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Football, alcohol, and domestic abuse[☆]

Ria Ivandić[a,b], Tom Kirchmaier[a,c,*], Yasaman Saeidi[a], Neus Torres Blas[a]

[a] London School of Economics, United Kingdom
[b] University of Zagreb, Croatia
[c] Copenhagen Business School, Denmark

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ABSTRACT

We study the role of alcohol and emotions in explaining the dynamics in domestic abuse following major football games. We match confidential and uniquely detailed individual call data from Greater Manchester with the timing of football matches over a period of eight years to estimate the effect on domestic abuse. We find that a football game changes the dynamics of abuse throughout the day. We first observe a decrease in incidents during the 2-hour duration of the game suggesting a substitution effect of football and domestic abuse. However, following the initial decrease, and after the game, domestic abuse starts increasing and peaks about ten hours after the game. We find that these effects are the strongest for early games and are driven by male perpetrators that had consumed alcohol. We find that football games lead to changing the dynamics from earlier to later periods in the day consistent with displacement effects, yet in the case when games are early and the perpetrator is alcoholized, football games lead to a cumulative increase in abuse. Unexpected game results are not found to differently affect domestic abuse dynamics.

1. Introduction

> *"(...) also knew that if other guys in the pub, if they lost a match, I knew their wives would not be out at the weekend, because they had have a black eye...or busted ribs or something like that, I just knew". - Deb.*[1]

Reported domestic abuse victimization constitutes a sharp escalation point in a person's life, putting the individual on a different life trajectory. This leads to significant and sizeable economic loss. Bindler and Ketel (2019) find that being a victim of domestic abuse leads to an 18% decrease in earnings and increases the time of receiving welfare benefits by 42%. First-time victimization also sets the trajectory to more victimization and criminal involvement (Grogger et al., 2020; Bland and Ariel, 2015). Spillovers of domestic violence are shown to affect the incidence of adverse birth outcomes exacerbating inter-generational inequality (Currie et al., 2018) and decrease educational outcomes for both the affected children and their school peers (Carrell and Hoekstra, 2010).

Equally pertinent to understanding domestic abuse victimization is how widespread it is. One out of three women in the United Kingdom, and worldwide, report having experienced domestic abuse at one point in their lives (Office for National Statistics (ONS), 2019; Hirschel et al., 2017). Although this life event leads to irreversible economic losses both for the individual and society as a whole, there is limited evidence about what triggers domestic violence. Factors that have been identified in the literature include wage inequality within the household (Aizer, 2010; Anderberg and Rainer, 2013; Anderberg et al., 2015) and backlash after the desire to divorce or to leave the relationship (Ellis et al., 2015; Ellis, 2016).

While the majority of the identified causes of domestic abuse result from drastic changes in life circumstances, there is also anecdotal evidence (Swallow, 2017) of how exogenous events lead to spikes in domestic abuse, one of them being sporting events. Police forces around the world have identified surges in domestic abuse reports following big sport events in national and international competitions like the football World Cup.[2] In spite of the anecdotal evidence given by police

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* Corresponding author at: London School of Economics, United Kingdom.
E-mail address: t.kirchmaier@lse.ac.uk (T. Kirchmaier).

[1] Victim testimonies from Swallow (2017).

[2] Dearden, Lizzie. 2015. "Domestic abuse reports soared during the World Cup, police figures show", *The Independent*, 08 September 2018.

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forces and organizations like victim shelters, the existence of a causal link between football and domestic abuse and the mechanism through which it runs has not been comprehensively studied (with the exception of Card and Dahl (2011)). In this paper, we use uniquely detailed data to estimate the hourly dynamics of intimate partner domestic abuse during and after a football game. Moreover, we investigate the channels through which sport is related to domestic abuse, whether through heightened emotional states or increased alcohol consumption. To conclude, we discuss what policy changes around the organization of games would help reduce domestic abuse incidence.

This paper uses confidential and uniquely detailed high-frequency administrative data from a major police force in the United Kingdom – the Greater Manchester Police – that combines five datasets on the population of calls and crimes over an eight-year period. The novelty of these datasets allows us to investigate the channels through which football affects domestic abuse with great precision. These records contain detailed information on the timing, location, description, type of relationship, information on the victim and information on the perpetrator, among others. We complement this with data on all football matches of Manchester United and Manchester City in tournaments held between April 2012 and June 2019 – amounting to almost 800 games – with detailed data on the timing, location, result, and ex-ante winning probabilities of the game. We construct 2-hourly time series data on the incidence of different types of abuse and run event study specifications with controls to account for the time dynamics of domestic abuse by season, day of week, and time of day.

We study the dynamic treatment effects using four leads before the event and eight lags after. The cumulative game effect of a football game is therefore captured by the effect during the game and the eight lags spanning 16 h after the start of a game. We examine the effect on other types of domestic abuse such as ex-partner abuse to test whether the effect is driven by the presence of a partner during and in the aftermath of a football game. Using individual descriptions of the call to the police, we also determine whether the perpetrator was under the influence of alcohol. In addition, we use the difference between the ex-ante probability of winning and the ex-post result of a match to disentangle if the effect is driven by emotional reactions to unexpected results or increased consumption of alcohol.

We establish that a football game changes the dynamics of domestic abuse (DA). First, we observe a 5% decrease in DA incidents during the 2-h duration of the game suggesting a substitution effect of football and domestic abuse. However, following the initial decrease, domestic abuse incidents between current partners start increasing after the game and peak about 10–12 h later. For this outcome, football games change the dynamics of domestic abuse without increasing the overall level of abuse throughout the day as the initial displacement of abuse during the game is substituted with higher levels in the aftermath of the game.

Our second finding speaks to the mechanism that explains why football can lead to higher incidence of domestic abuse in the hours after the game. We show that the increases in domestic abuse are driven by the increase in alcohol-related domestic abuse incidents following early games, while DA caused by non-alcoholized perpetrators remains stable and games scheduled later in the day do not lead to an increase in abuse. We observe that following early games, domestic abuse with alcoholized perpetrators starts increasing after the match and peaks 10 h later when the increase is 10% of the mean. When the perpetrator is under the influence of alcohol and games are earlier in the day, we find a positive and statistically significant cumulative effect of a football game on domestic abuse throughout the day. We hypothesize that early games lead perpetrators to start drinking alcohol earlier and continue to do so through the afternoon and evening. For games later in the day, we do not observe any cumulative increase in either alcoholized or non-alcoholized domestic abuse. To the best of our knowledge, this is also the first causal evidence of the role of day drinking on domestic abuse.

We test whether the outcome of the game (win or loss) or any surprise element associated with it affects the probability of abuse and find no evidence for this. This suggests that the increase in domestic abuse is a result of increased alcohol consumption, but not the direct effect of heightened emotions. Once we disaggregate the data by gender of the perpetrator, we find that the effect is entirely driven by male-on-female abuse while female-on-male abuse remains unchanged. Similarly, we find that the dynamics of DA between ex-partners remain unaffected by football games demonstrating that even though the timing of the games is not necessarily exogenous, it does not correlate to the times that domestic abuse generally occurs.

Our research contributes to the role of sports as initiators of domestic abuse (Montolio and Planells-Struse, 2016; Rees and Schnepel, 2009). Specifically, we are able to add very precise domestic abuse time dynamics that follow a football game. Our main contribution is understanding the mechanism behind these effects. Using comprehensive data on all games played over the course of almost a decade, we find that the changes in domestic abuse are mainly driven by increased alcohol consumption, and not the direct effect of heightened emotions triggered by the games themselves (Card and Dahl, 2011). We also find that the football game leads to a decrease in domestic abuse during its duration. However, our research design is not able to rule out that heightened emotions, while not having a short-run effect, increase the likelihood of alcohol consumption in the medium run, which in turn would increase the likelihood of committing domestic abuse.

Our results point to the main role of alcohol and direct exposure of the victim to the perpetrator as determinants of domestic abuse in the aftermath of a game. Watching football games earlier in the day coincides with much higher levels of alcohol consumption which in turn – when mixed with the presence of one's partner (Bindler et al., 2020) in an alcoholized state – incites intimate partner abuse. Our insights have important policy implications when thinking about mitigating the relationship between sports and abuse. Scheduling games later in the day and implementing policies that reduce drinking can prevent a majority of football-related abuse from occurring.

The paper is organized as follows. Section 2 provides a literature review of the existing evidence of the effect of football on domestic abuse. The subsequent section describes the institutional background, data, and event study methodology. Section 4 depicts the results and Section 5 concludes with a brief discussion of our contribution and its implications.

2. Causes of domestic abuse victimization: alcohol and football

Risk factors identified in the Economics and Criminology literature that increase the likelihood of domestic abuse victimization can be grouped into socio-demographic factors, risky behaviors, and environmental factors (Bindler et al., 2020). Within explanations around how one's environment can increase the chance of their victimization, the role of sports has been discussed. White et al. (1992) document a statistically significant increase in female hospital admissions following a win of the local baseball team, while Boutilier et al. (2017) establish a rise in domestic violence calls to the police following important football matches. During the 2010 FIFA World Cup, Brimicombe and Cafe (2012) document a 27.7% increase in domestic violence cases in Greater London on days when England won a match, and a 33.9% increase when they lost, while Kirby et al. (2013) report a comparable impact in Lancashire. Similarly, Williams et al. (2013) show increases after local derbies in Glasgow. Finally, Trendl et al. (2021) capture an increase in the reported number of alcohol-related domestic abuse cases in the West Midland police force area on days when the England national team plays in a national football tournament. In sum, across a wide variety of sports and contexts, domestic abuse is shown to increase following a game. However, these studies share the disadvantage of examining generally a very low number of salient games and lack high-quality micro-level victimization data. Therefore they are unable to differentiate whether the effects are due to generally higher likelihood of abuse occurring at times when games are scheduled (e.g. the weekend) or whether these effects are present exclusively for the very salient and competitive games. These limitations are overcome in Card and Dahl (2011) that use the difference in pre-game expectations and the result of the game as exogenous variation in the triggered emotional response and find increases in domestic abuse primarily driven by an upset loss. However, while their estimates capture *an average effect of an unexpected emotional shock*, they do not estimate the *average effect of a football game*. We overcome the data limitations previously met in the literature by exploiting unique administrative data on all calls to the police over a period of eight years matched to all football games played during that time. The wealth of the data allows us to test the plausibility of the exogeneity of the timing of the game to DA and to differentiate between the short and long-term effects of a game by hour on domestic abuse.

Understanding why football games lead to domestic abuse can have important implications for public policy, including how games are organized or how information campaigns are designed. Two main explanations have been put forward in the literature: strong emotional reactions caused by the game and increased alcohol consumption.

The first argues that the increase in domestic abuse is caused by strong emotional reactions of football fans to the game, which are stronger after unexpected results due to the effect of reference dependence (Wann, 1993). As discussed, Card and Dahl (2011) use betting odds to control for pre-game expectations and find a 10% increase in male-on-female domestic abuse immediately after an upset loss compared to after tied matches. Similar emotional reactions are shown after upset losses across other types of violent behavior (Rees and Schnepel, 2009; Kirby et al., 2013; Munyo and Rossi, 2013). The strength of the emotional reaction will also depend on the importance of the game: Dickson et al. (2015) only find evidence of loss aversion as a trigger of domestic abuse after matches with high stakes in the tournament, and several studies report statistically significant effects after more salient matches: derbies, traditional rivalries or popular tournaments (Sachs and Chu, 2000; Williams et al., 2013). However in the majority of these studies as Bindler et al. (2020) discuss, "one cannot disentangle whether these larger emotional shocks trigger more aggression directly, or whether it is indirect via an increase in alcohol consumption". Our contribution to this literature is to use the precise time stamp of calls to disentangle short-term effects, during and immediately after the game when emotions would plausibly be highest (Stieger et al., 2015; Newson et al., 2020; Van Der Meij et al., 2015) and the effect would be direct. Moreover, using alcohol and drug abuse flags of the perpetrator and victim involved we can explicitly test whether unexpected results lead to more DA under the influence of alcohol.

Literature has emphasized the role of increased alcohol consumption as a trigger for criminal behavior. Francesconi and James (2015) find a 45% increase in arrests for alcohol-related incidents due to binge drinking in the UK and Grönqvist and Niknami (2014) use alcohol sale restrictions in Sweden to estimate the effect on crime. Barron et al. (2022) find that a nationwide alcohol sales ban in South Africa led to a sharp drop in violent crime. Correlational analyses in Leonard (2005) also links higher alcohol consumption to higher rates of domestic violence, both in frequency and severity of the assaults, after controlling for mediator factors like marital conflicts, anti-social tendencies, and aggressive tendencies of the perpetrator. Besides triggering criminality, alcohol also increases the risk of victimization: Chalfin et al. (2019) use an increase in the probability of alcohol consumption at the legal age cutoff to estimate an effect of 7% higher violent crime victimization for men and 25% increased risk of sexual assault for women. Furthermore, in a study of college football games and crime in the US, Rees and Schnepel (2009) find sharp increases in assaults, vandalism, arrests for disorderly conduct, and arrests for alcohol-related offenses on game days. Lindo et al. (2018) show a positive correlation between college football games and rape on campus, with pronounced effects for upset wins, suggesting intense partying and alcohol consumption around the game as the likely causal pathway. Montolio and Planells-Struse (2016) find a rise in a number of crime types including domestic violence around football and attribute the effect to alcohol consumption during these periods. Yet, as sports often go hand-in-hand with increased alcohol abuse, it is even more difficult to disentangle how much of the increase in abuse can be causally interpreted as a consequence of alcohol. Our contribution overcomes the data limitations previously met in the literature by exploiting the very precise timing of the game and the reported domestic abuse with detailed flags on the alcohol abuse of the perpetrator. We further exploit the different kick-off times within a tournament to estimate the differential effect of an early versus a late game, as the former allows longer alcohol consumption.

3. Data

3.1. Data on domestic abuse

The setting of our analysis is Greater Manchester in the United Kingdom due to the salient presence of football among its population and its two well-known football clubs, while at the same time well recorded individual level police data. Greater Manchester (GM) is a metropolitan county and combined authority area in North West England, with a population of 2.8 million. It is the third largest authority area in England and Wales by the size of its population. Greater Manchester is also the largest sub-regional economy in the UK outside London and South East England, and the economic center of the North West region of England. Greater Manchester is also a county with some of the largest inequalities in the UK, where some of the UK's most deprived and most affluent boroughs can be found. It is home to a diverse population and is a multicultural agglomeration with an ethnic minority population comprising around 8% of the total population in the recent Census. The territorial police force responsible for law enforcement in GM is the Greater Manchester Police, the second largest police force in England and Wales.

Our data on domestic abuse[3] includes the population of all calls to the police in the Greater Manchester metropolitan area from April 2012 to June 2019. This confidential data, that requires police vetting to access, is provided by the Greater Manchester Police (GMP), the local police force, and is drawn from five different datasets: the calls for service from the command and control central,[4] the crime register, a victim dataset, an alleged perpetrator dataset, and a dataset with information on the relationship between victim and perpetrator.

The GMP command and control center deals with all calls for service either from an emergency number (911), a non-emergency number (101) or the police themselves. Every call to the police is answered by a call handler and given a unique identifier number. The handler assigns the urgency of the response to the incident, and one or more

[3] The UK defines domestic abuse as "any incident of controlling, threatening behavior, violence or abuse (physical, emotional, psychological, sexual or financial) between those aged 16 or over who are or have been intimate partners or family members regardless of gender or sexuality". This can include incidents between siblings, incidents between adult children and parents, or intimate-partner incidents involving current or past spouses or romantic partners; it also encompasses a wide range of behaviors that can be offenses of assault, harassment, etc. Home Office (2012).

[4] In Table A.1, we discuss summary statistics of domestic abuse reports and compare the details of reports on game days and non-game days. 65% of domestic abuse incidents are reported by calling 999. In 61% of incidents, the victims themselves call to report the incidence. Each call received is being given a particular urgency grade. 37% of all incidents are categorized as immediate at the very first stage that they are reported.

opening codes that give information about the type of incident, which are later complemented by closing codes once the incident has been resolved. Together with information on the nature of the call, the command and control dataset also contains information on the caller, whether they are a victim, a witness or a third person, how the incident was reported (phone, radio, emergency services), the incident location and premises, the intervention of the police, the incident outcome (a penalty or caution, if charges were pressed or not) and finally a crime reference number if the call resulted in a crime report. Every incident also has a recorded date and time of reporting and a set of coordinates.

We restrict our analysis to domestic abuse incidents for the period April 2012 to June 2019, a period for which we have complete information on the relationship between victim and perpetrator.[5] During this period, 477,765 DA incidents were recorded; which is 6.64% of the population of 7,192,735 recorded incidents. Of those, 91.1% hold data on either the victim and perpetrator, or both, and can be linked to the respective victim and alleged perpetrator datasets. The dataset contains variables like ethnicity, gender, and age of the victim and perpetrator. It also contains information related to the incident such as its risk level, whether any injury was suffered, if the perpetrator was under the influence of alcohol or drugs when the officer attended the scene (this is tested and reported by the police officer), and if they were arrested for domestic abuse or other reason. Using the unique identifiers we link both the command and control data and domestic abuse dataset that records the relationship between perpetrators and primary victims.[6] Finally, we merge incident data with the GMP's crime register through the crime reference number to get further information on the nature of the crime, as well as on the victims and perpetrators. 37% of the domestic incidents constituted a crime.

After keeping observations with both victim and perpetrator data, we obtain a final dataset of 434,596 DA calls from April 2012 to June 2019; out of those, we focus on domestic abuse between intimate partners (including both current and ex-partners, hetero and homosexual) which represent 70% of those incidents. The dataset is then collapsed in a two-hourly time series dataset. Our choice to define the unit of observation as a two-hour interval was informed by the fact that, on average, a football game lasts two hours. Table 1 depicts the summary statistics for this dataset. On average, there were about 9 recorded cases of domestic abuse between intimate partners across Greater Manchester every 2 h. Most of these incidents were acts of male-on-female partner violence (77% of all partner incidents, or 83% of heterosexual couples) and mainly occurred at home (88%). There were almost as many incidents between ex-partners as between current partners, and alcohol was also twice as likely to feature in DA between current partners. Overall, perpetrators were under the influence of alcohol in a third of all cases reported to the police. in Table A.2 we show additional descriptive statistics on domestic abuse with the presence of alcohol.

The temporal distribution of calls to the police is such that domestic incidents are spread more or less equally over the week, with higher incidence on Friday, Saturday, and Sunday[7]– calls on the weekend (between Friday 6 PM and Monday 6 AM) amount to 36% of the sample. Most domestic abuse calls were made in the early afternoon (32%) or evening (29%). Calls late at night or in early morning constitute 20% of the sample each.

3.2. Football matches

In order to study the effect of football on domestic abuse we focus on the two main football clubs in the city: Manchester United and Manchester City. For this, we collected data on all their matches over the observation period. In total, both teams played a combined 780 games, split equally between the two. They played 38 games in each Premier League season as well as other knockout competitions both at the national level (EFL and FA Cups) and European level (Champions League and Europa League). Additionally, teams might have played in other competitions like the FA Community Shield or the UEFA Super Cup.[8]

Table A.3 shows the descriptive statistics on the games. Football games are scheduled throughout the week, with evening games likelier during the week while weekend games have kick-off times through the

Table 1
Descriptive statistics on domestic abuse.

	(1)		(2)	
	Original sample		*Collapsed 2 h sample*	
	Mean	Std.Dev.	Mean	Std.Dev.
Domestic abuse by relationship				
Partners	0.69	0.46	9.47	5.25
Current partners	0.36	0.48	4.85	3.40
Ex-partners	0.34	0.47	4.61	3.14
Male on female current partner	0.27	0.44	3.68	2.71
Female on male current partner	0.06	0.23	0.77	0.99
Current partners -alcohol	0.15	0.36	2.04	2.49
Ex-partners -alcohol	0.08	0.27	1.10	1.24
M. on f. current partner -alcohol	0.11	0.31	1.52	1.95
F. on m. current partner -alcohol	0.03	0.16	0.36	0.70
Location of domestic abuse incident				
At home	0.89	0.31	12.24	6.52
Alcohol use				
Alcoholized Perpetrator	0.31	0.46	4.31	4.13
Alcoholized victim	0.20	0.40	2.81	3.28
No alcohol	0.65	0.48	8.90	5.72
Gender of victim and perpetrator				
Male on female	0.77	0.42	7.40	4.19
Female on male	0.15	0.36	1.46	1.38
Male on male	0.05	0.22	0.48	0.75
Female on female	0.01	0.11	0.11	0.34
Type of domestic abuse incident				
DA Crime	0.37	0.48	5.06	3.81
Day of week of domestic abuse incident				
Weekends	0.36	0.48	5.00	8.33
Monday	0.14	0.34	1.87	5.40
Tuesday	0.13	0.34	1.80	5.20
Wednesday	0.13	0.33	1.77	5.09
Thursday	0.13	0.33	1.76	5.00
Friday	0.16	0.36	2.18	5.86
Saturday	0.17	0.38	2.37	6.33
Sunday	0.15	0.35	2.02	5.74
Time of day of domestic abuse incident				
Before 6 h	0.19	0.39	2.56	5.12
6–12 h	0.20	0.40	2.79	5.48
12–18 h	0.32	0.47	4.37	7.88
18-00 h	0.29	0.46	4.05	7.81

Note: This table shows the means and standard deviations of all the variables listed on the left. Domestic abuse crimes are a subgroup of domestic abuse incidents that meet the severity criteria to be recorded as a crime. Columns (1) refer to the descriptive statistics of the original sample of all 434,596 domestic abuse incidents, where every observation is an incident and the variables are binary. For example, the mean of 0.69 for the variable Partners indicates that 69% of domestic incidents were between intimate partners. Columns (2) show the descriptive statistics of the original sample collapsed in a time series of the sum of domestic incidents every 2 h. The mean of 9.47 for Partners indicate that, on average, there were 9.47 incidents between intimate partners every 2 h.

[5] In order to do that we filter out those observations that have a closing code of "domestic" assigned by GMP.

[6] This allows us to identify those incidents of domestic abuse that were committed between intimate partners.

[7] We count days as starting at 6 AM until 6 AM the next day.

[8] The majority of the games were played in the Premier League (69%), and then Champions League (14%), FA Cup (8%) and EFL Cup (6%). Seasons in the Premier League run from August to May with each team playing 38 matches. The Champions League usually runs from September until early June, with the group stage played from September to December, whilst the knock-out stage starts in February. The final is typically held at the end of May or the beginning of June.

entire day. Late games (after 7 PM) make up 37% of the sample, while early and mid-afternoon games account for 17% and 46% respectively. There is also a higher frequency of matches on Friday evenings and the weekend, with 61% of the games occurring then. We record the match result as well as other match characteristics like overtime, penalties, or it being a derby, although the latter only constitutes 6% of the sample. We count a "derby" as a match between Manchester City and Manchester United but also between Manchester United and Liverpool, given their close proximity and long-standing rivalry. Together with the observed outcome, we also record the expected results as measured by betting odds sourced from the two main betting providers, Bet365 and William Hill. As there was little discrepancy between the two, in our analysis we use only Bet365 odds to capture pre-game expectations.[9] Given that both Manchester United and Manchester City are among the strongest clubs in the UK, they went on winning most of the games (62%), while losing only 20% of the time. The remaining 18% were draws. In Table A.4, we also break down the descriptive statistics on games across early and late kick off times and show that these games are not different across their expected and end game results, their competitiveness nor which clubs played them.

4. Research design

We are interested in estimating the differential time dynamics on a day when there is a football game. To do so, our research design estimates an event study specification by generalized least squares on a time series of two-hour intervals of all domestic incidents in Greater Manchester. Since games take place at different times and days of the week, which also vary depending on the week, we exploit the hourly variation in game timings over the eight year period to identify the causal effect of the sporting event on domestic abuse incidents every two hours. We specify the model by including eight lags and four leads capturing the full 24 hours around the game, with t indicating the start of it.[10] The cumulative effect of a football game is therefore captured by eight lags spanning the 16 hours following the start of the game. This extended time window is able to capture all the time dynamics of domestic abuse on a given game day in the immediate aftermath of the match, later in the day and in the early hours of the following morning. A shorter time span would leave out all incidents resulting from escalating conflicts that may have been triggered by the match, especially those involving drugs or alcohol, which have been proven to play a prominent role in domestic violence. The unit of observation in our specification is a two-hour interval t.

In addition, four leads are included to model pre-trends in the 8 hours prior to the game. For ease of 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 $t-1$. In Section 5.4, we explore the robustness of our results to alternative omitted reference categories. Given the length of the two-hourly time series, all periods outside $t=-4,-3,\ldots,7,8$ are binned in a dummy variable $Game_{\tau_t}$. Eq. (1) depicts the main estimating model:

$$DA_t = \alpha + \sum_{s=-4}^{8} \beta_s Game_{t+s} + \gamma_0 Game_{\tau_t} + \theta_t + \epsilon_t \tag{1}$$

DA_t is the sum of all domestic abuse incidents that were recorded in the two-hour period t, $Game_{t+s}$[11] is a dummy variable equal to 1 if a match started s periods ago and $Game_{\tau_t}$ is the dummy that bins the rest of periods. $Game_{t-1}$ is omitted from the regression. θ_t represents the full set of time fixed effects: year and quarter, day of the week, hour, interaction effects of day of the week with hour of the day, and a holiday dummy. Finally, ϵ_t is a random error term. As our outcome variables, DA_t, we use: DA between current partners, current partners with a male perpetrator and female victim, current partners with a female perpetrator and male victim, current partners with an alcoholized perpetrator, current partners with a non-alcoholized perpetrator, and ex-partners.

The leads and time fixed effects control for any linear and non-linear time trends of unobservables that may affect domestic abuse on a given day. Quarter fixed effects account for seasonal trends as crime surges in summer months, which coincides with the interruption of the football season,[12] while weekday and hour interactions additionally capture the changes in daily patterns that happen during the week. Figure A.1 shows the descriptive variation of DA incidence across the day of the week and time of day. We also control for national holidays to account for a surge in domestic incidents around those days, in particular around the Christmas and New Year period (Card and Dahl, 2011). Our identification assumption for estimating the causal effect of the games is that, conditional on the time trends, the domestic abuse incidence would have evolved similarly over time in the absence of the game. Hence our control group constitutes days when a football game does not occur, allowing us to compare, for example, the hourly dynamics of domestic abuse on a Saturday in February when a game is played compared to a Saturday in February when a game is *not played*. In this sense, the variation of the control group can be thought of as 'never-treated' (De Chaisemartin and d'Haultfoeuille, 2020). The $\sum_{s=0}^{8} \beta_s$ identifies the cumulative effect of a game on domestic abuse.

A valid concern might be that football games are scheduled in advance and therefore may lead to anticipation effects, either on the side of the police or the victims themselves. Note that the specifics of domestic abuse, occurring within private homes of victims in around 90% of cases, hinder the police from proactively reacting by increasing patrols. Moreover, GMP officers do not routinely contact victims of DA unless previously agreed to ensure that the contact itself is not an onset for violence. If patrolling changed, we could expect a bigger share of calls reported by police radio but we do not observe a difference in the descriptive statistics between game (3% of calls) and no game days (4%) (Table A.1). However, to check whether police reporting changes as a result of football games, using the model in Eq. (1), we test whether games have an effect on the channels of reporting. While we cannot directly test whether victims anticipate and change their behavior on the days football games occur (apart from verifying the parallel trends assumption on the dynamics preceding the game), if it were true that victims do anticipate the violent behavior and avoid their partners by staying elsewhere during game days, our estimates can be interpreted as the lower bound of the true effect.

[9] We classify a match as an expected win if the probability of winning assigned by the betting market was equal or higher than 55%; as an expected loss if it was smaller than 45%, and as a close match if the winning probability was between both values. The contrast between the *ex-ante* market prediction and the result *ex-post* makes it possible to further classify a football match between six exhausting categories: an upset loss, an upset win, a close loss, a close win, a predicted win or a predicted loss. In Table A.5 we show how descriptively our sample of games compares to Card and Dahl (2011).

[10] A typical football game without overtime lasts 90 min, plus a 15 min break in between, which amounts to close to two hours in total. This has motivated our choice of using 2-h interval time series.

[11] Since we include matches of two football teams, it would be possible to have two games happening at close times so the sum of all game indicator lags would be bigger than 1, however, this occurs in only 3.4% of the observations.

[12] In alternative specifications, we included month fixed effects as well.

We also explore differential effects. Any game characteristics of interest like the start time or its salience are included in the general model as interactions with $Game_t$. For example, in the case of early start games we create the indicator variable $Early$ that is equal to 1 if there is a game starting before 7 PM at time t[13]:

$$DA_t = \alpha + \sum_{s=-4}^{8} \beta_s Game_{t+s} + \sum_{s=-4}^{8} \mu_s Early \times Game_{t+s} + \gamma_0 Game_{\tau_t} + \gamma_1 Game_{\tau_t} \times Early_{\tau_t} + \theta_t + \epsilon_t \quad (2)$$

In this model, $\sum_{s=-4}^{8}(\beta_s)$ represents the cumulative effect of late games (those starting after 7 PM). The cumulative effect of an early game is then the sum of the coefficients of $Game$ and $Early$: $\sum_{s=-4}^{8}(\beta_s + \mu_s)$.

We estimate the models in Eqs. (1) and (2) by feasible generalized least squares (GLS) and perform a Cochrane-Orcutt transformation of the models to account for the serial correlation in the residuals due to the time series nature of our data (Cochrane and Orcutt, 1949). We do so to correctly estimate the standard errors in a time-series setting with serial auto-correlation. Both the Durbin–Watson and the Breusch–Godfrey tests for serial correlation of Eq. (1) for domestic abuse between current partners, current partners with an alcoholized perpetrator, and ex-partners indicated a small and positive serial correlation with the first lag. This estimation method assumes errors to follow a first-order auto-regressive process and homoskedasticity.

Finally, we explore an alternative research design by conducting the analysis in absolute time of the game day, as compared to a non-game day, controlling for the same series of time dynamics. We show the raw mean of domestic abuse reports in absolute time (by 2-h intervals) for (a) non-game days, (b) early games, and (c) late games as depicted in Figure A.2. The corresponding model specification is shown in Eq. (3):

$$DA_t = \alpha + \sum_{s=(6-8\text{ am})}^{(2-4\text{ am})} \gamma_s hourly_{t=s} + \sum_{s=(6-8\text{ am})}^{(2-4\text{ am})} \beta_s hourly_{t=s} \times Game_{t=s} + \theta_t + \epsilon_t \quad (3)$$

DA_t is the sum of all domestic abuse incidents that were recorded in the two-hour period t, $hourly_{t=s}$ indicates the two-hours time intervals during a day which starts from 6 to 8 am and ends at 4 to 6 am. The time interval from 4 to 6 am is omitted from the regression as the reference category. $Game_{t=s}$ is a dummy variable equal to 1 if there is a match occurring on that particular day. θ_t represents the full set of time fixed effects: year and quarter, day of the week, and a holiday dummy. Finally, ϵ_t is a random error term. As our outcome variables, DA_t, we use: DA between current partners, current partners with a male perpetrator and female victim, current partners with a female perpetrator and male victim, current partners with an alcoholized perpetrator, current partners with a non-alcoholized perpetrator, and ex-partners.

In order to study the effect of having an early game on a particular day versus having a late game on a day on domestic abuse incidents, we can alter the absolute timing model as follows in Eq. (4):

$$DA_t = \alpha + \sum_{s=(6-8\text{ am})}^{(2-4\text{ am})} \gamma_s hourly_{t=s} + \sum_{s=(6-8\text{ am})}^{(2-4\text{ am})} \mu_s hourly_{t=s} \times Game-early_{t=s} + \sum_{s=(6-8\text{ am})}^{(2-4\text{ am})} \beta_s hourly_{t=s} \times Game-late_{t=s} + \theta_t + \epsilon_t \quad (4)$$

All individual components mirror the ones from Eq. (3). This time, we study the effect separately for the days with early games (games before 7 pm) and the days with late games. $Game-early_{t=s}$ is a dummy variable equal to 1 if there is an early match occurring on that particular day. $Game-late_{t=s}$ is a dummy variable equal to 1 if there is a late match occurring on that particular day.

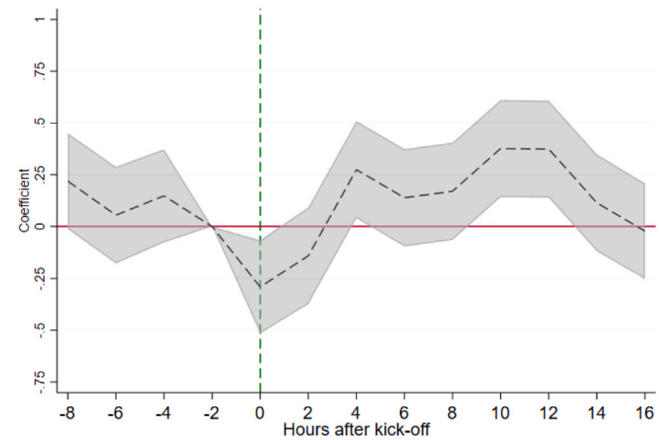

Fig. 1. Effect of a football game on domestic abuse between current partners. Note: The figure plots the coefficients from Eq. (1) as the dashed line and their 95% confidence intervals as the gray shaded area across 2-h intervals. $T = 0$ denotes the game kick-off. The coefficient for t−1 (two hours before the game) has been normalized to zero.

We prefer to use the event study framework as our main specification to study the dynamics of domestic abuse around football games. An event study allows us to separate the pre-event behavior from the dynamics during and after the game, while absolute timing tends to conflate it and average out the pre-trends to the post-game coefficients. In the most extreme case, the average of late and early games with opposite magnitudes could lead to zero in an absolute timing framework. In contrast, in an event study, we can separate those dynamics by estimating relative-to-game time dummies. It also allows us to correctly disentangle the leads to the game and test for differential behavior leading up to the game. Our identification assumption for estimating the dynamic causal effect of games is that – conditional on time trends – the domestic abuse incidence would have evolved similarly over time in the absence of the game.

Eq. (3) does not allow us to study the dynamics of the aftermath of a football game, as we cannot differentiate between immediate and long-run effects throughout the day. We also believe that the event study specification is more rigorous as it estimates the within ‘time and day’ variation across different relative-to-game periods, while the absolute timing specification can only speak about the average difference of that fixed time period on a game day versus a non-game day.

5. Results

In this section, we present the main results on the hourly dynamics of domestic abuse around the timing of a football game. We then disaggregate the total domestic abuse by the type of relationship and the gender of the perpetrator and victim.

First, we examine the effect of a football game on current intimate partners estimating the model in Eq. (1). We report the results in Table 2 which are visualized in Fig. 1. The immediate effect of a football game is a decrease of 5% of DA incidents (in absolute terms about 0.27 fewer incidents) during the game, compared to incidents two hours before the game (t−1). This initial decrease is statistically significant and lasts the 2-h duration of the game, after which domestic abuse levels return to their pre-game state. This pattern signals a crowding-out between leisure and domestic abuse, as potential perpetrators give their attention to the game during that time. This substitution effect could come either from watching the televised match from home (DellaVigna and Ferrara, 2015) or from a public setting like a pub or the stadium

[13] As a robustness check, in another set of results, we define $Early$ that is equal to 1 if the game starts before 5 PM.

itself, which reduces the risk of criminalization. After the match, reports of domestic abuse incidents reverse and start growing by 5% every two hours in the first 4 hours following the game. The highest increases in magnitude (7.4%) occur between 10 to 12 hours after the start of the game and then the effect disappears around 16 h after the game. For an average match that started at 3 PM, that would mean the first increases in reporting would happen at 7 PM at a rate of 0.3 domestic abuse calls more every two hours and they would peak between 1 and 2 AM, at 0.4 calls more per two hours. While we cannot exactly pinpoint the timing of the start of the abuse or assault, it is likely that victims report domestic abuse about 1–2 hours after the conflict had started and once it has escalated, which would mean the largest increases in conflict start at around 11 pm to midnight.[14]

The leads before the game are jointly non-significant with an F-value of 1.49 (Prob > F = 0.162). Even though the timing of football games is set in advance, the absence of pre-trends helps to rule out any anticipatory changes in behavior made in advance of the sporting event. Cumulatively, we find that football games affect the dynamics of intimate partner abuse among current partners while not increasing the total level of the abuse — but shifting it to later periods in the day.

We hypothesize that the timing of the game might be an important contributing factor to domestic abuse incidence as an earlier start allows spectators on and off the ground to consume alcohol for a longer period before pubs close at 11 pm. To test this empirically, we include a dummy for early games interacted with the "Game" indicator as shown in Eq. (2) and plot the estimated effects of an early or late game in the lags. We define an early game as one that takes place in the afternoon (with a start time before 7 pm), which constitutes 63% of all games.[15] The results are shown in the second and third column of Table 2 and plotted in Fig. 2.

We observe that statistically significant increases in domestic abuse cases happen only after early games. Evening games do not lead to any significant changes: the point estimates are negative during the game, then show an increasing trend in 4 hours after the game but the confidence intervals are too wide to reject the null, becoming close to zero thereafter. The result in Fig. 1 is therefore driven by games starting between 12 PM and 6:30 PM. During an early game, domestic abuse calls to the police are 5.3% lower than the two-hour average (0.25 incidents less in absolute terms) as potential perpetrators are focused on the game. Then they return to average values and begin growing in the afternoon, 4 hours after the game starts, until they peak 10–12 hours after the kick-off time, which corresponds to a time window between 10 PM and 4 AM. While we cannot exactly pinpoint the timing of the start of the abuse or assault, it is likely that victims report domestic abuse about 1–2 hours after the conflict had started. Therefore when thinking about the time dynamics, while we find the peak in reporting from 10 PM to 4 AM, it is plausible this conflict started earlier from 8/9 PM to 2/3 AM. During that time there are 0.50 calls more every two hours; which in relative terms is an increase of 10.6%. Early games lead to a cumulative increase in current partner domestic abuse over the 16 hours following the game (with a p-value of 0.075). Taken together, evidence shows football games lead to a higher number of domestic abuse incidents in private settings later in the evening, as the causal effect takes approximately 8 hours to appear and is only present after early games.

Table 2
Effects of a football game and its timing on domestic abuse between current partners.

	(1) All incidents	(2) Late games	(3) Early games
Game, t−4	0.24**	0.08	0.21
	(0.12)	(0.20)	(0.15)
Game, t−3	0.08	−0.18	0.10
	(0.12)	(0.21)	(0.50)
Game, t−2	0.17	0.14	0.08
	(0.12)	(0.20)	(0.59)
Game	−0.27**	−0.50**	−0.25*
	(0.12)	(0.20)	(0.07)
Game, t+1	−0.12	−0.34	−0.13
	(0.12)	(0.21)	(0.38)
Game, t+2	0.29**	−0.09	0.37**
	(0.12)	(0.22)	(0.01)
Game, t+3	0.13	−0.30	0.24*
	(0.12)	(0.22)	(0.10)
Game, t+4	0.13	−0.21	0.19
	(0.12)	(0.21)	(0.18)
Game, t+5	0.36**	−0.14	0.51***
	(0.12)	(0.21)	(0.00)
Game, t+6	0.35**	0.06	0.39**
	(0.12)	(0.21)	(0.01)
Game, t+7	0.11	0.01	0.04
	(0.12)	(0.21)	(0.79)
Game, t+8	−0.03	−0.27	−0.02
	(0.12)	(0.20)	(0.90)
Holiday	1.71***	1.68***	1.68***
	(0.11)	(0.11)	(0.11)
Quarter FE	Yes	Yes	Yes
Day of week × Hour FE	Yes	Yes	Yes
Binned endpoints	Yes	Yes	Yes
R-squared	0.42	0.42	0.42
Observations	31 582	31 582	31 582
Prob > F (leads)	0.162	0.437	0.542
Prob > F (lags)	0.000	0.235	0.000
Cumulative sum of lags	0.95	−1.78	1.35
P-value Cumulative sum of lags	0.151	0.177	0.075

Note: This table reports the estimates on the outcome: domestic abuse among current partners. The results in column (1) are obtained from the specification in Eq. (1). The results in columns (2) and (3) are estimated in the same regression as the specification in Eq. (2) describes, but for ease of reading the results have been shown here in two columns (hence R-squared, and the Holiday coefficient are the same). T = 0 denotes the game kick-off. The coefficient for t−1 (two hours before the game) has been normalized to zero. Prob > F (leads) report the p-value of the F test on the joint significance of the leads to the event ($\beta_{t-4}\ldots\beta_{t-1}$). Prob > F (lags) report the p-value of the F test on the joint significance of the lags to the event ($\beta_t\ldots\beta_{t+8}$). The cumulative sum of lags displays the sum of the lags, i.e. $\sum \beta_t + (\ldots)\beta_{t+8}$, and the p-value reports the p-value of the F-test on whether this sum is different than zero. Standard errors are shown in parentheses.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.001$.

5.1. Mechanism: Alcohol

In the following, we disentangle the role of alcohol as the mechanism underlying the increase in domestic abuse after football matches. Throughout the period of our sample, on average 1/3 of domestic abuse perpetrators were under the influence of alcohol when the incident was recorded (Table 1). To check whether football games lead to domestic abuse through increased consumption of alcohol or through heightened emotions, we repeat our analysis by disaggregating the

[14] Due to the lack of precise empirical data on this (police officers do not routinely ask or record when the abuse started), we are unable to precisely estimate this lag in hours. To this extent, we asked the head of Domestic abuse policing to comment on this issue from their experience: "While it is hard to give an exact estimate of the length of the abuse at the time of the report to the police, from our officers' experience in cases that are reported on the same day, it is common that the argument had been going on for 1–2 h beforehand and was escalating when the victim, or witness, decided to report the domestic abuse to the police. It is typical that it is an escalation of matters that leads to the police being called, however, this often leads to the uncovering of unreported abuse going back some time, on occasion years". (Detective Superintendent for Domestic Abuse, GMP, 2018–2022).

[15] As a robustness check, in another set of results, we define $Early$ that is equal to 1 if the game starts before 5 PM. These results are presented in Figure A.3.

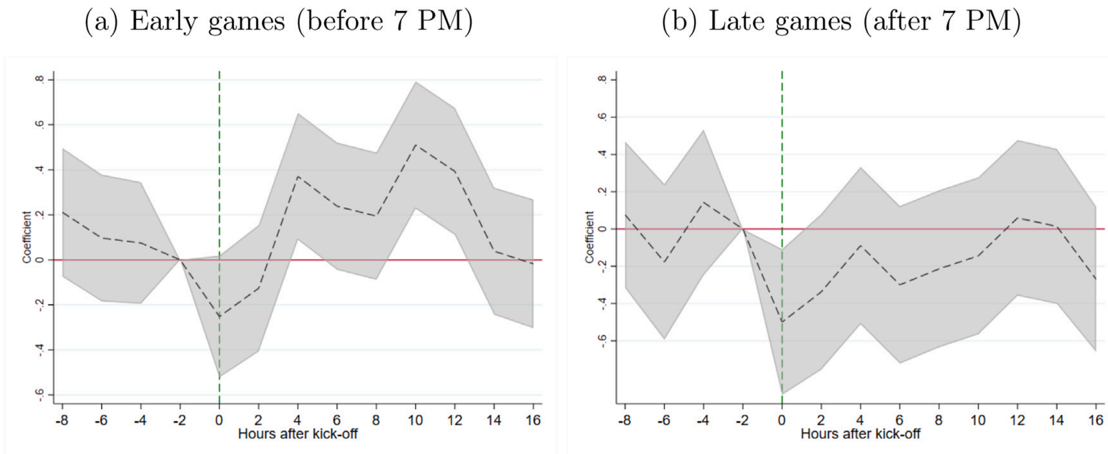

Fig. 2. Effect of early and late games on DA between current partners. Note: The figure plots the coefficients from Eq. (2) as the dashed line and their 95% confidence intervals as the gray shaded area across 2-h intervals. $T = 0$ denotes the game kick-off. Figure (a) plots the sum of *Game* and the interaction term of *Game x Early*, the change in domestic abuse incidents per 2-h after an early football game. Figure (b) shows the coefficients of *Game*. The coefficient for $t-1$ (two hours before the game) has been normalized to zero.

outcome variable across *DA with alcoholized perpetrators* and *DA with non-alcoholized perpetrators*.

The results are shown in Table A.6 and the estimated β_ss are plotted in Figure A.4. If heightened emotions were the only mechanism, we would expect that non-alcoholized abuse also increases in the aftermath of the game. Yet for perpetrators with no alcohol presence, a football game does not lead to any significant changes. If anything, watching football diverges perpetrators that have not consumed alcohol from committing abuse. When the perpetrator had consumed alcohol, the effect starts growing 6 hours after the game, until it peaks 10 hours later, when it starts decreasing again. At that peak, the number of DA is 0.33 incidents higher, which represents 6.8% incidents more every two hours in that period. Cumulatively, this also leads to an overall positive significant effect of a football game on domestic abuse over the 16 hours after the game. Therefore, we observe that in the aftermath of a game, the increase in domestic abuse is driven entirely by alcoholized perpetrators.

Taken together, the results of Figs. 2 and A.4 point to the combination of earlier games and the presence of alcohol as the drivers behind the surge in domestic incidents following a game. To precisely isolate these effects, we interact the timing of the game as shown in Eq. (2) on *alcoholized* versus *non-alcoholized* abuse. The results are shown in Table 3 and displayed in Fig. 3. Graphs (a) and (c) of Fig. 3 plot the coefficient estimates for the incidents where the perpetrator had consumed alcohol as opposed to (b) and (d), where the dependent variables are incidents with non-alcoholized perpetrators.

The magnitude of the effect of a game before 7 PM on domestic abuse incidents with alcoholized perpetrators (Fig. 3(a)) shows a clear pattern.[16] We observe that following early games, domestic abuse incidents with alcoholized perpetrators start increasing after the first two hours after the match and keep increasing until they reach a maximum 10 hours later (likely reflecting a peak in conflict 8–9 hours after the game due to the plausible lag in reporting). At the peak, this equates to 0.49 incidents more or 10% of the mean. The cumulative effect is an increase of 1.37 incidents more or 8% of all incidents over the 16-hour period which is an economically sizeable effect.

By contrast, we observe no statistically significant effect when the perpetrator is sober (Figs. 3(b) and 3(d)). We also do not observe any significant cumulative effect when the game is late. Additionally, we test whether these effects depend exclusively on the alcohol presence of the perpetrator or both individuals. In the Appendix (Table A.7), we show that the effect of an early game is even bigger and rises faster when incidents with any alcohol involvement (either in the perpetrator or in the victim) are considered (Figure A.5a), while it disappears when no one drank (Figure A.6a) or alcohol was consumed only by the victim (Figure A.7b). It is the consumption of alcohol by the perpetrator that makes a difference in domestic abuse after a football game.

The detailed analysis by timing and alcohol presence sheds new light on the mechanisms behind the initial results observed in Fig. 1. The finding that during the game there is a decrease in incidence and domestic abuse only starts increasing 4 hours after the game, points to the fact that domestic abuse is not driven by a short-term emotional reaction to the game, but increases in the medium-term when the perpetrator has consumed alcohol.

For domestic abuse among current partners, football games change the dynamics of domestic abuse while not increasing the overall level of abuse throughout the day — with the displacement of abuse from the period of the game as spectators are busy with watching it to later periods 8–10 hours after the game ends. The exception to this is when games are early and the perpetrator is under the influence of alcohol. For this combination, football games lead to an overall cumulative increase in domestic abuse, and it is also under this combination that we find the highest magnitudes of the effects in the aftermath of the game. This leads us to conclude that domestic abuse does depend on the occurrence of games (both decreasing it contemporaneously and increasing it in the aftermath), but it is through the mechanism of alcohol consumption that the early games particularly reinforce its effects, leading to a positive cumulative effect.

5.2. Mechanism: Emotional cues

Loss aversion can incite a more aggressive emotional response to a lost game if the expectations about the game were positive (Card and Dahl, 2011). More generally, the response to the game can be more intense if the end result is different from the expected one. To estimate the effect of emotional cues on domestic abuse we estimate a model similar to Card and Dahl (2011) using the betting odds from the most

[16] As a robustness check, in another set of results, we define $Early$ that is equal to 1 if the game starts before 5 PM. These results are presented in Figure A.3.

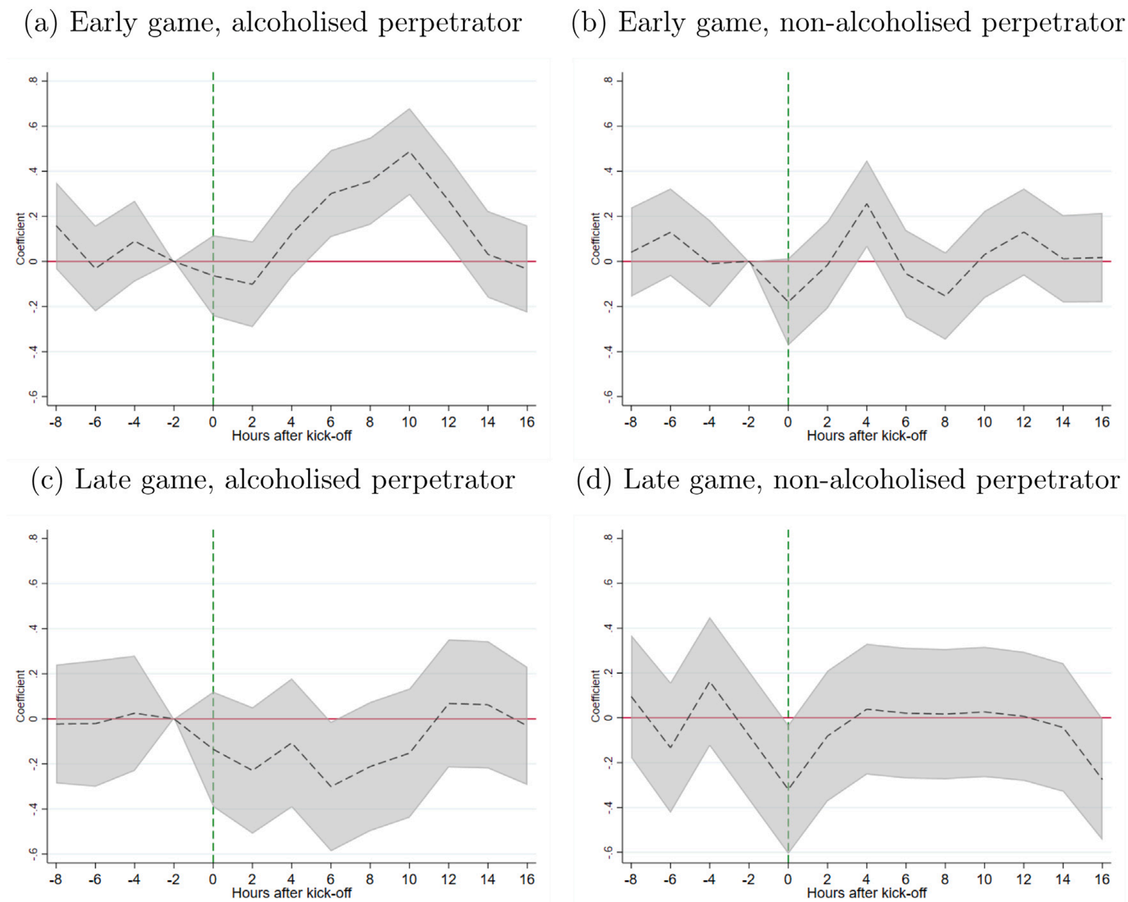

Fig. 3. Role of alcohol in early and late football games, DA between current partners. Note: The figure plots the coefficients from Eq. (2) as the dashed line and their 95% confidence intervals as the gray shaded area across 2-h intervals. $T = 0$ denotes the game kick-off. Graph (a) and (c) include those incidents between current partners where the perpetrator was under the influence of alcohol, while graph (b) and (d) only includes those without alcohol involvement. The coefficient for t−1 (two hours before the game) has been normalized to zero.

popular sports betting portal *Bet365* to derive the expectations prior to the football game. We classify a game as an expected win if the probability of winning assigned by the betting market was equal to or higher than 55%; as an expected loss if it was smaller than 45%, and as a close match if the estimated winning probability is in-between. The contrast between the *ex-ante* market prediction and the *ex-post* results makes it possible to further classify a football match as one of six distinct categories, depending on whether the end result was better or worse than the expected one. These are an upset loss, an upset win, a close loss, a close win, a predicted win, or a predicted loss.[17] The distribution of these six categories can be found in Figure A.8.

To check if domestic abuse increases as a result of an emotional response, we estimate the following linear model on daily domestic abuse incidents, following as closely as possible (Card and Dahl, 2011):

$$DA_t = \alpha_0 + \delta_1 Upset\ loss_t + \delta_2 Upset\ win_t + \delta_3 Close\ loss_t + \delta_4 Close\ win_t + \delta_5 Predicted\ loss_t + \delta_6 Predicted\ win_t + \theta_t + \epsilon_t \quad (5)$$

where DA_t are daily[18] domestic abuse incidents that occurred on day t, δ_1 and δ_2 are the coefficients of interest, θ_t is a set of time fixed effects including season, week, day of week and holidays, and ϵ_t as the random error term. We also include an indicator variable for holidays to take into account the surges in domestic abuse on national holidays like New Year's Eve or Christmas. We restrict the sample to the football season that lasts from August to May.

In this model, non-game days are the reference category. According to prospect theory, the magnitude of the coefficient of *Upset loss* should be larger in absolute value than *Predicted loss* as the perceived decrease in utility is bigger. Similarly, *Upset win* would have a larger effect in absolute than *Predicted win*.

Table A.8 shows the results of estimating the model on domestic abuse between current partners. We estimate the model on *current partners (column 1), current partners with an alcoholized perpetrator (column 2), current partners with non-alcoholized perpetrator (column 3), current partners with both victim and perpetrator alcoholized (column 4) and current partners with no alcohol (column 5)*. Overall, most of the estimates are not statistically significant. Across the different outcome variables, we only find that an upset win (i.e. when the team wins a game they were predicted to lose) significantly increases domestic

[17] In practice, we create six indicator variables from the interaction between the three dummy variables of expected results with two other dummies indicating the actual result: $Upset\ loss_t = 1(Expected\ win_t) \times 1(Loss)$, $Upset\ win_t = 1(Expected\ loss_t) \times 1(Win)$, $Close\ win_t = 1(Close\ game_t) \times 1(Win)$ $Close\ loss_t = 1(Close\ game_t) \times 1(Loss)$, $Predicted\ win_t = 1(Expected\ win_t) \times 1(Win)$, $Predicted\ loss_t = 1(Expected\ loss_t) \times 1(Loss)$. For the purpose of the model, draws are considered losses in case the team played at home or played a derby.

[18] Given the amount of domestic abuse and other criminal activities and anti-social behavior that happen after midnight but should be attributed to the day before, we count days as starting from 6 AM to 6 AM. Card and Dahl (2011) restricted the sample to Sundays after 12 AM.

Table 3
Effects of a football game and its timing on domestic abuse between alcoholized and non-alcoholized current partners.

	(1) Late, Alc	(2) Late, No-alc	(3) Early, Alc	(4) Early, No-alc
Game, t−4	−0.02	0.10	0.16	0.04
	(0.13)	(0.14)	(0.11)	(0.68)
Game, t−3	−0.02	−0.13	−0.03	0.13
	(0.14)	(0.15)	(0.75)	(0.19)
Game, t−2	0.02	0.16	0.09	−0.01
	(0.13)	(0.15)	(0.32)	(0.92)
Game	−0.14	−0.32**	−0.06	−0.18*
	(0.13)	(0.15)	(0.49)	(0.07)
Game, t+1	−0.23	−0.08	−0.10	−0.02
	(0.14)	(0.15)	(0.30)	(0.88)
Game, t+2	−0.11	0.04	0.12	0.26**
	(0.15)	(0.15)	(0.21)	(0.01)
Game, t+3	−0.30**	0.02	0.30**	−0.05
	(0.15)	(0.15)	(0.00)	(0.58)
Game, t+4	−0.21	0.02	0.36***	−0.15
	(0.15)	(0.15)	(0.00)	(0.12)
Game, t+5	−0.15	0.03	0.49***	0.03
	(0.15)	(0.15)	(0.00)	(0.76)
Game, t+6	0.07	0.01	0.27**	0.13
	(0.14)	(0.15)	(0.01)	(0.19)
Game, t+7	0.06	−0.04	0.03	0.01
	(0.14)	(0.15)	(0.75)	(0.91)
Game, t+8	−0.03	−0.28**	−0.03	0.02
	(0.13)	(0.14)	(0.73)	(0.86)
Holiday	1.39***	0.25***	1.39***	0.25***
	(0.08)	(0.07)	(0.08)	(0.07)
Quarter FE	Yes	Yes	Yes	Yes
Day of week × Hour FE	Yes	Yes	Yes	Yes
Binned endpoints	Yes	Yes	Yes	Yes
R-squared	0.47	0.32	0.47	0.32
Observations	31 582	31 582	31 582	31 582
Prob > F (leads)	0.987	0.264	0.192	0.595
Prob > F (lags)	0.324	0.216	0.000	0.030
Cumulative sum of lags	−1.04	−0.61	1.37	0.04
P-value Cumulative sum of lags	0.248	0.497	0.010	0.930

This table reports the estimates of the regression specified in Eq. (2) on two outcomes: domestic abuse among current partners with alcoholized, and non-alcoholized perpetrators. The results in columns (1) and (3) are estimated in the same regression on alcoholized current partner abuse, but for ease of reading the results have been shown here in two columns (hence R-squared, and the Holiday coefficient are the same). In column (3), the estimates shown for "Game" correspond to the sum of Game + Early. The same has been done in columns (2) and (4) which are estimated in the same regression and report the effect of Late and Early games on the outcome of non-alcoholized current partner abuse. T = 0 denotes the game kick-off. The coefficient for t−1 (two hours before the game) has been normalized to zero. Prob > F (leads) report the p-value of the F test on the joint significance of the leads to the event ($\beta_{t-4}...\beta_{t-1}$). Prob > F (lags) report the p-value of the F test on the joint significance of the lags to the event ($\beta_t...\beta_{t+8}$). The cumulative sum of lags displays the sum of the lags, i.e. $\sum \beta_t + (...)\beta_{t+8}$, and the p-value reports the p-value of the F-test on whether this sum is different than zero. Standard errors are shown in parentheses.

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.001$.

abuse committed by non-alcoholized perpetrators.[19] However, we do not find evidence that upset losses, likeliest to induce the strongest negative emotional reaction, have any effects on domestic abuse incidence in incidents with or without alcohol. While our aim was to match as closely as possible the analysis reported in Card and Dahl (2011), this came with a trade-off of a smaller sample size as the unit of observation became a day. While the coefficients (and the differences between them) are not precisely estimated and do not provide enough support for claiming the role of emotions drives the increases in domestic abuse, we do find that the coefficient for upset loss, while not being significant, is greater than for close and predicted loss, and that losses have a larger effect than wins on changes in domestic abuse.

To further understand whether emotional reactions are an important mechanism dynamically, we estimate our baseline model in Eq. (2) and include the effects of *Upset loss, Upset win, Predicted win, Predicted loss, Close win, Close loss*, with the category *Non game days* as the baseline. This also allows us to disentangle short versus long-term emotional reactions. The prediction would suggest that during and immediately after the game, emotions would be highest and the effect on DA would be direct. In the medium term, the role of emotions would be muted and the effects on DA would either be smaller or indirect through more alcoholized abuse. The results are presented in Table A.9 on the DA outcomes: *current partners, current partners with an alcoholized perpetrator, current partners with non-alcoholized perpetrator, current partners with both victim and perpetrator alcoholized and current partners with no alcohol*. Similarly to the previous results, we do not find sufficient evidence for the role of emotions in the short-term or the medium-term on domestic abuse. Overall the magnitudes of the estimates do not confirm the theoretical predictions on the importance of an unexpected result. In the longer run, we do find that – on average – 6–10 hours after the game reported current partner domestic abuse increases following predicted wins and upset losses in Figure A.9. However, the magnitudes do not necessarily follow prospect theory expectations, such that the coefficient for upset loss would be greater than for close loss, which would be greater than for close win. We, however, confirm that the effects seem to be mitigated by the pervasive role of alcohol. When we split the sample by alcohol abuse in Figure A.10, we still find that the effect is exclusively driven by alcoholized perpetrators later in the evening and that for alcoholized perpetrators upset losses, close losses and predicted wins lead to the highest changes in magnitude. When the effects after the game are assessed cumulatively, we find that for upset losses there is a statistically significant positive cumulative effect. When the perpetrator is not alcoholized, as shown in Figure A.11 we do not find any significant effects regardless of the unexpected results. This suggests emotional cues on their own are not determining domestic abuse in the aftermath of football games.

We also test whether the timing of the game, namely whether it has an early or late kick-off, interacts with the emotional cues from unexpected results to alter domestic abuse dynamics. These results are shown in Table A.10 and Figures A.12 and A.13. There are no significant effects on domestic abuse when the perpetrator is not under the influence of alcohol regardless of the timing of the game and the unexpected results, which is strongly suggestive of the result that emotional cues are not an important contributor to domestic abuse dynamics following games. Figure A.12 zooms into the role of emotions for the case of early games and domestic abuse with alcoholized perpetrators. We observe again the highest increases in domestic abuse 8–12 hours after early games for close losses, upset losses, and predicted wins. However, this pattern does not confirm predictions from prospect theory, which would hypothesize a larger immediate increase for upset losses compared to close losses - a relative effect we do not find in the data. In Figure A.13, we show that in the aftermath of late games, there is no effect on alcoholized domestic abuse following unexpected game results.

Finally, in additional analyses we tested whether more competitive games (later in the tournament) or salient games (knockout matches, derbies) led to a differential effect on DA (following Eq. (2)), but found no discernible effects across any of the outcomes, further confirming that the *stakes of the game* do not affect the change in domestic abuse.

5.3. Effect on domestic abuse depending on the gender of the perpetrator and between ex-partners

In this section, we disaggregate domestic abuse among current partners by gender of both victim and aggressor and estimate the effects on domestic abuse among ex-partners. First, we are interested in

[19] It is worth noting that these games are very few in our sample.

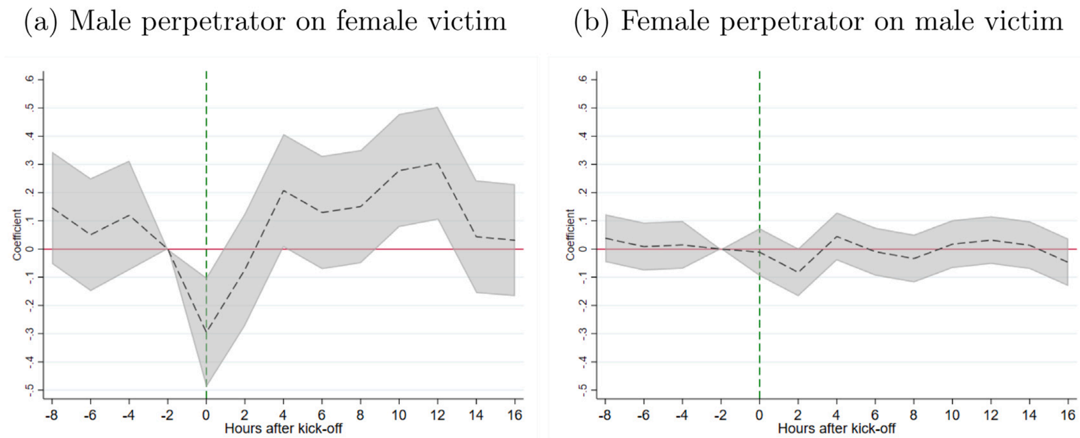

Fig. 4. Effect of a football game on DA between current partners, by gender. Note: The figure plots the coefficients from Eq. (1) as the dashed line and their 95% confidence intervals as the gray shaded area across 2-h intervals. $T = 0$ denotes the game kick-off. The coefficient for t−1 (two hours before the game) has been normalized to zero.

understanding whether the abuse was committed by a male perpetrator on a female victim, or a female perpetrator on a male victim.[20] Fig. 4 depicts the results of estimating Eq. (1) with these two new dependent variables, with the coefficients in columns 2 and 3 of Table A.11.

The changes in domestic abuse between current partners are driven exclusively by male perpetrators on female victims, shown in Fig. 4(a) and in Table A.11. We observe that the effect of the game on female-on-male intimate partner abuse is insignificant and estimated precisely at zero.[21] This is also evidence that we are not capturing an effect that is spurious to general time dynamics of domestic abuse (for example, as games are in the evening, and more abuse occurs in the evening), but is driven by predominantly male, football spectators watching a game.

We repeat our analysis for domestic abuse cases between ex-partners, which constitute about half of all intimate partner domestic abuse cases (see Table 1). As they do not cohabitate together, the risk of 'formal' interaction and exposure to the perpetrator after a game is reduced, and hence there should be less risk of DA following a football game. Nevertheless, we estimate the effect on ex-partners for two reasons. First, it serves as a placebo test to check that both the timing of the game and the timing of domestic abuse are not driven by a third factor. This allows us to confirm the validity of our research design. Second, and equally important, the differential effect between current and ex-partners can be interpreted as the importance of exposure as a factor of domestic abuse victimization. We display these results in Figs. 5 and 6 and Tables A.12 and A.13.

We can establish that football does not have an effect on domestic incidents between ex-partners. We observe no negative substitution effect while the game is ongoing, and no jointly statistically significant effect after the game. We repeat the previous analysis of incidents of current partners by again stratifying the sample by alcohol and kick-off time, and again observe no significant effect on either of these two dimensions.[22] This makes us confident that our effects are a result of the football games rather than endogenous to the timing of the games. It also shows that while football games are likely to heighten alcohol consumption and emotions, this in reverse does not translate to seeking out violence against an ex-partner, but only happens if the victim is already present — pointing to the role of exposure in victimization.

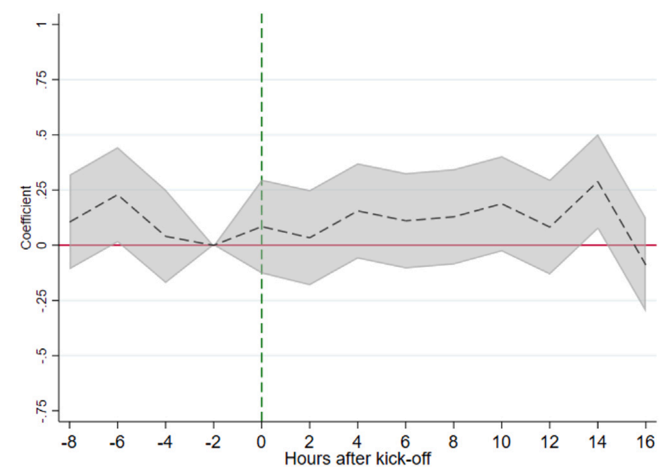

Fig. 5. Effect of a football game on DA between ex-partners. Note: The figure plots the coefficients as the dashed line and their 95% confidence intervals as the gray shaded area across 2-h intervals. $T = 0$ denotes the game kick-off.

5.4. Robustness

Domestic abuse is considered to be widely under-reported to police authorities and social services. For example, in the United Kingdom where this research is set, the differences in reporting across the Crime Survey of England and Wales (CSEW) and the police reported figures from the Home Office estimate that only about 1/5 of domestic abuse gets reported to the police (Office for National Statistics (ONS), 2019, 2020). While our estimates are based on police-recorded data, it is

[20] Homosexual couples were omitted here due to the small sample size. Heterosexual pairings made up 92% of all intimate partner domestic abuse incidents in our sample, i.e. 77% were male-on-female violence and 15% of female-on-male violence, while homosexual male couples represent only 5% of all cases and female ones about 1% of the sample (Table 1).

[21] Both the leads and lags from the regression of female-on-male violence are jointly not significant at 95% confidence levels, with p-values of 0.787 and 0.402 respectively. While the coefficients of the leads of male-on-female violence are jointly not statistically significant at 95% level (with a p-value of 0.322), the joint significance of the lags of the event, i.e., $\beta_0 \ldots \beta_8$ is highly statistically significant with a p-value of 0.000. This is reported in Table A.11.

[22] The only statistically significant increase takes place after an early game for those incidents with alcohol presence on the perpetrator and takes place between 6 and 8 hours after kick-off time. The positive coefficient is very small in magnitude.

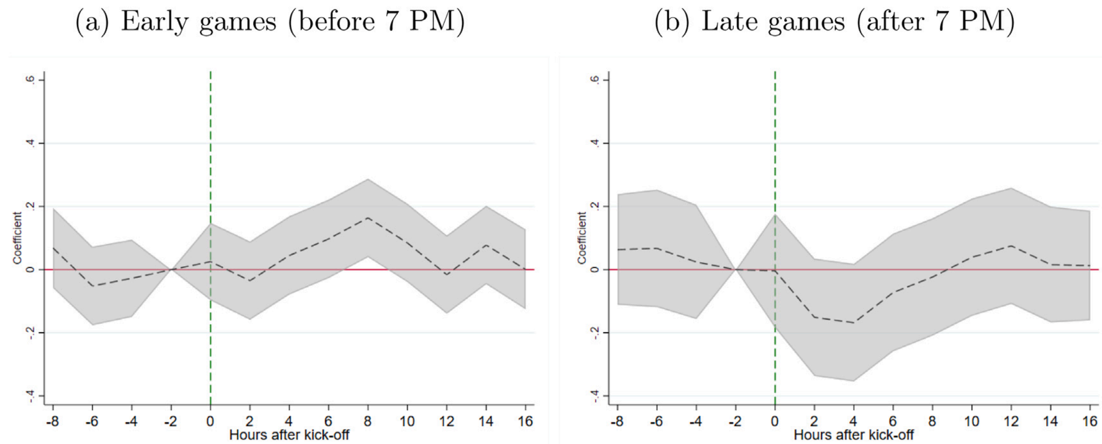

Fig. 6. Effect of a football game on DA between ex-partners where perpetrator had consumed alcohol. Note: The figure plots the coefficients from Eq. (1) as the dashed line and their 95% confidence intervals as the gray shaded area across 2-h intervals. $T = 0$ denotes the game kick-off. Figure (a) plots the sum of Game and the interaction term of Game x Early, the change in domestic abuse incidents per 2-h after an early football game. Figure (b) shows the coefficients of *Game*. The coefficient for t−1 (two hours before the game) has been normalized to zero.

worth discussing whether football games are likely to change not only the incidence of domestic abuse but also its reporting likelihood. We believe football games predominantly change the incidence of domestic abuse, hence that our research design estimates the effects on incidence, conditional on constant under-reporting. We cannot directly test this assumption using survey data as questions on domestic abuse victimization in surveys such as the CSEW do not capture the detailed time dynamics we are interested in. It could be that football games lead to more policing presence during the hours of the game, and in turn, more police presence leads to a higher likelihood of reporting. However, we do not think this explains the results we find for three reasons. First, we find the largest increases in domestic abuse incidence 8–12 hours after the game. Second, we find the increases in domestic abuse only among certain types of perpetrators and victims, while other groups like ex-partners and female on male abuse remain unaffected, which is suggestive that police presence is not increasing the likelihood of their reporting. And finally, most importantly, 89% of the reported domestic abuse occurs within the home and hence would not be subject to an increased likelihood of reporting following higher police presence near stadiums or the city center. However, we additionally test whether police reporting changes as a result of the game. Using the model in Eq. (1), we test whether games have an effect on the likelihood of reporting by victims or third parties as compared to reporting by police officers. The results are reported in Figures A.14 and A.15. If higher police presence was explaining the changes in reported domestic abuse, we would expect a lower share of incidents to be reported by victims and third parties and a higher share of incidents reported by the police. We find no differences in the share of calls reported by the victim or third parties in the hours before and after the game.

To describe the dynamics of the effects in the aftermath of the game, we conduct a series of robustness checks using alternative omitted periods, specifically t = −2 which is the time period four to two hours before the game, t = −3 which spans the time period six to four hours before the game, and t = −4 for period eight to six hours before the game. This is to mitigate the concerns around the sensitivity of the results across alternative time periods. We use the same specification as in Eq. (1) with the inclusion of day of the week and hour interactions. This is reported in Figures A.16, A.17 and A.18 in the Appendix. The results are also summarized in Table A.14 to Table A.25. As the outcome, we have used the total 2-hourly count of domestic abuse committed by current partners (panel a), by ex-partners (panel b), current partners with an alcoholized perpetrator (panel c), current partners with a non-alcoholized perpetrator (panel d), current partners with an alcoholized perpetrator in case of early games (panel e), and current partners with an alcoholized perpetrator in case of late games (panel f). The main conclusions of our baseline results hold regardless of the choice of the omitted period being t = −2, −3, or −4. Across all these specifications, we find consistent results that during a football game domestic abuse incidence between current partners decreases, for it to start increasing and peak around 10–12 h after the game.

We find that the null hypothesis of the joint significance of the leads to the game cannot be rejected with a p-value smaller than 0.05. This gives us confidence in the internal validity of our research design. Yet the joint significance of the lags following the game is consistently statistically significant (with a p-value smaller than 0.05).

When we next examine the joint significance of the cumulative impact of games on incidents (including the period of the game and all periods after the game) across the robustness analyses when changing the baseline period or the empirical specification, we find similar results as in our baseline specification. Across most outcomes of domestic abuse, football games change the dynamics of domestic abuse while not increasing the overall level of abuse throughout the day — with the displacement of abuse from the period of the game as spectators are busy with watching it to later periods 8–10 hours after the game ends. However, when games are early and the perpetrator is under the influence of alcohol, football games lead to an overall cumulative increase in domestic abuse.

We have also examined the effects of the home games and away games separately. The results are shown in Tables A.26, A.27, A.28, A.29, A.30, A.31, A.32, and A.33. We do not find differential effects between home and away games. The main conclusions of our general results hold regardless of the location of the game. Across these specifications, we find consistent results that during a football game domestic abuse incidence between current partners decreases, for it to start increasing and peak around 10–12 hours after the game.

Moreover, in the Appendix, we show that estimating our OLS model with Newey–West standard errors yields very similar results to the GLS and the OLS with robust White standard errors. We also ran Poisson estimations. The results of specifications using the Poisson Model, Ordinary Least Squares with Heteroskedasticity Robust Standard Errors, and Ordinary Least Squares with Newey–West Standard Errors are summarized in Figures A.19, A.20, and A.21 respectively. We also run all of our models by adding an additional quarter fixed effect. The result is reported in Figure A.22. The full results of these robustness analyses are shown in Tables A.34 to A.49.

All of our results are robust to different definitions of early games shown in Figure A.3 and the corresponding Table A.50. In these results, early games are defined as games before 5 pm as an alternative to our main definition which defines early games as games before 7 pm.

Finally, we use an alternative research design and use absolute timing instead of an event study model. The result of this exercise is visualized in Figure A.23 in Appendix. The outcomes shown in Figure A.23 are the total 2-hourly count of domestic abuse committed by current partners (panel a), by ex-partners (panel b), current partners with an alcoholized perpetrator (panel c), current partners with an non-alcoholized perpetrator (panel d), current partners with an alcoholized perpetrator in the case of early games (panel e), and current partners with an alcoholized perpetrator in the case of late games (panel f). We reaffirm our main findings that we observe the peak about 10–12 hours after the game, which equates to the time period from around 10 pm to 4 am. The effect is highest in the case of early games when the perpetrator has consumed alcohol (albeit the leads to the game are jointly significant). The results are shown in Table A.51, A.52, A.53, and A.54. In these Tables "Cumulative sum of lags, all" sums up all the pre-game, game, and post-game coefficients. Across specifications that include all games (Table A.51, A.52, and A.54), these are not statistically different than zero. In Table A.53 that separates this across early and late games, we find a positive and statistically significant cumulative effect for early games when the perpetrator is under the influence of alcohol. This is in line with our earlier interpretation that for the majority of games and across most outcomes of domestic abuse, football games change the dynamics of domestic abuse while not increasing the overall level of abuse throughout the day — with the exception of early games when the perpetrator is under the influence of alcohol.

Next, in Tables A.51, A.52, A.53, and A.54, we also show the "Cumulative sum of lags, post" which sums up the coefficients of all time intervals after 2 pm. While this is an imperfect measure as it might include pre-game coefficients for later games, we use this as the best approximation considering that more than 90% of games in our samples happen after 2 pm. We find that the cumulative effect for the post-game coefficients is significant for the domestic abuse between current partners when the perpetrator is under the influence of alcohol, and when the game is early and the perpetrator is under the influence of alcohol. The magnitude of the effect is higher when we only focus on time intervals after 2 pm. There is no significant effect when we study the days when there was a late game happening. However, our preferred specification is the one using relative-to-game time periods as in Eqs. (1) and (2), as this specification allows us to study the dynamic effects of games on domestic abuse and differential behavior leading up to the game. Across all baseline specifications and robustness analysis the F-tests reveal that the leads are not jointly significant. This gives us confidence that there is no anticipation or other behavior leading up to the game.

6. Conclusion

Our empirical results show that football games change the dynamics of domestic abuse victimization. Although domestic abuse decreases during the two-hour period when the game is played, reporting of domestic abuse starts to increase in its aftermath and this effect peaks between 10 and 12 hours following the game. While we cannot exactly pinpoint the timing of the start of the abuse or assault, it is likely that victims report domestic abuse about 1–2 hours after the conflict had started hence the rise in domestic abuse conflict likely peaks about 8–10 hours after the game. We find that football games affect the dynamics of intimate partner abuse among current partners while not increasing the total level of the abuse — but shifting it to later periods in the day. However, when games are early and the perpetrator is under the influence of alcohol, football games lead to the highest increases in domestic abuse and an overall cumulative increase in domestic abuse. This leads us to conclude that domestic abuse does depend on the occurrence of games (both decreasing it contemporaneously and increasing it in the aftermath), but it is through the mechanism of alcohol consumption that the early games particularly reinforce the size of the effects. Games scheduled at midday or afternoon enable perpetrators to start drinking early and continue throughout the day, leading to a peak in domestic abuse by alcoholized perpetrators in the (late) evening. Delaying the start of the games until the evening and scheduling them on weekdays would help prevent a considerable amount of domestic abuse.

Aside from the timing of the game, it is also important to implement policies aimed at reducing alcohol consumption during and where possible after sporting events. Alcohol is heavily linked to football specifically and sporting events more generally. Sports sponsorship by alcohol brands is very common; visual references to alcohol nearly average two per minute during televised top-class English football matches thanks to television ads and advertising e.g. in sports merchandising and football stadiums (Graham and Adams, 2013). Hence we speculate that restricting alcohol marketing during football games and sponsorship of professional teams would also help reduce domestic abuse.

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.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary figures and tables discussed in this article can be found online at: https://doi.org/10.1016/j.jpubeco.2023.105031.

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