given AoS, which is allocated to a certain football team, in a single two hour period in the Championship football season between 2004 and 2014. For instance, a single observation in my dataset will contain the number of car crashes that were recorded as occurring in the two hour window from 2:00 PM to 4:00 PM on August 7, 2004, in the AoS for a specific team.[4]

In addition, I remove all observations that fall outside the dates of the football season for each year. For example, for the 2004/2005 season, I keep only the accidents that occurred from August 7, 2004, until May 5, 2005, because after these dates, there were no Championship matches. This period aligns with the vacation period featuring global or European national team competitions, which are not relevant to this study. I apply the same criteria for each subsequent year, up to 2014. For the 2014 season, I keep observations from August 8, 2014, until December 30, 2014, which is the end of my dataset. This ensures that the data only includes periods when Championship matches were being played, providing a relevant time period for analysis. Once the data is collapsed in this manner, the traffic accidents data contains 1,775,904 observations.

[4] Observations are created for an Area of Support (AoS) even if no traffic accidents are recorded in a given two-hour window.

This format provides me with detailed information on the number of accidents that occurred in each team's AoS during each two-hour interval and allows for a detailed examination of how football games affect the numbers of traffic accidents in the specific support regions of Championship teams.

Table 1
Frequency of Matches by Day of the Week and Hour at Kickoff

	Kickoff										
Day	**11:00**	**12:00**	**13:00**	**14:00**	**15:00**	**16:00**	**17:00**	**18:00**	**19:00**	**20:00**	**Total Matches**
Sunday	8	33	134	21	78	6	1				281
Monday		6	8		164		12		61	18	269
Tuesday		3	3		55				984	135	1180
Wednesday		2	1		30				140	12	185
Thursday		1	1		8		1		5		16
Friday		1	4	2	34	1	8		137	6	193
Saturday		183	43	2	3321		133	1	1		3684
	8	**229**	**194**	**25**	**3690**	**7**	**155**	**1**	**1328**	**171**	**5808**

Football matches data

To analyze the effect of football games on traffic accidents, I focus on the English Championship matches. I collect data on all the matches from the 2003/04 season to the 2013/14 season, covering the same period as the road traffic accident data. The dataset includes a total of 5,808 matches, with the games occurring between 11:00 AM and 8:00 PM. It is important to note that I do not include all the games from the 2014/15 season, as the road traffic accident data is only available up to December 31, 2014. Therefore, my analysis period ranges from 7 August, 2004, to 30 December 2014.

In Table 1, I present the descriptive statistics about the timing variation on the football matches. Football games are scheduled throughout the week, with evening games more common during weekdays, while weekend games have kick-off times spread throughout the entire day. Specifically, the late games (after 7 PM) represent a significant part of the sample, with a high frequency on Tuesday evenings, where 19:00 kick-offs account for 984 matches. The largest portion of games, however, occurs in the early and mid-afternoon, particularly on Saturdays, where 15:00 kick-offs host 3,690 matches, making it the most common kick-off time in the dataset. Saturday matches dominate the schedule with 3,684 games, similar to the traditional scheduling of football games on weekends. The second-highest frequency is observed on Tuesday, with 1,180 matches, showing a preference for midweek evening fixtures. The least common day for matches is Thursday, with only 16 games scheduled.

The dataset consists of 52 different teams that were involved in championship games in the 10 years of my study. For each football team, an AoS of supporters is created based on the team's home stadium and the geographical borders. It is hypothesized that any accident occurring within a 20-kilometer around of the team's home stadium can be attributed to supporters of that football team. Using QGIS, I create a map shaping the borders of the Championship football teams' AoS. For teams located in the same city, such as London or Sheffield, where multiple local teams exist, I consulted various literature and internet studies to correctly establish the borders of each team's AoS. For example, web resources such as Hidden London and Earthly Mission[5], provide insights into the distribution of fan bases across the city of London and beyond. Figure 1 analytically shows the map of London and how the supporters are distributed across the city. After taking these boundaries into account I am able to correctly attribute each accident to the correct support area.

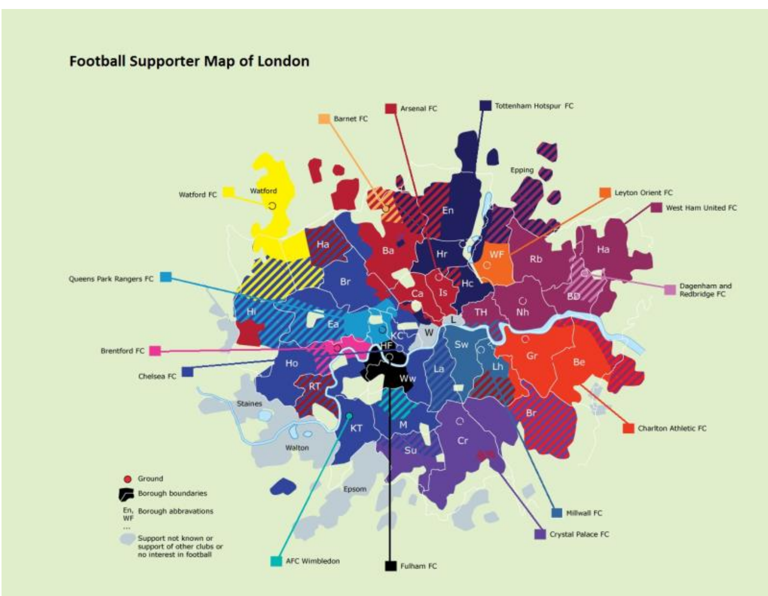
Additionally, the football games dataset includes analytical betting information from various bookmakers, such as Bet365, Blue Square, and Interwetten, providing betting odds on

[5] For more detailed maps and information on the geographical distribution of football team AoS, refer to the following resources: Hidden London: London Football Geography & Earthly Mission: Football Fan Map of London

win/draw/loss outcomes for each match. For this study, I use only the information from Bet365, as it is the most popular platform among UK fans. The betting odds allows me to calculate the pre-match probabilities of each team winning and to categorize football results as surprises, upsets, or expected outcomes based on these probabilities.

In the final step, I merge the traffic accident data with the football games data based on the two-hour interval variable and the Team ID, which represents the specific AoS for each team. Specifically, I include information about the football game and its outcome to time-windows within an AoS around which a football game involving that AoS occurs. This merging process results in an extensive dataset containing 1,775,904 AoS-by-2-hour-window observations. These observations represent all the two-hour intervals for each of the 52 team AoS over the approximately 10-year study period. This merged dataset includes a total of 5,808 football games to be examined, analyzing the relationship between football match outcomes and traffic accidents in UK.

Figure 1



Notes: This map represents the shaped boundaries of the Championship football teams' Areas of Support (AoS) within London. For cities with multiple local teams, such as London, the boundaries were determined through consultation with various online resources and literature, including Hidden London and Earthly Mission. These resources provided insights into the distribution of fan bases across the city.

Source: https://flowingdata.com/2011/01/11/football-supporter-map-of-london/

4. RESEARCH DESIGN

My research design closely follows the methodology by Ivandić et al. (2024). I aim to estimate the differential time dynamics on days when football games occur. To determine the causal relationship between football events and traffic accidents, I analyze hourly changes in accident rates over a ten-year period, considering the variation in game days and times throughout the week. I use eight lags and four leads to capture the entire 24-hour period around each game, with t denoting the kick-off time.

A significant difference in my methodology compared to the paper by Ivandić et al. (2024) is that I use panel data. While their study focused solely on the city of Manchester, making time t their unit of observation, my study includes all AoS for 52 Championship teams over ten years. Consequently, my unit of observation is i (the AoS corresponding to each Championship team), and the wave of the panel data is the two-hour intervals t. This approach provides a more detailed understanding of how football matches impact traffic accidents across different regions. The overall observations represent all the two-hour intervals for each of the 52 teams' AoS over the approximately ten-year study period.

Modelling

To capture the dynamics, I include eight lags to model the 16 hours following the game and four leads to model the pre-trends in the 8 hours prior to the game. In my interpretation, the two hours immediately before the game $t-1$ are used as the reference category, so the coefficients capture the change in the dependent variable relative to $t-1$. This approach helps in isolating the direct effects of the football game itself, making $t-1$ the reference period for comparison. Additionally, given the length of the two-hourly time series, all periods outside $t = -4, -3, ..., 7, 8$ are binned into a dummy variable $Game_{\tau_t}$.

This longer time frame allows for an analysis of all the time dynamics traffic accidents during the immediate post-match, during the day, and in the early hours of the next morning on a given game day. A shorter period of time would exclude all events that came about as a result of aggressive and not careful driving behaviors that were maybe started by the match.

Model for First Hypothesis

My base research model uses an event-study like design to estimate the effect of football games on traffic accidents in the United Kingdom.

The Eq. (1) below shows the base model, estimated by OLS.

$$Accidents_{it} = \alpha + \sum_{s=-4}^{8} \beta_s Game_{t+s} + \gamma_o Game_{\tau_t} + \theta_i + \delta_t + \varepsilon_{it} \quad (1)$$

$Accidents_{it}$ represents the total number of traffic accidents in AoS i during the two-hour interval t, while $Game_{t+s}$ is a dummy variable equal to 1 if a match started s intervals before or after the current interval t, $Game_{\tau_t}$ is the dummy variable that bins the rest of the periods outside the specified intervals, θ_i represents AoS fixed effects to control for unobserved heterogeneity across different team AoS. Coefficient δ_t is a vector of time-date fixed effects. Finally ε_{it} is a random error term.

In my analysis, I use three different regressions to assess the impact of football games on traffic accidents. On my first approach I do not include any controls or fixed effects. My second regression follows the strategy of Ivandić et al. (2024) and includes the Coefficient δ_t which accounts for temporary and seasonal variations by including year, quarter, day of the week, and other interaction effects. Finally my third regression, which I consider to be preferred model, includes the Coefficient δ_t which now introduces two-hour interval fixed effects, capturing any time-specific factors common to all Areas of Support (AoS) within each two-hour window. These two-hour interval fixed effects for England are common to all AoS in the two-hour window, such as weather conditions, seasonality, day of the week and public holidays. This approach of three different regressions allows for a robust comparison of results and ensures that the observed effects are not driven by unobserved heterogeneity.

In all three regression models, I cluster the standard errors at the level of the different Areas of Support (AoS). This approach helps to account for potential correlations within observations linked to each football team and their corresponding AoS. For example, if two areas share similar characteristics, such as poor road conditions, high traffic, or specific driving patterns, these shared features could bias the results. By clustering at the AoS level, I address these within-area correlations, to estimate more accurate results across my dataset.

My coefficients of interest in regression (1) are the β_s which capture the effect of a football game on traffic accidents at various time intervals before and after the game. I model four leads (covering 8 hours before the game) and eight lags (covering 16 hours after the game), and I use the two-hour period immediately before the game as the reference category. These allow me to test the hypotheses that (1) the presence of a Championship football game significantly influences the number of traffic accidents in the cities of the teams involved, particularly before and after the game. Specifically, I aim to determine if there is an effect in traffic accidents during the game due to spectators' focus on the game, and whether an impact on accidents exists before or after the game due to increased traffic to and from the stadium or celebratory behaviors.

In these regressions, I analyze the effect of football matches on traffic accidents by running the models separately for home and away teams. This allows me to examine the effect of a football match on traffic accidents separately depending on where the match takes place. For example, home games usually bring thousands of people to the area, increasing traffic and the likelihood of more road accidents. Away games, on the other hand, might have a different effect on road accidents because supporters gather in different places, such as pubs or homes, to watch the game, while consuming higher amounts of alcohol.

Model for Second Hypothesis

In addition, I hypothesize (2) that the outcome of the game might be an important factor to the number of traffic accidents. A win can create a celebratory atmosphere, often associated with increased alcohol consumption, which might lead to a higher number of accidents, with losses might lead to a more accidents due to emotional responses, particularly after the game.

To test this empirically, I include a dummy variable Win for whether the team won or did not win, interacted with the $Game_{t+s}$ indicator. The variable Win takes value 1 when the team in the AoS we are examining won, regardless of whether they played at home or away. In addition, I include a dummy variable $Draw$ for whether the team draw a game or not, interacted with the $Game_{t+s}$ indicator. The variable $Draw$ again takes value 1 when the team in the AoS I am examining draw, regardless of whether they played at home or away. I include the interaction terms of draws and wins in order to isolate the effect of a game outcome on the number of traffic accidents. This approach allows for comparisons relative to a loss (reference category), shaping the basis of my hypothesis that game outcomes—whether a win, draw, or loss—affect the number of traffic accidents, with losses expected to lead to a higher number of accidents due to increased negative emotions.

I then run the same regression, as specified in Equation 1 of my basic model separately for home and away matches, but I restrict the analysis to observations within the event window, focusing only on the leads and lags around the day when a football game occurred. To address potential endogeneity and heterogeneity in the data, I control for the probabilities of winning or drawing the game, using betting odds included in my football games dataset. These betting odds provide a measure of expected results, addressing bias in estimating the effect of different game outcomes on traffic accidents.

The following equation (Eq. 2) presents the estimation model for testing the hypothesis that not only the occurrence of a football game but also the game outcome influences traffic accidents rates.

$$Accidents_{it} = \alpha + \sum_{s=-4}^{8} \beta_s Game_{t+s} + \gamma_o Game_{\tau_t} + \sum_{s=-4}^{8} \mu_s Win * Game_{t+s} + \sum_{s=-4}^{8} v_s Draw * Game_{t+s} + \pi_1 P(win) + \pi_2 P(draw) + \theta_i + \delta_t + \varepsilon_{it} \quad (2)$$

In this model the coefficient $\sum_{s=-4}^{8}(\beta_s)$ represents the effect of Accidents on the time before/after a loss (the reference category). The dataset of this model includes only game days, thus this coefficient represents the effect when the local team loses, as there are no other categories outside win and draw. The coefficient $\sum_{s=-4}^{8}(\mu_s)$ captures the additional effect of the team winning the game on traffic accidents. The coefficient $\sum_{s=-4}^{8}(\nu_s)$ captures the additional effect of the team drawing the game on traffic accidents.

I include win and draw probabilities (excluding loss to avoid multicollinearity) as control variables to control for anticipatory behavior, such as perceived easy wins, which may lead to early celebrations. Furthermore, not all wins (or losses) have the same effect. For example, a highly anticipated win may lead to less dramatic celebratory behavior than an unexpected win, which could lead to more intense celebrations and potentially more traffic accidents. I want to ensure that the estimated effect of a win, loss or draw on road traffic accidents is only related to the outcome of the match and not to pre-match expectations.

My coefficients of interest in regression (2) are the β_s terms, the μ_s terms and the ν_s terms. These allow me to test the hypothesis that football games losses, wins, and draws each have different impacts on traffic accidents. By examining these coefficients, I can focus on the specific effects of game losses, wins, and draws on traffic accidents, using losses as the reference group.

Model for Third Hypothesis

Additionally, I hypothesize that the timing of the game—whether it is played early or late in the day—may have a differential effect on the total number of traffic accidents. The idea behind this hypothesis is that early games might lead to increased risky behaviors later in the day, such as excessive alcohol consumption, resulting in more traffic accidents. In contrast, late games, occurring later in the day, may influence traffic conditions and public behavior differently, thereby affecting accident rates in another manner.

To test this empirically, I include a dummy variable $Early$ which indicates whether the game was played early or late. This variable is interacted with the $Game_{t+s}$ indicator. The variable $Early$ takes value 1 for games that start before 19:00 and 0 for games that start after 19:00, regardless of whether they were home or away games. I include the interaction terms of early games in order to isolate the effect of a game timing on the number of traffic accidents.

Similar to the second model, I run separate regressions for home and away games, and I restrict the analysis to observations within the event window, focusing only on the leads and lags around the day when a football game occurred. This approach allows for comparisons relative to late games (reference category), forming the basis of my hypothesis that early games might lead to a higher number of traffic accidents.

I run the same regression as specified in the second model but with different interaction terms. The following equation (Eq. 3) presents the estimation model for testing the hypothesis that the timing of the game kick off might have differential effect on the number of accidents:

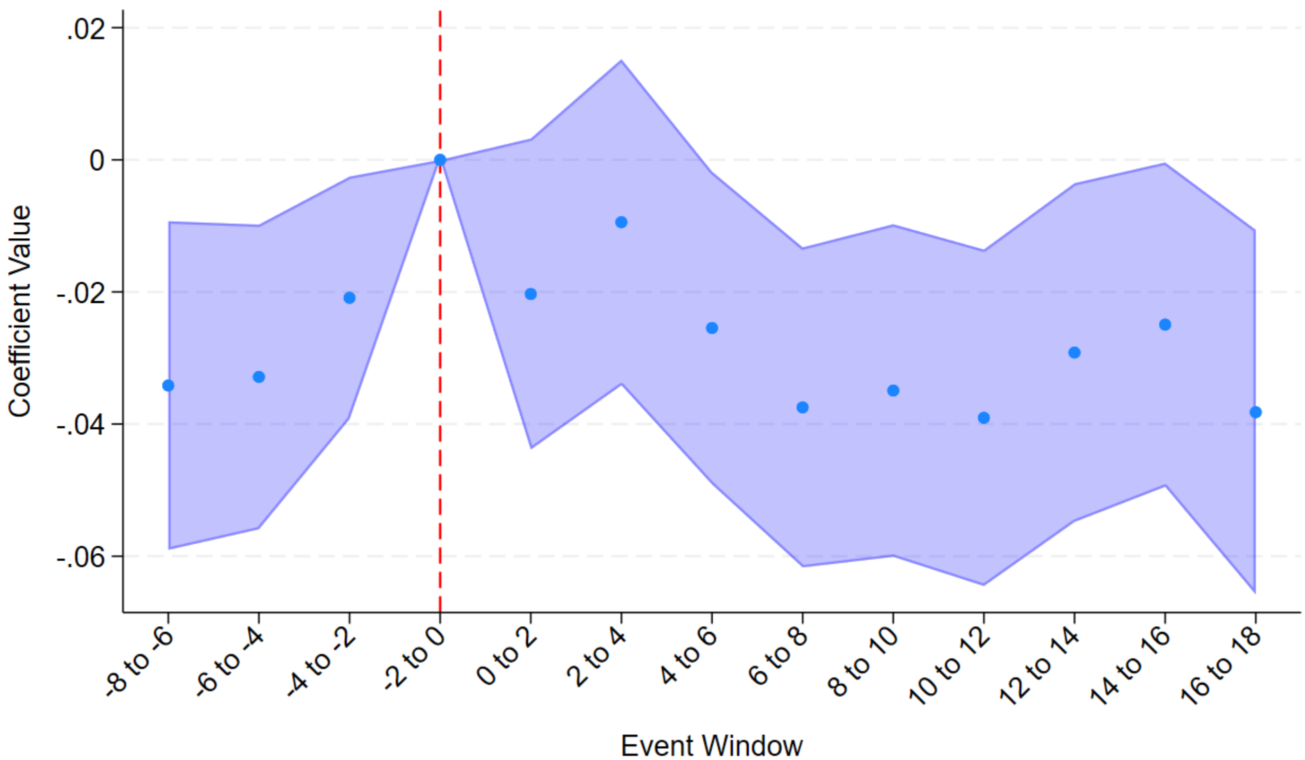
$$Accidents_{it} = \alpha + \sum_{s=-4}^{8} \beta_s Game_{t+s} + \gamma_o Game_{\tau_t} + \sum_{s=-4}^{8} \lambda_s Early * Game_{t+s} + \theta_i + \delta_t + \varepsilon_{it} \quad (3)$$

Similar to the second model, the dataset includes only game days and late games are then used as reference category. In this model the coefficient $\sum_{s=-4}^{8}(\beta_s)$ represent the effect of timing for late games only, so this coefficient represents the effect of games starting after 19:00. The interaction coefficients show the change in the effect when the game is an early game. Thus, the coefficient $\sum_{s=-4}^{8} \lambda_s$ captures the additional effect of early football games on traffic accidents.

My coefficients of interest in regression (3) are the β_s terms, and the λ_s terms. These allow me to test the hypotheses that the timing of football games (early versus late) games each has different impacts on traffic accidents. By examining these coefficients, I can focus on the specific effects of early versus late games on traffic accidents, using late games as the reference group.

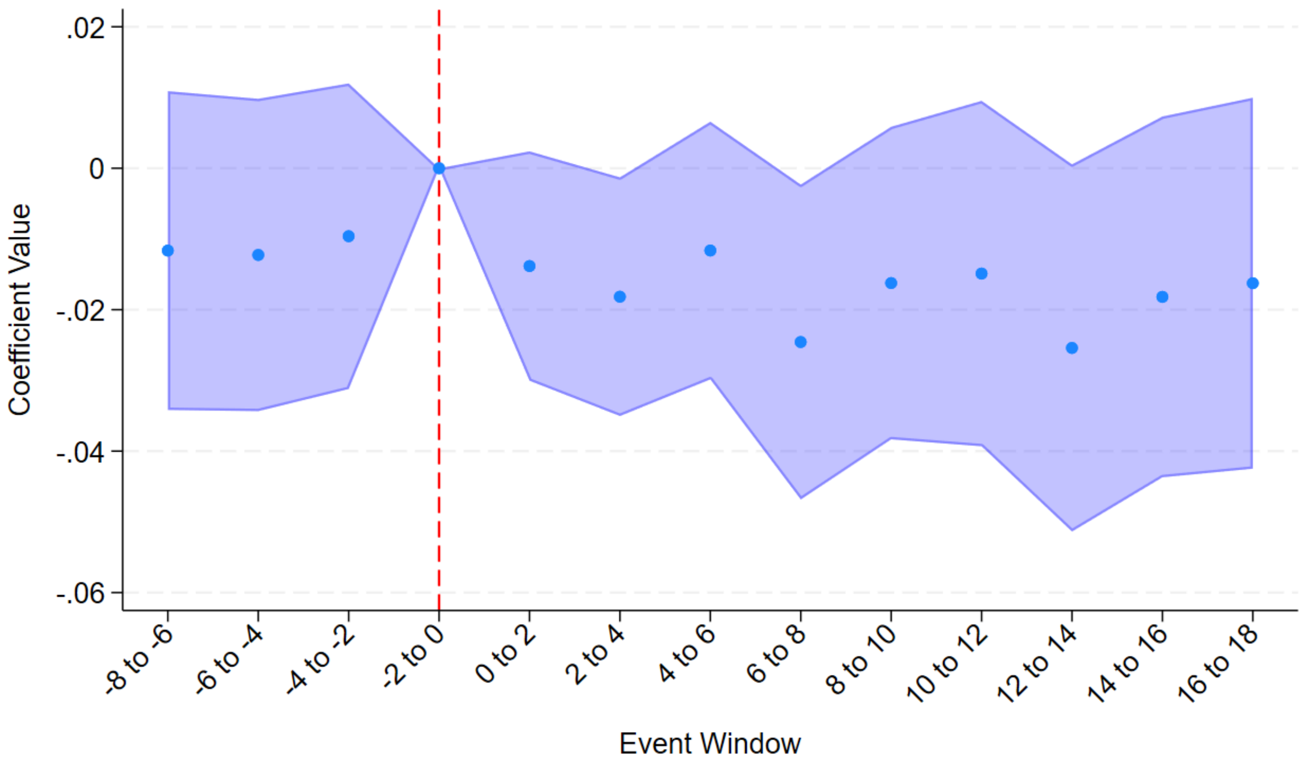
5. RESULTS

Figure 2
Coefficient Estimates for the Impact of Home Football Games on Traffic Accidents in an AoS when the local team plays a home game (Column 3 of Table 2)



Note: Column 3 controls for two-hour interval fixed effects, capturing all time-date-related factors such as weather conditions, seasonal effects, day of the week, hour, and holidays.

Figure 3
Coefficient Estimates for the Impact of Home Football Games on Traffic Accidents in an AoS when the local team plays an away game (Column 6 of Table 2)



Note: Column 6 controls for two-hour interval fixed effects, capturing all time-date-related factors such as weather conditions, seasonal effects, day of the week, hour, and holidays.

Table 2

Effects of Football Game Outcomes and Timing on Traffic Accidents

	(1) Home	(2) Home	(3) Home	(4) Away	(5) Away	(6) Away
Game, t-4	-0.190***	-0.0389**	-0.0342**	-0.172***	-0.0179	-0.0116
	(0.0217)	(0.0123)	(0.0124)	(0.0190)	(0.0113)	(0.0112)
Game, t-3	-0.151***	-0.0439***	-0.0329**	-0.134***	-0.0247**	-0.0123
	(0.0186)	(0.0117)	(0.0115)	(0.0162)	(0.0108)	(0.0110)
Game, t-2	-0.0713***	-0.0210**	-0.0209**	-0.0618***	-0.0104	-0.00961
	(0.0106)	(0.00871)	(0.00914)	(0.0114)	(0.0104)	(0.0108)
Game	-0.0551***	-0.0244**	-0.0203*	-0.0492***	-0.0182**	-0.0138*
	(0.0123)	(0.0114)	(0.0117)	(0.00905)	(0.00840)	(0.00808)
Game, t+1	-0.0649***	-0.0148	-0.00944	-0.0723***	-0.0230**	-0.0182**
	(0.0136)	(0.0119)	(0.0123)	(0.00966)	(0.00824)	(0.00840)
Game, t+2	-0.110***	-0.0263**	-0.0255**	-0.0976***	-0.0132	-0.0116
	(0.0145)	(0.0111)	(0.0118)	(0.0122)	(0.00919)	(0.00907)
Game, t+3	-0.164***	-0.0362**	-0.0375**	-0.153***	-0.0242**	-0.0246**
	(0.0186)	(0.0119)	(0.0121)	(0.0183)	(0.0108)	(0.0111)
Game, t+4	-0.178***	-0.0321**	-0.0349**	-0.162***	-0.0146	-0.0162
	(0.0199)	(0.0123)	(0.0125)	(0.0182)	(0.0112)	(0.0110)
Game, t+5	-0.193***	-0.0388**	-0.0390**	-0.172***	-0.0161	-0.0149
	(0.0224)	(0.0128)	(0.0127)	(0.0201)	(0.0118)	(0.0122)
Game, t+6	-0.176***	-0.0313**	-0.0292**	-0.174***	-0.0278**	-0.0254*
	(0.0205)	(0.0128)	(0.0128)	(0.0197)	(0.0126)	(0.0129)
Game, t+7	-0.168***	-0.0247*	-0.0249**	-0.163***	-0.0184	-0.0182
	(0.0189)	(0.0124)	(0.0122)	(0.0185)	(0.0125)	(0.0127)
Game, t+8	-0.198***	-0.0438**	-0.0382**	-0.179***	-0.0232*	-0.0163
	(0.0234)	(0.0138)	(0.0138)	(0.0210)	(0.0130)	(0.0131)
Holiday	No	Yes	No	No	Yes	No
Year Quarter	No	Yes	No	No	Yes	No
Day of week	No	Yes	No	No	Yes	No
Hour of day	No	Yes	No	No	Yes	No
Day * Hour	No	Yes	No	No	Yes	No
2Hour FE	No	No	Yes	No	No	Yes
Observations	1775904	1775904	1775904	1775904	1775904	1775904

Notes: This table reports presents the estimates on the outcome: the number of accidents in an AoS, derived from the specification in Equation (1). Columns (1) to (3) report results for home games, where the AoS team played at home, while columns (4) to (6) show results for away games. Column (1) (and column (4) for away games) represent the baseline model without controls or fixed effects. Columns (2) and (5) include controls for year, quarter, day of the week, and hour of the day. Finally, columns (3) and (6) represent the preferred model, incorporating two-hour interval fixed effects, accounting for time-specific factors such as weather and public holidays. The coefficient for the periods outside the leads and lags has been suppressed for clarity, as it is not central to the analysis. The coefficient for t−1 (two hours before the game) has been normalized to zero. (Reference category).

Standard errors are clustered at the AoS level and they are shown in parentheses.

="* p<0.10 ** p<0.05 *** p<0.001"

Base Model

In this section, I aim to test my first hypothesis and present the main results on the hourly dynamics of road accidents around the timing of a football championship game. Table 2 shows the effect of a football game and its timing on traffic accidents in an AoS when the local team plays a home game and an away game. The analysis of away matches serves as a robustness check, ensuring that the effects are not only due to traffic around the stadium, but also apply to general fan behavior and emotional responses, even when not watching the match from the stadium.

Column (1), reports the number of accidents when the local team plays a home game without any controls. The immediate effect of a football game is a statistically significant reduction in traffic accidents during the game (Game). Specifically, there are 0.0551 fewer accidents during the game than there were two hours prior to kickoff (Game, t-1), significant at the 1% level. This initial decrease suggests that spectators are less likely to be on the road during the match, likely due to their attention being focused on watching the game either at home or at public places such as pubs or stadiums. Four hours before the game (Game, t-2), there are 0.0713 fewer accidents than there were two hours before the game, and this reduction is statistically significant. Two hours after the game (Game, t+1), the reduction continues with 0.0649 fewer accidents, significant at the 1% level.

Column (2) includes a variety of controls, such as year and quarter, day of the week, hour, interactions between the day of the week and the hour of the day, and a holiday dummy. With these controls, the magnitude of the coefficients generally decreases but they remain significant. For example, during the game (Game), the reduction in accidents with controls is 0.0244, significant at the 5% level. This suggests that part of the observed reduction can be attributed to factors accounted for by the control variables, but the effect of the game itself remains significant. Interestingly, two hours after the game (Game, t+1), the coefficient is not significant, while all other periods around the game show significant reductions. In fact, the time interval in which the most accidents take place is the reference category; 2 hours before kickoff. This suggests that, for cities in which a team is about to play a match, the increase in traffic bringing supporters to the match increases the probability of a car accident to occur.

Column (3) controls for fixed effects of the two-hour interval, capturing all time-specific factors common to all the AoS during the two-hour window, such as daily events, weather, season, day of the week, hour, and holidays. This specification is my preferred model as it isolates the impact of the game itself from other time-varying factors. The reduction in accidents during the game (Game) compared to two hours before the game is 0.0203, significant at the 10% level. While the effect two hours after the game remains insignificant, similar to column 2, all other periods around the game show significant reductions. Similar to column 2, the highest number of accidents occur two hours before the kick off.

The fact that the coefficients two hours after the game (Game, t+1) are not significant in both Columns (2) and (3) suggests that the immediate post-game period might not be as important in influencing traffic accidents as the periods before and during the game itself. This could be due to various reasons, such as spectators taking time to leave the stadium or staying longer before heading home.

Figure 2 visualizes the coefficients from Column (3). The graph shows the estimated coefficients for the two-hour intervals before, during, and after the game. The coefficients are mostly negative, showing a reduction in traffic accidents around the time of the game, compared to the peak of the accidents which happens two hours before the game. The second highest number of accidents are also seen immediately after the game, suggesting that the occurrence of the game increases traffic activity in the surrounding area. However, as shown in Table 2, the immediate effect after the game is not statistically significant. The number of accidents diminishes over time and the effect remains statistically significant for several periods after the game.

Columns (4), (5), and (6) report the number of accidents in an AoS when the local team plays an away game. During the game (Game), there are 0.0492 fewer accidents than there were two hours prior to kick off, without controls, 0.0182 fewer with controls, and 0.0138 fewer when controlling for fixed effects of the two-hour interval, all significant at different levels. This shows that the occurrence of the game, regardless of whether the team is playing at home or away, significantly impacts reducing traffic accidents.

Interestingly, when including controls in columns (5) and (6), there is a significant reduction in accidents in the immediate hours after the game (Game, t+1) compared to the immediate hours before the game. This contrasts with the home games where the immediate post-game period did not show significant reductions. Additionally, my preferred model, column (6), reveals no significant reductions before the game, unlike the home games where pre-game reductions were observed. The leads before the game (e.g., Game, t-4, Game, t-3) are generally non-significant, indicating no anticipatory changes in traffic rates before the game.

As a result, in column 6, the significant results appear later in the post-game period rather than before the game, which shows a different pattern in traffic accident reductions when the local team plays away. These results also further suggest the effects seen for home teams is likely to be a mechanical effect of more traffic being on the road, rather than anything specifically football related.

Figure 3 visualizes the coefficients from Column (6). Similarly with the home games, the most accidents take place in the reference category; 2 hours before the game. However, the pattern of reductions in traffic accidents is different from Figure 2. The magnitude of reductions is more stable across all periods, unlike in Figure 2 where the highest number of accidents are immediately before and after the game. For away games, the total number of traffic accidents appears to be more evenly distributed throughout the periods surrounding the game.

Overall, traffic accidents in an AoS appear to be highest in the two-hour interval right before each game regardless of whether the team of support that area is playing at home or away. For home games of the team AoS, there is some evidence of significant reduction on the number of traffic accidents before and after the game. However, there is limited evidence that football games have a strong effect on accidents for those AoS involved in a game but when the game is hosted in another city, although there appears to be some evidence of a slight reduction in accidents in these areas post-game. These two results partially support my first hypothesis that "The presence of a

Championship football game significantly influences the number of traffic accidents in the cities of the teams involved, particularly before, during, and after the game,".

Table 3

Effects of football game Outcomes and Timing on Traffic Accidents

	(1) Home	(2) Home	(3) Away	(4) Away
Game, t-4	-0.0653*	-0.0627	0.0262	0.0416*
	(0.0326)	(0.0391)	(0.0205)	(0.0235)
Game, t-3	-0.0696**	-0.0726*	0.0188	0.0388
	(0.0288)	(0.0367)	(0.0223)	(0.0233)
Game, t-2	-0.0395*	-0.0396	0.00446	0.0158
	(0.0234)	(0.0306)	(0.0244)	(0.0254)
Game	-0.0464**	-0.0340	-0.00783	-0.00382
	(0.0206)	(0.0260)	(0.0171)	(0.0216)
Game, t+1	-0.0278	-0.0332	-0.0119	0.0117
	(0.0265)	(0.0332)	(0.0222)	(0.0253)
Game, t+2	-0.0331	-0.0491	0.00873	0.0106
	(0.0291)	(0.0374)	(0.0219)	(0.0228)
Game, t+3	-0.0575**	-0.0579	-0.0136	-0.000300
	(0.0269)	(0.0357)	(0.0234)	(0.0257)
Game, t+4	-0.0666**	-0.0725*	-0.000274	0.0131
	(0.0301)	(0.0363)	(0.0217)	(0.0244)
Game, t+5	-0.0690*	-0.0652	0.0180	0.0306
	(0.0346)	(0.0425)	(0.0224)	(0.0266)
Game, t+6	-0.0685*	-0.0646	0.0218	0.0360
	(0.0350)	(0.0411)	(0.0200)	(0.0225)
Game, t+7	-0.0455*	-0.0361	0.0215	0.0256
	(0.0258)	(0.0336)	(0.0183)	(0.0215)
Game, t+8	-0.0562**	-0.0405	0.0179	0.0315
	(0.0264)	(0.0338)	(0.0252)	(0.0278)
Win		-0.0105		0.0271*
		(0.0208)		(0.0156)

Game, t-4 * Win	0.000591	-0.0410*
	(0.0242)	(0.0209)
Game, t-3 * Win	0.0106	-0.0482**
	(0.0231)	(0.0192)
Game, t-2 * Win	-0.00340	-0.0291
	(0.0243)	(0.0229)
Game * Win	-0.0128	0.00351
	(0.0225)	(0.0223)
Game, t+1 * Win	0.0138	-0.0442*
	(0.0257)	(0.0256)
Game, t+2 * Win	0.0229	-0.0203
	(0.0235)	(0.0192)
Game, t+3 * Win	0.00976	-0.0346
	(0.0226)	(0.0228)
Game, t+4 * Win	0.0196	-0.0414**
	(0.0196)	(0.0194)
Game, t+5 * Win	0.0103	-0.0327*
	(0.0229)	(0.0172)
Game, t+6 * Win	0.00622	-0.0422**
	(0.0205)	(0.0199)
Game, t+7 * Win	0.00456	-0.0297
	(0.0213)	(0.0178)
Game, t+8 * Win	-0.0100	-0.0340*
	(0.0242)	(0.0177)
Draw	0.000818	0.0122
	(0.0196)	(0.0177)
Game, t-4 * Draw	-0.0153	-0.00627
	(0.0240)	(0.0215)
Game, t-3 * Draw	-0.0153	-0.0186
	(0.0222)	(0.0196)
Game, t-2 * Draw	0.00110	-0.00838
	(0.0253)	(0.0229)
Game * Draw	-0.0225	-0.0183
	(0.0232)	(0.0242)
Game, t+1 * Draw	0.00398	-0.0370*
	(0.0272)	(0.0209)
Game, t+2 * Draw	0.0302	0.0163
	(0.0290)	(0.0242)
Game, t+3 * Draw	-0.00488	-0.0132
	(0.0239)	(0.0233)
Game, t+4 * Draw	0.00321	-0.00760
	(0.0165)	(0.0181)
Game, t+5 * Draw	-0.0133	-0.0145
	(0.0202)	(0.0179)

Game, t+6 * Draw		-0.00150		-0.0163
		(0.0220)		(0.0197)
Game, t+7 * Draw		-0.0158		0.00150
		(0.0225)		(0.0203)
Game, t+8 * Draw		-0.0184		-0.0306
		(0.0226)		(0.0190)
2Hour FE	Yes	Yes	Yes	Yes
Probability of Win	No	Yes	No	Yes
Probability of Draw	No	Yes	No	Yes
Observations	70770	70761	70769	70760

Notes: This table presents the estimates on the outcome: the number of traffic accidents in an AoS, derived from the specification in Equation (2). All columns include two-hour interval fixed effects to account for time-specific factors and other temporal characteristics common to all AoS within the two-hour window. Columns (1) and (2) report results for home games, while columns (3) and (4) show results for away games. Column (1) and (3) present the model without interactions, while Columns (2) and (4) include interaction terms with game results (Win and Draw) and additional controls based on betting odds. In this analysis, only observations from game days are included, making the reference category a loss. This approach provides a comparison of how wins and draws influence accident rates relative to losses. Standard errors are clustered at the AoS level and shown in parentheses."* p<0.10 ** p<0.05 *** p<0.001"

Second Model

For my second hypothesis, I examine the additional impact of football game outcomes on traffic accidents. I conduct an analysis focusing on the time periods around each game, examining the effects of a win or a draw result compared to a loss outcome. Similar to the previous results section, this analysis is performed for both home and away matches of the team within the AoS of interest.

The results are displayed in Table 3, with particular attention given to coefficient of loss games as well as the interaction terms and controls for win and draw probabilities in Columns (2) and (4).

For home games, Column (1) shows significant reductions in traffic accidents during the game (Game) with a coefficient of -0.0464, significant at the 5% level. However, the main coefficients of interest are in Column (2), which includes interaction terms and controls for the probability of win or draw. In this column, notably the majority of coefficients without interaction terms which represent the effect of a lost game are not significant, which indicates no significant change in the number of accidents before, during and after a loss. The interaction terms for Win are not significant, suggesting that winning the game does not significantly influence the number of accidents for home games compared to losses (the reference category). Similarly, the interaction terms for Draw are also not significant, indicating that drawing the game does not significantly change the number of accidents compared to losses.

For away games, Column (3) shows no significant reductions in accidents during the game or in the immediate periods before and after the game. However, the more extensive analysis in Column (4), which includes interaction terms and probability controls, reveals significant findings. Similarly to home games the coefficients without interaction terms (referring to a loss) are not significant. However, several interaction terms for Win are significant. For instance, Game, t+1 * Win has a coefficient of -0.0442, significant at the 10% level, and Game, t+4 * Win has a coefficient of -0.0414, significant at the 5% level. These results indicate significant reductions in traffic accidents following a win for away games compared to losses. Additionally, most interaction terms for Draw are not significant, except for Game, t+1 * Draw, which has a coefficient of -0.0370, significant at the 10% level. This suggests that drawing a game might only lead to reductions in accidents for away games compared to losses two hours after the game and not in other intervals.

The inclusion of interaction terms and probability controls in Columns (2) and (4) does not suggest clear effects based on game outcomes. The coefficients of the interaction terms indicate that while the occurrence of a football game itself leads to reductions in traffic accidents, the specific outcomes of the games (wins or draws) do not have additional significant effects. Winning a game is associated with significant reductions in traffic accidents in the periods following the game, but this effect is only observed for away games. This could be due to celebratory behaviors that might involve less driving. Interaction terms for draws show that drawing games do not significantly add any extra influence on traffic accidents and these effects are not consistently observed across all specifications.

In summary, the second model does not provide strong evidence supporting my second hypothesis that different outcomes of football games have distinct effects on traffic accidents. However, there is limited evidence that less accidents occur in the AoS of an away team after a win, rather than a loss.

Table 4
Effects of Early vs. Late Football Game Timing on Traffic Accidents

	(1) Home	(2) Home	(3) Away	(4) Away
Game, t-4	-0.0653*	-0.204**	0.0262	0.0332
	(0.0326)	(0.0701)	(0.0205)	(0.0550)
Game, t-3	-0.0696**	-0.192**	0.0188	-0.0191
	(0.0288)	(0.0589)	(0.0223)	(0.0485)
Game, t-2	-0.0395*	-0.127**	0.00446	-0.0954
	(0.0234)	(0.0448)	(0.0244)	(0.0572)
Game	-0.0464**	-0.0394	-0.00783	-0.0613
	(0.0206)	(0.0373)	(0.0171)	(0.0613)
Game, t+1	-0.0278	-0.0438	-0.0119	-0.0704
	(0.0265)	(0.0339)	(0.0222)	(0.0530)
Game, t+2	-0.0331	-0.0441	0.00873	-0.0340
	(0.0291)	(0.0329)	(0.0219)	(0.0453)
Game, t+3	-0.0575**	-0.0765*	-0.0136	-0.0238
	(0.0269)	(0.0396)	(0.0234)	(0.0423)
Game, t+4	-0.0666**	-0.121**	-0.000274	0.00536
	(0.0301)	(0.0518)	(0.0217)	(0.0450)
Game, t+5	-0.0690*	-0.162**	0.0180	0.0396
	(0.0346)	(0.0676)	(0.0224)	(0.0460)
Game, t+6	-0.0685*	-0.172**	0.0218	0.0276
	(0.0350)	(0.0752)	(0.0200)	(0.0390)
Game, t+7	-0.0455*	-0.119*	0.0215	0.00396
	(0.0258)	(0.0600)	(0.0183)	(0.0414)
Game, t+8	-0.0562**	-0.168**	0.0179	-0.00738
	(0.0264)	(0.0600)	(0.0252)	(0.0496)
Early		-0.0922*		-0.00307
		(0.0541)		(0.0489)
Game, t-4 * Early		0.180**		0.00960
		(0.0628)		(0.0665)
Game, t-3 * Early		0.157**		0.0612
		(0.0561)		(0.0540)
Game, t-2 * Early		0.109**		0.135**

		(0.0463)		(0.0622)
Game * Early		0.00195		0.0751
		(0.0431)		(0.0666)
Game, t+1 * Early		0.0453		0.0841
		(0.0519)		(0.0588)
Game, t+2 * Early		0.0501		0.0651
		(0.0558)		(0.0519)
Game, t+3 * Early		0.0707		0.0241
		(0.0545)		(0.0528)
Game, t+4 * Early		0.126**		0.00699
		(0.0621)		(0.0547)
Game, t+5 * Early		0.185**		-0.00931
		(0.0725)		(0.0537)
Game, t+6 * Early		0.202**		0.0167
		(0.0783)		(0.0478)
Game, t+7 * Early		0.146**		0.0556
		(0.0647)		(0.0521)
Game, t+8 * Early		0.185**		0.0705
		(0.0629)		(0.0588)
2Hour FE	Yes	Yes	Yes	Yes
Observations	70770	70770	70769	70769

Notes: This table presents the estimates on the outcome: the number of traffic accidents in an AoS, derived from the specification in Equation (3) All columns include two-hour interval fixed effects to account for time-specific factors and other temporal characteristics common to all AoS within the two-hour window. Columns (1) and (2) report results for home games, while columns (3) and (4) show results for away games. Column (1) and (3) present the model without interactions, while Columns (2) and (4) include interaction terms with the timing of the game (Early vs. Late) to assess their differential impact on accident rates. In this analysis, only observations from game days are included, making the reference category "late games" (games starting after 19:00). This approach provides a focused comparison of how early games influence accident rates relative to late games.
Standard errors are clustered at the AoS level and are shown in parentheses.
* p<0.10 ** p<0.05 *** p<0.001

Third Model

Table 4 presents the estimated effects of early versus late football game timings on the number of traffic accidents in the areas of support (AoS) for the teams in my dataset. The table shows the results for both home and away games, focusing on the main variables of interest: the various intervals around the game themselves (represent effect of the late games), and interaction terms which represent the effect for early games.

For home games, Column (1) without controls shows a significant reduction in traffic accidents during late home games. The coefficient for Game (-0.0464) indicates a 4.64% reduction in accidents during the game compared to two hours before the game. However, a deeper analysis in Column (2), which includes interaction terms and controls, shows interesting findings. The coefficient for Early is -0.0922, significant in 10% significance level, suggesting fewer accidents during early home games compared to late home games. Interaction terms such as Game, t+5 * Early (0.185) and Game, t+6 * Early (0.202) show significant increases in accidents later in the day. These results suggest that early home games might lead to more accidents some hours after the game compared to late games, because of prolonged celebrations or similar activities.

For away games, Column (3) shows no significant changes in traffic accidents during late away games, compared to two hours before the game. In contrast, Column (4), which includes interaction terms and controls, shows in general no significant difference in accidents for early away games. However, the only interaction term that shows significant result is the Game, t-2 * Early (0.135**) which indicates significant increases in accidents before early away games, compared to late away games. This can be attributed to potential pre-game traffic effects.

In summary, early home games are associated with increased accidents later in the day, compared to late games, potentially due to extended post-game celebrations. For away games, the timing (early vs. late) appears to have small overall impact on traffic accidents, except from some early away games may increase pre-game traffic. These findings partially support the hypothesis that early football games (starting before 19:00) result in a higher number of traffic accidents compared to late games (starting after 19:00), mainly because of celebrations following early home games, and happen for the rest of the day, around the stadium and in the local city in general.

6. CONCLUSION

In my thesis, I investigated the effect of Championship football matches on the number of traffic accidents in the AoS of the teams of interest, focusing on the periods before, during and after the matches. I also investigated whether the outcome of these matches, (a win, draw or loss), or the timing of the game (early, late) had a different effect on the number of road accidents. My findings provide important information about the emotions provoked by football and their influence driving behavior, as well as suggestions for public safety.

My analysis showed that the highest number of traffic accidents is two hours before the kick off. The presence of a football game is also associated with a reduction in traffic accidents during the game. This might be true based on the logic that the majority of the people are focused on the game and less of them are driving on the streets. This pattern is partially consistent with the mechanism observed by Ivandic et al. (2024), who found that domestic abuse incidents decrease during the game. However, while Ivandic et al. (2024) found that violence incidents increased later in the night, my post-game results showed a decrease in traffic accidents compared to before the game, suggesting a different effect between aggressive driving and domestic violence following a football game. This might be based on the fact that the emotional responses evoked by football might manifest in a different pattern depending on the environment. The different results of these two papers suggest that fans behave in a different way when they are in a familiar environment like their home, which can make them more aggressive, while they appear more responsible when they are aware that they should drive after the game, which might reduce the number of accidents. Additionally, my research contributes to the literature by examining the specific timing of road accidents around football matches, extending the approach of Ivandic et al. (2024) to road safety. While previous studies, such as those by Hu et al. (2013) and Yam et al. (2013), found a significant relationship between football games and traffic accidents, my findings highlight that the most critical period for accidents is two hours before the game, offering a more detailed understanding of when these incidents are most likely to occur.

Furthermore my hypothesized heterogeneous effect of different match outcomes showed limited evidence. My results only suggest that winning a match, particularly for away matches, is associated with a significant reduction in post-game accidents, suggesting a potential celebratory effect that reduces driving by fans who celebrate without driving. However, this insight is in contrast with previous literature by Wood et al., (2011), where they found that winning supporters were more likely to be involved in traffic accidents after the game, while that fans whose team lost were more likely to return home safely. It is also in contrast with Mesken et al. (2007) who found that angry drivers often drove faster and made more aggressive moves, which raised the risk of an accident. However, the relaxation following a win, as highlighted by Kerr (2005), might explain why fans drive more cautiously, providing a clue from previous literature that confirms my thesis results. The significant reduction in accidents following a win, especially for away games, might be attributed to the positive emotions that have been created and the probability of less aggressive driving behavior especially after a winning result. This challenging of previous ideas is considered an important addition to the already existing literature as it highlights the dual effect of football fans emotions to traffic accidents which should be taken into consideration for the effective planning of public safety measures.

Furthermore, my analysis showed that the timing of the game has partially some influence on the traffic accidents rates, especially for home games. Early home games (starting before 19:00) are associated with significantly higher traffic accidents in the hours following the game compared to late home games (starting after 19:00). For away games, the timing did not significantly affect the number of accidents. These finding aligns with Ivandic et al. (2024), who found that early football matches often lead to prolonged aggressive behavior, such as increased domestic violence, due to extended periods of drinking. These aggressive behaviors, explained in previous literature, are closely connected with risky driving, which can lead to more traffic accidents. Interestingly, my thesis findings provide additional contribution and new insights in the concept of traffic accidents as they challenge the theory that late matches and fatigue cause more accidents, as suggested by Yam et al. (2020). Finally, my analysis is consistent with the results of Card and Dahl (2011), who stated that the timing of games is important in explaining the increase in post-game violence, a clue which explains that timing of a football game is indeed crucial for understanding the effects on behaviors associated with the game, including traffic accidents.

The insights of this research have implications about public safety and public transport policies. There is an urgent need for improved public transportation choices immediately following early home matches, as seen by the reported increase in post-game accidents. The possibility of supporters using a vehicle while intoxicated or under the influence of alcohol can be greatly decreased by offering easily available and practical substitutes for driving, especially in the hours after an early game. This policy can go beyond football and be implemented in a general scope, after major events that are possible to lead to early drinking and intense emotional shocks. In addition, the idea proposed by Ivandic et al (2024) of postponing the start of games until later in the evening and moving them to weekdays in order to prevent a significant amount of domestic violence could also prove effective in the context of traffic accidents. Delaying the kick off would prevent the football fans to start drinking from early times in the day which might be important for the reduction of alcohol consumption in the celebratory atmosphere during the pre-game period. Furthermore, the reduction in traffic accidents following a victory, highlights how crucial it is to control drivers' emotions. Driving behavior that is safer seems to be influenced by positive emotional results, such the feeling of a win. Thus, public awareness programs that inform drivers of the risks associated with driving while under emotional stress, whether it be positive or negative, have the potential to be very successful. These advertisements could be especially focused on specific moments and areas that have a strong emotional impact, such as after big athletic events or festivals. In addition, Sloan (2020) emphasizes the importance of stricter alcohol charges and stricter BAC limits in reducing accident rates. Thus, tougher alcohol restrictions, especially two hours before the opening of public events, should be taken into account supplementing the measures mentioned before. These regulations can be crucial for controlling the risk of accidents driven on by the positive and negative emotions that football games or bigger major events create.

One of the limitations of this study is the assumption that traffic accidents within a 20-kilometer around the stadium are attributed to football fans. This might not be valid for all the traffic accidents in each area. There might be some other huge events like concerts or festivals which create huge traffic and increased risk of traffic accidents. Also it is possible that the football fans are not so evenly distributed between their areas and their stadiums. Thus, attributing all the accidents in a small area to the football fans of a team might cause biased estimates, as those accidents might be caused by football fans of another team whose fans have traveled to watch an away game or tourists as well. Furthermore, despite the fact that I include control variables such as two-hour interval fixed effects in the model to account for many time-varying characteristics such as UK-wide weather conditions, seasonality, day of the week, time of day and public holidays, there may still be other relevant factors that are not captured by this control. These factors could include temporary poor road conditions, or specific driving behaviors that reflect local traditions or dangerous routines. As a result, there may be some bias in the estimates, based on unobserved characteristics.

Future research that includes a wider range of other leagues or countries is a desirable direction for future work. This would be important to find out if my findings are consistent across different cultural and geographical settings. In addition, future research can investigate how other popular sports or major festivals affect road safety in an event case study model to gain more insight into the relationship between public events, emotions and driving behavior.

In conclusion, this study highlights the varying influence of football games on traffic accidents, depending on many factors such as the timing, the outcome and the period's before and after the game. The results suggest that some specific policies could create both a celebratory atmosphere but also safer driving environment on the English roads.

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