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Abstract

This paper quantifies how much of violent crime in society can be attributed to football-related violence. We study the universe of professional football matches played out in Germany's top three football leagues over the period 2011-2015. To identify causal effects, we leverage time-series and cross-sectional variation in crime register data, comparing the number of violent crimes on days with and without professional football matches while controlling for date heterogeneity, weather, and holidays. Our main finding shows that violent crime increases by 17 percent on a match day. In the regions and time period under consideration, professional football matches explain 1 percent of all violent assaults, and generate social costs of roughly 295 million euros. Exploring possible mechanisms, we establish that the match day effect cannot be explained by emotional cues stemming from either unsettling events during a match or unexpected game outcomes, nor is it driven by increases in domestic violence. Instead, we find that the match day effect can be attributed to violence among males in the 18-39 age group, rises to 63 percent on days with high-rivalry derby matches, and that a non-negligible share of it stems from violent crimes committed by group offenders and assaults on police officers. Most of the empirical facts we document can be accommodated by social identity explanations of football hooliganism, while frustration-aggression theories of sports-related violence can explain only some of the findings in isolation.

JEL-Codes: J190, K420, Z130, Z290.

Keywords: violent crime, football hooliganism.

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1 Introduction

Over the last century, association football (henceforth, football) has evolved from a popular recreational activity to a professionally organized team sport attracting large collective followings. For instance, the *Bundesliga*, Germany's top professional football league, is a major reason for public mass gatherings and had with 42,700 spectators the highest average attendance per match of all European leagues in the season 2017/18. In economic terms, football is synonymous with big business, as is exemplified by the fact that the *Bundesliga* has surpassed the revenue threshold of three billion euros a few years ago (Deloitte, 2019). Due to their great popularity, professional football matches generate many external effects. On the positive side, they lead to higher consumer spending (e.g., merchandising, catering, and accommodation), and therefore increase local tax revenues. On the negative side, there are *inter alia* substantially increased travel volumes on match days, which bring with it more air pollution, noise pollution, and traffic accidents. Most importantly however, professional football has grappled for decades with violent crowd behavior, which negatively impacts individuals' health and safety, police forces, and the penal system.

In this paper, we provide a comprehensive assessment of the magnitude of the football violence problem and explore mechanisms that might explain it. We collect and merge data from various sources to analyze violent crime surrounding the universe of football matches played out in Germany's three professional football leagues over the period 2011-2015. First, detailed information on 4,461 matches is obtained via web scraping.[1] Second, the primary outcome variable, the number of violent assaults, is derived from comprehensive registry data provided by the Federal Criminal Police Office. It includes records of all victims subject to crimes against their legally protected personal rights that have been investigated by the police from 2011 until the end of 2015. Third, data from local weather monitors and a time-series of holidays are matched to the data to account for possible confounders. Last, population figures from the Federal Statistical Office are merged with the crime data. To identify causal effects, we employ a generalized difference-in-differences approach that exploits within-municipality variation in the timing of the football games. Specifically, we compare the level of assaults on days with and without home games while controlling for municipality fixed effects and any potential source of heterogeneity across days of the week, month, and year. We also take into account other possible confounding variation from weather or holidays.

In a first step, we quantify how much of violent crime in Germany can be attributed to football-related violence. We find significant and robust evidence that football matches lead to a large increase in violent crime. A home game increases the number of simple assaults by roughly 13 percent. Aggravated assaults which cause serious bodily injury

[1] This includes, but is by no means limited to the time and location of the games. Furthermore, we exploit betting odds that reflect pregame expectations.

increase by 25 percent on game days. The fact that we find larger proportional effects for severe violent crimes where underreporting is not a concern suggests that changes in crime reporting/recording behavior on game days are not driving our results. We show that the game day effect is not offset by reductions in violent acts on days adjacent to the game day or in nearby areas. Our focus on home games is also not a threat to identification because we provide strong evidence that away games do not reduce the level of physical assaults in the home district. These findings are robust to a battery of robustness checks, including those using machine learning based approaches to obtain a data-driven selection of confounders (Belloni *et al.*, 2014a) and placebo matches. Back-of-the-envelope calculations based on our estimates indicate that the crime costs of professional football games are substantial. In the regions and time period studied, football games in the top three German leagues cause 3,079 additional simple assaults and 2,963 additional aggravated assaults, which together account for roughly 1 percent of all violent assault reports. Based on published estimates for the social costs of simple and aggravated assaults (Glaubitz *et al.*, 2016), we calculate that this implies annual social costs of roughly 67 million euros caused by football games.

In a second step, we explore factors that may explain these results. There are a number of behavioral theories rationalizing spectator violence. To begin with, we consider the relevance of the frustration-aggression hypothesis (FAH), first proposed by Dollard *et al.* (1939) and able to explain sports-related violence in the United States (Rees and Schnepel, 2009, Card and Dahl, 2011). The FAH conjectures that violent fan behavior is an act to rehabilitate individual self-esteem reduced by a frustrating event, such as the defeat of one's favorite team. We test whether this theory can serve as an explanation for the increase in violent crime on match days. We first show that a large portion of football-related behavior manifests itself in post-game behavior, which is consistent with the FAH. We then explore the relevance of emotional cues from either emotionally unsettling events during a match or when game outcomes do not align with pregame expectations. In both cases, there is no evidence to support the FAH. Another mechanism consistent with the FAH would be if our estimated match day effect were largely explained by increases in domestic violence (Card and Dahl, 2011). We find this not to be the case, as violence between intimate partners turns out to only account for 1.5 percent of football-related assaults.

We next explore social identity theory (SIT) as a possible explanation for our results. Generally, SIT posits that the simple act of grouping can lead to conflict and violence, between in-groups and out-groups (Tajfel and Turner, 1986). In the context of football-related violence, SIT asserts that violence-prone football fans are motivated by identity fusion—a profound sense of "oneness" between their personal and social identity—to fight with and defend fellow fans in the face of perceived out-group threats from rivaling fan groups or the police. We find several pieces of evidence consistent with SIT. First, we show that a SIT-related type of concentration effect plays an important role in the game day effect we estimate. In particular, we find that while the increase in violent crime is unaffected by overall levels of game attendance, it significantly increases with the number of potential away-supporters at matches. This can be interpreted as some first evidence that violent interactions between rivaling fan groups might play an important role. Second and substantiating this, a non-negligible share of the game day effect stems from violence committed by group offenders, which suggests that acting as a group is an integral part of football-related violence. Third, the match day effect on violent crime is almost entirely driven by male victims and is most pronounced in the 18-39 age group. This is indeed the demographic group SIT, when applied to football violence, centers around (Spaaij, 2008). Fourth, the perception of outgroup threats—especially perceived territorial threats from fans of rivaling teams in the same area—form an essential part of social identity explanations of football violence (Mondello, 2016). We show that on days with derby matches—high-rivalry games between two clubs of the same city or region—violent crime increases by 63 percent, an effect almost four times as large as our baseline estimate. Finally, another important dimension of football violence that can be understood in terms of perceived territorial outgroup threats is fan violence targeted at police forces (Stott and Reicher, 1998). We establish that this dimension plays a non-negligible role in the match day effect we estimate, showing that violent assaults on police officers increase by 92 percent on match days and account for 22 percent of all assaults caused by football games.

The paper relates to previous literature that investigates the impact of large scale sporting events on various types of criminal behavior. Studies in the US American context typically use offense reports from the National Incident Based Reporting System to investigate the impact of American (college) football games on crime. Rees and Schnepel (2009) exploit within agency variation to study the effects of Division I-A college American football games on various offense categories for the years 2000-2005.[2] They find a 9 percent increase in violent assaults on match days. Larger effects are associated with unexpected game outcomes, defined as when lower ranked teams win against higher ranked teams. Lindo *et al.* (2018b) examine the effect of college party culture in the context of Division 1 American football games on sexual assaults. They show that the daily reports of rape victimization among 17-24-year-old women increase by 28 percent on game days. In this study, too, game outcomes matter: unexpected wins lead to a strong increase in the number of rapes. Card and Dahl (2011) analyze the impact of emotionally unsettling events associated with wins and losses of professional American football teams on family violence for the years 1995-2006. They find a 10 percent increase in intimate partner violence in the event of unexpected losses (when the home team was expected to win), but no effects for unexpected wins or when the game expectations predict a close match.

These three studies have an interesting common thread in that they establish that sports-related violence in the US is triggered by emotional cues stemming from unexpected game outcomes. Interestingly, our results strongly suggest that unexpected game outcomes do

[2] Almost all of the following studies exploit within law enforcement agency variation over time while controlling for weather, holidays and other sources of heterogeneity over time.

not drive violent crime in the context of professional football matches in Germany. Instead, we find evidence consistent with social identity theories of football hooliganism. At the heart of these theories is the idea that football violence is rooted in group dynamics which become activated if perceived outgroup threats—especially territorial ones—are high. From a policy perspective, our results suggest the need for non-conventional interventions aimed at debiasing fan groups with high levels of outgroup threat perception. By contrast, dense police presence and invasive police tactics may well backfire, as they might serve to increase violence by inflating perceived threat levels. Poutvaara and Priks (2017) provide a review of empirical work that studies how football violence can be prevented.

In the European setting, three insightful studies have examined the effects of football matches on different types of crime in the urban contexts of London and Barcelona, respectively. The questions addressed in these studies are different from those we explore, as they focus on how the crime profile of a given city is spatially and temporally affected by football matches. Marie (2016) investigates the effect of football matches on crime in London using hourly offense data from the Metropolitan Crime Statistics System. His results show that property crimes increase (decrease) by 4 percent (3 percent) for every additional 10,000 spectators attending a home (away) game. Violent crimes are only affected by derby matches. Montolio and Planells-Struse (2016) study the temporal impact of football matches on criminal behavior in Barcelona (2007-2011). They match reports of registered crime with football matches played by the Football Club Barcelona (FCB) to see whether the games lead to temporal shifts in criminal activity. Their results indicate temporal shifts for criminal activities of thefts, criminal damage, robberies, and gender violence. Moreover, instances of gender violence increase after home defeats. In a follow-up study, Montolio and Planells-Struse (2019) investigate the spatial dimensions of crime externalities associated with football games in Barcelona. Their findings show that, in the event of a home game, theft rates (mainly pickpocketing) increase in the entire city. The impact is larger for regions in close proximity to the stadium. The effects of football matches on assaults are analogous to thefts.

The remainder of the paper is structured as follows. The next section provides information about football games, their relationship with violent spectator behavior, and previous literature. Section 3 explains the data and the variables. Section 4 contains a description of the empirical framework. Section 5 reports results, validity checks, a discussion on potential channels, and robustness tests. Section 6 concludes.

2 Background

2.1 The German Football League System

The three fully professional divisions in the German football league system are managed under the jurisdiction of the German Football Association (DFB) and the German Football League (DFL). While the top two leagues, *Bundesliga* and *2. Bundesliga*, are organized by the DFL, the third division, *3. Liga*, is run by the DFB itself. Teams can be promoted or relegated from one league to another. The top two divisions consist of 18 teams playing 17 home and away games in one season. The third league contains 20 teams playing 19 home and away games.

The empirical approach of this paper exploits the variation in the scheduling of matches. Since 2006, the match schedules for the *Bundesliga* and the *2. Bundesliga* are created with a software that uses integer linear programming.[3] The software outlines the rough details such as the matches per gameday. The exact date and time, however, are determined in the course of the season. The later exact scheduling makes it possible to take into account guidelines from local authorities, security bodies, the Central Sports Intelligence Unit (ZIS), international football associations (FIFA/UEFA), fans, clubs, and stadium operators. In addition to obvious restrictions such as the fact that home games of neighboring clubs should be scheduled at different times, the DFL has to consider public holidays, other major events, or match dates of international competitions.[4]

2.2 Football and Violent Crime

Spectator violence has a long tradition in the context of professional football in Germany. The change in names for football fans illustrates that spectator behavior has changed considerably (Pilz, 2005). In the 1960s and 1970s, the peaceful fan base was refereed to as *camp-followers*, while one decade later the first problems of spectator violence emerged with the so-called *football rowdies*. In the 1980s, spectator violence was omnipresent, mainly due to the hooligan movement. Since the late 1990s, a new group has appeared in the stadiums, the *ultras*. Originally from Italy, the *ultras* are dedicated to fighting the commercialization of football and to revitalizing traditional football culture (see, e.g., Doidge and Lieser, 2018, Frosdick and Marsh, 2013). Over the last years, the number of violent fans has been increasing. The police distinguish between three types of football fans. Category A includes peaceful fans, category B consists of fans inclined to violence, and category C contains fans who actively seek violence (violent criminals). Originally, the *ultras* were predominantly assigned to category A and occasionally to category B. Recently,

[3] For details on how the match schedules are created, please refer to https://www.bundesliga.com.

[4] Home games of neighboring clubs are scheduled at different times so as to avoid fan agglomerations as well as traffic and public transport congestion.

however, a substantial share of the *ultras* has been classified as members of categories B and C.

Alcohol is often cited as playing a crucial role in the context of violence in and around football stadiums.[5] Cook and Durrance (2013) describes the pharmacological effects of alcohol consumption on aggression and cognitive functions. Alcohol consumption is associated with a loss of inhibition and impaired judgment. Furthermore, experiments have shown that participants exhibit more aggressive behavior after drinking. The 2018 edition of the Police Crime Statistics specifies that more than one in four assaults (26.2 percent) were committed under the influence of alcohol. While in some countries alcoholic beverages are prohibited on the premises (e.g.„ in Brazil since 2003), the rules in German stadiums are somewhat ambiguous. The DFB's security guidelines stipulate that the sale of alcoholic beverages is forbidden before and during games in the stadium. Nevertheless, with the approval of the responsible local security bodies, the hosting clubs can deviate from the regulations, on their own responsibility. Only in the case of high-risk games, the clubs are urged to comply with the ban.[6] The clubs, however, have a strong incentive to deviate from the ban as more than one-sixth (538 million Euros in the 2017/18 season) of the *Bundesliga* clubs' earnings are generated by matchday revenues (e.g., tickets and catering) and the sale of alcoholic beverages is a substantial part of this (Deloitte, 2019). For this reason, alcohol is very present in German football arenas, raising concern about its potential effects on violence.

3 Data

The data set used for the analysis covers the time window from 2011 to 2015 and contains 59 municipalities in which professional football games take place. These 59 municipalities cover a population of slightly more than 20 million people which represents roughly 25 percent of the total German population. Municipalities are the smallest territorial division in Germany, and constitute the level at which our analysis is conducted. We combine various data sources to examine the impact of professional football games on violent behavior.

3.1 Crime Data

The crime data is derived from the German Police Crime Statistics, which is provided by the Federal Criminal Police Office.[7] It includes the universe of individuals who were

[5] As we will later discuss, this view is not necessarily share by social scientists who work on football-related violence, as there are considerable cross-country differences in the consumption of alcohol of football fans and its apparent effects on violent behavior.

[6] For details, please refer to: `https://www.sueddeutsche.de`.

[7] Many aspects of the data preparation are inspired by Hener (2019) who uses the same data to examine the causal effect of noise pollution on criminal activities.

victim to a crime against their legally protected personal rights between 2011 and 2015. However, as the data is not reported until after police procedures are completed, only data from January 2011 to May 2015 is used to avoid problems with lags between the occurrence of the crime and the time of reporting. Besides, the month of June is excluded from the main analysis as there are generally no matches during that time of the year. In addition to the time and place (municipality level) of the crime, the data include the crime type code, the victim's age and gender, information on how the attack was carried out (attempt/completed act, usage of a firearm, lone operator/crime was committed by a group) and information on the relationship between victim and suspect.[8] Roughly 40 percent of victims are female, the average age is 32 years, and 40 percent of the victims had no prior relationship with the suspect.

The micro-data is aggregated to the municipality-day level. The main outcome we focus on are assaults, defined as actions involving physical violence. We group together the crime type codes 'simple willful bodily harm' (*Vorsätzliche einfache Körperverletzung*, § 223 StGB), 'dangerous bodily harm' (*Gefährliche Körperverletzung*, § 224 StGB), and 'grievous bodily harm' (*Schwere Körperverletzung*, § 226 StGB). There are roughly 120 types of criminal offenses (recorded in 6 digit codes), with the vast majority of cases classified by only a handful of codes.[9] Figure A.1 in the Appendix shows the distribution of cases per crime key for the twenty most common offense types in 2014. The three types of assaults we consider in the analysis account for roughly 62 percent of these cases. For parts of our analysis, we will distinguish between simple assaults (simple willful bodily harm, 45 percent of these cases) and aggravated assaults (dangerous or grievous bodily harm; 17 percent of theses cases).

Figure 1 shows the distribution of assaults over time. Panel A displays the variation of assaults per hour of the day.[10] The number of assaults increases during the day and peaks around midnight. To assign the cases that occur in the early morning hours to the day on which they originate, we define a day as beginning at 6:00AM and ending at 5:59AM. Panel B shows the distribution of assaults by day of the week. There are relatively more assaults on Fridays and Saturdays, whereas the other days exhibit slightly smaller assault rates. Panel C shows that the number of assaults has a strong seasonal pattern, with the highest value recorded in May and the smallest in August.[11] Panel D confirms this impression by plotting the daily number of assaults. New Year's Eve is a particularly impressive outlier.[12]

[8]The relationship between victim and suspect is retrieved in two ways. On the one hand, formal relationships are recorded (such as types of kinship or acquaintance). On the other hand, relationships are defined in spatial-social terms (for instance living in the same household, or being in an educational or care relationship).

[9]The top 10 of the most prevalent crime keys account for more than 90 percent of the cases.

[10]Roughly 15 percent of the observations do not contain hourly information. This has no consequences for the main analysis, as we examine daily variation in the assault rate.

[11]Panel C shows the monthly number of assaults while adjusting for the number of days per month.

[12]Panels C and D show data for the year 2014 only.

3.2 Football Data

The data on football matches are self-collected and are obtained via web scraping from www.kicker.de and www.transfermarkt.com. All matches played in the first three leagues of the German football league system in the period from January 2011 until May 2015 are recorded. We are able to observe detailed information on each match, including time and location, number of spectators, pregame point difference, goals, penalties, cards, referee characteristics, among others. Furthermore, the data contain comprehensive information on the individual teams, such as team size, average age, market value, and the number of foreign players. Appendix Table B.1 shows the teams and cities included in the analysis and provides descriptive statistics for them. The stadiums were the matches take place are geographically encoded. Figure 2 depicts a map with all 69 stadiums included in the data set.

Figure 3 illustrates insights into key variables. Panel A shows the number of matches per day of the week and league. The vast majority of matches takes place between Friday and Sunday. Games of the lower leagues occasionally also take place during the week. Such games are held only in the evenings. In contrast, matches on weekends usually take place in the afternoon. The inclusion of day-of-week fixed effects in the baseline specification helps to account for the higher share of games played on weekends, which are associated with higher levels of criminal behavior. Spectator number vary substantially across the three professional leagues, as depicted in Panel C. The *Bundesliga* attracts the most spectators with an average of 44,000 viewers per game, followed by the second league with an average of 17,000 fans per match, and the lowest league attracts slightly less than 6,000 fans per game on average.

When investigating channels of how football games may affect assaults, we exploit betting odds obtained from www.oddsportal.com via web scraping. The betting odds give an idea of pregame expectations. We translate the odds of the three game outcomes to probabilities which are the inverse of the betting odds. The probabilities serve as suitable predictors for game outcomes, as shown in Appendix Figure A.3.[13]

3.3 Weather Data

The weather data is derived from Germany's National Meteorological Service (*Deutscher Wetterdienst*). In order to construct the weather control variables, we use those weather monitors which measure the relevant weather variables in the sample period.[14] From this

[13] Panel A of Figure A.3 shows the close relationship between the realized score differential and the probability spread. Panels B and C demonstrate that the probability of winning increases the higher the probability spread.

[14] We use daily averages of the following weather variables: daily average, minimum and maximum air temperature, minimum ground temperature, vapor pressure, air pressure, cloud cover, air humidity, precipitation, hours of sunshine, snow depth, and wind velocity.

set of monitors, we choose the weather monitor with the closest proximity to a stadium. The assigned monitor-stadium pairs can be found in Figure 2. There is a high quality of the matches between weather monitors and stadiums, as the average distance between stadiums and monitors is 15 kilometers. Few of the weather variables have missing data, which are filled in by propagating forward from the last valid observation to the next valid observation (i.e. 'forward fill').[15]

3.4 Holidays

In our analysis, we include controls for public and school holidays, which may differ at the state level.[16] Furthermore, we also include a dummy variable for New Year's Eve and the days surrounding Carnival, which are not official holidays. As has been pointed out by Lindo *et al.* (2018b), the inclusion of these controls is important because holidays and special days such as New Year's Eve are often associated with systematic changes in violent crime. Failure to account for these days risks biased estimates, either through an association between holidays and the days on which games are played or because holidays fall on particular days of the week.

3.5 Regional Database

The Federal Statistical Office and the statistical offices of the Länder provide a database of detailed statistics by various subject areas at a very granular spatial level. We use information on population to adjust our empirical model for the different sizes of the municipalities being analyzed.

4 Empirical Strategy

In order to identify the causal effect of football matches on criminal behavior, we exploit within-region variation over time. To be precise, we compare assaults in a given region on a game day to the expected assaults in absence of the game conditional on the day of the week, month, and year, while additionally accounting for other possible confounding variation due to weather and holidays. To intuitively understand our approach, suppose a football game is scheduled in Munich on a Saturday in April 2012. The counterfactual (i.e., expected assaults in absence of the game) is then assumed to be given by the city's assaults on other match-free Saturdays in April 2012.

[15] The weather variables with missing data are (with the share of missing data in parenthesis): Cloud cover (<1.2 percent) and snow depth (<0.6 percent).

[16] The data on school holidays comes from 'The Standing Conference of the Ministers of Education and Cultural Affairs of the Länder in the Federal Republic of Germany' (*Kultusminister Konferenz*). The data on public holidays is collected from `https://www.schulferien.org/deutschland/feiertage/`.

Given the count nature of our crime data and the nontrivial proportion of observations equal to zero,[17] we employ a Poisson pseudomaximum likelihood (PPML) model with multi-way fixed effects to estimate the effect of game days on violent crime:

$$\begin{aligned} &E\left[\text{Assaults}_{rdmy} \,|\, \text{Gameday}_{rdmy}, \vartheta_r, \text{date}_{dmy}, \mathbf{X}_{rdmy}\right] \\ &\qquad = exp\left(\beta\ (\text{Gameday}_{rdmy}) + \vartheta_r + \text{date}_{dmy} + \lambda \mathbf{X}_{rdmy}\right), \end{aligned} \tag{1}$$

where Assaults_{rdmy} is the number of assaults in region r, on day-of-the-week d, in month m and year y. Gameday_{rdmy} is a binary variable that equals one when there is a home game, and zero otherwise. Region fixed effects ϑ_r capture time-invariant differences between regions and ensure that the identification is driven by within instead of between region variation over time. The vector date_{dmy} contains fixed effects for the day-of-the-week (γ_d), month (η_m), and year (θ_y). This way, the model flexibly controls for day-of-week specific heterogeneity, seasonal effects, and long-run time trends. For an extended specification, we expand the baseline model by adding in region-by-day-of-week fixed effects, region-by-month fixed effects, and region-by-year fixed effects. These interactions account for systemic changes in the degree of violent behavior over the year for each region. The vector $\mathbf{X}_{rdmy}$ includes indicators for school and public holidays, and weather controls.[18] Population size is used as an exposure variable to adjust the Poisson models for the different sizes of the regions being analyzed (see, e.g., Lindo *et al.*, 2018a). To account for potential overdispersion in our data, we follow Cameron and Trivedi (2005) and compute robust (or "sandwiched") standard error estimates allowing errors to be correlated over time within a region. In a robustness check, we will verify that our results are almost identical when estimating a conditional fixed effects negative binomial model. We implement equation 1 using the ppmlhdfe command in Stata (Correia *et al.*, 2020). The estimator is robust to statistical separation and convergence issues, i.e., it correctly detects and drops singleton observations or those separated by fixed effects to speed up computation. The observations that are dropped do not contribute to the estimation of the parameters, and there are no sample selection issues by dropping them. Percent effects for the parameter of interest can be calculated as $(e^{\beta} - 1) \times 100$ (Halvorsen and Palmquist, 1980).

The implicit assumption for interpreting the parameter of interest β as the causal effect of a home game on violent behavior is that the location and the time of a football match are orthogonal to the number of assaults, conditional on the covariates. However, displacement effects may pose a threat to identification. On the one hand, this refers to spatial displace-

[17] Our estimation sample contains 88,028 municipality-day level observations, and of these 30.8 percent have crime counts equal to zero.

[18] Public holiday controls include binary variables (at the level of the Federal States) for All Saints' Day, Ascension Day, Assumption Day, Christmas, Corpus Christi, Epiphany, Easter, German Unity Day, Good Friday, Labor Day, New Year's Day, Penance Day, Pentecost, and Reformation Day. Moreover, it contains dummy variables for Carnival and New Year's Eve.
Weather controls (at the regional level) include average air temperature, maximum air temperature, minimum air temperature, minimum ground temperature, steam pressure, cloud cover, air pressure, humidity, average precipitation, hours of sunshine, snow depth, and wind speed.

ment effects, which may occur when (violence-prone) people from distant regions visit a game. On the other hand, this includes temporal displacement effects, which happen when assaults are shifted from adjacent days to game days. In both cases, the parameter would overestimate the impact of a football match on violent behavior as the offense would have been committed regardless, but at a different time or place. To rule out the possibility that displacement effects compromise the validity of the identification strategy, we investigate the effect of football games on neighboring regions and on days adjacent to game days in section 5.2. We find that the main results, namely an increase in violent behavior in regions where football games take place, are not neutralized by a decrease in the number of assaults in surrounding regions or on days adjacent to game days.

Given the design of the empirical approach, there could be another potential threat to the validity of the identification strategy. By focusing on home games in the main analysis, the counterfactuals may be biased downwards as days with away games are part of the control group. This control group problem may be due to violent fan groups traveling with their team to away games, potentially leading to a decline in the number of assaults in the home region. To address this concern, we perform the analysis again, differentiating between home and away games. When considering distinct effects for home and away games, we find that away games do not significantly affect assaults in the regions and time period being analyzed.

5 Results

5.1 Main Results

Before presenting the regression results, Figure 4 gives a descriptive preview of the main findings. Using the same data as in the main analysis, it shows the number of assaults across the days of the week. The numbers are presented for days with and without home games. It is evident that the number of assaults is higher in weeks when a home game is played than when no game is played. The difference in means is statistically significant for all days except Wednesdays. The empirical model exploits the variation in the number of assaults across the days of the week, and in particular how the pattern varies between weeks with and without games.

Table 1 reports estimates corresponding to equation 1 when sequentially adding more controls. In Panel A, the dependent variable is total number of assaults, broadly defined to include both simple and aggravated assaults. In column 1, we include region, day-of-week, month, and year fixed effects. In column 2 weather controls are added. Holidays fixed effects are included in column 3. In column 4, we control for region-specific date fixed effects. Note that although the estimates vary marginally across columns, we use throughout the paper the model presented in column 4 for the analyses that follow. The estimate from the preferred specification in column 4 suggests that a home game increases the number of violent crimes by 17 percent. In Appendix Table A.2, we re-estimate the game day effect separately for the three professional German football leagues. We continue to find large and significant game day effects for each of the three leagues, with the effect size most pronounced in Germany's top league.

Given that we draw on reported crime data, our estimates might overstate the true effect of football matches on assaults if crime reporting/recording is also affected on game days. In our setting, the concern is that an increased deployment of police officers on game days may lead a higher fraction of otherwise unreported assaults to be recorded by the police. Thus, part of the game day effect we estimate may be capturing changes in crime reporting/recording behavior, and not an increase in actual crime. Although there is no direct test to address this interpretational concern, there are indirect means by which to asses it. One intuitive approach is to re-estimate the game day effect separately for simple and aggravated assaults. With a reporting rate of only 37 percent, simple assaults are prone not to enter reported crime data,[19] and the game day effect for this assault type might therefore indeed be picking up changes crime reporting/recording behavior. Aggravated assaults, on the other hand, are much less prone to under-reporting, as these are crimes which cause serious bodily injury, including fractured or dislocated bones, deep cuts, or serious damage to internal organs. Panels B and C of Table 1 displays the game day effects for simple and aggravated assaults, respectively. The estimates from our preferred specification indicate that a home game increases the number of simple assaults by 13 percent. By contrast, aggravated assaults which cause serious bodily injury increase by 25 percent. The fact that we find much larger proportional game day effects for violent crimes where under-reporting is less of a concern goes against the notion that changes in reporting/recording behavior might be driving our results. To substantiate this further, one of our subsequent results will show that a large share of the additional aggravated assaults caused by football games are attacks on police officers, where under-reporting is not a concern at all.

The estimated coefficients in Panels B and C of Table 1 imply that professional football matches in Germany precipitated an additional 3,079 simple assaults and an additional 2,963 aggravated results in the regions and time period studied. We reach this conclusion based on the estimated game day effects equal to 13.3 percent for simple assault (Panel B, column 4) and 24.6 percent for aggravated assault (Panel C, column 4); the baseline number of assaults on days without football games equal to 5.19 for simple assaults and 2.70 for aggravated assaults; and 4,461 home games played in the period January 2011 to May 2015. Appendix Table A.3 shows that the game day effect is not restricted to assaults. Column 1 shows that stealing by force or threat of force (i.e., bag-snatching and robberies) also significantly increases on game days. The estimated coefficient implies that football

[19] This figure is based on the 2017 German Victimization Survey (Birkel *et al.*, 2019).

games caused an additional 525 robberies in the regions and time period being studied. In the case of sexual assaults and coercion in column 2, there is no football-related increase in crime.

5.2 Potential Threats to Identification and Validity of the Design

In this section, we consider the possibility that our results do not reflect additional assaults due to football games, but merely shifts in offenses. Furthermore, we test the sensitivity of the main results by additionally including away games in the model. Previously, we have presented evidence that football games increase violent crime. However, it is possible that we only capture an effect that shifts offenses. For example, the increase in violent behavior may be offset by a decline in assaults in other areas or at different times (Lindo *et al.*, 2018b). In other words, the assault would have been committed regardless, but at a different time or location. One explanation may be different population flows around days on which games take place.

In order to estimate *spatial displacement effects*, we investigate the impact of football matches on neighboring regions. A neighboring region is a municipality that shares a border with a region in which a stadium is located.[20] Figure 2 shows a map of the selected regions. The sample of neighboring regions exhibits a considerably higher number of observations. This is owed to the fact that a region with a stadium has on average slightly more than 11 neighboring municipalities. Panel A of Table 2 shows the estimates of the impact of a home game on these neighboring regions. In comparison to the baseline effects, the spatial spillover coefficients are small and not significantly different from zero. Consequently, the results do not suggest offsetting spatial spillover effects.

In the next step, *temporal displacement effects* are considered. To capture these effects, we include a one-day lead and lag of the game day indicator. Panel B of Table 2 contains the estimates when including the temporal spillover components in the baseline model. The estimates of the game day itself are not significantly different from the baseline model. Moreover, in our preferred specification, all of the coefficients for the day before and after the game are virtually equal to zero and not statistically significant. This evidence strongly argues against the idea that football games might only shift offenses in time.

As discussed above, the baseline model considers the effect of football matches, but only for home games. This restriction may compromise the validity of the design. When away matches are not accounted for, they end up in the control group. The control observations might be biased downwards if the most devoted (and possibly violent) fans leave their home municipality to accompany their local team to an away game. The resulting decrease in assaults at home due to the absence of local agitators imply that days with away matches

[20] If two municipalities share a border and each of the regions contains a stadium, both regions will not serve as neighbor regions and they are dismissed from the set of spatial spillover candidates.

can no longer function as control units. To address this concern, we investigate the *effect of home and away matches separately.* To analyze the effect of away matches, the design of our data set must be modified. In the baseline version, the football data is merged with other datasets at the match level (the region ID of the home team serves as the identifier). In this case, we use the football data at the table standings level. In other words, both the home and away teams are matched with a region. This approach leads to ambiguity regarding the treatment status of individual regions.[21] For instance, the treatment status of regions with more than one team is ambiguous when there is a home and an away match on the same day. To alleviate this concern, we exclude the third league from the sample and focus exclusively on the first two leagues.[22] This approach helps considerably to clarify the treatment status of a region. Table 3 shows the results when home and away matches are examined separately. To compare the estimated effects, column 1 shows estimates retrieved from the baseline model (home matches only) when the sample is adjusted as described above. Column 2 presents the estimates that incorporate the impact of home and away games on violent assaults. The effect of a home game is sizable, suggesting that it increases the number of assaults by 18.5 percent. The coefficient is essentially of the same magnitude than, and not significantly different from, that in column 1. A negative and significant estimate of an away game would compromise the identification strategy. However, the estimate of an away game is positive and small in magnitude. Thus, the results suggest that focusing exclusively on home games does not render the identification strategy invalid.

5.3 Robustness Tests

We perform several sensitivity and placebo tests to assess the robustness of the findings. Overall, the sensitivity tests demonstrate that the main results are robust to alternative specifications and estimations, indicating that football games do indeed lead to more assaults.

Alternative Econometric Specifications.— We begin by showing that our results are robust to different *estimation procedures*. In column 1 of Table 4, we report estimates from a conditional fixed effects negative binomial model. Although this method has been shown not to be a true fixed effects model (Allison and Waterman, 2002), it is sometimes favored to correct for potentially overdispersed data. The results from this specification

[21] When only considering home games, the treatment status is not a problem. This is due to the fact that local authorities do not allow two home games on the same day.

[22] Some ambiguities remain, but they are solved as follows: 12 percent of the matches still include a duplication of two teams per region playing on the same day, either one home and one away game, or two away games. In the latter case, the status of the region is defined as 'away'. In the former case, it is defined as 'home'.

are virtually identical to our baseline estimate from Table 1.[23] In column 2, we return to our Poisson specification and use football season rather than year fixed effects since the former runs over two calendar years. The idea is that this might account better for how well teams are doing in a specific season and also capture the impact that relegation or promotion could have on fan behavior. The results do not appreciably change with respect to our baseline estimate. The next two columns demonstrate that the results are not sensitive to alterations in the *sample*. Adjustments to the sample may be necessary as some of the games are played on different days than originally planned. Deviation from the original match schedule may pose a risk to the allocation of games that is plausibly random. For this reason, we exclude in column 3 the set of rescheduled games from the analysis. The results are almost identical to the baseline results.[24] Finally, column 4 shows that our results are also insensitive to including the month of June in our estimation sample.

Machine Learning Based Approach of Selecting Confounders.—In order to interpret the estimated effects of professional football games on assaults as causal, the empirical approach relies on a conditional independence assumption, namely that the time and location of football matches are orthogonal to the potential number of assaults, conditional on the covariates. The conditional-on-observables identification strategy requires that all confounding variation has to be controlled for (Belloni *et al.*, 2014a). Up to now, economic intuition suggested potential control variables. In this robustness check, we apply the *post-double-selection* method to obtain a data-driven selection of confounders, as proposed by Belloni *et al.* (2014b). We use the Least Absolute Shrinkage and Selection Operator (LASSO) for selecting variables that are predictive for either the treatment or the outcome variable. The set of potential controls includes the variables contained in the extended baseline specification plus interactions. In the last step, we regress the number of assaults on the gameday indicator plus the union of selected controls. The results of the post-double selection estimator are presented in column 5 of Table 4 and use 96.7 percent of the original covariates. The estimator is almost identical to the preferred specification. The similarity of the estimates complements economic intuition and adds rigor and robustness to the model selection.

Placebo Games.—We estimate the impact of *placebo games* on assaults to test whether the previous results are only due to chance.[25] The actual matches take place on about five percent of the days in the sample. To estimate the effect of placebo games, we drop the affected days with the actual matches and randomly assign dummy indicators with the

[23] We also ran OLS regressions with the natural logarithm of the assault rate (per million population, with one added to the rates) as the dependent variable, and obtained similar though somewhat higher game day effects.

[24] Of the 4,461 games in the sample, 2.24 percent are rescheduled. The vast majority of rescheduled matches (95 percent) take place in league three.

[25] Unfortunately, there are no offenses that can function as placebo outcomes. This is because most of the offenses covered in the PCS are potentially affected by football games.

same frequency of the real matches.[26] Subsequently, we estimate the model as shown in equation 1. This procedure is carried out 3,000 times and the results are shown in Figure 5. Panel A displays the distribution of the coefficients. As expected, the coefficients are centered around zero. Panel B illustrates the distribution of the t-statistics. The red area below the kernel density indicates significant estimates for a significance level of $\alpha = 0.05$. Note that the t-statistics of the preferred specification in Table 1 is still higher than the largest observed value in any of the 3,000 simulations. Panel C shows that with 3,000 iterations, 8.77 percent of the estimates are significantly different from zero. At a significance level of $\alpha = 0.01$, there are 4.57 percent significant estimates. The low levels of significant coefficients confirm that the previous results are not due to chance.

5.4 Channels

This section investigates potential mechanisms through which football games may cause additional assaults. We start with concentration effects and alcohol as possible explanations. In addition, and not mutually exclusive to these, we explore the relevance of two behavioral theories of spectator violence.

Concentration.—Concentration effects have been suggested by previous research to be potentially important factors in explaining football-related violence (Rees and Schnepel, 2009, Marie, 2016). The idea is that the potential number of violent interactions increases with the overall level of attendance at a sporting event. Moreover, professional football games typically draw thousands of away-team supporters into cities, who constitute a particularly salient group of potential victims. To explore the role of concentration effects, we now expand the analysis by including in our regression model for each match (i) the overall level of stadium attendance and (ii) a proxy for the number of away-supporters. For the time period we study, direct information on (ii) is not available. To overcome this data issue, we use the *potential* number of away-team supporters, proxied by the visiting team's football season-specific average attendance at home games.[27] Table 5 reports the results. Column 1 shows that the game day effect does appreciably change with the total level of attendance at matches. By contrast, in column 2 where we add in the number of potential away-team supporters, we observe that the "raw" game day effect is one-third lower than in our baseline specification, but increases by roughly 2 percent with each additional 10,000 potential away-team supporters added in. We reach a very similar conclusion when we simultaneously include both concentration variables in column 3. That overall crowd size *per se* appears not to matter, but that the number of potential away-team supporters does, is consistent with the notion that violent interactions between rivaling fan groups might play an important role. We shall return to this issue shortly.

[26] Our randomization also preserves the "true" relative frequency of football games on the different days of the week.

[27] We are grateful to an anonymous reviewer for suggesting this proxy.

Alcohol.—Football violence is often reported as resulting from excessive alcohol consumption. However, research by social scientists has long emphasized that this view may not hold up empirically, as it ignores stark cross-country differences in the consumption of alcohol by football fans and its apparent effects. Frosdick and Marsh (2013) provide two stark examples for this. On the one hand, drunkenness is very common among Danish football fans (so-called *Roligans*), but it is typically accompanied by positive sociability and not violence. On the other hand, violent-prone football fans in Italy (so-called *Ultras*) hardly drink to excess when attending matches, and hence the role of alcohol in football violence is thought to be insignificant in that country.

Our data allows for an empirical (albeit imperfect) test for the role of alcohol. In particular, we observe for each incident whether the victim—but not the offender—was under the influence of alcohol. With this limitation in mind, Table 6 explores the impact of football games on alcohol-related victimization. Overall, the results indicate that football games cause significantly more assaults where the victim is under the influence of alcohol. However, this game day effect only plays out for simple assaults and is not detectable for aggravated assaults. Magnitude wise, the effect is, however, negligible. In particular, given that alcohol-related victimization occurs only very infrequently in our data (mean on non-game days=0.20), these assaults can only explain a very small fraction (roughly 1.5 percent) of all assaults caused by football games. Of course, this estimate must be interpreted extremely cautiously, as we only observe whether victims have excessively consumed alcohol. As we will later demonstrate, the finding that alcohol-related victimization plays no role in aggravated assaults on game days can be explained with a substantial portion of victims in these cases being police officers.

In the next step, we consider two prominent behavioral theories of spectator violence and investigate to what extent they might explain the effects we have uncovered so far.

Frustration-Aggression Hypothesis (FAH).—First, we consider emotional cues. This is motivated by the findings of Card and Dahl (2011) who demonstrate that unexpected defeats of local football teams trigger family violence. The results can be best explained with the FAH, first proposed by Dollard *et al.* (1939), which predicts aggressive behavior in the event of frustrating events. Rees and Schnepel (2009) similarly show that there are more violent offenses when the local college football team suffers a defeat.

As a first test for whether the FAH has bite, we explore the dynamics of violent crime before, during, and after a game. The idea is that emotional cue-triggered violence should manifest itself in post-game behavior. In Figure 6, we estimate violent crime effects for eight pre-game 3-hour blocks, the 3-hour block including the game, and eight post-game 3-hour blocks. We observe that on game days, violent crime (i) builds up rapidly in the two 3-hour blocks leading up to a game, (ii) peaks in the three-hour block including the game, (iii) remains fairly substantial in the two 3-hour blocks following game, and (iv) then returns to the assault levels on non-game days over the next couple of 3-hour blocks.

While finding (i) cannot be rationalized with FAH, results (ii) and (iii) are consistent with it.[28]

To dig deeper into the relevance of FAH, we next analyze in Table 7 whether visceral factors may be the reason for the assaults caused by football games. In column 1, we investigate whether an emotionally upsetting event during a game leads to more assaults. To answer this question, we create an indicator that equals one for games that include at least one of the following potentially troubling events: a penalty is awarded (20 percent of all games), a player receives a red card (10 percent of all games), or the referee receives an insufficient grade (15 percent of all games). The indicator shows that 35 percent of all games involve at least one upsetting episode as defined in the previous categories. In column 1, we include the indicators for an upset event and for no upset event, both interacted with our game day variable. The estimates do not suggest that emotional cues trigger more violent behavior since the estimates for games with and without upsetting events are of equal magnitude and not significantly different. In the second and third column, we show estimates following the approach of Card and Dahl (2011). We examine the impact of game outcomes relative to their pregame expectations. Pregame expectations are included in the analysis as matches with contrasting predictions may be very different from each other. By including predicted outcomes, we can estimate the effect that results from the defeat of a team that was expected to win, and vice versa. Using data from oddsportal.com, we define a game as unpredictable when the absolute probability difference between winning and loosing is smaller than 20 percentage points.[29] When the spread's value exceeds the threshold, a win or a loss of the home game is expected. Around 45 percent of the games are expected to be close, another 45 percent are expected to be won, while 10 percent of the games are expected to be lost. The significantly larger share of expected victories may be attributed to the home-advantage. In column 2, we first examine the effects of matches with distinct predicted match outcomes. The estimates do not suggest that the effect of games with different predicted outcomes vary systematically from each other. In column 3, we additionally include interactions between expected and actual game outcomes. The estimates are relatively small in magnitude and not significantly different from zero, implying that unexpected wins/losses do not cause additional assaults.

Another piece of evidence consistent with the FAH would be if our match day effect were largely explained by increases in domestic violence. Table 8 sheds light on this issue. First, columns 1 and 2 show the effect heterogeneity by gender. Although the estimates for women and men are statistically different from zero, the vast majority of additional victims on a match are male. Assaults on males increase by 23 percent on game days. The increase in assaults for males accounts for 87 percent of the effect found for the entire sample. Second,

[28]In Appendix Figure A.4, we show the same figure using 6-hour blocks instead 3-hour blocks. Beyond confirming the results from Figure 6, it further assuages concerns about any 'pre-trends' or significantly delayed temporal displacement effects.

[29]Similar results are obtained when we define different threshold values and when we deviate from the symmetry around the origin.

we explore effect heterogeneity according to the relationship between victim and suspect. Columns 3 and 4 distinguish the relationships from a formal perspective, such as kinship or acquaintance. Although both estimates are positive and statistically significant, the majority of additional assaults involves victims with no prior connection to the suspect. Assaults by strangers increase by 27 percent on game days. This implies that almost two out of three additional cases involve this type of victim-suspect pairing. Column 5 considers spatial-social relationships, namely whether victim and suspect live in the same household. A football game increases the number of domestic assaults by 3 percent. This implies that only a small portion of the match day effect (less than 3 percent) can be explained by domestic assault cases. In a related study, Montolio and Planells-Struse (2016) obtained a similar result, showing that home matches played by the Football Club Barcelona (FCB) have no impact on domestic violence.

Taken together, while the fact that a large portion of football-related violence manifests itself in post-game behavior could be rationalized with FAH, the broader evidence we have presented is inconsistent with the notion that emotional cues are a key driver of sports-related violence in Germany.

Social Identity Theory (SIT).—Individuals frequently identify themselves as a member of a group, care about that identity, and categorize people around them into opposing groups (i.e., ingroup vs. outgroup). Football fandom has been argued to intensify ingroup/outgroup categorizations among fans, which can result in negative social consequences such as biased interpretations of outgroup actions, ridicule of outgroups, and even violence towards them (Branscombe and Wann, 1992). There are several aspects of SIT explanations of football violence that we are able to explore empirically: (i) some scholars argue that it is especially young males for whom membership in violent-prone fan groups provides recognition and reputation that enables them to achieve a sense of personal worth and identity (Spaaij, 2008); (ii) intensified ingroup/outgroup categorizations that can result in violence are most likely to arise when the perception of outgroup threats—especially perceived territorial threats from fans of rivaling teams in the same area—are high (Mondello, 2016); (iii) an important dimension of football violence that is difficult to explain with individual level-factors but can be understood in terms of social identity theories is violence targeted at police forces. The argument is that the context created by police presence and action leads to the emergence of a social identity among fans where the police is perceived as a threatening outgroup. This social identity then feeds a norm among fans based around the perceived legitimacy of retaliation and aggression against the police.

To provide evidence on aspect (i), Figure 7 shows the age profile of the impact of football games on the assault rate for each gender. For women, the point estimates are fairly small in magnitude, except for women aged 40-49. In contrast, the effects for adult men are quantitatively large for all age-groups. The largest effects for males are found in 18-29 and 30-39 age groups and decreases thereafter. Implicit in aspect (i) is also the view that football-related violence is a group phenomenon. Our data allows for a fairly direct test of this. In particular, for each offense it includes information on whether it has been perpetrated by group or individual offenders. Thus, in columns 1 and 2 of Table 9, we decompose the game day effect into assaults committed by group versus individual offenders. The dependent variables are the number of assaults committed by group and individual offenders, respectively. Column 1 shows that assaults by group offenders increase by roughly 19 percent on game days, an effect roughly one-seventh larger than that for assaults by individual offenders. The estimate implies that football games cause an additional 1,362 group assaults over the time period and regions being analyzed, which explains roughly 23% of the 6,042 assaults caused by football games. Thus, group offending appears to play a non-negligible role in the game day effect we estimate.

To shed light on aspect (ii), we compare the impact of matches played between known rival teams to regular matches. To that end, we estimate the game day effect separately for high-rivalry and regular matches. Local derbies (games between two competing teams that are based in regions of close geographical proximity) constitute high-rivalry matches.[30] The estimates are shown in columns 3 and 4 of Table 9. Games classified as high-rivalry matches increase the number of assaults by 63 percent, an effect almost four times as large as our baseline estimate. Although the standard errors are relatively large, considering that only 2.5 percent of the games are classified as high-rivalry matches, the effect is significantly different from that for regular matches.

Finally, to explore aspect (iii), we estimate the impact of football games on violent behavior directed at police officers on duty. In the model of Poutvaara and Priks (2009), violence targeted at police can be rationalized by social identity-concerned hooligan groups facing aggressive, harsh, and indiscriminate policing tactics. Given that the approach taken by German authorities to reducing football violence ultimately relies on such deterrence (Krahm, 2007, German Police Union, 2012), this makes it conceivably that assaults on police officers could play an important role. Column 1 of Table 10 shows that assaults against police officers increase by 92 percent on a match day. In columns 2 and 3, where we distinguish between simple and aggravated assaults against officers, we find that it is severe forms of violence against police which dramatically increase on game days. The estimate in column 3 suggests that aggravated assaults against officers increase by more than 200 percent.[31] This implies that in the regions and time period studied, football games precipitated 1,111 additional aggravated assaults against police, which can explain 38 percent of the 2,963 aggravated assaults caused by football games. The estimate in column 4 suggests that a substantial portion of aggravated assaults against police is due to group offending. Group assaults against police officers increase by almost 150 percent on

[30] Appendix Table A.4 gives an overview of high-rivalry matches.

[31] The estimates in Table 9 use the same set of controls as column 4 in Table 1. Appendix Table A.5 shows that estimates are robust to all the specifications we have used in Table 1.

game days, and can explain 36 percent of all football-related aggravated assaults against police.

6 Conclusion

This paper had two central objectives. The first was to quantify how much of violent crime in Germany can be attributed to football-related violence. The second was to explore empirically the factors that might explain it. To achieve these, we matched web-scraped information on 4,461 football games with data on local crime, weather, holidays, and population figures to construct a panel at the municipality-day level for the period 2011-2015. To estimate the causal effects of football games on violent crime, we used a generalized difference-in-differences approach that exploits variation in the timing of matches.

Our first main finding was that football games cause large spikes in violent crime: on a match day, the number of simple assault increase 13 percent and aggravated assaults by 25 percent. This estimate has important implications. Most importantly, the economic costs associated with football violence are far from negligible. Back-of-the-envelope calculations indicate that football matches in the top three leagues of the German league system precipitated an additional 6,042 assaults (3,079 simple; 2,963 aggravated) in the regions and time period studied. This translates into social costs of almost 295 million euros for the 53 months from January 2011 to May 2015, or 67 million euros annually.[32] For comparison, Lindo *et al.* (2018b) estimate that Division 1A American Football games in the US cause 724 additional rapes of college-age victims per year, and calculates associated social costs of 193 million dollars annually. On aggregate, football matches can explain around 1 percent of all violent assaults in the regions and time period under consideration. The question faced by policy makers then is how these year-on-year crime costs of football can be reduced.

An answer to this question requires an understanding of the channels driving football-related violence. Our second set of findings sheds some light on this issue. We found that the match day effect cannot be explained by emotional cues stemming from unexpected game outcomes, nor is it driven by increases in domestic violence. This findings are contrary to frustration-aggression theories that can explain sports-related violence in the United States. Exploring the match day effect further, we found that it can be attributed to violence among males in the 18-39 age group, frequently involves assaults perpetrated by groups of offenders, almost quadruples on days with high-rivalry derby matches, and can to a non-negligible extent also by explained by violent assaults on police officers. We view

[32] To calculate the social costs, we use an estimated cost of 14,190 euros (in 2014 prices) per simple assault and 69,940 euros per aggravated assault. The estimated social costs are average estimates from 14 international studies (covering the US, Great Britain, New Zealand and Germany), synthesized in Table 2 in Glaubitz *et al.* (2016).

this evidence as consistent with social identity models of football hooliganism. Although the frustration-aggression might explain some of these results in isolation (e.g., the large effects for high-rivalry games), it has a hard time explaining the entirety of our findings.[33]

On a cautionary note, our findings do not necessarily allow us to draw general conclusions for settings other than Germany. Research has highlighted that both the nature and the extent of football-related violence are influenced by different historical, social, economic, political and cultural factors in different countries (Frosdick and Marsh, 2013). For example, while religious sectarianism is thought to be an important factor in Scotland and Northern Ireland, historical regional antagonisms are often cited as root causes for football violence in Italy. There are, however, also some cross-country similarities that have been highlighted. For example, football-related violence often involves violent encounters between fan groups and police officers (Frosdick and Marsh, 2013). One of our main findings—i.e, the fact that almost 40 percent of all additional severe assaults on match days involve police officers—highlights the scale of this problem. Social psychologists investigating crowd violence have highlighted that a move away from a deterrence towards a dialogue and facilitation-based policing approach by local police forces can result in a decline in football-related violence (Holgersson and Knutsson, 2011, Stott *et al.*, 2012). It is thought to do so by maximizing perceptions of police legitimacy in the use of discretionary force during crowd events. Therefore, an interesting task for future research is to identify settings in which police forces have changed their approach to policing football events, and to causally explore the impacts of these changes.

[33] By contrast and as mentioned before, there is considerable evidence that sports-related violence in the US can be explained by frustration-aggression theories. All the major professional sports in the US operate based on the "franchise" system, which prevents intense fan rivalries based on local, religious or political antagonism as they often exist in Europe. Instead, professional sports in the US are often associated with partying behavior and excessive alcohol consumption. This has been argued to intensify with emotional cues stemming from unexpected game outcomes, ultimately causing spikes in crimes such as domestic violence and sexual assault (Card and Dahl, 2011, Lindo *et al.*, 2018b).

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Figures and Tables

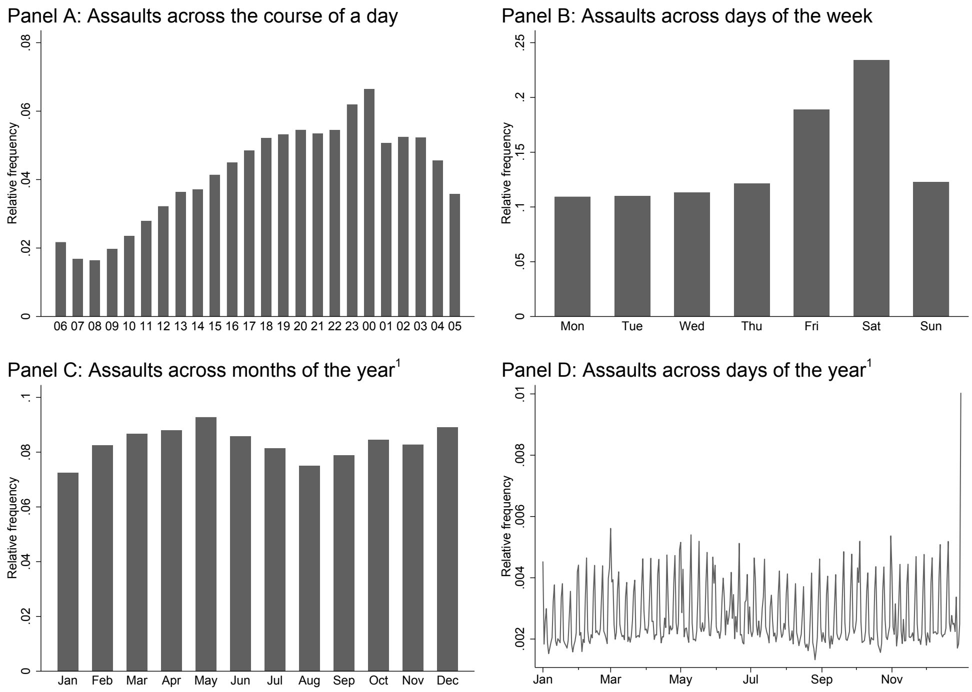

Figure 1. Distribution of assaults across time

Notes: The figure shows the distribution of assaults across hours of the day, days of the week, across months (adjusted for the number of days per month), and across the days of the year in the Federal Republic of Germany.

[1] The figures in panel C and D are solely based on the year 2014. Please consult the appendix for figures from the other years.

(a) The closest weather monitors

(b) Spatial displacement - neighboring regions

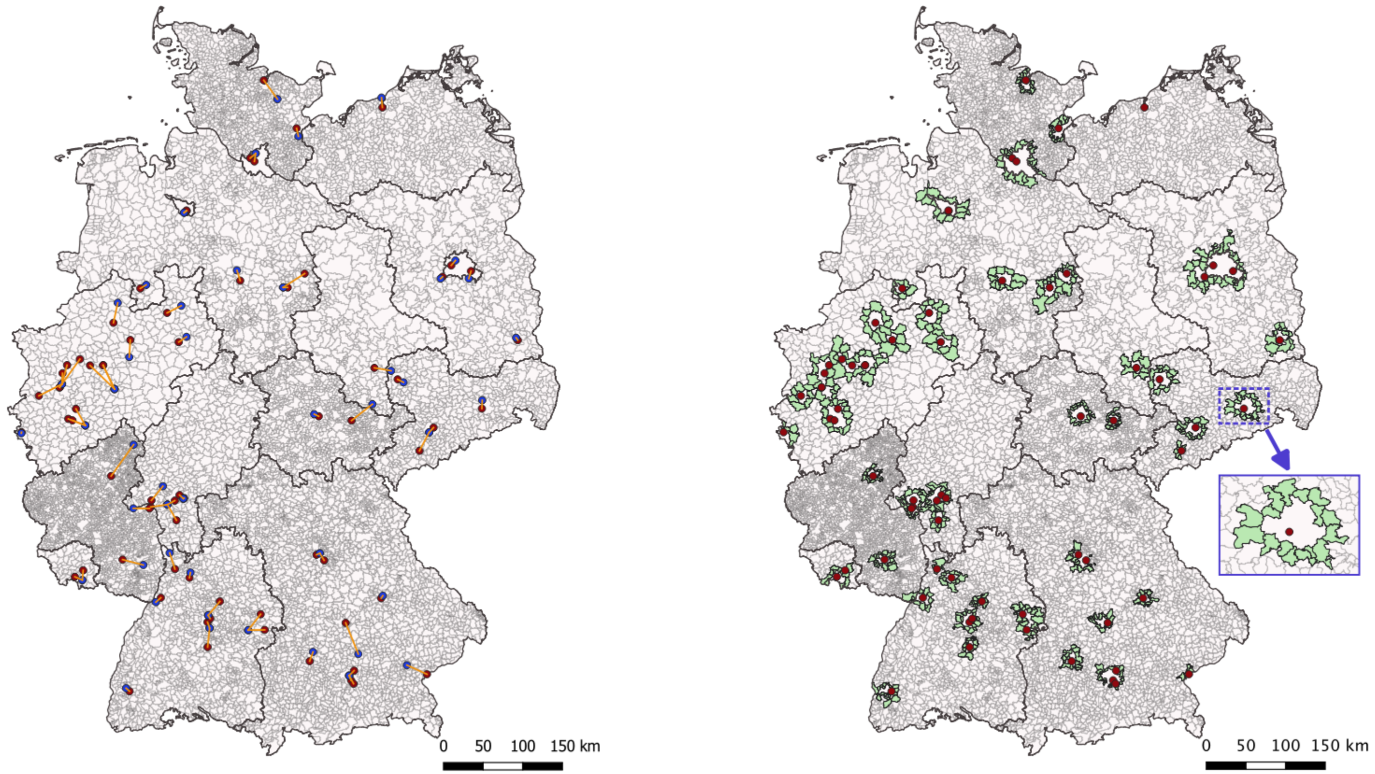

Figure 2. The stadiums with the closest weather monitors and neighboring regions

Notes: The map on the left shows the stadiums used in the analysis over the seasons 2010/11 until 2014/15 (red dots) and their closest weather monitors (blue dots). The orange lines indicate how the weather monitors are assigned to the stadiums. The map on the right shows the regions that are used in the analysis for spatial displacement effects. The neighboring municipalities are chosen to be in the sample for estimating spatial displacement effects if they have a common border with a region that contains a stadium. The red dots are the stadiums, the black outlines indicate federal state boundaries.

Source: Own representation with data from the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR).

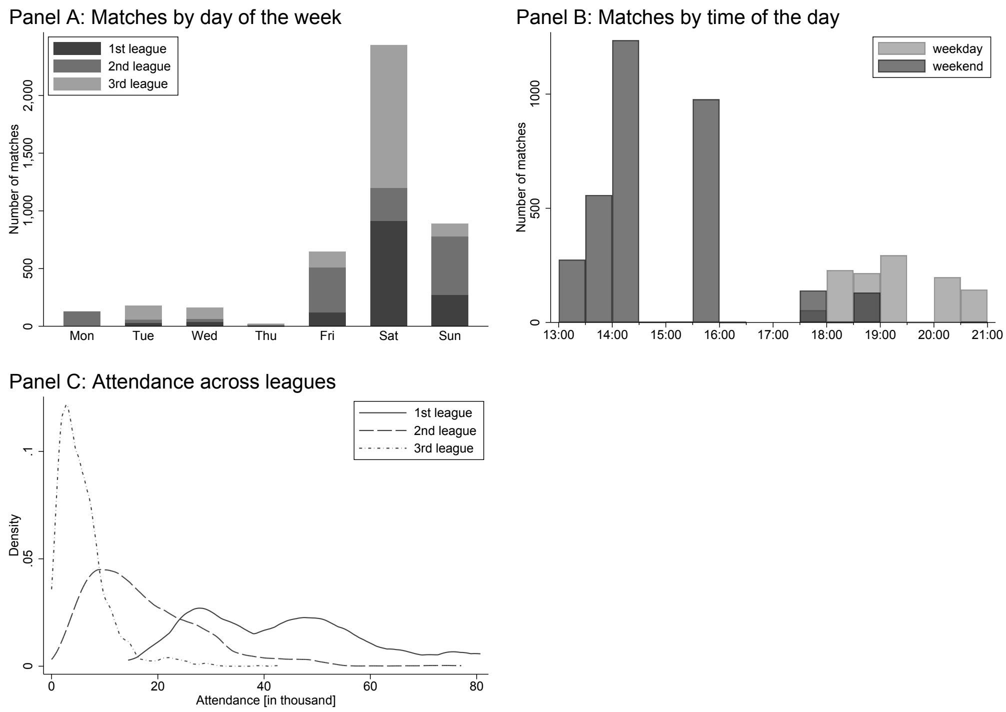

Figure 3. Football matches

Notes: The figures show key aspects of football games in the data set. Panel A shows how the number of matches vary over the course of a week, Panel B plots the distribution of matches over the course of a day, and Panel C shows kernel densities for the number of spectators (in thousand) across the three leagues.

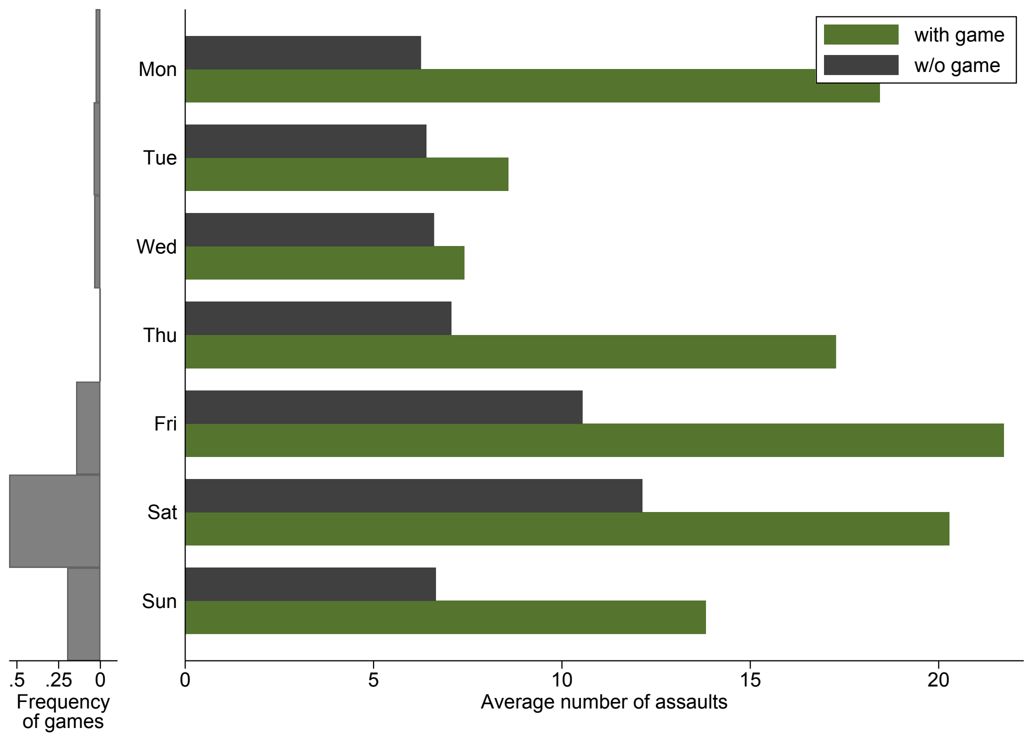

Figure 4. Average number of assaults on gamedays and days where no game takes place
Notes: The figure shows the daily average number of assaults for regions that host games of a football team from the top three leagues. Assaults are crimes classified as simple willful, dangerous, or grievous bodily harm. The daily numbers are shown for weeks in which a game is played and for weeks in which no game takes place.

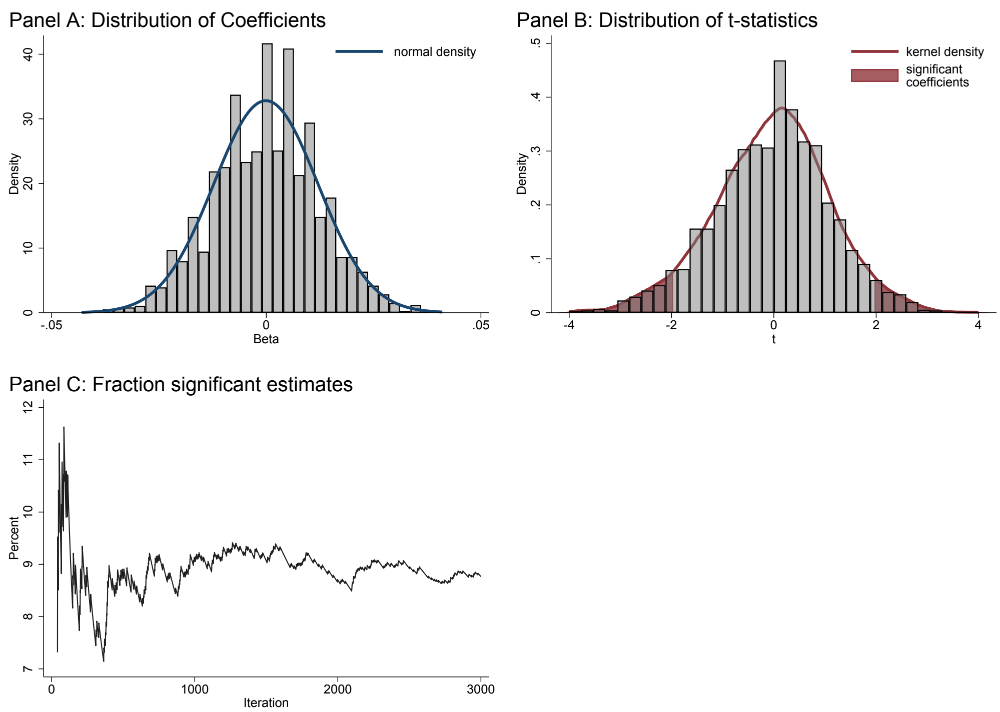

Figure 5. The effect of placebo games

Notes: The figure shows the effect of placebo games. Panel A presents the distribution of the coefficients (along with a normal density) after 3,000 iterations. Panel B shows the distribution of the t-statistics and the resulting ranges of significant coefficients, with a level of significance $\alpha = 0.05$. Panel C shows the fraction of significant estimates across the number of iterations.

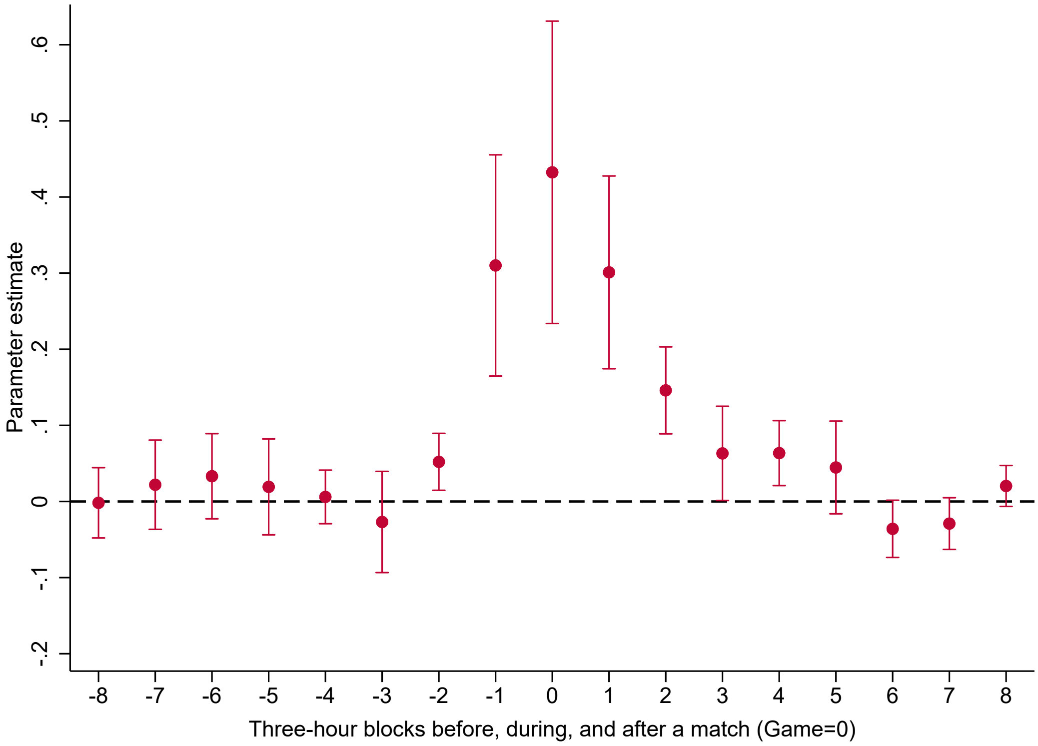

Figure 6. Dynamics of assaults before, during, and after a game

Notes: The figure shows estimates and 95 percent confidence intervals from equation 1 using *hourly* data spanning the time window 2011-2015 for regions that host games of a football team from the top three leagues of the German football league system. The game day dummy is replaced with indicators for 3-hour blocks before, during, and after a game. The regression includes the same set of controls as column 4 of Table 1, but with *Interact FE* replaced by municipality-by-year-by-month and day-of-the-week-by-hour-of-day fixed effects. See notes to Table 1 for additional details. The dependent variable is *All Assaults*, defined as the number of crimes classified as simple willful, dangerous, or grievous bodily harm. Robust standard errors estimates are clustered at the municipality level.

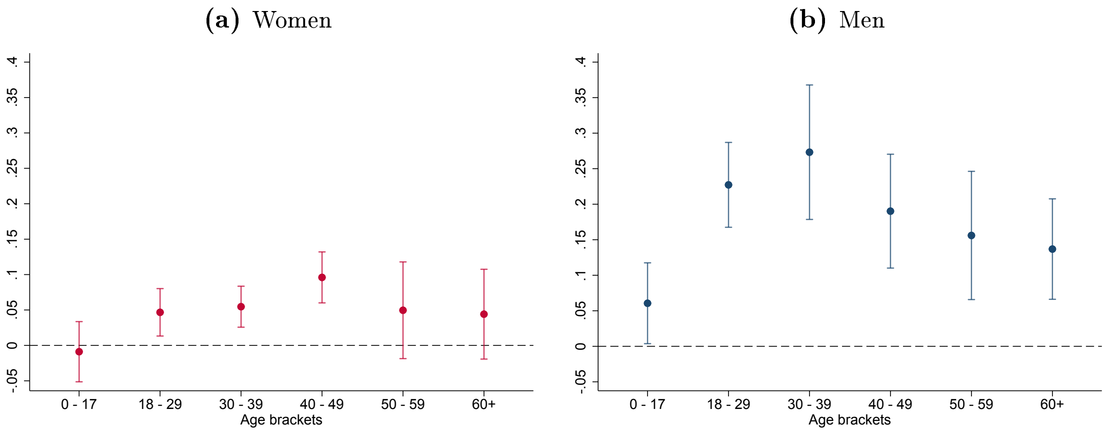

Figure 7. The age profile of the impact of football matches on assaults

Notes: The figure shows estimates and 95% confidence intervals across age brackets and by gender. The estimates are based on the model shown in equation 1 and use the same set of controls as column 4 of Table 1. See notes to Table 1 for additional details. The dependent variable is *All Assaults*, defined as the number of crimes classified as simple willful, dangerous, or grievous bodily harm. Robust standard errors estimates are clustered at the municipality level.

Table 1. Effects on assaults

	(1)	(2)	(3)	(4)
Panel A: All assaults				
Game day	0.154***	0.156***	0.163***	0.159***
	(0.033)	(0.033)	(0.033)	(0.029)
Effect size [%]	16.63	16.91	17.66	17.23
Dep. var. mean	7.83	7.83	7.83	7.85
Observations	88,028	88,028	88,028	87,873
Panel B: Simple assaults				
Game day	0.121***	0.123***	0.127***	0.124***
	(0.029)	(0.029)	(0.029)	(0.024)
Effect size [%]	12.87	13.11	13.56	13.25
Dep. var. mean	5.16	5.16	5.16	5.19
Observations	88,028	88,028	88,028	87,475
Panel C: Aggravated assaults				
Game day	0.210***	0.213***	0.224***	0.220***
	(0.041)	(0.041)	(0.040)	(0.037)
Effect size [%]	23.31	23.70	25.10	24.64
Dep. var. mean	2.67	2.67	2.67	2.70
Observations	88,028	88,028	88,028	87,307
Region FE	✓	✓	✓	✓
Date FE	✓	✓	✓	✓
Weather controls	-	✓	✓	✓
Holiday FE	-	-	✓	✓
Interact FE	-	-	-	✓

Notes: Estimates are based on the model shown in equation 1. The specifications use daily data (excluding June) spanning the time window 2011-2015 for regions that host games of a football team from the top three leagues of the German football league system. In Panel A, the dependent variable, *All Assaults*, is the number of crimes classified as simple willful bodily harm, dangerous bodily harm, or grievous bodily harm. In Panel B, the dependent variable, *Simple Assaults*, is the number of crimes classified as simple willful bodily harm. In Panel C, the dependent variable, *Aggravated Assaults*, is the number of crimes classified as dangerous or grievous bodily harm. Days are defined to run from 6:00AM until 5:59AM the following day to accommodate the fact that offenses committed in the early morning hours have their origin in the preceding day. Control variables shown as *Date FE* include dummies for day-of-week, month, and year. *Weather controls* include air temperature (average, maximum, and minimum), minimum ground temperature, vapor pressure, air pressure, cloud cover, air humidity, precipitation, hours of sunshine, snow depth and wind velocity. *Holiday FE* are dummy variables for public and school holidays, as well as for other peculiar days. Control variables shown as *Interact FE* consist of interactions of region dummies with all elements of the date fixed effects. Effect size is calculated as $(e^{\beta} - 1) \times 100$. Dependent variable mean is the average number of assaults on days without a football game. Robust standard errors allowing for clustering at the municipality level are reported in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2. Displacement effects

	(1)	(2)	(3)	(4)
Panel A: Spatial displacement				
Game day	0.014	0.015	0.017	0.017
	(0.013)	(0.013)	(0.013)	(0.012)
Effect size [%]	1.43	1.53	1.74	1.73
Dep. var. mean	0.18	0.18	0.18	0.24
Observations	944,436	944,436	944,436	723,758
Panel B: Temporal displacement				
Game day	0.152***	0.155***	0.161***	0.162***
	(0.036)	(0.036)	(0.035)	(0.030)
Day after game	-0.021*	-0.018	-0.016	0.010
	(0.012)	(0.012)	(0.012)	(0.009)
Day before game	-0.003	-0.001	0.004	0.010
	(0.017)	(0.017)	(0.015)	(0.012)
Effect size [%]	16.38	16.71	17.53	17.58
Dep. var. mean	7.82	7.82	7.82	7.83
Observations	87,438	87,438	87,438	87,283
Region FE	✓	✓	✓	✓
Date FE	✓	✓	✓	✓
Weather Controls	-	✓	✓	✓
Holiday FE	-	-	✓	✓
Interact FE	-	-	-	✓

Notes: Panel A contains specifications that use daily data (excluding June) spanning the time window 2011-2015 for regions that share a border with a distract in which a stadium is located. Panel B shows specifications that use daily data (excluding June) spanning the time window 2011-2015 for regions that host games of a football team from the top three leagues. Estimates are based on the model shown in equation 1. See notes to Table 1 for additional details. The dependent variable is *All Assaults*, defined as the number of crimes classified as simple willful, dangerous, or grievous bodily harm. Robust standard errors allowing for clustering at the municipality level are reported in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3. Effects on assaults, distinction between home and away games

	(1)	(2)
	Baseline w/o L3	Distinction home/away[1]
Game day	0.166***	
	(0.035)	
Home game day		0.170***
		(0.036)
Away game day		0.022*
		(0.013)
Effect size [%]	18.01	18.50
Dep. var. mean	10.25	10.89
Observations	61,172	61,172

Notes: The specifications use daily data (excluding June) spanning the time window 2011-2015 for regions that host games of a football team from the top two leagues. The estimates are based on the model shown in equation 1 and use the same set of controls as column 4 of Table 1. See notes to Table 1 for additional details. The dependent variable is *All Assaults*, defined as the number of crimes classified as simple willful, dangerous, or grievous bodily harm. Robust standard errors allowing for clustering at the municipality level are reported in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Effects on assaults, robustness tests

	(1)	(2)	(3)	(4)	(5)
	Negative binomial	Season FE	Drop delayed games	Include June	Post double selection
Game day	0.174***	0.159***	0.159***	0.160***	0.160***
	(0.007)	(0.024)	(0.029)	(0.030)	(0.030)
Effect size [%]	19.03	17.24	17.24	17.36	17.36
Dep. var. mean	7.83	7.85	7.85	7.95	7.84
Observations	88,028	87,773	87,773	96,573	86,052

Notes: Column 1 shows estimates from a conditional fixed effects negative binomial model, implemented using the *xtnbreg* command in Stata. Columns 2 to 5 show estimates similar to those in Table 1, but with season instead of year fixed effects in column 2, without delayed games in column 3, and including the month of June in column 4. The estimates in columns 1 to 4 use the same set of controls as column 4 of Table 1. See notes to Table 1 for additional details. Column 5 applies the post-double-selection method to obtain a data-driven selection of confounders. The dependent variable is *All Assaults*, defined as the number of crimes classified as simple willful, dangerous, or grievous bodily harm. Robust standard errors allowing for clustering at the municipality level are reported in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Concentration effects

	(1)	(2)	(3)
Game day	0.131***	0.108***	0.115***
	(0.030)	(0.022)	(0.029)
Stadium attendance	0.009		-0.006
(in 10,000s)	(0.008)		(0.008)
Potential away-team supporters		0.019*	0.023***
(in 10,000s)		(0.010)	(0.009)
Effect size [%]	13.96	11.38	12.24
Dep. var. mean	7.85	7.85	7.85
Observations	87,873	87,873	87,873

Notes: The estimates are based on the model shown in equation 1 and use the same set of controls as column 4 of Table 1. See notes to Table 1 for additional details. The dependent variable is *All Assaults*, defined as the number of crimes classified as simple willful, dangerous, or grievous bodily harm. Robust standard errors allowing for clustering at the municipality level are reported in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. The role of alcohol

	(1)	(2)	(3)
	Victim under the influence of alcohol		
	All assaults	Simple assaults	Aggravated assaults
Game day	0.092***	0.144***	0.024
	(0.020)	(0.019)	(0.036)
Effect size [%]	9.69	15.50	2.39
Dep. var. mean	0.20	0.13	0.10
Observations	70,075	61,704	58,576

Notes: The estimates are based on the model shown in equation 1 and use the same set of controls as column 4 of Table 1. See notes to Table 1 for additional details. Dependent variables are defined as in Table 1, but are now the number of cases in which the victim was under the influence of alcohol. Robust standard errors allowing for clustering at the municipality level are reported in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. Effect of emotional cues

	(1)	(2)	(3)
		Card & Dahl (2011) specification	
	Upset event indicator	Predicted outcomes	Predicted and actual outcomes
Upset event (Indicator)	0.154***		
	(0.028)		
No upset event (Indicator)	0.162***		
	(0.031)		
Expected to lose		0.188***	0.180***
		(0.051)	(0.051)
Expected to win		0.162***	0.164***
		(0.029)	(0.031)
Expected to be close		0.150***	0.148***
		(0.028)	(0.030)
Expected to lose and won (upset win)			0.042
			(0.042)
Expected to be close and lost (upset loss)			0.004
			(0.026)
Expected to win and lost (upset loss)			-0.013
			(0.019)
Dep. var. mean	7.85	7.85	7.85
Observations	87,873	87,873	87,873

Notes: The gameday indicator is replaced by indicators capturing upset and no upset events during a game, respectively. The upset event indicator in column 1 is defined as a dummy variable equal to one if one of the following events take place: a penalty is awarded (20% of all games), a red card is being issued (10% of all games), or the referee receives a non-sufficient grade (15% of all games). In columns 2 and 3, we use data from oddsportal.com to classify games as expected to win/lose/be close. The estimates are based on the model shown in equation 1 and use the same set of controls as column 4 of Table 1. See notes to Table 1 for additional details. The dependent variable is *All Assaults*, defined as the number of crimes classified as simple willful, dangerous, or grievous bodily harm. Robust standard errors allowing for clustering at the municipality level are reported in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8. Effects on assaults, by gender of victim and victim-suspect relationship

	(1)	(2)	(3)	(4)	(5)
	Gender		Victim-suspect-relationship		
	Women	Men	Strangers[a]	Prior[a] relation	Domestic[b]
Game day	0.049***	0.208***	0.236***	0.089***	0.033*
	(0.013)	(0.036)	(0.037)	(0.020)	(0.020)
Effect size [%]	4.99	23.06	26.57	9.36	3.35
Dep. var. mean	2.79	5.10	3.26	4.65	0.98
Observations	87,325	87,563	86,706	87,573	85,108

Notes: The estimates are based on the model shown in equation 1 and use the same set of controls as column 4 of Table 1. See notes to Table 1 for additional details. The dependent variable is *All Assaults*, defined as the number of crimes classified as simple willful, dangerous, or grievous bodily harm. Robust standard errors allowing for clustering at the municipality level are reported in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
[a] covers formal relationships (e.g. types of kinship or acquaintance).
[b] covers spatial-social relationships (whether victim and suspect live in the same household).

Table 9. Effects for group vs. individual offending and derby vs. regular matches

	(1)	(2)	(3)	(4)
	Group offender	Single offender	High-rivalry matches	Regular matches
Game day	0.176***	0.155***	0.490***	0.145***
	(0.024)	(0.032)	(0.095)	(0.026)
Effect size [%]	19.20	16.79	63.27	15.56
Dep. var. mean	1.59	6.32	7.86	7.85
Observations	84,552	87,873	83,377	87,762

Notes: The estimates are based on the model shown in equation 1 and use the same set of controls as column 4 of Table 1. See notes to Table 1 for additional details. The dependent variable is *All Assaults*, defined as the number of crimes classified as simple willful, dangerous, or grievous bodily harm. Columns 1 and 2 distinguish between assaults by group and individual offenders, respectively. In columns 3 and 4, the gameday indicator is replaced by interactions with dummy variables for high-rivalry and regular matches, respectively. Robust standard errors allowing for clustering at the municipality level are reported in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10. Assaults on police officers

	(1)	(2)	(3)	(4)
	Victim is a police officer			
	All assaults	Simple assaults	Aggravated assaults	Aggravated group assaults
Game day	0.651***	0.419***	1.123***	0.910***
	(0.135)	(0.097)	(0.194)	(0.262)
Effect size [%]	91.77	52.09	207.54	148.44
Dep. var. mean	0.32	0.25	0.12	0.06
Observations	73,108	68,148	55,763	15,995

*Notes:*The estimates are based on the model shown in equation 1 and use the same set of controls as column 4 of Table 1. See notes to Table 1 for additional details. The dependent variables are defined as in 1, but are now the number of cases in which the victim is a police officer. Column 4 uses as dependent variable aggravated assaults on police officers perpetrated by a group of offenders. Robust standard errors allowing for clustering at the municipality level are reported in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix A: Additional Figures and Tables (Intended for Online Publication)

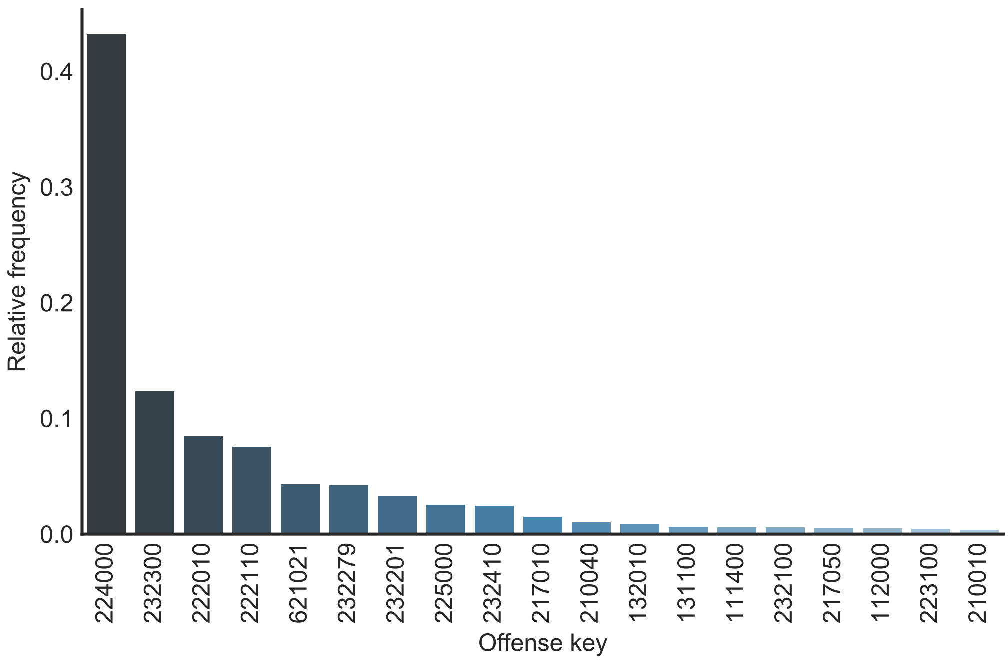

Figure A.1. The types of criminal offenses

Notes: The figure depicts the frequency distribution of the most common criminal offenses in the Federal Republic of Germany in 2014. The most common offense type is simple willful bodily harm (224000), followed by threats (232300), and two forms of dangerous and serious bodily injury (222110 & 222010). These four offense types together comprise around 75% of all criminal offenses.

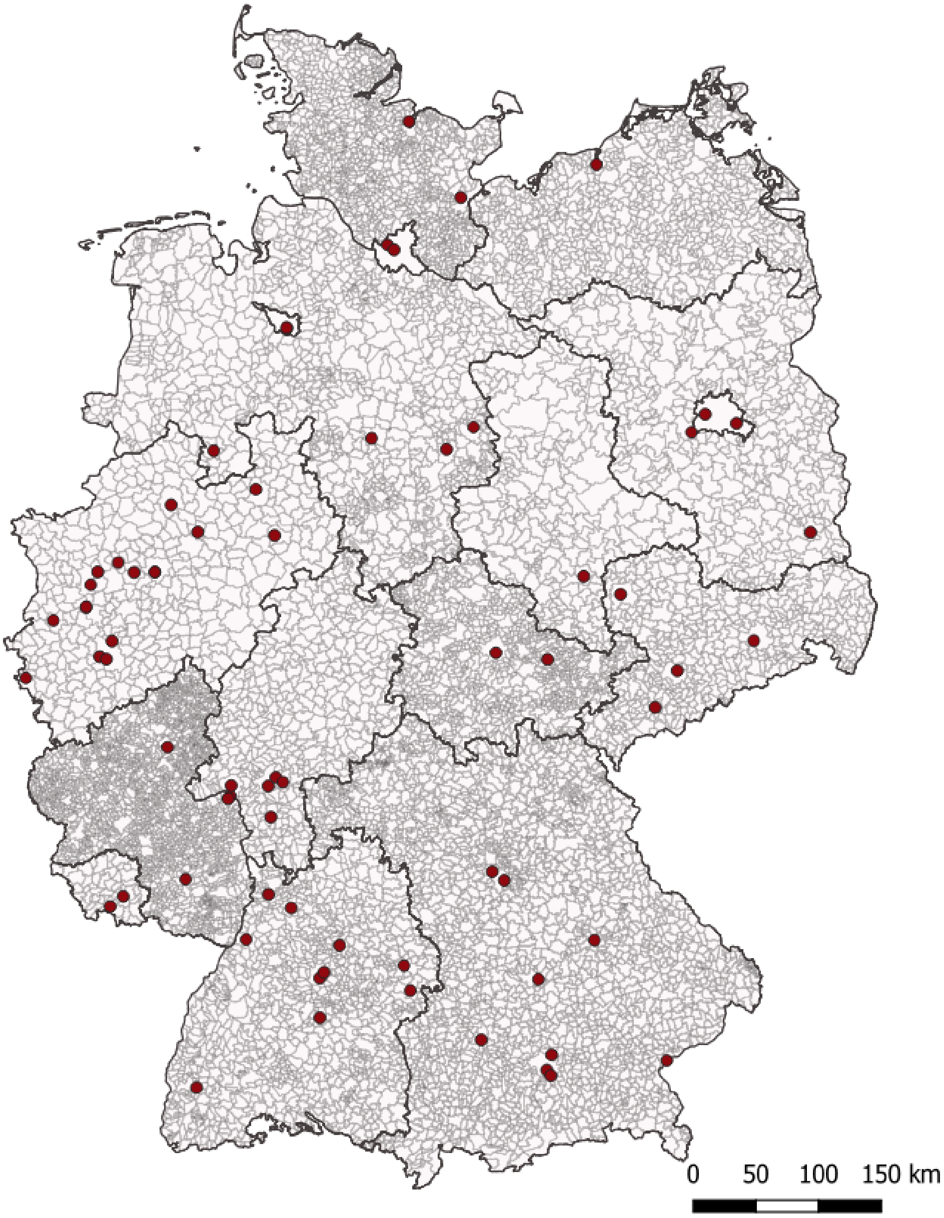

Figure A.2. The stadiums

Notes: This map shows the stadiums used in the analysis over the seasons 2010/11 until 2014/15. The black outlines indicate federal state boundaries.

Source: Own representation with data from the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR).

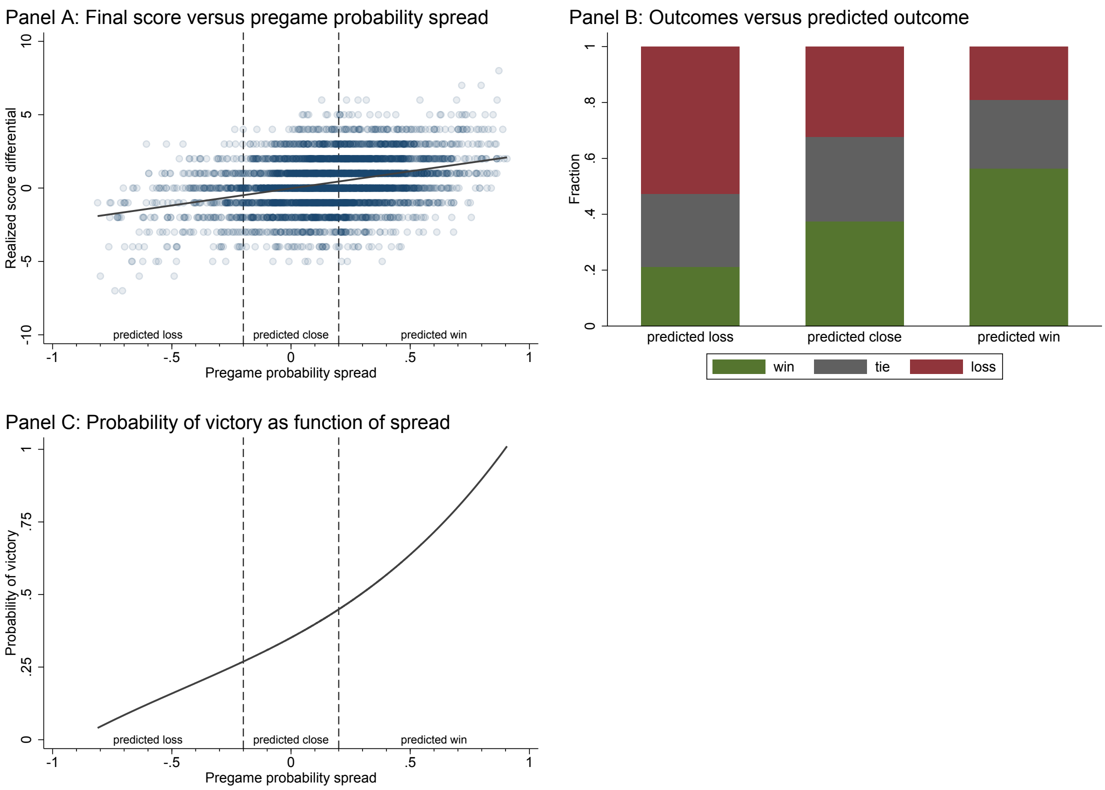

Figure A.3. Pregame probability spread and actual game outcomes

Notes: Panel A shows the relationship between realized score differential versus the pregame probability spread. The realized score differential is defined as the home team's minus the guest team's final score. The plotted regression line has an intercept of -0.020 (s.e. =0.29) and a slope of 2.328 (s.e. = 0.095). Panel B presents the fraction of actual game results by predicted outcome classifications. Panel C shows the probability of winning a game as a function of the probability spread. The curve is obtained from a regression using a third-order polynomial.

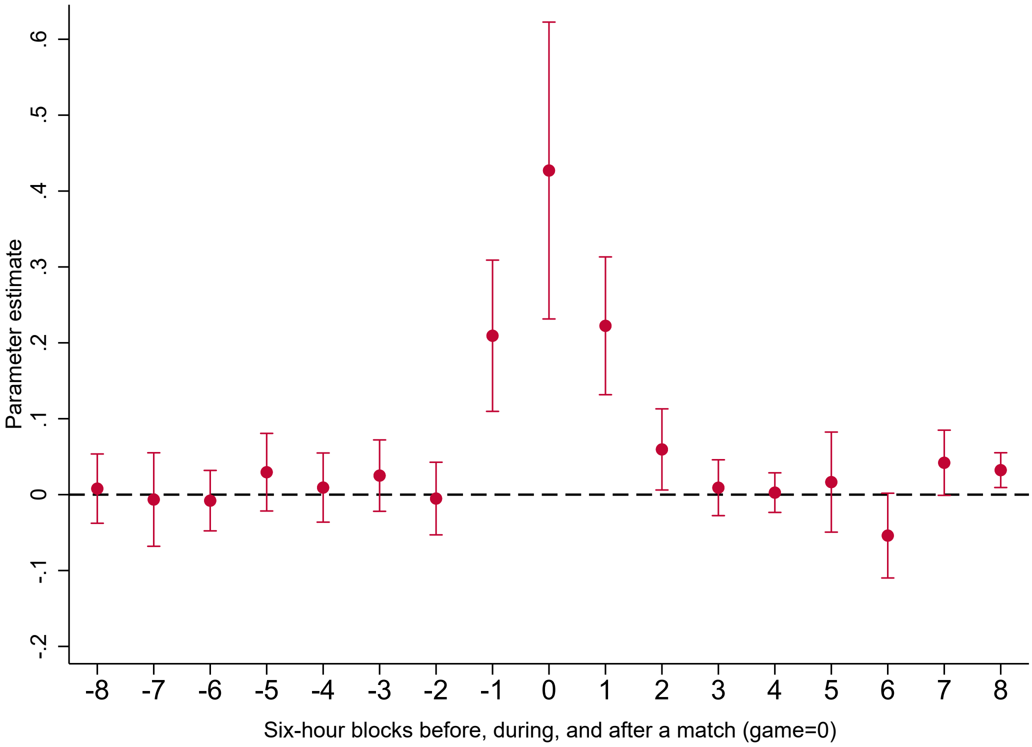

Figure A.4. Dynamics of assaults before, during, and after a game

Notes: The figure shows estimates and 95 percent confidence intervals from equation 1 using *hourly* data spanning the time window 2011-2015 for regions that host games of a football team from the top three leagues of the German football league system. The game day dummy is replaced with indicators for 6-hour blocks before, during, and after a game. The regression includes the same set of controls as column 4 of Table 1, but with *Interact FE* replaced by municipality-by-year-by-month and day-of-the-week-by-hour-of-day fixed effects. See notes to Table 1 for additional details. The dependent variable is *All Assaults*, defined as the number of crimes classified as simple willful, dangerous, or grievous bodily harm. Robust standard errors estimates are clustered at the municipality level.

Table A.1. Coding of assault offenses

	(1) offense key	(2) § StGB
Simple willful bodily harm	224000	223
Dangerous bodily harm	222010,222110	224
Grievous bodily harm	222020,222120	226

Notes: The table shows how the keys of the Police Crime Statistics are translated into the corresponding paragraphs of the German Criminal Code (*StGB*).

Table A.2. Effects on assaults by league

	(1)	(2)	(3)
	League 1	League 2	League 3
Game day	0.182***	0.151***	0.123***
	(0.040)	(0.036)	(0.028)
Effect size [%]	19.98	16.33	13.04
Dep. var. mean	12.27	11.46	4.06
Observations	19,219	21,854	24,513

Notes: The estimates are based on the model shown in equation 1 and use the same set of controls as column 4 of Table 1. See notes to Table 1 for additional details. The dependent variable is *All Assaults*, defined as the number of crimes classified as simple willful, dangerous, or grievous bodily harm. Robust standard errors allowing for clustering at the municipality level are reported in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3. Effects on crimes other than assault

	(1)	(2)
	Stealing by force or threat of force	Rape and sexual coercion
Game day	0.160***	0.017
	(0.045)	(0.028)
Effect size [%]	17.30	1.69
Dep. var. mean	0.68	0.12
Observations	79,415	73,729

Notes: The estimates are based on the model shown in equation 1 and use the same set of controls as column 4 of Table 1. See notes to Table 1 for additional details. In column 1, the dependent variable is the number of offenses classified as bag-snatching or robberies on streets, roads, and squares. In column 2, the dependent variable is the number of offenses classified as rape or sexual coercion. Robust standard errors allowing for clustering at the municipality level are reported in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4. High-rivalry matches

(1) team A	(2) team B	(3) comment
Aalen	Heidenheim	Ostalbderby
Aue	Dresden	Sachsenderby
Bielefeld	Münster	Westfalenderby
Braunschweig	Hannover	Niedersachsenderby
Bremen	Hamburg	Nordderby
Dortmund	München	'German Clasico'
Dortmund	Schalke	Revierderby
Dresden	Rostock	Ostderby
Düsseldorf	Köln	Rheinderby
Düsseldorf	Gladbach	Rheinderby
Erfurt	Jena	Thüringenderby
Frankfurt	K'lautern	Südwestderby
Frankfurt	Mainz	Rhein-Main-Derby
Frankfurt	Nürnberg	Derby
Fürth	Nürnberg	Frankenderby
Gladbach	Köln	Rheinderby
Hertha	Union	Berlinderby
Köln	Leverkusen	Rheinderby
Köln	Schalke	Derby
München	Nürnberg	Bayernderby
Münster	Osnabrück	Derby
Rostock	St. Pauli	Derby

Notes: The table shows prominent matches between teams that are known rivals. The above mentioned fixtures make up almost 2.5% of all matches in the sample.
Source: Spiegel (2020), 90min.de (2020), derbys.org (2020)

Table A.5. Assaults on police officers, all specifications

	(1)	(2)	(3)	(4)
Panel A: All assaults				
Game day	0.601***	0.605***	0.624***	0.651***
	(0.130)	(0.129)	(0.131)	(0.135)
Effect size [%]	82.46	83.18	86.57	91.77
Dep. var. mean	0.27	0.27	0.27	0.32
Observations	88,028	88,028	88,028	73,108
Panel B: Simple assaults				
Game day	0.410***	0.411***	0.418***	0.419***
	(0.093)	(0.094)	(0.094)	(0.097)
Effect size [%]	50.61	50.87	51.84	52.09
Dep. var. mean	0.19	0.19	0.19	0.25
Observations	88,028	88,028	88,028	68,148
Panel C: Aggravated assaults				
Game day	0.980***	0.985***	1.036***	1.123***
	(0.201)	(0.198)	(0.194)	(0.194)
Effect size [%]	166.43	167.80	181.72	207.54
Dep. var. mean	0.08	0.08	0.08	0.12
Observations	86,536	86,536	86,536	55,763
Region FE	✓	✓	✓	✓
Date FE	✓	✓	✓	✓
Weather controls	-	✓	✓	✓
Holiday FE	-	-	✓	✓
Interact FE	-	-	-	✓

Notes: Estimates are based on the model shown in equation 1. See notes to Table 1 for additional details. Dependent variables are as defined in Table 1, but are now the number of cases in which the victim was a police officers. Robust standard errors allowing for clustering at the municipality level are reported in parentheses.
Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix B: Descriptive Statistics for Teams Included in the Analysis (Intended for Online Publication)

Table B.1. Teams descriptive statistics

Home team	Municipality	Average attendance at home games	Number of home games...	...in league 1	...in league 2	...in league 3
1860 München	München	21,431	77	0	77	0
Aachen	Aachen	15,621	45	0	26	19
Aalen	Aalen	6,242	80	0	51	29
Ahlen	Ahlen	2,594	11	0	0	11
Aue	Aue	9,354	78	0	78	0
Augsburg	Augsburg	28,682	77	68	9	0
Babelsberg	Potsdam	2,761	48	0	0	48
Bayern München	München	70,763	76	76	0	0
Bayern München II	München	1,261	10	0	0	10
Bielefeld	Bielefeld	12,950	82	0	25	57
Bochum	Bochum	15,710	76	0	76	0
Braunschweig	Braunschweig	21,358	77	17	51	9
Bremen	Bremen	40,585	77	77	0	0
Bremen II	Bremen	700	29	0	0	29
Burghausen	Burghausen	2,525	67	0	0	67
Chemnitz	Chemnitz	5,193	76	0	0	76
Cottbus	Cottbus	9,670	78	0	59	19
Darmstadt	Darmstadt	8,164	74	0	17	57
Dortmund	Dortmund	80,473	77	77	0	0
Dortmund II	Dortmund	2,467	57	0	0	57
Dresden	Dresden	2,4114	79	0	51	28
Duisburg	Duisburg	13,280	80	0	42	38
Düsseldorf	Düsseldorf	33,599	77	17	60	0
Elversberg	Spiesen-Elversberg	1,523	19	0	0	19

Home team	Municipality	Average attendance at home games	Number of home games...	...in league 1	league 2	league 3
Erfurt	Erfurt	5,739	86	0	0	86
FSV Frankfurt	Frankfurt am Main	6,346	76	0	76	0
Fortuna Köln	Köln	2,267	18	0	0	18
Frankfurt	Frankfurt am Main	45,369	77	60	17	0
Freiburg	Freiburg im Breisgau	23,230	76	76	0	0
Fürth	Fürth	12,447	76	17	59	0
Gladbach	Mönchengladbach	50,560	76	76	0	0
Großaspach	Aspach	2,418	19	0	0	19
Haching	Unterhaching	2,116	86	0	0	86
Halle	Halle (Saale)	7,651	57	0	0	57
Hamburger SV	Hamburg	53,073	77	77	0	0
Hannover	Hannover	44,669	76	76	0	0
Heidenheim	Heidenheim an der Brenz	8,722	82	0	17	65
Hertha	Berlin	49,461	76	51	25	0
Hoffenheim	Sinsheim	27,402	77	77	0	0
Ingolstadt	Ingolstadt	7,973	76	0	76	0
Jena	Jena	5,338	28	0	0	28
K'lautern	Kaiserslautern	35,745	77	26	51	0
Karlsruhe	Karlsruhe	15,315	79	0	60	19
Kiel	Kiel	5,781	38	0	0	38
Koblenz	Koblenz	4,892	9	0	0	9
Köln	Köln	45,930	77	43	34	0
Leipzig	Leipzig	20,650	36	0	17	19
Leverkusen	Leverkusen	28,678	76	76	0	0
Mainz	Mainz	30,311	76	76	0	0
Mainz II	Mainz	1,163	19	0	0	19
Münster	Münster	8,298	76	0	0	76
Nürnberg	Nürnberg	39,180	77	60	17	0
Oberhausen	Oberhausen	4,414	28	0	9	19
Offenbach	Offenbach am Main	6,628	48	0	0	48

Home team	Municipality	Average attendance at home games	Number of home games...	...in league 1	league 2	league 3
Osnabrück	Osnabrück	9,584	84	0	8	76
Paderborn	Paderborn	10,790	77	17	60	0
Regensburg	Regensburg	4,360	84	0	17	67
Rostock	Rostock	11,392	84	0	17	67
Saarbrücken	Saarbrücken	4648	66	0	0	66
Sandhausen	Sandhausen	4,427	79	0	51	28
Schalke	Gelsenkirchen	61,363	76	76	0	0
St. Pauli	Hamburg	25,051	76	8	68	0
Stuttgart	Stuttgart	50,167	76	76	0	0
Stuttgart II	Stuttgart	1,144	83	0	0	83
Stuttgarter Kickers	Reutlingen	4,090	55	0	0	55
Union Berlin	Berlin	17,696	77	0	77	0
Wehen Wiesbaden	Wiesbaden	3,487	85	0	0	85
Wolfsburg	Wolfsburg	27,836	77	77	0	0