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Football, alcohol and domestic abuse

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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 first observe a 5% 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, after the game, domestic abuse starts increasing and peaks about ten hours after the game, leading to a positive cumulative effect. We find that all increases are driven by perpetrators that had consumed alcohol, and when games were played before 7pm. Unexpected game results are not found to have a significant effect.

Key words: domestic abuse, crime, football, alcohol
JEL codes: J12; I12; K36

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1 Introduction

"I used to dread the World Cup 'cos he wasn't a drinker my husband but could guarantee come the World Cup he'd drink, 'cos he'd be with all his friends watching it at whoever's house, mine, in pub, wherever, and that's where he drinks and he get even nastier when he's had a drink, not a very nice person." - Ann

"(...) also knew that if other guys in the pub, if they lost a match, I knew their wives wouldn't be out at the weekend, because they'd 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 receiving welfare benefits by 42%. First time victimisation 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, Mueller-Smith and Rossin-Slater (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, McCormack and Buzawa (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

[1]Victim testimonies from Swallow (2017).

(2010); Anderberg and Rainer (2013); Anderberg et al. (2015)) and backlash after the desire to divorce or to leave the relationship (Ellis, Stuckless and Smith (2015), Ellis (2016)).

While the majority of the identified causes of domestic abuse result from drastic changes in life circumstances, there is also considerable anecdotal evidence (Swallow (2017)) 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 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 (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 organisation of games would help reduce domestic abuse incidence.

This paper uses uniquely detailed and confidential 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 this dataset(s) 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 other. We complement this with data on all football matches of Manchester United

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

and Manchester City in different 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 effect of a football game is therefore captured by eight lags spanning the 16 hours following the start of the game. We examine the effect on other types of domestic abuse such as ex-partner abuse to show that the effect is truly 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-hour duration of the game suggesting a substitution effect of football and domestic abuse. However, following the initial decrease, and after the game current partner domestic abuse starts increasing and peaks about 10-12 hours later. In aggregate, the short and long-term increase offsets the initial substitution effect leading to a positive cumulative effect. This amounts to an average hourly increase of 2.8% for each hour of a game day.

Once we disaggregate the data by gender of 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 doesn't correlate to the times that domestic abuse generally occurs.

Our second finding speaks to the mechanism that explains why football can lead to higher incidence of domestic abuse. We argue that the increase in domestic abuse is a result of increased alcohol consumption, but not the effect of heightened emotions. We establish the latter by testing 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. Therefore, we show that the increases in domestic abuse are exclusively driven by the increase in alcohol related domestic abuse incidents following a game, while DA caused by a non-alcoholized perpetrators remains stable.

Finally, we find that the largest increases in domestic abuse occur when football games are scheduled early in the day. We hypothesise that this leads perpetrators to start drinking alcohol earlier and continuing to do so through the afternoon and evening. On such days, we estimate strong increases in domestic abuse driven solely by alcoholized perpetrators. For games later in the day, we do not observe any increase in 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.

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 in close to a decade, we are able to rule out that any role of heightened emotional responses triggered by the games themselves (Card and Dahl (2011)).

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 the game. Watching football games coincides with much higher levels of alcohol consumption which in turn, when mixed with presence of one's partner (Bindler, Ketel and Hjalmarsson (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 evening and implementing policies that reduce drinking can prevent a majority of the football related abuse from occurring.

The paper is organized as follows. Section II provides a literature review of the existing evidence of the effect of football on domestic abuse. The subsequent sections describe the institutional background, data and event study methodology. Section IV depicts the results and Section V concludes with 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 behaviours and environmental factors (Bindler, Ketel and Hjalmarsson (2020)). Within explanations around how one's environment can increase the chance of their victimization, the role of sports has been discussed. White, Katz and Scarborough (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, Francis and O'Flaherty (2013) report a comparable impact in Lancashire. Similarly, Williams et al. (2013) show increases after local derbies in Glasgow. 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 victimisation 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 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 organised 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, that 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 behaviour (Rees and Schnepel (2009), Kirby, Francis and O'Flaherty (2013) and Munyo and Rossi (2013)). The strength of the emotional reaction will also depend on the importance of the game: Dickson, Jennings and Koop (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 majority of these studies as Bindler, Ketel and Hjalmarsson (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 be highest and the effect would be direct. We also then estimate the medium term effects later in the day when the role of emotions would be muted. 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 emphasised the role of increased alcohol consumption as a trigger for criminal behaviour. Francesconi and James (2015) find a 45% increase on 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. 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, Hansen and Ryley (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, Siminski and Swensen (2018) show a positive correlation between college football games and rape on campus, which they argue is due to the intense partying and alcohol consumption around the game. Montolio and Planells-Struse (2016) find a rise in a number crime types including domestic violence around football and attributes 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

Our data on domestic abuse[3] includes the population of all calls to the police in the Greater Manchester metropolitan area (UK) 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, 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 centre 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 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 and a set of coordinates.

[3]The UK defines domestic abuse as "any incident of controlling, threatening behaviour, 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 behaviours that can be offences of assault, harassment, etc. (Home Office (2012)).

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.[4] During this period, 523,546 DA incidents were recorded; which is 7.23% of the population of 7,239,053 recorded incidents. Of those, 90.9% 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, 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.[5] 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. 36% of the domestic incidents constituted a crime.

We study domestic abuse between intimate partners (including both current and ex-partners, hetero and homosexual) which represents about 2/3rd of total domestic abuse. After keeping observations with both victim and perpetrator data, a final sample of 429,491 DA calls from April 2012 to June 2019 is formed which is collapsed in a two-hourly time series dataset. Table 1 depicts the summary statistics for this dataset. On average, there were about 9 recorded cases of domestic abuse across Greater Manchester every 2 hours. Most of these incidents were acts of male on female partner violence (77% of all partner incidents, or 83% of heterosexual

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

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

couples) and mainly occurred at home (89%). There were almost as many incidents between current partners as between ex-partners, albeit 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.

The temporal distribution of calls to the police is such that domestic incidents are spread equally over the week, with higher incidence on Friday, Saturday and Sunday– calls on the weekend amount to 40% of the sample[6]. Most domestic abuse calls were made in the early afternoon(32%) or evening(29%). Calls late at night or in early morning constitute 18% of the sample.

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 (see 3). 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.

Football games are scheduled throughout the week, with evening games likelier during the week while weekend games have kick-off times through the entire day. Late games (after 7 PM) make up 37% of the sample, while early and mid-afternoons games account for 17% and 46% respectively. There is also a higher frequency of matches on Friday evenings and the weekend, with 36% of the games occurring then. We record the match result as well as other match characteristics like overtime,

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

penalties or 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.[7] 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.

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 a 10 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.[8] The cumulative effect of a football game is therefore captured by eight lags spanning the 16 hours following the start of

[7] We classify a match as expected win if the probability of winning assigned by the betting market was equal or higher than 55%; as 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.

[8] A typical football game without overtime lasts 90 min, plus a 15 min break in-between, amounts to close to two hours in total.

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, specially those involving drugs or alcohol, which have been proven to play a prominent role in domestic violence.

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 $t-1$. Given the length of the two-hourly time series, all periods outside $t = -4, -3, ..., 7, 8$ are binned in a dummy variable $Game_{\tau_t}$. Equation 1 depicts the main estimating model:

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

DA_t is the sum of all domestic abuse incidents that were recorded in the two-hour period t, $Game_{t+s}$[9] 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.

[9]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.

The leads and time fixed effects control for any linear and non-linear time trends of unobservables that may affect domestic abuse in 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,[10] while weekday and hour interactions additionally capture the changes in daily patterns that happen during the week. Figure 8 shows the descriptive variation of DA incidence across day of 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 as football games are scheduled in advance and therefore lead to anticipation effects, either on the side of the police or victims themselves. Note that the specifics of domestic abuse, occurring within private homes of victims in around 90% of cases, hinders the police to proactively react by increasing patrols. Moreover, GMP officers do not routinely contact victims of DA unless previously agreed to ensure that the contact itself isn't 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

[10] In alternative specifications, we included month fixed effects as well, but the coefficient estimates did not change.

game (3% of calls) and no game days (4%) (Table 2). However, to check that police reporting isn't affected, using the model in Equation 1, we test whether games have an effect on shares of reporting by the police radio (as opposed to victims, third parties, witnesses, ...). While we cannot directly test whether victims anticipate and change their behaviour 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 behaviour and avoid their partners by staying elsewhere during game days, our estimates can be interpreted as the lower bound of the true effect.

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:

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

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 $Late$: $\sum_{s=-4}^{8}(\beta_s + \mu_s)$.

We estimate the models in Equation 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.[11]

[11] Both the Durbin-Watson and the Breusch-Godfrey tests for serial correlation of the OLS model 1 for domestic abuse between current partners and for ex-partners indicated a small and positive serial correlation in the error term. Estimating our OLS model with Newey–West standard errors yields very similar results to those of the GLS one.

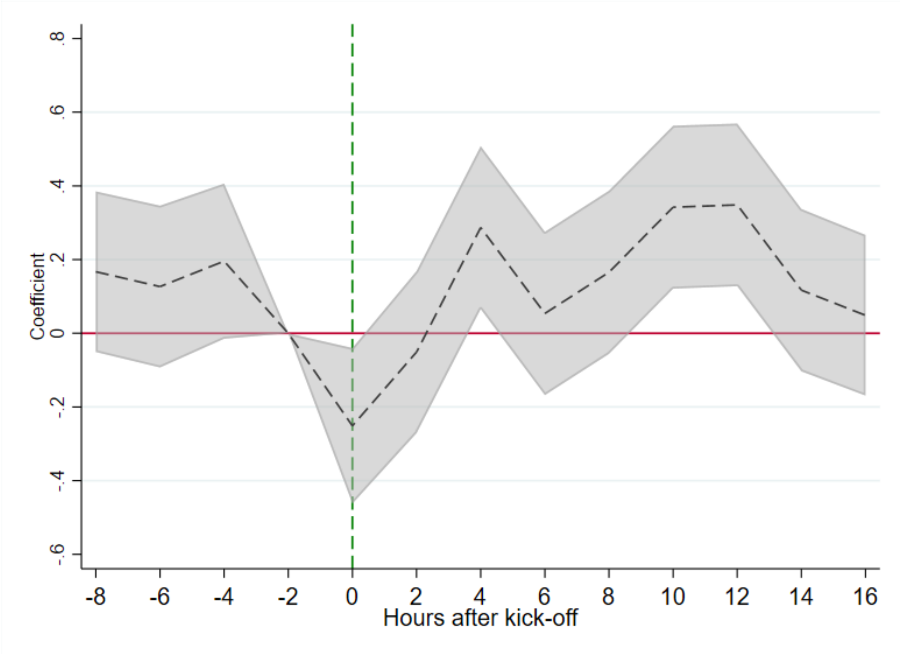
5 Results

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 Equation 1. We report the results in Table 6 which are visualised in Figure 1. The immediate effect of a football game is a decrease of 5% of DA incidents (in absolute terms about 0.25 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-hour 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 itself, which reduces the risk of criminalization. After the match, 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 (8.5%) occur between 10 to 12 hours after the start of the game and then the effect disappears around 16 hours after the game. For an average match that started at 3 PM, that would mean the first increases 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. We later present a separate analysis for early afternoon and evening games for a more accurate interpretation.

The leads before the game are jointly non-significant with a F-value of 1.49 (Prob $>$ F = 0.216). Even though the timing of football games is set in advance, the absence of pre-trends helps to rule out any anticipatory changes in behaviour made

Figure 1: Effect of football game on DV between current partners



Note: The figure plots the change in domestic abuse incidents per 2-hour intervals. T=0 denotes kick-off.

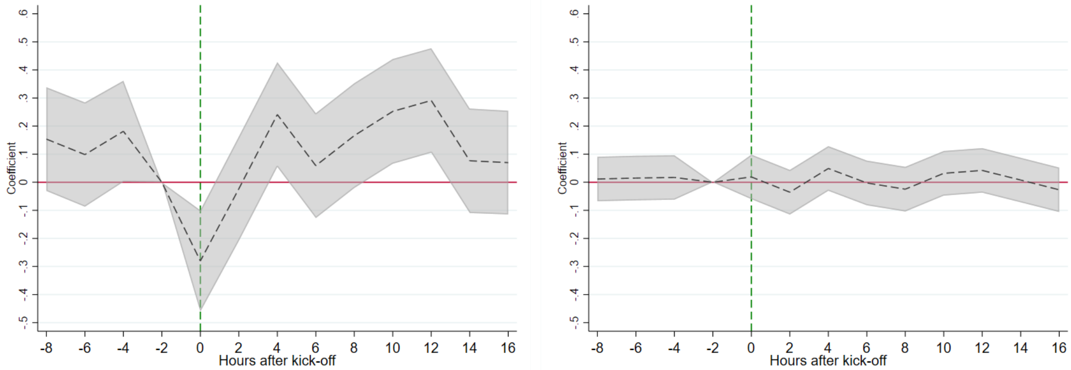
in advance of the sporting event. Together, the short and long-term increases offset the initial negative crowding-out during the game, leading to a cumulative effect of all lags that is positive and amounts to a 2.8% increase over the 16 hour period. The regression coefficients of the eight lags after the game are jointly significant at 99% confidence level with an F-test of 3.79.

Next, we disaggregate domestic abuse among current partners by gender of both victim and aggressor. We are interested in understanding whether the abuse was committed by a male perpetrator on a female victim, or a female perpetrator on a male victim.[12] Figure 2 depicts the results of estimating equation 1 with these two new dependent variables, with the coefficients in columns 2 and 3 of table 6.

[12]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).

Figure 2: Effect of a game on DA between current partners, by gender

(a) Male perpetrator on female victim (b) Female perpetrator on male victim



Note: The figure plots the coefficients of change in domestic abuse incidents per 2-hour intervals after a football game, by gender of the perpetrator and victim. The coefficient for t-1 (two hours before the game) has been normalized to zero.

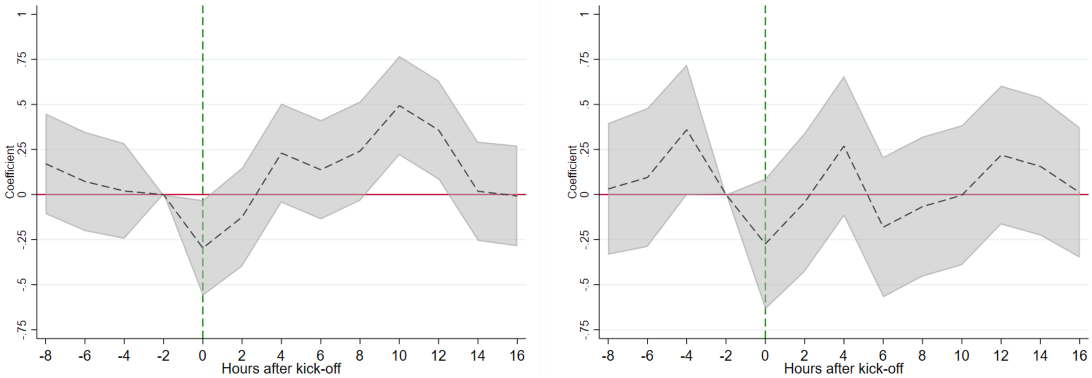
The changes in domestic abuse between current partners are driven exclusively from male perpetrators on female victims, shown in Figure 2a. We observe that the effect of the game on female on male intimate partner abuse is insignificant and estimated precisely at zero.[13] This is also evidence that 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.

The timing of the game is an important factor that shapes the dynamics in domestic abuse in the hours after a match. We define an early game as one that takes place in the afternoon (with a start time before 7pm), which constitutes 63% of all games. We hypothesise 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 before and after the game. To test

[13]The β_{-4}, β_{-3} ... β_8 from the regression on female on male violence are jointly non-significant at 90% confidence level (F(9, 31481) = 0.73 Prob > F = 0.6828) while the coefficients of male on female violence are jointly statistically significant at 99% level, i.e. F(9, 31481) = 4.25 Prob > F = 0.00.

Figure 3: Effect of early and late games on DA between current partners

(a) Early games (before 7 PM) (b) Late games (after 7 PM)



Note: Figure (a) plots the sum of *Game* and the interaction term of *Game x Early*, the change in domestic abuse incidents per 2-hour 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.

this empirically, we include a dummy for early games interacted with the "Game" indicator as shown in Equation 2 and plot the cumulative effect of an early or late game in the lags. The results are shown in the first column of table 8 and plotted in Figure 3.

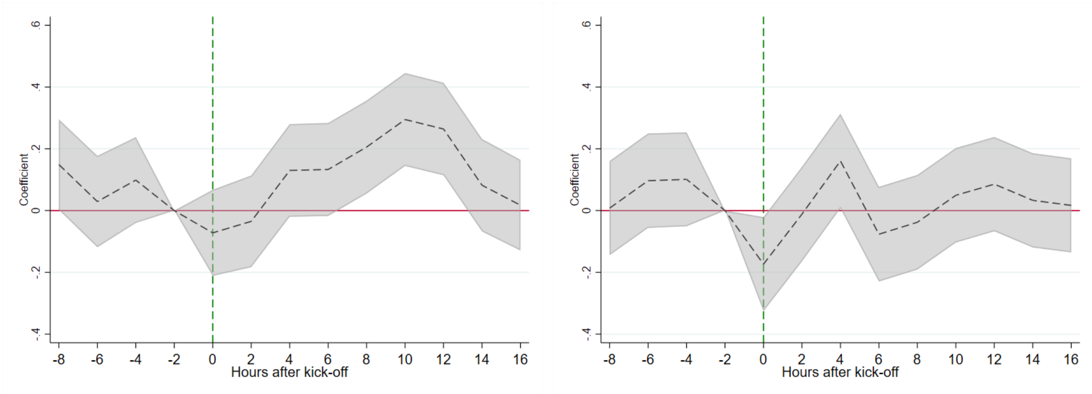
We observe that statistically significant increases in domestic abuse cases happen only after early games while evening games do not lead to any significant changes; while the point estimates are negative during the game and increase 4 hours after the game, the confidence intervals are too wide to reject the null and the point estimates become close to zero thereafter. The general 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 afternoon, 6h after the game start, until they peak 10-12 hours after the kick-off time, which corresponds to a time window between 10 PM and 4 AM. In that time there are 0.50 calls more every two hours; which in relative terms is an increase of 10.6%. 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. It is reasonable to expect that the precise time the call arrives to the police that we have used in the analysis comes with a lag of one or two hours after the conflict started, and since it began to escalate.

5.1 Mechanism: alcohol

In what follows we disentangle the role of alcohol as the mechanism underlying the increase in domestic abuse after football matches. Although the majority of perpetrators are not under the influence of alcohol when they commit domestic abuse (68%), alcohol is still present in a number of cases. 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 outcome variable across *DA with alcoholized perpetrators* and *DA with non-alcoholized perpetrators*. The results are shown in columns 2 and 3 of table 7 and the estimated β_ss are plotted in Fig. 4. If heightened emotions were the only mechanism, we would expect that non-alcoholized abuse also increase in the aftermath of the game. Yet, for perpetrators with no alcohol presence, a football game does not lead to any significant changes. When the perpetrator had consumed alcohol, the effect starts growing 6h until it reaches a maximum 10h later, when it starts decreasing again. At that peak the number of DA is 0.29 incidents higher, which represents 14.5% incidents more every two hours. Therefore, we observe that in the aftermath of a game the increase in domestic abuse is driven entirely by alcoholized perpetrators. These results indicate that it is through the presence of alcohol in the perpetrator that football leads to increased domestic abuse over the 12 hours following the match.

Figure 4: Effect of football games on DA - alcohol present

(a) Perpetrator had consumed alcohol (b) Perpetrator had not consumed alcohol

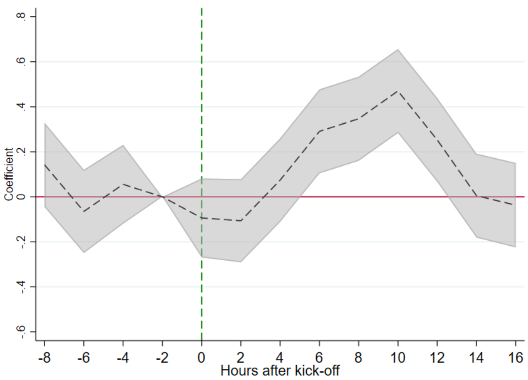


Note: The figure plots the coefficients of change in domestic abuse incidents per 2-hour intervals after a football game, stratifying incidents by whether a perpetrator had consumed alcohol or not. The coefficient for t-1 (two hours before the game) has been normalized to zero. All figures are between current partners. Two hourly mean of alcoholized perpetrators is 2 incidents, while the two hourly mean on non-alcoholized perpetrators is 2.7 incidents.

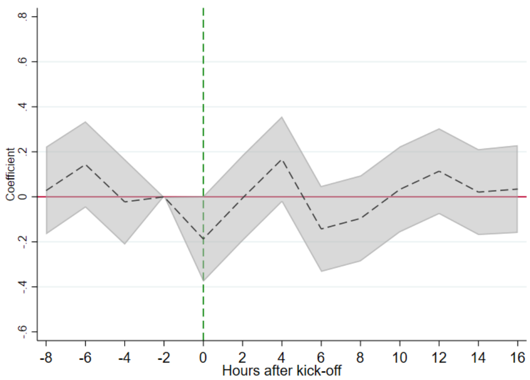
Taken together, the results of Figures 3 and 4 point to the combination of earlier games and the presence of alcohol as the drivers behind the surge in domestic incidents following a game. To precisely isolate these effects we interact the timing of the game as shown in Equation 2 on *alcoholized* versus *non-alcoholized* abuse. The results are shown in columns 2 and 3 of table 8) and displayed in Figure 5. Graphs (a) and (c) 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 sober perpetrators. In comparison, the magnitude of the effect of a game before 7 PM on domestic abuse incidents with intoxicated perpetrators (figure 5a) shows a clear pattern.

Figure 5: Role of alcohol in early vs. late football games, DA between current partners

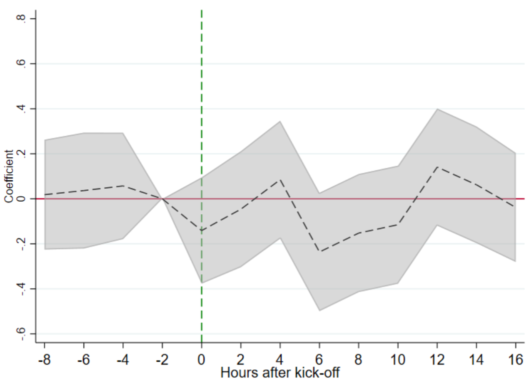
(a) Early game, alcoholized perpetrator



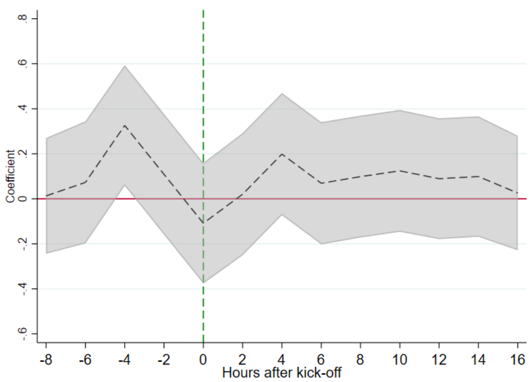
(b) Early game, no alcohol



(c) Late game, alcoholized perpetrator



(d) Late game, no alcohol



Note: The figure plots the coefficients for change in domestic abuse incidents between current partners per 2-hour after a football game. 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.

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. At the peak this equates to 0.5 incidents more, or 25.3% of the mean. The cumulative effect is an increase of 7.6% of all incidents over the 16 hour period. By contrast, we observe no statistically significant effect when the perpetrator is sober (Figures 5b and 5d). Additionally, we test whether these effects depend exclusively on the alcohol presence of the perpetrator or both individuals. In the Appendix (Table 9), 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 (10a), while it disappears when no one drank (11a) or alcohol was consumed only by the victim (12b). It is the consumption of alcohol by the perpetrator that makes a difference for domestic abuse after a football game.

The detailed analysis by timing and alcohol presence sheds a new light on the mechanisms behind the initial results observed in Figure 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.

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 match 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 popular sports betting portal *bet365* to derive the expectations prior the football match. 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 estimated winning probability 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.[14].

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):

$$\begin{aligned} DA_t = \alpha_0 + \delta_1 Upset\ loss_t + \delta_2 Upset\ win_t + \delta_3 Close\ loss_t + \delta_4 Close\ win_t \\ + \delta_5 Predicted\ loss_t + \delta_6 Predicted\ win_t + \theta_t + \epsilon_t \end{aligned} \tag{3}$$

where DA_t are daily[15] domestic abuse incidents that occurred in 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 the 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 12 shows the results of estimating the model on domestic abuse between current partners. We estimate the model on all incidents in column 1, alcoholized and non-alcoholized perpetrators (columns 2 and 3), both victim and perpetrator

[14] 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.

[15] 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 12AM.

alcoholized (column 4) and neither of the victim and perpetrator alcoholized (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 abuse committed by non-alcoholised perpetrators[16]. 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.

To further understand whether emotional reactions are an important mechanism, we estimate the Equation 2 and including the effects of *Upset loss, Upset win, Predicted win, Predicted loss, Close win, Close loss*, with the category *No 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 13 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 alcoholised 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 nor the medium term on domestic abuse. Overall most of the estimates are not significant and the magnitudes of the estimates do not confirm the theoretical predictions on the importance of an unexpected result. Finally, in additional analyses we tested whether more competitive games (later in the tournament) or salient games(knockout matches, derbies, overtime, penalties) led to a differential effect on DA (following Equation 2), but found no discernible

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

effects across any of the outcomes, further confirming that the *stakes of the game* do not affect the change in domestic abuse.

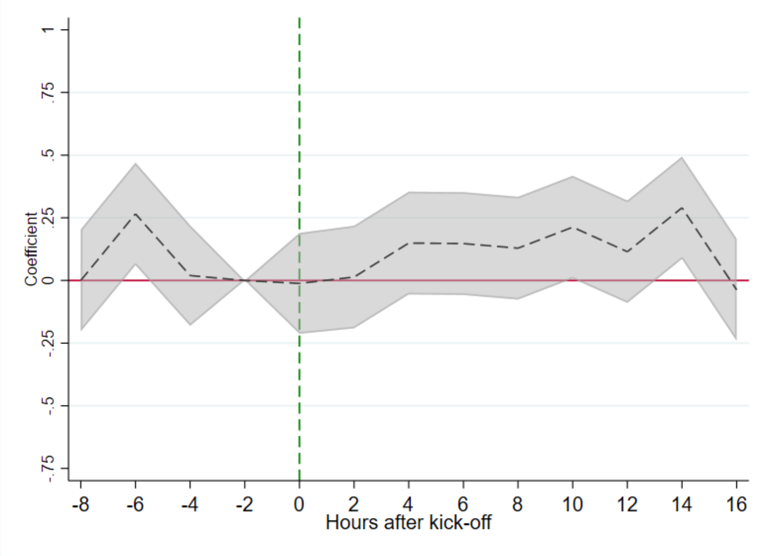
5.3 Effect on domestic abuse between ex-partners

We repeat our analysis for domestic abuse cases between ex-partners, which constitutes about half of all domestic violence 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 victimisation. We display these results in Figures 6 and 7 and Table 1.

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.[17] 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

[17] 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.

Figure 6: Effect of a game on DA between ex-partners



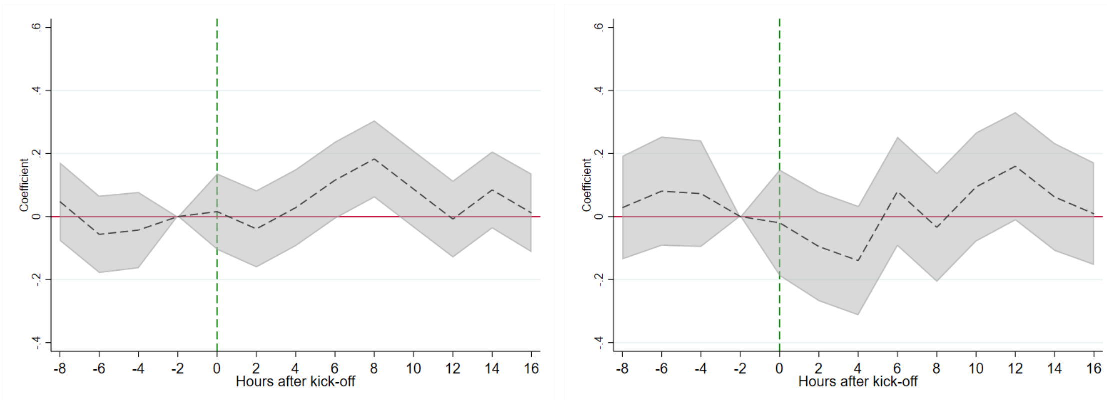
Note: The figure plots the coefficients for change in domestic abuse incidents between ex-partners for 2-hour intervals. T=0 denotes kick-off.

only happens if the victim is already present - pointing to the role of exposure in victimization.

Figure 7: Effect of a game on DA between ex-partners where perpetrator had consumed alcohol

(a) Early games (before 7 PM)

(b) Late games (after 7 PM)



Note: Figure (a) plots the sum of *Game* and the interaction term of *Game x Early*, the change in domestic abuse incidents per 2-hour 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.

5.4 Difference in Anti-Social Behaviour and Police Reporting

We next test whether there is a substitution effect of violence at home (domestic abuse) and violence in public spaces (anti-social behaviour), particularly whether the delayed increases in domestic abuse eight to ten hours at home after the game are preceded by an increase in anti-social behaviour in the vicinity of pubs in the immediate aftermath of the game. To do so, we estimate the same specification as in Equation 1. Figure 14 plots the coefficients of the effect of the football game on anti-social behaviour incidents in a public place for 2-hourly windows preceding and following the game. Anti-social behaviour (ASB) includes disturbances in public places, licensed premises and alcohol-related disturbances and excludes domestic incidents. The results do not point in this direction - if anything, the only statistically significant effect is a decrease in ASB during and immediately after the game. We find no differential effects for early and late games either.

While 90% domestic abuse occurs in the private home of victims, and hence, hinders the police to proactively react, to ensure that police reporting doesn't change as a result of the game, using the model in Equation 1, we test whether games have an effect on shares of reporting by the police radio (as opposed to victims, third parties, witnesses, ...). This is reported in Figures 15 and 16 . We find no differences in the share of calls reported by the victim nor third parties in the hours before and after the game.

6 Conclusion

Our empirical results show that a football game on average increases the risk of domestic abuse victimization. Although domestic abuse decreases during the two-hour period when the game is played, abuse starts to increase in its aftermath and this effect peaks between 10 and 12 hours following the game. We show that these effects are driven by male on female abuse among current partners, and present only when the perpetrator is under the influence of alcohol. The magnitude of these estimates is the strongest when the game has an earlier kick-off time allowing longer alcohol consumption in the aftermath of the game.

These results suggest that sporting events do not trigger domestic abuse by themselves, but rather through victim exposure coupled with the excessive alcohol consumption that usually follows these events. 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. Sport sponsorship by alcohol brands is very common; visual references to alcohol nearly average to two per minute during televised top-class English football matches thanks to television ads and advertising e.g. in sport 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.

References

Aizer, Anna. 2010. "The Gender Wage Gap and Domestic Violence." *American Economic Review* 100(4):1847–1859.

Anderberg, Dan and Helmut Rainer. 2013. "Economic abuse: A theory of intrahousehold sabotage." *Journal of Public Economics* 97:282–295.

Anderberg, Dan, Helmut Rainer, Jonathan Wadsworth and Tanya Wilson. 2015. "Unemployment and Domestic Violence: Theory and Evidence." *The Economic Journal* 126(597):1947–1979.

Bindler, Anna and Nadine Ketel. 2019. "Scaring or scarring? Labour market effects of criminal victimisation.".

Bindler, Anna, Nadine Ketel and Randi Hjalmarsson. 2020. *Costs of Victimization*. Cham: Springer International Publishing pp. 1–31.

Bland, Matthew and Barak Ariel. 2015. "Targeting Escalation in Reported Domestic Abuse." *International Criminal Justice Review* 25(1):30–53.

Boutilier, Sophia, Ali Jadidzadeh, Elena Esina, Lana Wells and Ron Kneebone. 2017. "The connection between professional sporting events, holidays and domestic violence in Calgary, Alberta.".

Brimicombe, Allan and Rebecca Cafe. 2012. "Beware, win or lose: Domestic violence and the World Cup." *Significance* 9(5):32–35.

Card, David and Gordon B. Dahl. 2011. "Family Violence and Football: The Effect of Unexpected Emotional Cues on Violent Behavior." *The Quarterly Journal of Economics* 126(1):103–143.

Carrell, Scott E. and Mark L. Hoekstra. 2010. "Externalities in the Classroom: How Children Exposed to Domestic Violence Affect Everyone's Kids." *American Economic Journal: Applied Economics* 2(1):211–228.

Chalfin, Aaron, Benjamin Hansen and Rachel Ryley. 2019. The minimum legal drinking age and crime victimization. Technical report National Bureau of Economic Research.

Cochrane, D. and G. H. Orcutt. 1949. "Application of Least Squares Regression to Relationships Containing Auto-Correlated Error Terms." *Journal of the American Statistical Association* 44(245):32–61.

Currie, Janet, Michael Mueller-Smith and Maya Rossin-Slater. 2018. Violence While in Utero: The Impact of Assaults during Pregnancy on Birth Outcomes. IZA Discussion Papers 11655 Institute of Labor Economics (IZA).

De Chaisemartin, Clément and Xavier d'Haultfoeuille. 2020. "Two-way fixed effects estimators with heterogeneous treatment effects." *American Economic Review* 110(9):2964–96.

DellaVigna, Stefano and Eliana La Ferrara. 2015. *Handbook of Media Economics*. Elsevier chapter Social and Economic Impacts of the Media.

Dickson, Alex, Colin Jennings and Gary Koop. 2015. "Domestic Violence and Football in Glasgow: Are Reference Points Relevant?" *Oxford Bulletin of Economics and Statistics* 78(1):1–21.

Ellis, Desmond. 2016. "Marital Separation and Lethal Male Partner Violence." *Violence Against Women* 23(4):503–519.

Ellis, Desmond, Noreen Stuckless and Carrie Smith. 2015. *Marital Separation and Lethal Domestic Violence*. Taylor and Francis Ltd.

Francesconi, Marco and Jonathan James. 2015. "The cost of binge drinking.".

Graham, Andrew and Jean Adams. 2013. "Alcohol Marketing in Televised English Professional Football: A Frequency Analysis." *Alcohol and Alcoholism* 49(3):343–348.

Grogger, Jeffrey, Sean Gupta, Ria Ivandic and Tom Kirchmaier. 2020. Comparing Conventional and Machine-Learning Approaches to Risk Assessment in Domestic Abuse Cases. Technical report.

Grönqvist, Hans and Susan Niknami. 2014. "Alcohol availability and crime: Lessons from liberalized weekend sales restrictions." *Journal of Urban Economics* 81:77–84.

Hirschel, David, Philip D. McCormack and Eve Buzawa. 2017. "A 10-Year Study of the Impact of Intimate Partner Violence Primary Aggressor Laws on Single and Dual Arrest." *Journal of Interpersonal Violence* p. 088626051773929.

Home Office. 2012. Cross-Government definition of domestic violence - A Consultation. Technical report.

Kirby, Stuart, Brian Francis and Rosalie O'Flaherty. 2013. "Can the FIFA World Cup Football (Soccer) Tournament Be Associated with an Increase in Domestic Abuse?" *Journal of Research in Crime and Delinquency* 51(3):259–276.

Leonard, Kenneth E. 2005. "Alcohol and intimate partner violence: when can we say that heavy drinking is a contributing cause of violence?" *Addiction* 100(4):422–425.

Lindo, Jason M., Peter Siminski and Isaac D. Swensen. 2018. "College Party Culture and Sexual Assault." *American Economic Journal: Applied Economics* 10(1):236–265.

Montolio, Daniel and Simón Planells-Struse. 2016. "How time shapes crime: The temporal impacts of football matches on crime." *Regional Science and Urban Economics* 61:99–113.

Munyo, Ignacio and Martín A. Rossi. 2013. "Frustration, euphoria, and violent crime." *Journal of Economic Behavior & Organization* 89:136–142.

Office for National Statistics (ONS). 2019. Domestic abuse in England and Wales overview: November 2019. Technical report.

Rees, Daniel I. and Kevin T. Schnepel. 2009. "College Football Games and Crime." *Journal of Sports Economics* 10(1):68–87.

Sachs, Carolyn J. and Lawrence D. Chu. 2000. "The Association Between Professional Football Games and Domestic Violence in Los Angeles County." *Journal of Interpersonal Violence* 15(11):1192–1201.

Swallow, Jodie. 2017. "An exploratory study of women's experiences regarding the interplay between domestic violence and abuse and sports events.".

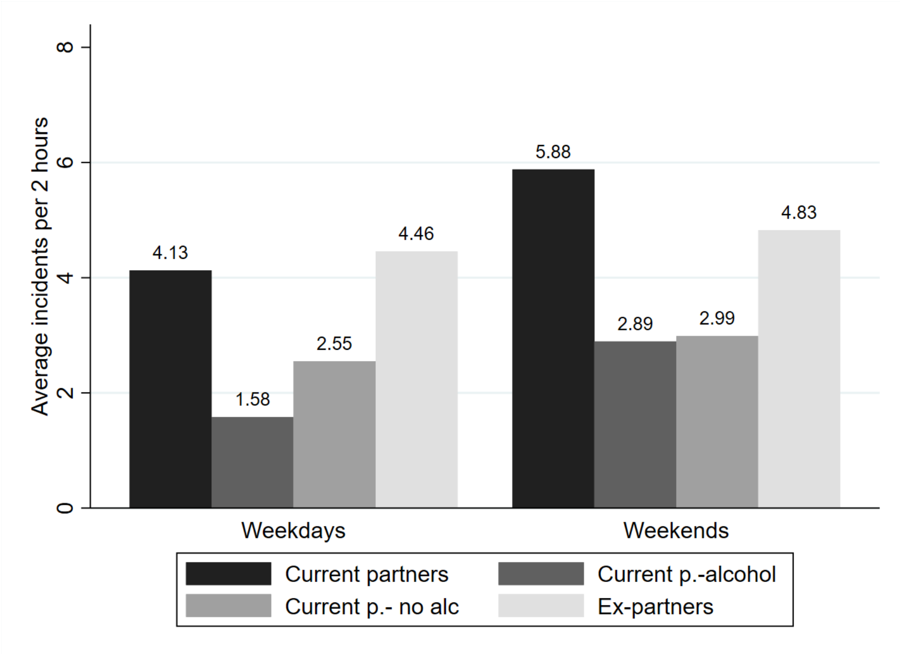
Wann, Daniel L. 1993. "Aggression Among Highly Identified Spectators as a Function of Their Need To Maintain Positive Social Identity." *Journal of Sport and Social Issues* 17(2):134–143.

White, Garland F., Janet Katz and Kathryn E. Scarborough. 1992. "The Impact of Professional Football Games Upon Violent Assaults on Women." *Violence and Victims* 7(2):157–171.

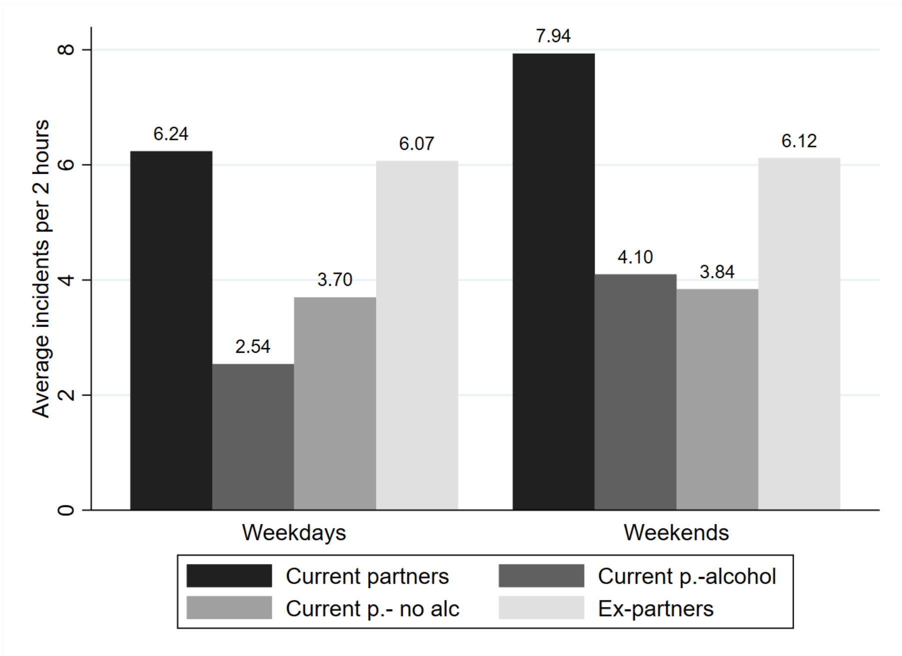
Williams, Damien J., Fergus G. Neville, Kirsty House and Peter D. Donnelly. 2013. "Association Between Old Firm Football Matches and Reported Domestic (Violence) Incidents in Strathclyde, Scotland." *SAGE Open* 3(3):215824401350420.

Figure 8: Average domestic abuse incidents every 2 hours

(a) All day

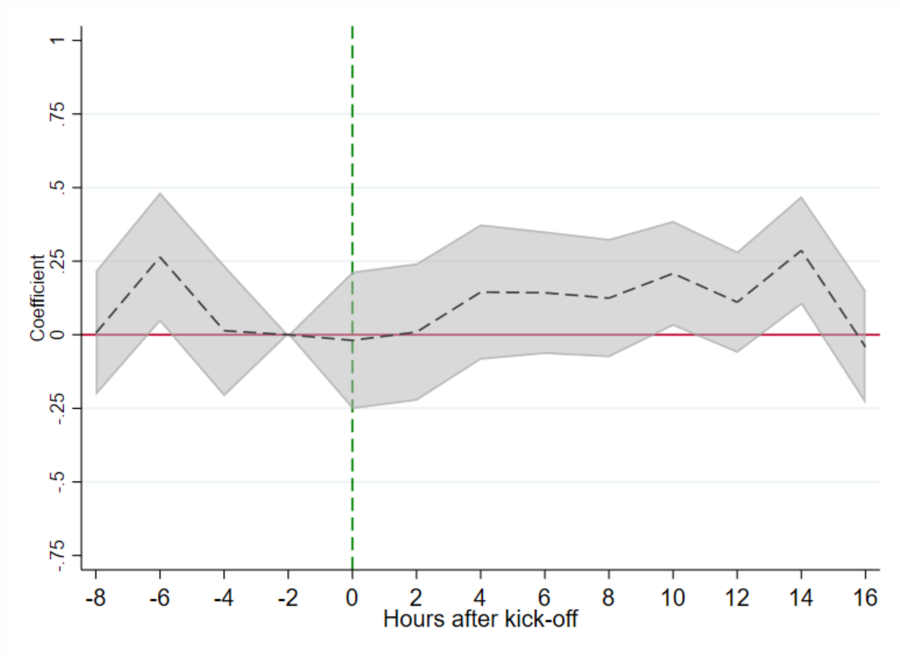


(b) After 8 PM



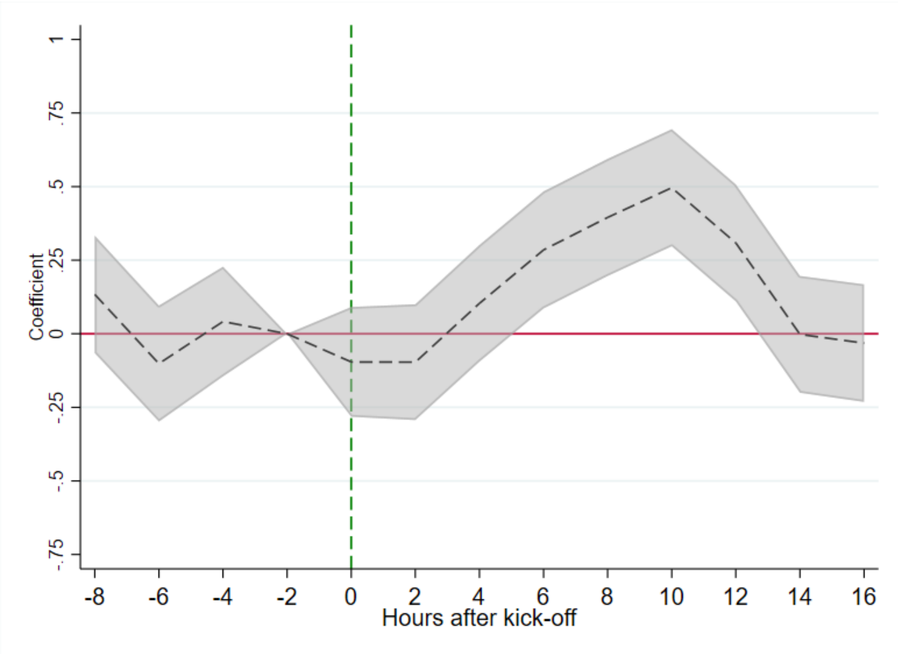
Note: The bar graphs represent average domestic abuse incidents (every 2 hours) by different types of relationship between the victim and perpetrator, and the presence of alcohol on the perpetrator. Weekends go from Friday 18PM to Monday 6AM.

Figure 9: Effect of a game on DA between ex-partners

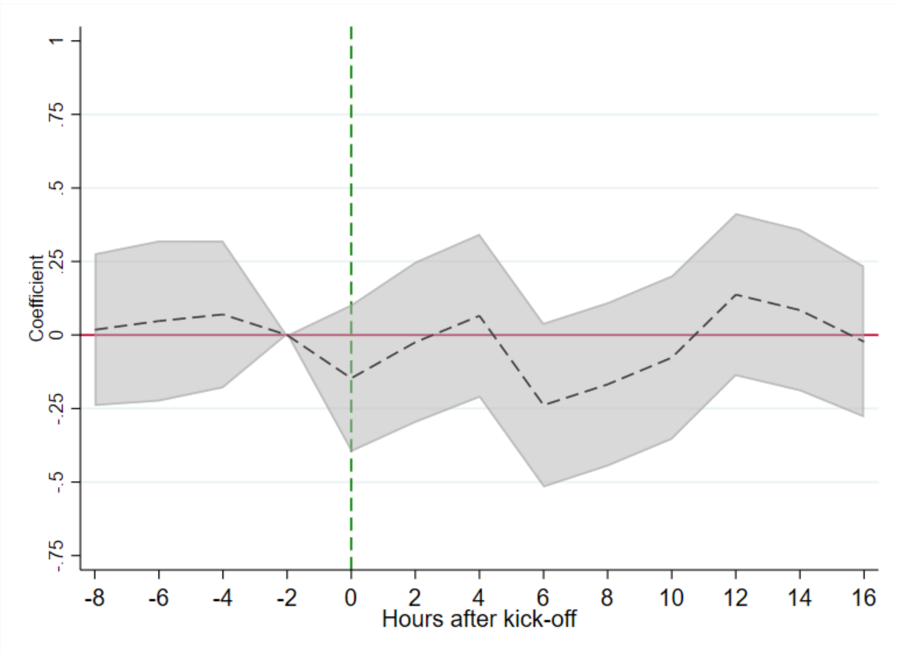


Note: The figure plots the coefficients for change in domestic abuse incidents between ex-partners per 2-hour after a football game. The coefficient for t-1 (two hours before the game) has been normalized to zero.

Figure 10: Effect of a game on DA where either victim or perpetrator consumed alcohol

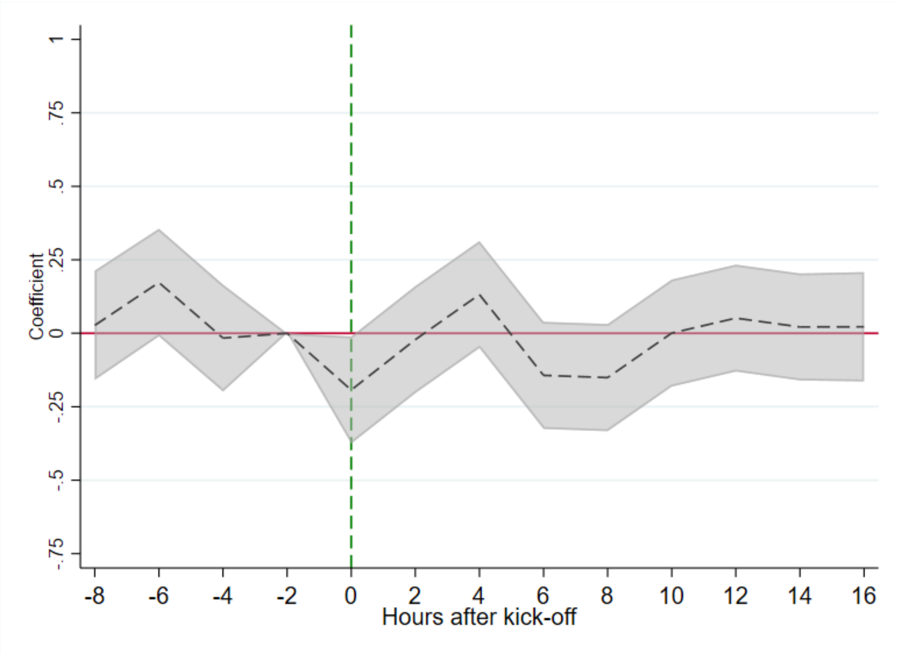


(a) Early game (before 7 PM)

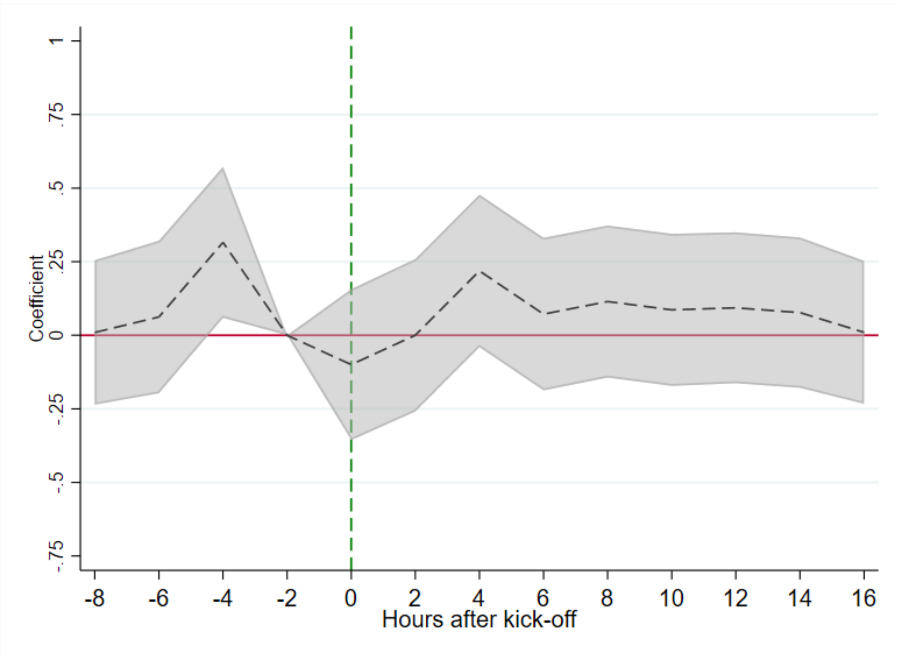


(b) Late game (after 7 PM)

Figure 11: Effect of a game on DA where neither victim nor perpetrator consumed alcohol

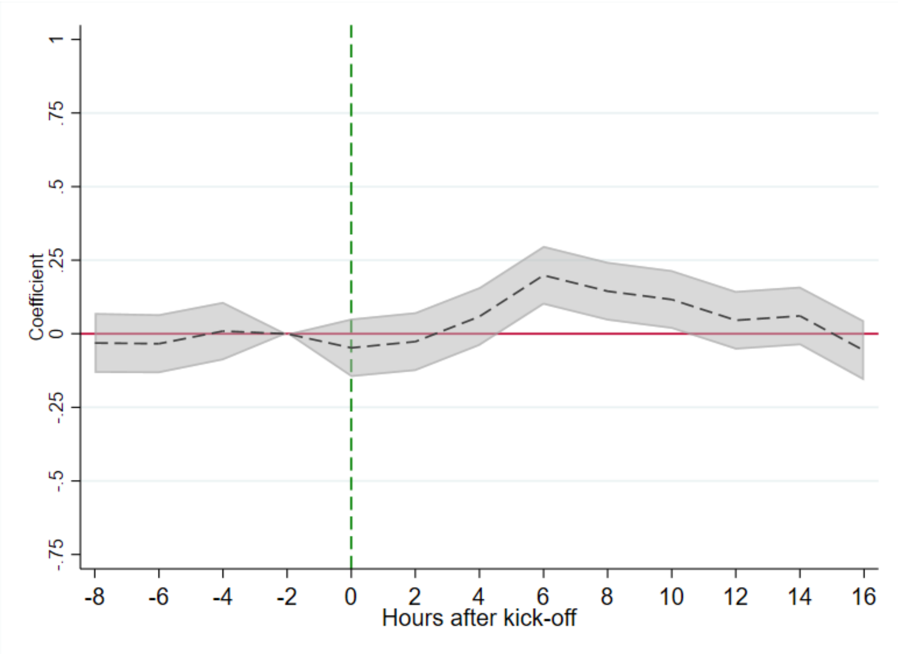


(a) Early game (before 7 PM)

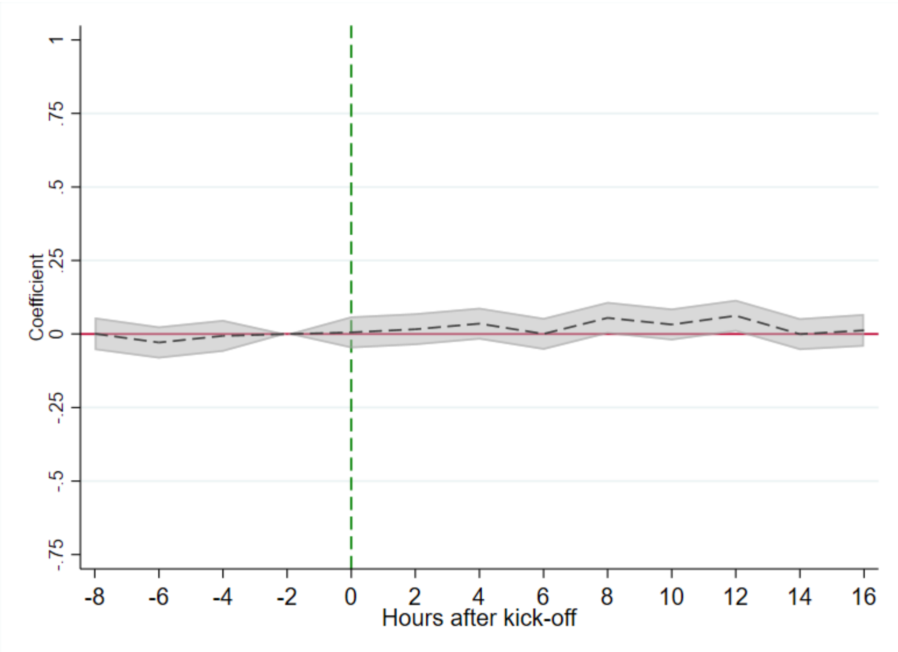


(b) Late game (after 7 PM)

Figure 12: Effect of an early game on DA where only victim or perpetrator consumed alcohol



(a) Only perpetrator consumed alcohol



(b) Only victim consumed alcohol

Figure 13: Distribution of game results

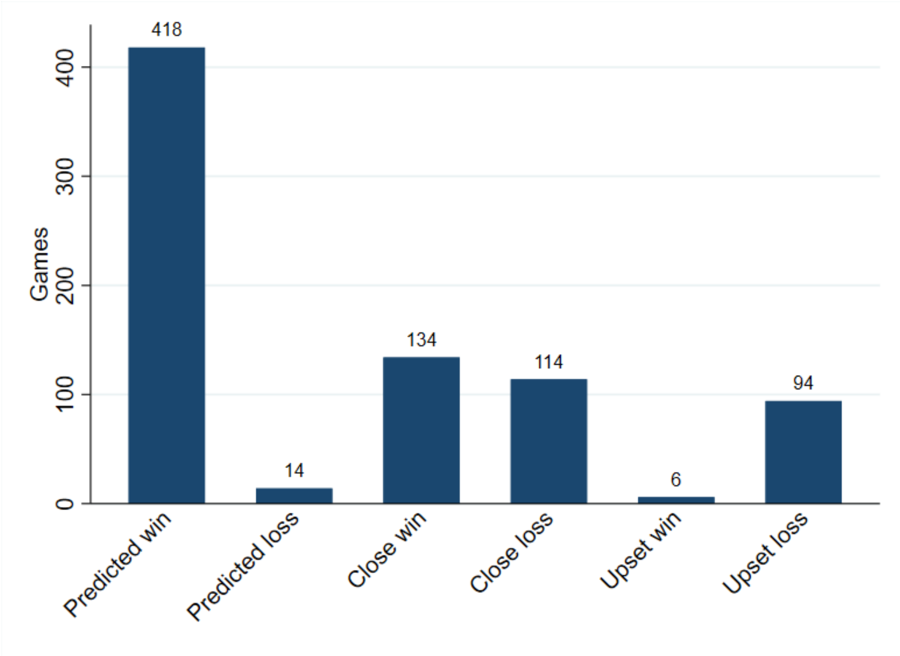
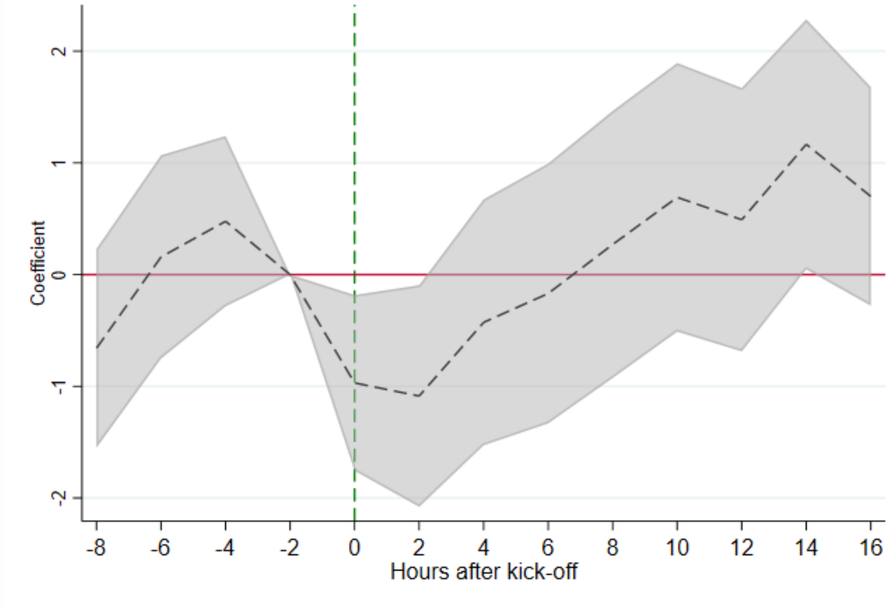
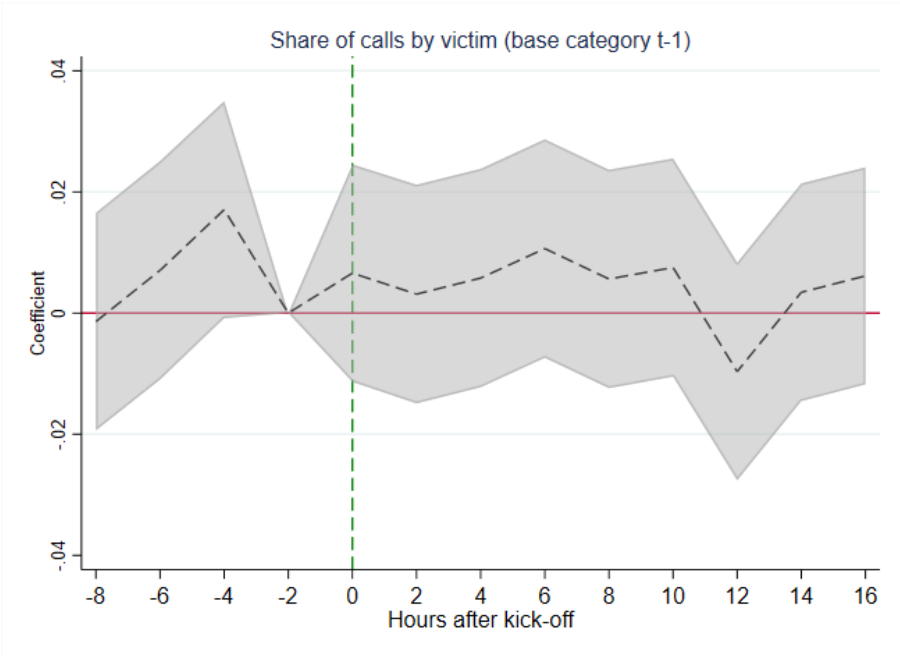


Figure 14: Effect of a game on anti-social behaviour



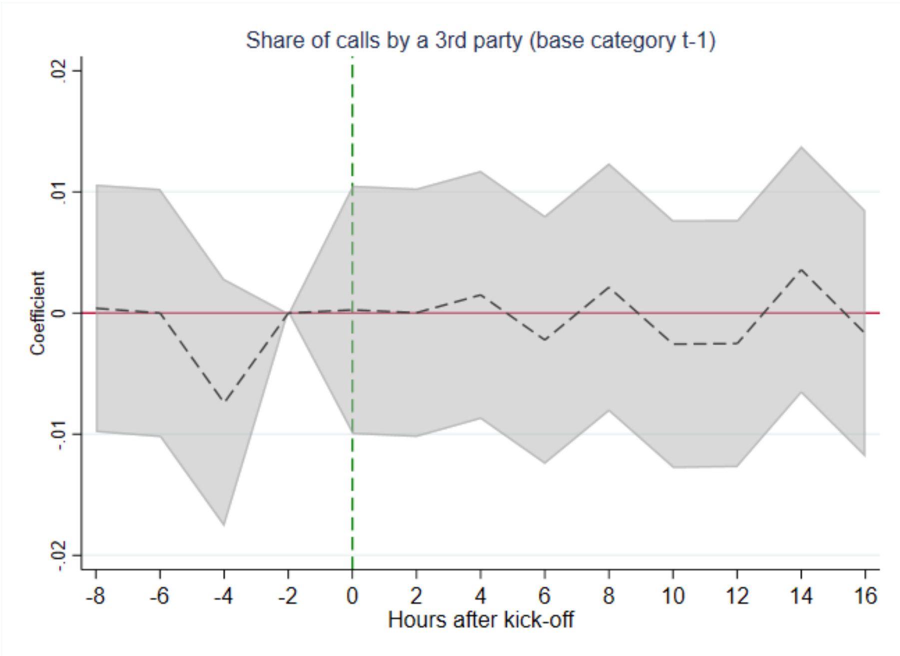
Note: The figure plots the coefficients for change in anti-social behaviour incidents in a public place per 2-hour after a football game. Anti-social behaviour includes disturbances in public places, licensed premises and alcohol-related disturbances and excludes domestic incidents. The coefficient for t-1 (two hours before the game) has been normalized to zero.

Figure 15: Effect of a game on the share of victim-reported calls



Note: The figure plots the coefficients for change in the share of domestic abuse calls (defined by a number between 0 and 1) reported by the victim per 2-hour after a football game. The coefficient for t-1 (two hours before the game) has been normalized to zero.

Figure 16: Effect of a game on the share of 3rd party-reported calls



Note: The figure plots the coefficients for change in the share of domestic abuse calls (defined by a number between 0 and 1) reported by a 3rd party per 2-hour after a football game. The coefficient for t-1 (two hours before the game) has been normalized to zero.

Table 1: Summary statistics on domestic abuse

	(1) *Original sample* Mean	Std.Dev.	(2) *Collapsed panel* Mean	Std.Dev.
Domestic abuse by relationship				
Partners	0.69	0.46	9.34	5.10
Current partners	0.35	0.48	4.72	3.32
Ex-partners	0.34	0.47	4.62	3.10
Male on female current partner	0.26	0.44	3.54	2.63
Female on male current partner	0.06	0.23	0.75	0.97
Current partners (alcohol*)	0.15	0.35	2.01	2.45
Ex-partners (alcohol*)	0.08	0.27	1.10	1.23
M. on f. current partner (alcohol*)	0.11	0.31	1.49	1.90
F. on m. current partner (alcohol*)	0.03	0.16	0.36	0.70
Location				
At home	0.89	0.31	12.11	6.50
Alcohol use				
Alcoholised Perpetrator	0.32	0.47	4.31	4.14
Alcoholised victim	0.20	0.40	2.78	3.25
No alcohol	0.65	0.48	8.80	5.74
Gender of victim and perpetrator				
Male on female	0.77	0.42	7.19	4.10
Female on male	0.15	0.36	1.42	1.36
Male on male	0.05	0.22	0.47	0.75
Female on female	0.01	0.12	0.13	0.38
Crime	0.37	0.48	5.06	3.83
Day of week				
Weekends	0.40	0.49	5.51	8.55
Monday	0.14	0.34	1.85	5.37
Tuesday	0.13	0.34	1.78	5.15
Wednesday	0.13	0.34	1.76	5.06
Thursday	0.13	0.33	1.75	4.96
Friday	0.16	0.36	2.15	5.81
Saturday	0.17	0.38	2.33	6.23
Sunday	0.15	0.35	1.99	5.66
Time of day				
Before 6h	0.18	0.39	2.51	5.01
6-12h	0.20	0.40	2.76	5.45
12-18h	0.32	0.47	4.35	7.85
18-00h	0.29	0.46	4.00	7.73

Note: The sample includes 429,491 domestic abuse incidents from April 2012 to June2019, collapsed in 31,530 2-hour intervals. All variables in the original sample are indicator variables.

* Incidents where the perpetrator had consumed alcohol.

Table 2: Summary statistics on domestic abuse: reporting

	(1) *All sample*		(2) *No game days*		(3) *Game days*	
	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Reporting method						
Phone	0.29	0.17	0.30	0.08	0.28	0.18
999	0.66	0.18	0.64	0.07	0.66	0.19
Radio	0.03	0.05	0.04	0.02	0.03	0.05
Miscellaneous	0.01	0.01	0.02	0.01	0.01	0.01
Ambulance	0.01	0.01	0.01	0.01	0.01	0.01
Fire	0.00	0.00	0.00	0.00	0.00	0.00
Informant						
Victim	0.61	0.18	0.62	0.04	0.61	0.19
Witness	0.13	0.14	0.11	0.03	0.13	0.14
Third Party	0.10	0.10	0.10	0.03	0.10	0.11
Other/missing	0.17	0.13	0.16	0.03	0.17	0.14
Urgency grade						
Immediate	0.37	0.17	0.36	0.05	0.38	0.18
Priority	0.58	0.17	0.59	0.05	0.58	0.18
Prompt	0.04	0.05	0.05	0.04	0.04	0.05
Arrested perp.	0.13	0.10	0.13	0.04	0.13	0.10
Prev. arrested DA	0.10	0.07	0.10	0.03	0.09	0.08

Note: The sample includes 429,491 domestic abuse incidents from April 2012 to June 2019, collapsed in 31,530 2-hour intervals. The table shows the average proportion from 0 to 1 of different call characteristics in the collapsed panel. All variables in the original sample are indicator variables.

Table 3: Description of football games

	Mean	Std.Dev.
Team		
Manchester City	0.49	0.50
Manchester United	0.48	0.50
Manchester United vs City	0.02	0.14
Result		
Win	0.62	0.49
Loss	0.20	0.40
Draw	0.18	0.38
Expected vs. End result		
Upset loss	0.12	0.33
Upset win	0.01	0.09
Close loss	0.15	0.35
Close win	0.17	0.38
Predicted win	0.54	0.50
Predicted loss	0.02	0.13
Game start		
Before/at 2.30pm	0.17	0.38
2.30pm - 7pm	0.46	0.50
After/at 7pm	0.37	0.48
Day of the week		
Weekends	0.36	0.48
Monday	0.05	0.22
Tuesday	0.13	0.33
Wednesday	0.17	0.38
Thursday	0.03	0.18
Friday	0.02	0.12
Saturday	0.35	0.48
Sunday	0.25	0.43
Competitive games		
Manchester United vs City/Liverpool	0.04	0.20
Overtime	0.01	0.09
Penalties	0.01	0.10
Tournament		
Premier League	0.69	0.46
Champions League	0.14	0.35
FA Cup	0.08	0.27
EFL Cup	0.06	0.24

Note: The sample includes 780 games of Manchester City and United. There are 16 derbies between them so the means of the result variables may not add up to 1.

Table 4: Game sample average comparison

	Card and Dahl	*0.6 - 0.4 betting odds*	*0.55 -0.45 betting odds*
Win	0.52	0.62	0.62
Loss	0.48	0.20	0.20
Expected win	0.33	0.55	0.65
Upset loss	0.09	0.08	0.12
Expected close	0.44	0.43	0.31
Close loss	0.14	0.07	0.15
Expected loss	0.24	0.02	0.03
Upset win	0.11	0.01	0.02
Highly salient	0.37	0.06	0.06
Derby/rivalry	0.23	0.04	0.04
Before 2.30	0.68	0.17	0.17
2.30-6.30	0.23	0.46	0.46
After 6.30	0.06	0.37	0.37

Note: The table compares sample averages of Card and Dahl (2011) vs. our results. Percentages have been computed over the full sample so they may not coincide with Card and Dahl (2011) averages on page 118. They report the mean of upset losses, close losses and upset wins over all expected wins/close/losses; multiplying the number for the mean of the sub-sample results in the numbers of this table. Example: the mean of upset losses is 0.28 over all predicted wins (0.33) = 0.28 x 0.33 = 0.09. "Predicted win(loss)" means that betting probabilities expected a win(loss).

Table 5: Alcohol influence in domestic abuse incidents during the week

	Workdays	Weekends	Total
Current partners			
No alcohol on perpetrator	60.4%	46.9%	57.5%
Alcohol on perpetrator	39.6%	53.1%	42.5%
Ex-partners			
No alcohol on perpetrator	78.2%	66.6%	76.2%
Alcohol on perpetrator	21.8%	33.4%	23.8%

Table 6: General model

	(1) Current partners	(2) Male on female c.p.	(3) Female on male c.p.
Game, t-4	0.17	0.15	0.01
	(0.11)	(0.09)	(0.04)
Game, t-3	0.13	0.10	0.01
	(0.11)	(0.09)	(0.04)
Game, t-2	0.20	0.18*	0.02
	(0.11)	(0.09)	(0.04)
Game	-0.25*	-0.28**	0.02
	(0.11)	(0.09)	(0.04)
Game, t+1	-0.05	-0.02	-0.04
	(0.11)	(0.09)	(0.04)
Game, t+2	0.29*	0.24*	0.05
	(0.11)	(0.10)	(0.04)
Game, t+3	0.05	0.06	-0.00
	(0.11)	(0.10)	(0.04)
Game, t+4	0.17	0.17	-0.02
	(0.11)	(0.10)	(0.04)
Game, t+5	0.34**	0.25**	0.03
	(0.11)	(0.10)	(0.04)
Game, t+6	0.35**	0.29**	0.04
	(0.11)	(0.09)	(0.04)
Game, t+7	0.12	0.08	0.01
	(0.11)	(0.09)	(0.04)
Game, t+8	0.05	0.07	-0.03
	(0.11)	(0.09)	(0.04)
Holiday	2.81***	2.09***	0.47***
	(0.11)	(0.09)	(0.03)
Quarter FE	Yes	Yes	Yes
WeekdayXHour FE	Yes	Yes	Yes
Binned endpoints	Yes	Yes	Yes
R-squared	0.43	0.37	0.18
Observations	31582	31582	31582

$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: Standard errors in parentheses. The table reports the coefficients of a distributed lag model that estimates the effect of a football game on domestic abuse incidents between current partners. The lag and lead coefficients represent the change in the number of incidents in that two-hour period, compared to 2h before the start of the game (*t-1*).

Table 7: Effect of alcohol on DA between current partners

	(1) Alcoholised perpetrator	(2) Non-alcoholised perpetrator
Game, t-4	0.15*	0.01
	(0.07)	(0.08)
Game, t-3	0.03	0.10
	(0.08)	(0.08)
Game, t-2	0.10	0.10
	(0.07)	(0.08)
Game	-0.07	-0.17*
	(0.07)	(0.08)
Game, t+1	-0.03	-0.01
	(0.08)	(0.08)
Game, t+2	0.13	0.16*
	(0.08)	(0.08)
Game, t+3	0.13	-0.08
	(0.08)	(0.08)
Game, t+4	0.21**	-0.04
	(0.08)	(0.08)
Game, t+5	0.29***	0.05
	(0.08)	(0.08)
Game, t+6	0.26***	0.09
	(0.08)	(0.08)
Game, t+7	0.08	0.03
	(0.08)	(0.08)
Game, t+8	0.02	0.02
	(0.07)	(0.08)
Holiday	2.35***	0.43***
	(0.08)	(0.07)
Quarter FE	Yes	Yes
Day of week x Hour FE	Yes	Yes
Binned endpoints	Yes	Yes
R-squared	0.48	0.31
Observations	31582	31582

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors in parentheses. The table reports the coefficients of a distributed lag model that estimates the effect of a football game on domestic abuse incidents between current partners, separated by alcohol intake of the perpetrator. The lag and lead coefficients represent the change in the number of incidents in that two-hour period, compared to 2h before the start of the game (*t-1*).

Table 8: Effect of alcohol and time of game - Current partners

	(1) All incidents	(2) Alcohol on perpetrator	(3) No alcohol on perpetrator
Game, t-4	0.03	0.02	0.01
	(0.19)	(0.12)	(0.13)
Game, t-3	0.09	0.04	0.07
	(0.20)	(0.13)	(0.14)
Game, t-2	0.36	0.06	0.33*
	(0.19)	(0.12)	(0.14)
Game	-0.27	-0.14	-0.11
	(0.19)	(0.12)	(0.14)
Game, t+1	-0.04	-0.05	0.02
	(0.20)	(0.13)	(0.14)
Game, t+2	0.27	0.09	0.20
	(0.20)	(0.13)	(0.14)
Game, t+3	-0.18	-0.24	0.07
	(0.20)	(0.13)	(0.14)
Game, t+4	-0.07	-0.15	0.10
	(0.20)	(0.13)	(0.14)
Game, t+5	-0.00	-0.12	0.12
	(0.20)	(0.13)	(0.14)
Game, t+6	0.22	0.14	0.09
	(0.20)	(0.13)	(0.14)
Game, t+7	0.16	0.06	0.10
	(0.20)	(0.13)	(0.14)
Game, t+8	0.01	-0.04	0.03
	(0.18)	(0.12)	(0.13)
Game x Early, t-4	0.14	0.12	0.01
	(0.23)	(0.16)	(0.16)
Game x Early, t-3	-0.02	-0.10	0.07
	(0.24)	(0.16)	(0.17)
Game x Early, t-2	-0.34	-0.00	-0.35*
	(0.23)	(0.15)	(0.17)
Game x Early	-0.02	0.05	-0.08

	(0.23)	(0.15)	(0.17)
Game x Early, t+1	-0.08	-0.06	-0.03
	(0.24)	(0.16)	(0.17)
Game x Early, t+2	-0.04	-0.01	-0.03
	(0.24)	(0.16)	(0.17)
Game x Early, t+3	0.32	0.53**	-0.21
	(0.24)	(0.16)	(0.17)
Game x Early, t+4	0.31	0.50**	-0.19
	(0.24)	(0.16)	(0.17)
Game x Early, t+5	0.50*	0.59***	-0.09
	(0.24)	(0.16)	(0.17)
Game x Early, t+6	0.14	0.11	0.02
	(0.24)	(0.16)	(0.17)
Game x Early, t+7	-0.14	-0.06	-0.08
	(0.24)	(0.16)	(0.17)
Game x Early, t+8	-0.02	0.00	0.01
	(0.23)	(0.16)	(0.16)
Holiday	2.79***	2.33***	0.43***
	(0.11)	(0.08)	(0.07)
Quarter FE	Yes	Yes	Yes
Day of WeekXHour FE	Yes	Yes	Yes
Binned endpoints	Yes	Yes	Yes
R-squared	0.43	0.48	0.31
Observations	31582	31582	31582

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors in parentheses. The table shows the results of estimating an event study on two-hour time series of all domestic abuse between current partners (1), when the perpetrator had consumed alcohol (2) and when he had not (3). The coefficients show the change in number of incidents every two hours, compared to the period two hours before the start of the game (*t-1*). The interaction coefficients of *Game* and *Early* capture the difference in effect of early games (those starting before 7PM) in relation to late games.

Table 9: Effect of alcohol consumption on victim and perpetrator on DA between current partners

	(1) Alcohol only on victim	(2) Alcohol only on perpetrator	(3) Alcohol on either	(4) Alcohol on both	(5) No alcohol presence
Game, t-4	0.00	0.03	0.02	-0.02	0.01
	(0.04)	(0.07)	(0.13)	(0.10)	(0.13)
Game, t-3	0.01	-0.02	0.05	0.05	0.06
	(0.04)	(0.07)	(0.14)	(0.10)	(0.13)
Game, t-2	0.01	0.08	0.07	-0.04	0.32*
	(0.04)	(0.07)	(0.13)	(0.10)	(0.13)
Game	-0.01	-0.00	-0.15	-0.16	-0.10
	(0.04)	(0.07)	(0.13)	(0.10)	(0.13)
Game, t+1	0.02	-0.05	-0.02	-0.01	0.00
	(0.04)	(0.07)	(0.14)	(0.10)	(0.13)
Game, t+2	-0.02	0.11	0.07	-0.03	0.22
	(0.04)	(0.07)	(0.14)	(0.11)	(0.13)
Game, t+3	-0.00	-0.05	-0.24	-0.20	0.07
	(0.04)	(0.07)	(0.14)	(0.11)	(0.13)
Game, t+4	-0.02	-0.01	-0.17	-0.14	0.11
	(0.04)	(0.07)	(0.14)	(0.11)	(0.13)
Game, t+5	0.04	-0.04	-0.08	-0.08	0.09
	(0.04)	(0.07)	(0.14)	(0.11)	(0.13)
Game, t+6	-0.00	0.04	0.14	0.10	0.09
	(0.04)	(0.07)	(0.14)	(0.11)	(0.13)
Game, t+7	0.02	0.03	0.08	0.03	0.08
	(0.04)	(0.07)	(0.14)	(0.11)	(0.13)
Game, t+8	0.01	-0.04	-0.02	-0.00	0.01
	(0.04)	(0.07)	(0.13)	(0.10)	(0.12)
Game x Early, t-4	-0.00	-0.07	0.12	0.20	0.02
	(0.05)	(0.09)	(0.17)	(0.13)	(0.16)
Game x Early, t-3	-0.04	-0.01	-0.15	-0.09	0.11
	(0.05)	(0.09)	(0.17)	(0.13)	(0.16)
Game x Early, t-2	-0.02	-0.07	-0.03	0.07	-0.33*
	(0.05)	(0.09)	(0.16)	(0.12)	(0.16)
Game x Early	0.01	-0.05	0.05	0.09	-0.09
	(0.05)	(0.09)	(0.16)	(0.12)	(0.16)
Game x Early, t+1	-0.00	0.02	-0.07	-0.08	-0.02

	(0.05)	(0.09)	(0.17)	(0.13)	(0.16)
Game x Early, t+2	0.06	-0.05	0.04	0.04	-0.09
	(0.05)	(0.09)	(0.17)	(0.13)	(0.16)
Game x Early, t+3	0.00	0.24**	0.52**	0.28*	-0.22
	(0.05)	(0.09)	(0.17)	(0.13)	(0.16)
Game x Early, t+4	0.07	0.16	0.56**	0.34**	-0.27
	(0.05)	(0.09)	(0.17)	(0.13)	(0.16)
Game x Early, t+5	-0.01	0.15	0.57**	0.43***	-0.09
	(0.05)	(0.09)	(0.17)	(0.13)	(0.16)
Game x Early, t+6	0.07	0.01	0.17	0.10	-0.04
	(0.05)	(0.09)	(0.17)	(0.13)	(0.16)
Game x Early, t+7	-0.02	0.03	-0.09	-0.09	-0.06
	(0.05)	(0.09)	(0.17)	(0.13)	(0.16)
Game x Early, t+8	-0.00	-0.02	-0.01	0.02	0.01
	(0.05)	(0.09)	(0.17)	(0.12)	(0.16)
Holiday	0.20***	0.62***	2.53***	1.75***	0.23***
	(0.02)	(0.04)	(0.08)	(0.06)	(0.06)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Day of week x Hour FE	Yes	Yes	Yes	Yes	Yes
R-squared	Yes	Yes	Yes	Yes	Yes
Observations	0.13	0.25	0.50	0.45	0.32
N	31582	31582	31582	31582	31582

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors in parentheses. The table shows the results of estimating an event study on two-hour time series of all domestic abuse between current partners, stratifying the sample by alcohol consumption on victim and/or perpetrator or on neither. The coefficients show the change in number of incidents every two hours, compared to the period two hours before the start of the game (*t-1*). The interaction coefficients of *Game* and *Early* capture the difference in effect of early games (those starting before 7PM) in relation to late games.

Table 10: General model - Ex-partners

	(1) Ex-partners
Game, t-4	0.00
	(0.10)
Game, t-3	0.27*
	(0.10)
Game, t-2	0.02
	(0.10)
Game	-0.01
	(0.10)
Game, t+1	0.01
	(0.10)
Game, t+2	0.15
	(0.10)
Game, t+3	0.15
	(0.10)
Game, t+4	0.13
	(0.10)
Game, t+5	0.21*
	(0.10)
Game, t+6	0.11
	(0.10)
Game, t+7	0.29**
	(0.10)
Game, t+8	-0.04
	(0.10)
Holiday	0.68***
	(0.09)
Quarter FE	Yes
Day of week x Hour FE	Yes
Binned endpoints	
R-squared	0
Observations	31582

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors in parentheses. The table reports the coefficients of a distributed lag model that estimates the effect of a football game on domestic abuse incidents between ex-partners. The lag and lead coefficients represent the change in the number of incidents in that two-hour period, compared to 2h before the start of the game (*t-1*).

Table 11: Alcohol in early games - Ex-partners

	(1) All incidents	(2) Alcohol on perpetrator	(3) No alcohol on perpetrator
Game, t-4	-0.05	0.03	-0.08
	(0.17)	(0.08)	(0.15)
Game, t-3	0.55**	0.08	0.47**
	(0.18)	(0.09)	(0.16)
Game, t-2	0.06	0.07	-0.01
	(0.18)	(0.09)	(0.16)
Game	-0.32	-0.02	-0.30
	(0.18)	(0.09)	(0.16)
Game, t+1	-0.11	-0.10	-0.02
	(0.18)	(0.09)	(0.16)
Game, t+2	0.09	-0.14	0.23
	(0.18)	(0.09)	(0.16)
Game, t+3	0.13	0.08	0.05
	(0.18)	(0.09)	(0.16)
Game, t+4	0.10	-0.03	0.13
	(0.18)	(0.09)	(0.16)
Game, t+5	0.29	0.09	0.19
	(0.18)	(0.09)	(0.16)
Game, t+6	0.31	0.16	0.15
	(0.18)	(0.09)	(0.16)
Game, t+7	0.51**	0.06	0.45**
	(0.18)	(0.09)	(0.16)
Game, t+8	-0.09	0.01	-0.10
	(0.17)	(0.08)	(0.15)
Game x Early, t-4	0.07	0.02	0.05
	(0.22)	(0.11)	(0.19)
Game x Early, t-3	-0.47*	-0.14	-0.33
	(0.23)	(0.11)	(0.20)
Game x Early, t-2	-0.06	-0.12	0.05
	(0.22)	(0.11)	(0.19)
Game x Early	0.50*	0.04	0.46*
	(0.22)	(0.11)	(0.19)
Game x Early, t+1	0.20	0.06	0.14
	(0.23)	(0.11)	(0.20)

Game x Early, t+2	0.09	0.17	-0.08
	(0.23)	(0.11)	(0.19)
Game x Early, t+3	0.01	0.04	-0.02
	(0.23)	(0.11)	(0.20)
Game x Early, t+4	0.04	0.22*	-0.17
	(0.22)	(0.11)	(0.19)
Game x Early, t+5	-0.13	-0.01	-0.13
	(0.22)	(0.11)	(0.19)
Game x Early, t+6	-0.33	-0.17	-0.16
	(0.22)	(0.11)	(0.19)
Game x Early, t+7	-0.38	0.02	-0.40*
	(0.22)	(0.11)	(0.19)
Game x Early, t+8	0.07	0.00	0.06
	(0.22)	(0.10)	(0.19)
Holiday	0.67***	0.95***	-0.28***
	(0.09)	(0.04)	(0.08)
Quarter FE	Yes	Yes	Yes
Day of WeekXHour FE	Yes	Yes	Yes
Binned endpoints	Yes	Yes	Yes
R-squared	0.46	0.22	0.51
Observations	31582	31582	31582

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors in parentheses. The table shows the results of estimating an event study on two-hour time series of all domestic abuse between current partners (1), when the perpetrator had consumed alcohol (2) and when he had not (3). The coefficients show the change in number of incidents every two hours, compared to the period two hours before the start of the game (*t-1*). The interaction coefficients of *Game* and *Early* capture the difference in effect of early games (those starting before 7PM) in relation to late games.

Table 12: Emotional cues from game results

	(1) All incidents	(2) Alcohol on perpetrator	(3) No alcohol on perp.	(4) Alcohol on victim and perp.	(5) No alcohol on victim and perp.
Upset loss	1.85	1.62*	0.23	0.65	0.30
	(1.08)	(0.79)	(0.68)	(0.65)	(0.63)
Upset win	2.63	-2.42	5.05**	-2.15	5.20*
	(3.32)	(1.71)	(1.88)	(1.17)	(2.15)
Close loss	1.20	1.06	0.14	0.38	0.04
	(1.02)	(0.74)	(0.61)	(0.61)	(0.61)
Close win	0.83	0.70	0.13	0.24	-0.03
	(0.93)	(0.66)	(0.57)	(0.51)	(0.56)
Predicted win	0.76	0.28	0.48	0.18	0.33
	(0.64)	(0.45)	(0.41)	(0.37)	(0.39)
Predicted loss	1.34	0.97	0.37	-0.06	0.14
	(2.49)	(1.44)	(1.75)	(0.87)	(1.74)
Holiday	20.31***	17.60***	2.71**	12.48***	1.21
	(2.39)	(2.07)	(0.88)	(1.70)	(0.79)
Season FE	Yes	Yes	Yes	Yes	Yes
Week of season FE	Yes	Yes	Yes	Yes	Yes
Day of week FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.66	0.72	0.19	0.68	0.13
Observations	2185	2185	2185	2184	2184

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Emotional cues from game results: event study

	(1) All incidents	(2) Alcohol on perpetrator	(3) No alcohol on perp.	(4) Alcohol on victim and perp.	(5) No alcohol on victim and perp.
Upset loss, t-4	-0.15	-0.02	-0.14	0.09	-0.10
	(0.25)	(0.17)	(0.18)	(0.13)	(0.17)
Upset loss, t-3	0.04	-0.06	0.09	0.04	0.14
	(0.25)	(0.17)	(0.18)	(0.14)	(0.17)
Upset loss, t-2	0.30	0.22	0.06	0.17	0.07
	(0.25)	(0.17)	(0.18)	(0.13)	(0.17)
Upset loss	-0.09	-0.10	0.00	-0.22	0.00
	(0.25)	(0.17)	(0.18)	(0.13)	(0.17)
Upset loss, t+1	-0.10	-0.02	-0.08	0.10	0.00
	(0.25)	(0.17)	(0.18)	(0.14)	(0.17)
Upset loss, t+2	0.49	0.19	0.30	-0.01	0.31
	(0.25)	(0.17)	(0.18)	(0.14)	(0.17)
Upset loss, t+3	0.21	0.19	0.02	0.03	-0.11
	(0.25)	(0.17)	(0.18)	(0.14)	(0.17)
Upset loss, t+4	0.58*	0.50**	0.08	0.23	0.03
	(0.25)	(0.17)	(0.18)	(0.14)	(0.17)
Upset loss, t+5	0.39	0.39*	0.00	0.07	-0.03
	(0.25)	(0.17)	(0.18)	(0.14)	(0.17)
Upset loss, t+6	0.48	0.52**	-0.03	0.38**	-0.04
	(0.25)	(0.17)	(0.18)	(0.14)	(0.17)
Upset loss, t+7	0.33	0.34*	-0.01	0.15	-0.03
	(0.25)	(0.17)	(0.18)	(0.14)	(0.17)
Upset loss, t+8	0.29	0.06	0.21	0.15	0.21
	(0.25)	(0.17)	(0.18)	(0.13)	(0.17)
Upset win, t-4	0.14	-0.75	0.96	-0.40	1.09
	(0.97)	(0.64)	(0.69)	(0.52)	(0.66)
Upset win, t-3	1.44	-0.10	1.56*	-0.28	1.32*
	(0.98)	(0.66)	(0.69)	(0.52)	(0.66)
Upset win, t-2	-0.70	-0.29	-0.33	-0.30	-0.38
	(0.97)	(0.64)	(0.69)	(0.52)	(0.66)
Upset win	-0.04	-0.56	0.60	-0.50	0.32
	(0.97)	(0.64)	(0.69)	(0.52)	(0.66)
Upset win, t+1	0.03	-0.78	0.82	-0.31	0.92
	(0.98)	(0.66)	(0.69)	(0.53)	(0.66)

Upset win, t+2	-0.31	-0.09	-0.22	-0.11	-0.07
	(0.98)	(0.66)	(0.69)	(0.53)	(0.66)
Upset win, t+3	0.83	0.79	0.05	0.67	0.12
	(0.98)	(0.66)	(0.69)	(0.53)	(0.66)
Upset win, t+4	0.01	-0.42	0.43	-0.24	0.41
	(0.98)	(0.66)	(0.69)	(0.53)	(0.66)
Upset win, t+5	-0.78	-0.51	-0.27	-0.21	-0.30
	(0.98)	(0.66)	(0.69)	(0.53)	(0.66)
Upset win, t+6	-0.38	0.38	-0.76	0.56	-0.59
	(0.98)	(0.66)	(0.69)	(0.53)	(0.66)
Upset win, t+7	-1.18	-0.69	-0.50	-0.62	-0.30
	(0.98)	(0.66)	(0.69)	(0.53)	(0.66)
Upset win, t+8	-1.24	-1.20	-0.09	-0.91	-0.24
	(0.97)	(0.64)	(0.69)	(0.52)	(0.66)
Predicted win, t-4	0.28*	0.18*	0.09	0.15*	0.08
	(0.13)	(0.09)	(0.09)	(0.07)	(0.09)
Predicted win, t-3	0.09	0.03	0.06	0.02	0.07
	(0.13)	(0.09)	(0.09)	(0.07)	(0.09)
Predicted win, t-2	0.16	0.03	0.13	0.01	0.15
	(0.13)	(0.09)	(0.09)	(0.07)	(0.09)
Predicted win	-0.33*	-0.03	-0.28**	-0.06	-0.26**
	(0.13)	(0.09)	(0.09)	(0.07)	(0.09)
Predicted win, t+1	-0.11	-0.19*	0.09	-0.18**	0.08
	(0.13)	(0.09)	(0.09)	(0.07)	(0.09)
Predicted win, t+2	0.03	-0.17	0.20*	-0.16*	0.21*
	(0.13)	(0.09)	(0.09)	(0.07)	(0.09)
Predicted win, t+3	-0.26*	-0.04	-0.21*	-0.05	-0.19*
	(0.13)	(0.09)	(0.09)	(0.07)	(0.09)
Predicted win, t+4	0.03	0.06	-0.02	0.03	-0.07
	(0.13)	(0.09)	(0.09)	(0.07)	(0.09)
Predicted win, t+5	0.39**	0.28**	0.11	0.28***	0.08
	(0.13)	(0.09)	(0.09)	(0.07)	(0.09)
Predicted win, t+6	0.35**	0.14	0.21*	0.12	0.14
	(0.13)	(0.09)	(0.09)	(0.07)	(0.09)
Predicted win, t+7	0.04	-0.02	0.06	-0.06	0.04
	(0.13)	(0.09)	(0.09)	(0.07)	(0.09)
Predicted win, t+8	-0.07	-0.05	-0.03	-0.03	-0.04
	(0.13)	(0.09)	(0.09)	(0.07)	(0.09)
Predicted loss, t-4	0.99	0.67	0.31	0.51	0.33

	(0.64)	(0.42)	(0.45)	(0.34)	(0.43)
Predicted loss, t-3	1.18	0.16	1.03*	0.09	1.04*
	(0.64)	(0.43)	(0.45)	(0.35)	(0.43)
Predicted loss, t-2	-0.06	0.33	-0.36	-0.05	-0.53
	(0.64)	(0.42)	(0.45)	(0.34)	(0.43)
Predicted loss	-0.37	-0.05	-0.28	-0.22	-0.28
	(0.64)	(0.42)	(0.45)	(0.34)	(0.43)
Predicted loss, t+1	-1.18	-0.53	-0.65	-0.47	-0.52
	(0.64)	(0.43)	(0.45)	(0.35)	(0.43)
Predicted loss, t+2	-0.01	0.49	-0.49	0.17	-0.35
	(0.64)	(0.43)	(0.45)	(0.35)	(0.43)
Predicted loss, t+3	1.59*	0.56	1.03*	0.47	0.76
	(0.64)	(0.43)	(0.45)	(0.35)	(0.43)
Predicted loss, t+4	0.26	0.29	-0.03	0.02	-0.05
	(0.64)	(0.43)	(0.45)	(0.35)	(0.43)
Predicted loss, t+5	-0.59	-0.31	-0.28	-0.17	-0.33
	(0.64)	(0.43)	(0.45)	(0.35)	(0.43)
Predicted loss, t+6	0.28	0.18	0.10	0.27	0.15
	(0.64)	(0.43)	(0.45)	(0.35)	(0.43)
Predicted loss, t+7	0.50	0.39	0.10	0.38	0.15
	(0.64)	(0.43)	(0.45)	(0.35)	(0.43)
Predicted loss, t+8	0.43	-0.17	0.57	-0.17	0.64
	(0.64)	(0.42)	(0.45)	(0.34)	(0.43)
Close win, t-4	0.28	0.09	0.15	0.13	0.14
	(0.21)	(0.14)	(0.15)	(0.11)	(0.14)
Close win, t-3	0.08	-0.07	0.14	-0.03	0.14
	(0.21)	(0.14)	(0.15)	(0.11)	(0.14)
Close win, t-2	-0.06	-0.05	0.02	-0.06	0.03
	(0.21)	(0.14)	(0.15)	(0.11)	(0.14)
Close win	-0.32	-0.19	-0.10	-0.04	-0.08
	(0.21)	(0.14)	(0.15)	(0.11)	(0.14)
Close win, t+1	-0.03	-0.04	0.01	-0.01	-0.03
	(0.21)	(0.14)	(0.15)	(0.11)	(0.14)
Close win, t+2	0.40	0.41**	-0.01	0.11	-0.08
	(0.21)	(0.14)	(0.15)	(0.11)	(0.14)
Close win, t+3	0.14	0.09	0.06	-0.12	0.06
	(0.21)	(0.14)	(0.15)	(0.11)	(0.14)
Close win, t+4	0.03	0.13	-0.10	0.03	-0.09
	(0.21)	(0.14)	(0.15)	(0.11)	(0.14)

Close win, t+5	0.19	0.17	0.01	0.14	-0.03
	(0.21)	(0.14)	(0.15)	(0.11)	(0.14)
Close win, t+6	0.13	0.16	-0.02	0.08	0.01
	(0.21)	(0.14)	(0.15)	(0.11)	(0.14)
Close win, t+7	0.20	0.07	0.13	-0.01	0.14
	(0.21)	(0.14)	(0.15)	(0.11)	(0.14)
Close win, t+8	-0.07	0.09	-0.17	0.07	-0.21
	(0.21)	(0.14)	(0.15)	(0.11)	(0.14)
Close loss, t-4	-0.13	-0.11	0.00	-0.05	0.05
	(0.23)	(0.15)	(0.16)	(0.12)	(0.16)
Close loss, t-3	-0.23	-0.07	-0.15	-0.04	-0.15
	(0.23)	(0.16)	(0.16)	(0.12)	(0.16)
Close loss, t-2	0.30	0.16	0.15	0.04	0.15
	(0.23)	(0.15)	(0.16)	(0.12)	(0.16)
Close loss	-0.33	-0.11	-0.21	-0.07	-0.19
	(0.23)	(0.15)	(0.16)	(0.12)	(0.16)
Close loss, t+1	-0.07	-0.01	-0.05	-0.01	-0.08
	(0.23)	(0.16)	(0.16)	(0.12)	(0.16)
Close loss, t+2	0.36	0.32*	0.05	0.11	0.02
	(0.23)	(0.16)	(0.16)	(0.12)	(0.16)
Close loss, t+3	0.42	0.35*	0.07	0.08	0.11
	(0.23)	(0.16)	(0.16)	(0.12)	(0.16)
Close loss, t+4	0.41	0.34*	0.07	0.29*	-0.01
	(0.23)	(0.16)	(0.16)	(0.12)	(0.16)
Close loss, t+5	0.27	0.26	0.01	0.03	-0.02
	(0.23)	(0.16)	(0.16)	(0.12)	(0.16)
Close loss, t+6	0.41	0.31*	0.10	0.23	0.06
	(0.23)	(0.16)	(0.16)	(0.12)	(0.16)
Close loss, t+7	-0.04	0.03	-0.07	0.02	-0.09
	(0.23)	(0.16)	(0.16)	(0.12)	(0.16)
Close loss, t+8	-0.07	0.02	-0.12	-0.02	-0.08
	(0.23)	(0.15)	(0.16)	(0.12)	(0.16)
Holiday	2.60***	2.14***	0.43***	1.61***	0.23***
	(0.11)	(0.08)	(0.07)	(0.06)	(0.07)
Quarter FE	Yes	Yes	Yes	Yes	Yes
Day of week x Hour FE	Yes	Yes	Yes	Yes	Yes
Binned endpoints	Yes	Yes	Yes	Yes	Yes
R-squared	0.44	0.49	0.31	0.46	0.32

Observations	31320	31320	31320	31320	31320

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Standard errors in parentheses. The table shows the results of estimating a event study on two-hour time series of domestic abuse between current partners. The dependent variable in column (1) corresponds to all incidents between current partners while columns (2) to (5) are stratified samples depending on the presence of alcohol on victim and/or perpetrator. The coefficients show the change in incidents every two hours in relation to *t-1* which corresponds to two hours before the start of the game.

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