

Fabel, Marc; Rainer, Helmut

**Working Paper**

## How Much Violence Does Football Hooliganism Cause?

CESifo Working Paper, No. 9431

**Provided in Cooperation with:**

Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

*Suggested Citation:* Fabel, Marc; Rainer, Helmut (2021) : How Much Violence Does Football Hooliganism Cause?, CESifo Working Paper, No. 9431, Center for Economic Studies and Ifo Institute (CESifo), Munich

This Version is available at:

<https://hdl.handle.net/10419/248976>

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*Marc Fabel, Helmut Rainer*

## **Impressum:**

CESifo Working Papers

ISSN 2364-1428 (electronic version)

Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH

The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute

Poschingerstr. 5, 81679 Munich, Germany

Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email [office@cesifo.de](mailto:office@cesifo.de)

Editor: Clemens Fuest

<https://www.cesifo.org/en/wp>

An electronic version of the paper may be downloaded

- from the SSRN website: [www.SSRN.com](http://www.SSRN.com)
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# How Much Violence Does Football Hooliganism Cause?

## 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 21.5 percent on a match day. In total, professional football matches explain almost 18 percent of all violent assaults in the regions studied, and generate annual social costs of 95 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 18-29 age group, rises to almost 70 percent on days with high-rivalry derby matches, and that a non-negligible share of it stems from violent assaults on police officers. These findings are inconsistent with frustration-aggression theories that can explain sports-related violence in the United States, but can be accommodated by social identity explanations of football hooliganism.

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

Keywords: violent crime, football hooliganism.

*Marc Fabel*

*ifo Institute – Leibniz Institute for Economic  
Research at the University of  
Munich / Germany  
fabel@ifo.de*

*Helmut Rainer*

*ifo Institute – Leibniz Institute for Economic  
Research at the University of  
Munich / Germany  
rainer@econ.lmu.de*

November 15, 2021

We are very grateful to Victoria Endl-Geyer, Juliane Neumeier, and Patrick Reich for valuable comments and discussions. Dominik Ammon provided excellent research assistance. All errors and omissions are our own.

# 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. Yet, there exists neither a full-scale assessment of the magnitude of the football violence problem, nor are the mechanisms that might explain it well understood empirically.

Our study sheds light on these open questions. 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.<sup>1</sup> Second, the primary outcome variable, the rate of violent assault, 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 to construct regression weights and create the outcome variable. To identify causal effects, we employ a generalized difference-in-differences approach that exploits the 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 any potential source of heterogeneity across days of the week, month, and year, and taking 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 rate of violent assault

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<sup>1</sup>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.

by on average 21.5 percent. We find no evidence that the effects of football games on the prevalence of assaults are offset by reductions in violent acts on days adjacent to the game day or in nearby areas. The focus on home games in the empirical framework does not pose a threat to the identification strategy, as away games do not change 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 season of 2014/15, for example, football games in the top three leagues of the German football league system explain 17.7 percent of all violent assault reports and lead to 18,770 additional assaults in the sample regions. Glaubitz *et al.* (2016) estimate the social cost of an assault at 5,067 euros (in 2020 prices), which implies an annual social cost of 95 million euros.<sup>2</sup>

In a second step, we explore factors that may explain these results. There are a number of 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 do so by exploring 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 4 percent of the baseline effect.

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. We find three pieces of evidence consistent with SIT. First, the match day effect on violent crime is almost entirely driven by male victims and is most pronounced in the 18-29 age group. This is indeed the demographic group SIT, when applied to football violence, centers

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<sup>2</sup>The estimated social costs of Glaubitz *et al.* (2016) are conservative compared to estimates from other countries. In the United States, the social costs of an assault range from 17,300 to 68,000 euros (Miller *et al.*, 1996, Cohen *et al.*, 2004). In New Zealand the social costs are estimated at 6,400 euros (Roper and Thompson, 2006), and in Great Britain the estimated costs are 2,300 euros (Dubourg *et al.*, 2005). All costs are in 2014 prices.

around (Spaaij, 2008). Second, 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 almost 70 percent, an effect more than three 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 97 percent on match days and account for 16 percent of the match day effect.

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.<sup>3</sup> 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.* (2018) 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 games 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 ten 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 emotional cues do 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

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<sup>3</sup>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.

police presence and invasive police tactics may well backfire, as they might serve to increase violence by inflating perceived threat levels.

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.<sup>4</sup> 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.

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

Alcohol plays a crucial role in the context of violence in and around German football stadiums. 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

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<sup>4</sup>For details on how the match schedules are created, please refer to <https://www.bundesliga.com>.

urged to comply with the ban.<sup>5</sup> 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 and its potential side effects are very present in German football arenas.

### 3 Data

The data set used for the analysis covers the time window from 2011 to 2015 and contains regions in which professional football games take place. The analysis is conducted at the municipality level, the smallest territorial division in Germany. 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.<sup>6</sup> It includes the universe of individuals who were 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 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.<sup>7</sup> 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 and the main outcome, the assault rate, is defined as the number of assaults per million population. Assaults are defined as actions involving physical violence. For that purpose, we use the crime type code 'simple willful bodily harm' (*Vorsätzliche einfache Körperverletzung*, § 223 StGB). There are roughly 120 types of criminal offenses (recorded in 6 digit codes), with the vast

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<sup>5</sup>For details, please refer to: <https://www.sueddeutsche.de>.

<sup>6</sup>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.

<sup>7</sup>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).

majority of cases classified by only a handful of codes.<sup>8</sup> Figure A.1 in the Appendix shows the distribution of cases per crime key for the twenty most common offense types in 2014. ‘Simple willful bodily harm’ is by far the most common offense, contributing to about 45 percent of all cases. Due to its prevalence and its association with aggression, we choose this offense type as the main outcome variable in the analysis.

Figure 1 shows the distribution of assaults over time. Panel A displays the variation of assaults per hour of the day.<sup>9</sup> 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.<sup>10</sup> Panel D confirms this impression by plotting the daily number of assaults. New Year’s Eve is a particularly impressive outlier.<sup>11</sup>

### 3.2 Football Data

The data on football matches is self-collected and is obtained via web scraping from [www.kicker.de](http://www.kicker.de) and [www.transfermarkt.com](http://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. The data contains detailed match and table standings parameters, e.g. time and place of the match, number of spectators, pregame point difference, goals, penalties, cards, referee characteristics, among others. Furthermore, there is comprehensive information on the individual teams, such as team size, average age, market value, and the number of foreign players. The stadiums where 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

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<sup>8</sup>The top 10 of the most prevalent crime keys account for more than 90 percent of the cases.

<sup>9</sup>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.

<sup>10</sup>Panel C shows the monthly number of assaults while adjusting for the number of days per month.

<sup>11</sup>Panels C and D show data for the year 2014 only.

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](http://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.<sup>12</sup>

### 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.<sup>13</sup> From this 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’).<sup>14</sup>

### 3.4 Holidays

In order to capture any variation in the crime rate between ordinary and special days, we add controls for public and school holidays, which may differ at the state level.<sup>15</sup> Furthermore, we add a dummy variable for peculiar days (New Year’s Eve and the days surrounding Carnival), which are not holidays, yet certainly shift the crime rate.

### 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. Thus, we are

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<sup>12</sup>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.

<sup>13</sup>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.

<sup>14</sup>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).

<sup>15</sup>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/>.

able to create a panel at the municipality-year level containing comprehensive information on topics such as territory, population, labor market, election results, housing, economic sectors, and public budgets. The information is used to construct weights for the regression analysis or to determine assault rates.

## 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 the regional assault rate on a game day to the expected assault level conditional on the day of the week, month, and year, while additionally accounting for other possible confounding variation due to weather and holidays. In other words, the counterfactual regional assault rate (what would be expected on a game day in absence of the game), e.g. a Saturday in April 2012, is obtained by using the regional assault rate on other Saturdays in April 2012 with no games scheduled.

The identification strategy is based on a generalized difference-in-differences approach to study the impact of football matches on violent behavior. Let  $\text{Assaults}_{rdmy}$  denote the assault rate in region  $r$ , on day-of-the-week  $d$ , in month  $m$  and year  $y$ . The assault rate is defined as the number of assaults per million population and is given by:

$$\text{Assaults}_{rdmy} = \alpha + \beta (\text{Gameday}_{rdmy}) + \vartheta_r + \underbrace{\gamma_d + \eta_m + \theta_y}_{\text{date}_{dmy}} + \lambda \mathbf{X}_{rdmy} + \varepsilon_{rdmy}. \quad (1)$$

$\text{Gameday}_{rdmy}$  is a binary variable that equals one when there is a home game, and zero otherwise. Region fixed effects  $\vartheta_r$  capture time-invariant differences between regions and ensure that the identification is driven by within instead of between region variation over time. The vector  $\text{date}_{dmy}$  contains fixed effects for the day-of-the-week ( $\gamma_d$ ), month ( $\eta_m$ ), and year ( $\theta_y$ ). This way, the model flexibly controls for day-of-week specific heterogeneity, seasonal effects, and long-run time trends. We expand the baseline model by adding interactions of region fixed effects with all elements of  $\text{date}_{dmy}$ , i.e. region-by-day-of-week fixed effects, region-by-month fixed effects, and region-by-year fixed effects. The interactions account for systemic changes in the degree of violent behavior over the year for each region. The vector  $\mathbf{X}_{rdmy}$  includes school and public holidays and weather controls.<sup>16</sup> We compute two-way cluster-robust standard errors to capture arbitrary correlation at the

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<sup>16</sup>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.

region-year and year-month levels. Observations are weighted with the population figures from the Federal Statistical Office.

The implicit assumption for interpreting the parameter of interest  $\beta$  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 displacement 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 assault rate 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 the assault rate in the home region.

## 5 Results

### 5.1 Main Results

Before presenting the regression results, Figure 4 gives an intuitive preview of the main findings. Using the same data as in the main analysis, it shows the assault rate across the days of the week.<sup>17</sup> The daily rates are presented for days with and without home games. The average daily assault rate is higher for weeks when a home game is played than when no game is played. The difference in means is statistically significant for all days except Tuesdays and Wednesdays.<sup>18</sup> The empirical model exploits the variation in the number

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<sup>17</sup>Appendix Figure A.4 shows the same scheme using the raw number of assaults across days of the week for days with and without games.

<sup>18</sup>The average assault rate on Thursdays with games is very high compared to Thursdays without games. This may be the result of very few games take place on a Thursday. In our sample, only 18 (0.4 percent) of all games take place on a Thursday.

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 continuously adding more controls. The dependent variable is the assault rate, which is defined as the number of offenses per million population. 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 assault rate by an average of 2.677 assaults per million population. This corresponds to an increase of 21.5 percent compared to the level without games.

## 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 the assault rate. 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.*, 2018). 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.<sup>19</sup> 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.

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<sup>19</sup>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.

Almost all of the coefficients for the day before and after the game are small in magnitude and not statistically significant. The only exception is the estimate for the day before the game in column 4, which implies that a football game leads to an average increase of 0.352 assaults per million population on the day before a game. The positive coefficient, however, does not suggest temporal displacement effects, which would require a negative estimate. Rather, it indicates additional assaults due to activity on the day preceding important games.

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 the assault rate at home due to the absence of local agitators imply that days with away matches 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.<sup>20</sup> 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.<sup>21</sup> 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 the assault rate. The effect of a home game is sizable, leading to an average increase in the assault rate of 2.910 assaults per million population. The coefficient is 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 small in magnitude and not significantly different from zero. Thus, the results suggest that focusing exclusively on home games does not render the identification strategy invalid.

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<sup>20</sup>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.

<sup>21</sup>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'.



### 5.3 Robustness Tests

We perform several sensitivity and placebo tests to assess the robustness of the findings. The results of these checks are reported in Table 4. 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.**—First, we show 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 the set of rescheduled games from the analysis. The results are almost identical to the baseline results.<sup>22</sup> Second, we show the effects of omitting population *weights* from the regressions. The effect of football matches without considering population weights is considerably larger: a home game leads to an increase in the average assault rate by 5.342 assaults per million population. The higher coefficient compared to the baseline specification indicates that the effects of rural areas must be larger, as they become more relevant when population weights are omitted. Third, we show that our results are robust to a different *estimation* procedure and an alternative measure of the *dependent variable*. In the following, we use the raw number of assaults as the outcome variable. Given the discrete nature of the dependent variable and the fact that there are many cells with zero reports, we employ a Poisson model. The corresponding regression specification reads as follows:

$$\begin{aligned} E[\text{Assaults}_{rdmy} | \text{Gameday}_{rdmy}, \vartheta_r, \text{date}_{dmy}, \mathbf{X}_{rdmy}] \\ = \exp(\beta (\text{Gameday}_{rdmy}) + \vartheta_r + \text{date}_{dmy} + \lambda \mathbf{X}_{rdmy}). \end{aligned} \quad (2)$$

Due to the nonlinearity of the model, the coefficient in Table 4 shows average marginal effects of a home game on the number of physical assaults.<sup>23</sup> A home game is predicted to lead to an average increase of 1.483 assaults. This represents a 28.55 percent increase in the number of assaults.

**Other Forms of Violence.**—Next, we investigate the robustness of the findings when considering at other forms of violence. First, a broader definition of assaults is considered. In addition to offenses coded as ‘simple willful bodily harm’, we further include negligent, dangerous, and grievous bodily harm as well as brawls. Appendix Table A.1 illustrates

<sup>22</sup>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.

<sup>23</sup>In nonlinear models, coefficients cannot be interpreted as marginal effects. The partial effect for a Poisson model is given by  $\frac{\partial E[\text{Assaults}_i | \mathbf{X}_i]}{\partial x_j} = \beta_j \exp(\mathbf{x}'\beta)$ . In order to present a single response value, we follow Cameron and Trivedi (2005) and report the average response:  $\frac{1}{N} \sum_i \frac{\partial E[\text{Assaults}_i | \mathbf{X}_i]}{\partial x_{ij}} = \hat{\beta}_j \times \frac{1}{N} \sum_i \exp(\mathbf{x}'_i \hat{\beta})$ .

which offenses are included in the expanded definition of assaults and how the penal codes of the German Criminal Code (*StGB*) are translated into the offense keys of the Police Crime Statistics. The effect size of 5.417 assaults per million population is significantly larger than the baseline coefficient. This indicates that football games also lead to an increase in other forms of physical violence. Second, we investigate the effect of football games on threats, which can be regarded as a precursor of physical violence. The effect size of 0.216 threats per million population is relatively small. The estimate represents a 5.4 percent increase.

**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 share of assaults on the gameday indicator plus the union of selected controls. The results of the post-double selection estimator are presented in Table 4 and use 96.7 percent of the original covariates. The estimator is almost identical to the preferred specification, while the standard errors increase slightly. 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 the assault rate to test whether the previous results are only due to chance.<sup>24</sup> 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 same frequency of the real matches. Subsequently, we estimate the model as shown in equation 1. This procedure is carried out 10,000 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 ( $2.677/0.284=9.43$ ) is almost 2.5 times higher than the largest observed value in any of the 10,000 simulations. Panel C shows that with 10,000 iterations, 6.57 percent of the estimates are significantly

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<sup>24</sup>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.

different from zero. At a significance level of  $\alpha = 0.01$ , there are 3.06 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 consider emotional cues and social identity-driven violence as potential channels.

**Frustration-Aggression Hypothesis.**—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 frustration-aggression hypothesis (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. For this reason, we analyze in [Table 5](#) whether visceral factors may be the reason for the additional assaults. In column 1, we investigate whether an emotionally upsetting event during a game leads to a higher assault rate. To answer this question, we create an index 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 index shows that 35 percent of all games involve at least one upsetting episode as defined in the previous categories. The estimates in column 1 do not suggest that emotional cues trigger more violent behavior since the estimates for games with and without upsetting events are 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 losing is smaller than 20 percentage points.<sup>25</sup> 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

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<sup>25</sup>Similar results are obtained when we define different threshold values and when we deviate from the symmetry around the origin.

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 our match day effect were largely explained by increases in domestic violence. Table 6 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. Male victimization rates increase on average by 2.432 offenses per million population. The increased assault rate for males accounts for more than 90 percent of the effect found for the entire sample. Second, 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. The victimization rate of strangers to the suspect increases by on average 1.939 assaults per million population. This implies that almost three out of four 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 on average 0.096 assaults per million population. This implies that only a small portion of the match day effect (4 percent) can be explained by domestic assault cases. Taken together, the evidence we have presented is inconsistent with the notion that emotional cues might also drive sports-related violence in Germany, as it does in the United States.

**Social Identity Theory.**—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 social identity 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 6 shows the age profile of the impact of football games on the assault rate for each gender. For women, the point estimates are small in magnitude and not significantly different from zero. Women aged 40-49 are the only exception. In contrast, the effects for adult men are throughout significant. The largest effect for males is found in the 18-29 age group and decreases thereafter.

To shed light on aspect (ii), we compare the impact of matches played between known rival teams to regular matches. The game day indicator from equation 1 is replaced by an interaction with a dummy variable that equals one for high-rivalry matches. Local derbies (games between two competing teams that are based in regions of close geographical proximity) constitute high-rivalry matches.<sup>26</sup> The estimates are shown in columns 1 and 2 of Table 7. Games classified as high-rivalry matches lead to an average increase of 8.320 assaults per million population. This corresponds to an increase of 67 percent, an effect more than three 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 (i), we estimate the impact of football games on violent behavior directed at police officers on duty. In column 3 of Table 7, we find that the victimization rate of police officers increases on average by 0.434 assaults per million population on a match day. This corresponds to an increase of 97 percent. Moreover, almost 16 percent of the additional assaults resulting from football games can be attributed to attacks on police officers. Another offense recorded by the police is resistance to law enforcement. Column 4 of Table 7 shows that offenses of this type increase by 46 percent on a match day.

## 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 assault rates, 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.

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<sup>26</sup>Appendix Table A.2 gives an overview of high-rivalry matches.

Our first main finding was that football games cause large spikes in violent crime: on a match day, the rate of violent assault increases by, on average, more than 20 percent. This estimate has two important implications. First, on aggregate, football matches can explain almost 18 percent of all violent assaults in the regions studied. Second, 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 18,770 assaults in the 2014/15 season alone,<sup>27</sup> which translates into annual costs of 95 million euros.<sup>28</sup> 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 main finding 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. Instead, it can be attributed to violence among males in the 18-29 age group, more than triples to almost 70 percent on days with high-rivalry derby matches, and can to a non-negligible extent also be explained by violent assaults on police officers. These findings are contrary to frustration-aggression theories that can explain sports-related violence in the United States, but they are consistent with social identity models of football hooliganism. The fact that almost 20 percent of additional assaults on match days involve police officers indicates that negative intergroup relationships between police and football fans are a concern in the context of Germany. Social psychologists investigating crowd violence have highlighted that a move away from a deterrence towards a dialogue and facilitation-based policing approach by the 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.

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<sup>27</sup>These calculations are based on an estimated reduction in assaults per million population per day, 335 days of the football season, and a population of 20,93 million in the affected regions. The number of prevented assaults for the 2014/15 season is:  $2.677 \times 335 \times \frac{20,930,000}{1,000,000} = 18,770$ .

<sup>28</sup>To calculate the annual social cost, we use an estimated cost of 5,067 euros (in 2020 prices) for one assault (Glaubitz *et al.*, 2016).

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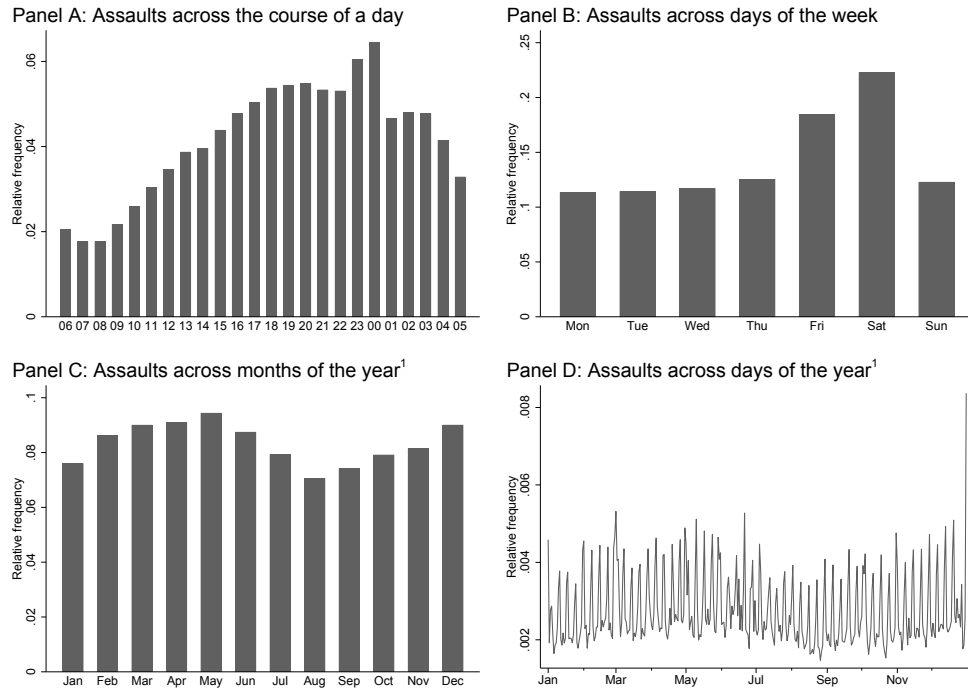
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## Figures and Tables

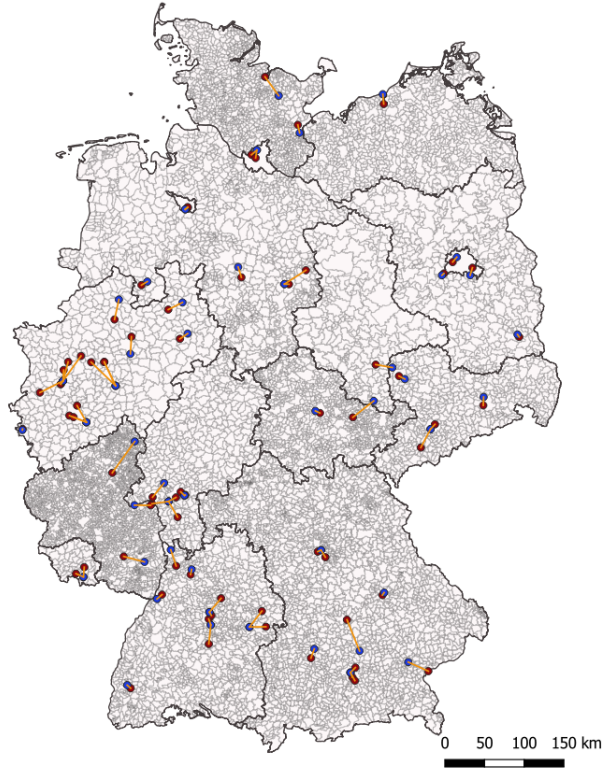


**Figure 1.** Distribution of assaults across time

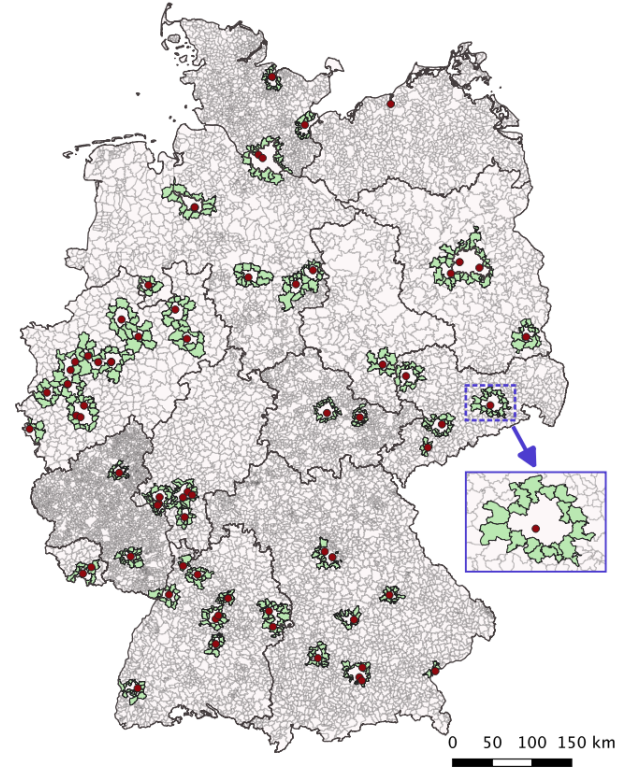
*Notes:* The figure shows the distribution of assaults across hours of the day, days of the week, across months (adjusted for the number of days per month), and across the days of the year in the Federal Republic of Germany.

<sup>1</sup>: 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



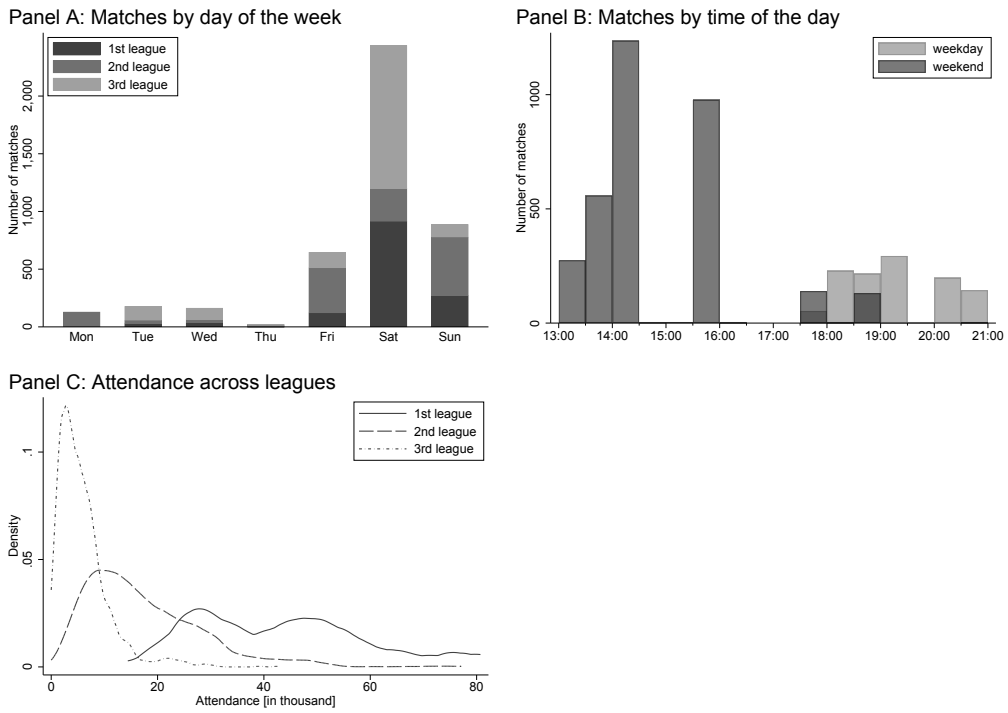
(b) Spatial displacement - neighboring regions



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

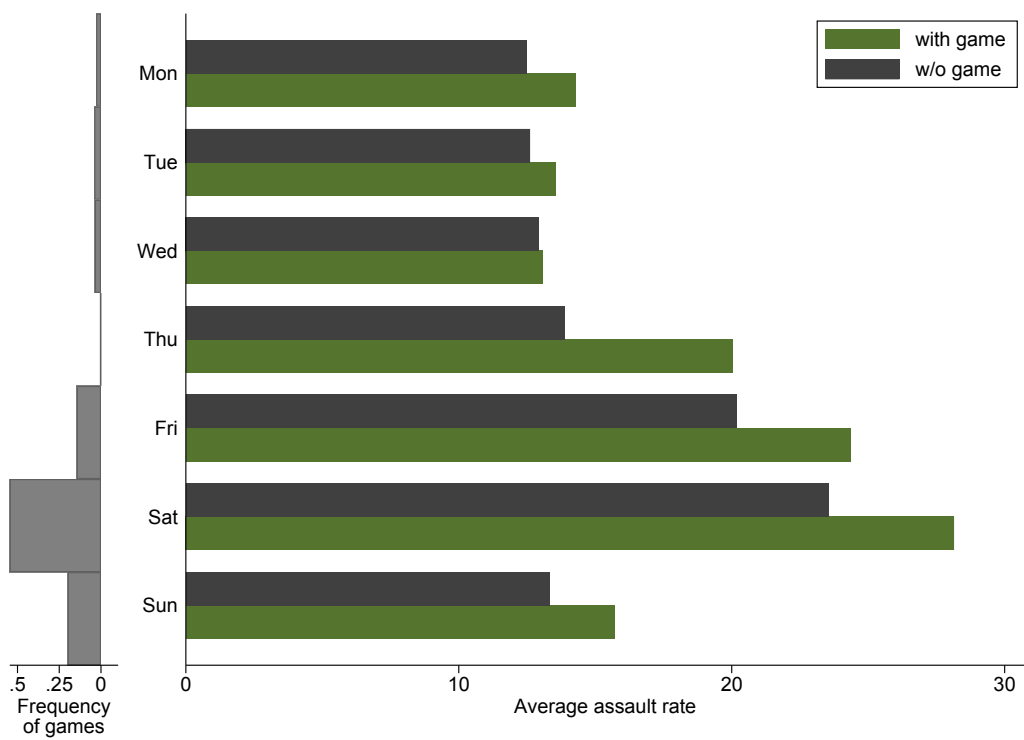
*Notes:* The map on the left shows the stadiums used in the analysis over the seasons 2010/11 until 2014/15 (red dots) and their closest weather monitors (blue dots). The orange lines indicate how the weather monitors are assigned to the stadiums. The map on the right shows the regions that are used 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).

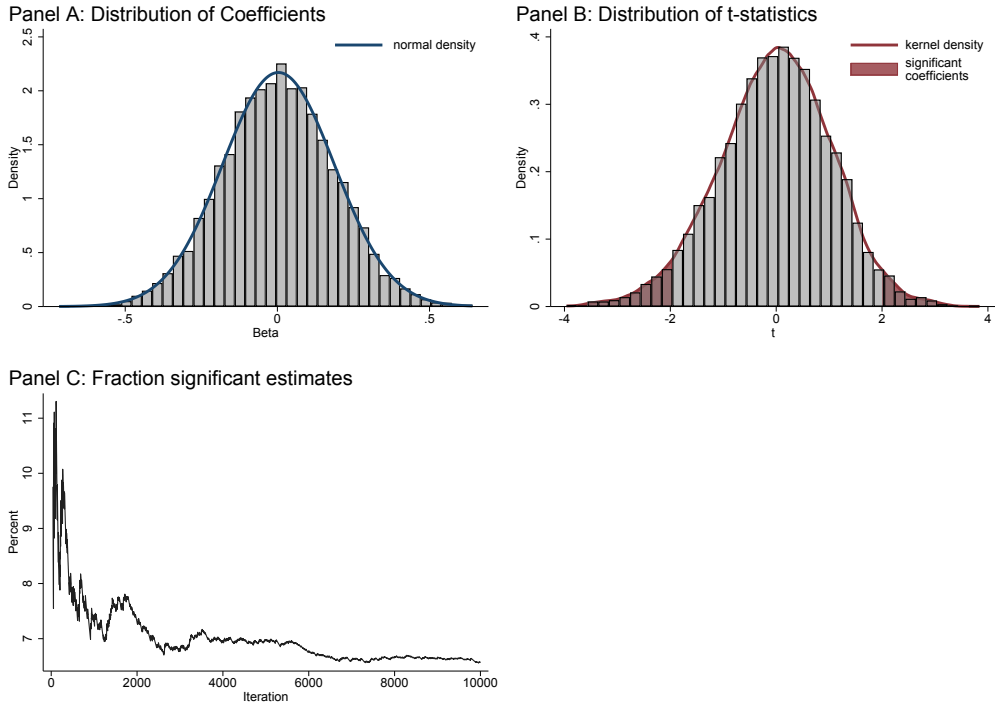


**Figure 3.** Football matches

*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.

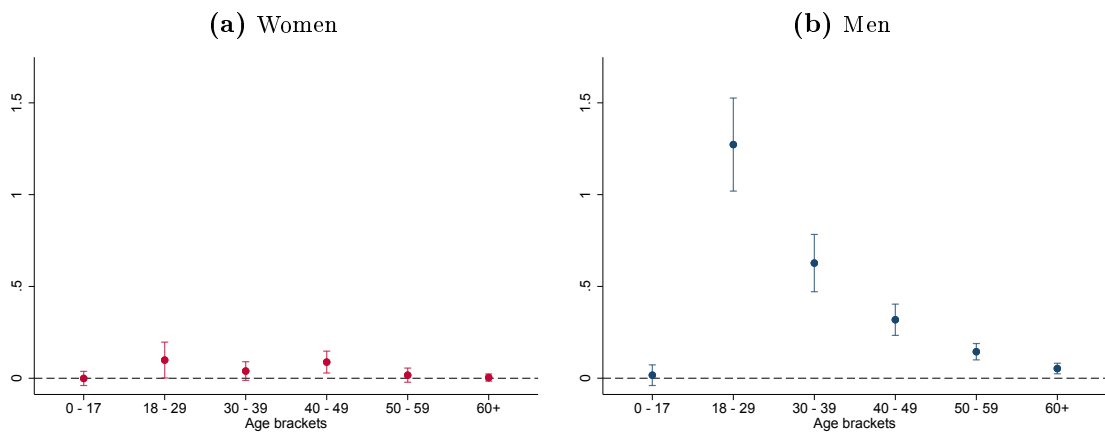


**Figure 4.** The average assault rate on gamedays and days where no game takes place  
*Notes:* The figure shows the daily average number of assaults per million population for regions that host games of a football team from the top three leagues. The daily rates are shown for weeks in which a game 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 10,000 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.** The age profile of the impact of football matches on the assault rate

*Notes:* The figure shows estimates and 95% confidence intervals across age brackets and by gender. To estimate the effect, I use the model shown in equation 1 in its richest specification with all covariates and population weights. The outcome variable is defined as the number of assaults per million population.

**Table 1.** Effects on assault rate

	(1)	(2)	(3)	(4)
Game day	2.740*** (0.319)	2.766*** (0.312)	2.813*** (0.313)	2.677*** (0.284)
Effect size [%]	22.00	22.21	22.59	21.50
Observations	88,028	88,028	88,028	88,028
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. The outcome variable is defined as the number of assaults per million population. Population-weighted coefficients show the change in the outcome variable due to a home game. 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. The effect size corresponds to the percent change of the assault rate due to a football game in relation to the mean when no game takes place. 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. Two-way clustered standard errors at region-year and year-month level are reported in parentheses.

Significance levels: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table 2.** Displacement effects

	(1)	(2)	(3)	(4)
<b><i>Panel A: Spatial displacement</i></b>				
Game day	0.144 (0.146)	0.153 (0.146)	0.170 (0.147)	0.210 (0.154)
Effect size [%]	2.58	2.74	3.04	3.75
Observations	960,848	960,848	960,848	960,848
<b><i>Panel B: Temporal displacement</i></b>				
Game day	2.777*** (0.346)	2.810*** (0.338)	2.857*** (0.336)	2.770*** (0.300)
Day after game	-0.105 (0.189)	-0.076 (0.190)	-0.065 (0.192)	0.279 (0.182)
Day before game	0.287 (0.241)	0.318 (0.238)	0.339 (0.229)	0.352* (0.206)
Effect size [%]	22.34	22.60	22.98	22.28
Observations	87,438	87,438	87,438	87,438
Region FE	✓	✓	✓	✓
Date FE	✓	✓	✓	✓
Weather Controls	-	✓	✓	✓
Holiday FE	-	-	✓	✓
Interact FE	-	-	-	✓

*Notes:* Estimates are based on the model shown in equation 1. Panel A contains specifications that use daily data (excluding June) spanning the time window 2011-2015 for regions that share a border with a district 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. The outcome variable is defined as the number of assaults per million population. Population-weighted coefficients show the change in the outcome variable due to a home game. 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. The effect size corresponds to the percent change of the assault rate due to a football game in relation to the mean when no game takes place. The estimates are based on the model shown in equation 1. See notes to Table 1 for additional details. Two-way clustered standard errors at region-year and year-month level are reported in parentheses.

Significance levels: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .



**Table 3.** Effects on assault rate, distinction between home and away games

	(1)	(2)
	Baseline w/o L3	Distinction home/away <sup>1</sup>
Game day	2.859*** (0.324)	
Home game day		2.910*** (0.335)
Away game day		0.325 (0.213)
Effect size [%]	21.22	21.97
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 (including region and date fixed effects, their interactions as well as holiday and weather controls). See Table 1 for additional details. Two-way clustered standard errors at region-year and year-month level are reported in parentheses.

Significance levels: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

<sup>1</sup>: Effect size corresponds to the coefficient of Home game day.

**Table 4.** Effects on assault rate, robustness tests

	(1)	(2)	(3)	(4)
	Coefficient	Standard error	Effect size [%]	$N$
<b>Baseline</b>	2.677***	(0.284)	21.50	88,028
<b>Econometric specification</b>				
Drop delayed games	2.699***	(0.288)	21.67	87,928
No population weights	5.342***	(0.566)	42.90	88,028
Poisson model <sup>1</sup>	1.483***	(0.238)	28.55	87,475
<b>Other forms of violence</b>				
Broadly defined assaults	5.417***	(0.529)	27.76	88,028
Threats	0.216***	(0.079)	5.44	88,028
<b>Post-double-selection method</b>	2.674***	(0.335)	21.48	88,028

*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 three leagues. The outcome variable is defined as the number of assaults per million population. Except where otherwise noted, the specifications use population-weights. 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. The effect size corresponds to the percent change of the assault rate due to a football game in relation to the mean when no game takes place. All specifications use region and date fe, their interactions, weather controls, and holiday FE. Two-way clustered standard errors at region-year and year-month level are reported in parentheses.

Significance levels: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

<sup>1</sup>: number of assaults is dependent variable.

**Table 5.** Effect of emotional cues

	(1)	(2)	(3)
		Card & Dahl (2011) specification	
	Upset event index	Predicted outcomes	Predicted and actual outcomes
Upset event (Index)	2.717*** (0.406)		
No upset event (Index)	2.655*** (0.289)		
Expected to lose		3.495*** (0.722)	3.376*** (0.836)
Expected to win		2.752*** (0.366)	2.907*** (0.356)
Expected to be close		2.437*** (0.321)	2.369*** (0.383)
Expected to lose and won			0.599 (1.554)
Expected to be close and lost			0.194 (0.610)
Expected to win and lost			-0.792 (0.667)
Observations	88,028	88,028	88,028

*Notes:* The gameday indicator is replaced by an index that captures unsettling events. The upset event index 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, I 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 (including region and date fixed effects, their interactions as well as holiday and weather controls). See Table 1 for additional details. Two-way clustered standard errors at region-year and year-month level are reported in parentheses. Significance levels: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

**Table 6.** Effects on assault rate, by gender of victim and victim-suspect relationship

	(1)	(2)	(3)	(4)	(5)
	Gender		Victim-suspect-relationship		
	Women	Men	Strangers <sup>a</sup>	Prior <sup>a</sup> relation	Domestic <sup>b</sup>
Game day	0.245*** (0.090)	2.432*** (0.232)	1.939*** (0.207)	0.738*** (0.116)	0.096** (0.045)
Effect size [%]	4.99	32.27	40.43	9.64	5.40
Observations	88,028	88,028	88,028	88,028	88,028

*Notes:* The estimates are based on the model shown in equation 1 and use the same outcome and controls as column 4 of Table 1 (including region and date fixed effects, their interactions as well as holiday and weather controls). See Table 1 for additional details. Two-way clustered standard errors at region-year and year-month level are reported in parentheses. Significance levels: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

<sup>a</sup>: covers formal relationships (e.g. types of kinship or acquaintance).

<sup>b</sup>: covers spatial-social relationships (whether victim and suspect live in the same household).

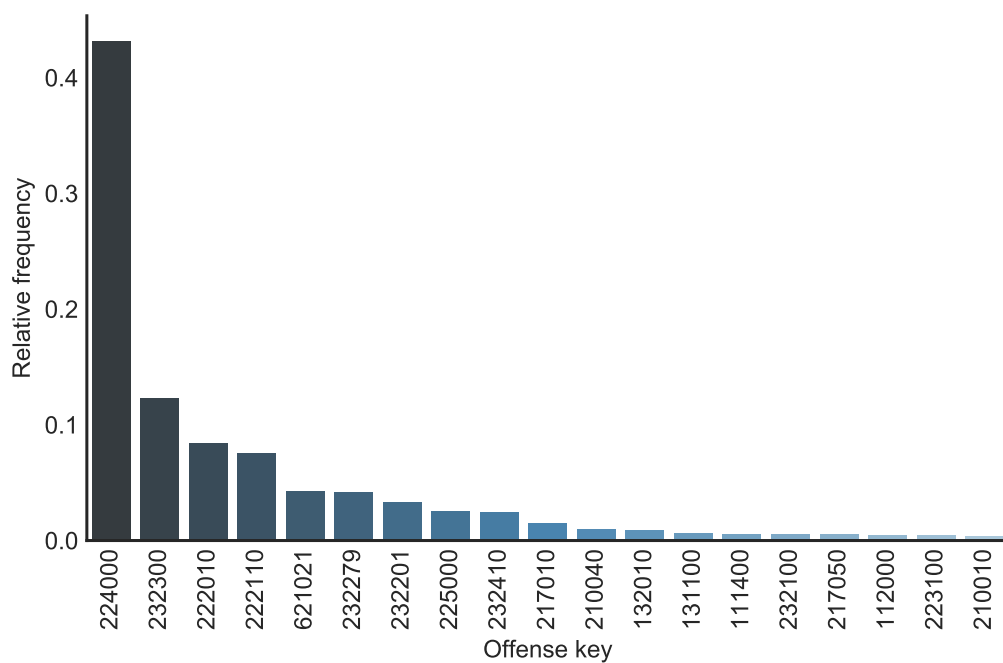
**Table 7.** Effects for derby vs. regular matches, assaults on police officers, and resistance to law enforcement

	(1)	(2)	(3)	(4)
	High-rivalry matches	Regular matches	Assaults on police officers	Resistance to enforcement
Game day	8.320*** (1.746)	2.387*** (0.275)	0.434*** (0.078)	0.775*** (0.103)
Effect size [%]	66.81	19.17	96.98	45.50
Observations	88,028	88,028	88,028	88,028

*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 (including region and date fixed effects, their interactions as well as holiday and weather controls). See Table 1 for additional details. In columns 1 and 2, the gameday indicator is replaced by interactions with dummy variables for high-rivalry and regular matches, respectively. Two-way clustered standard errors at region-year and year-month level are reported in parentheses.

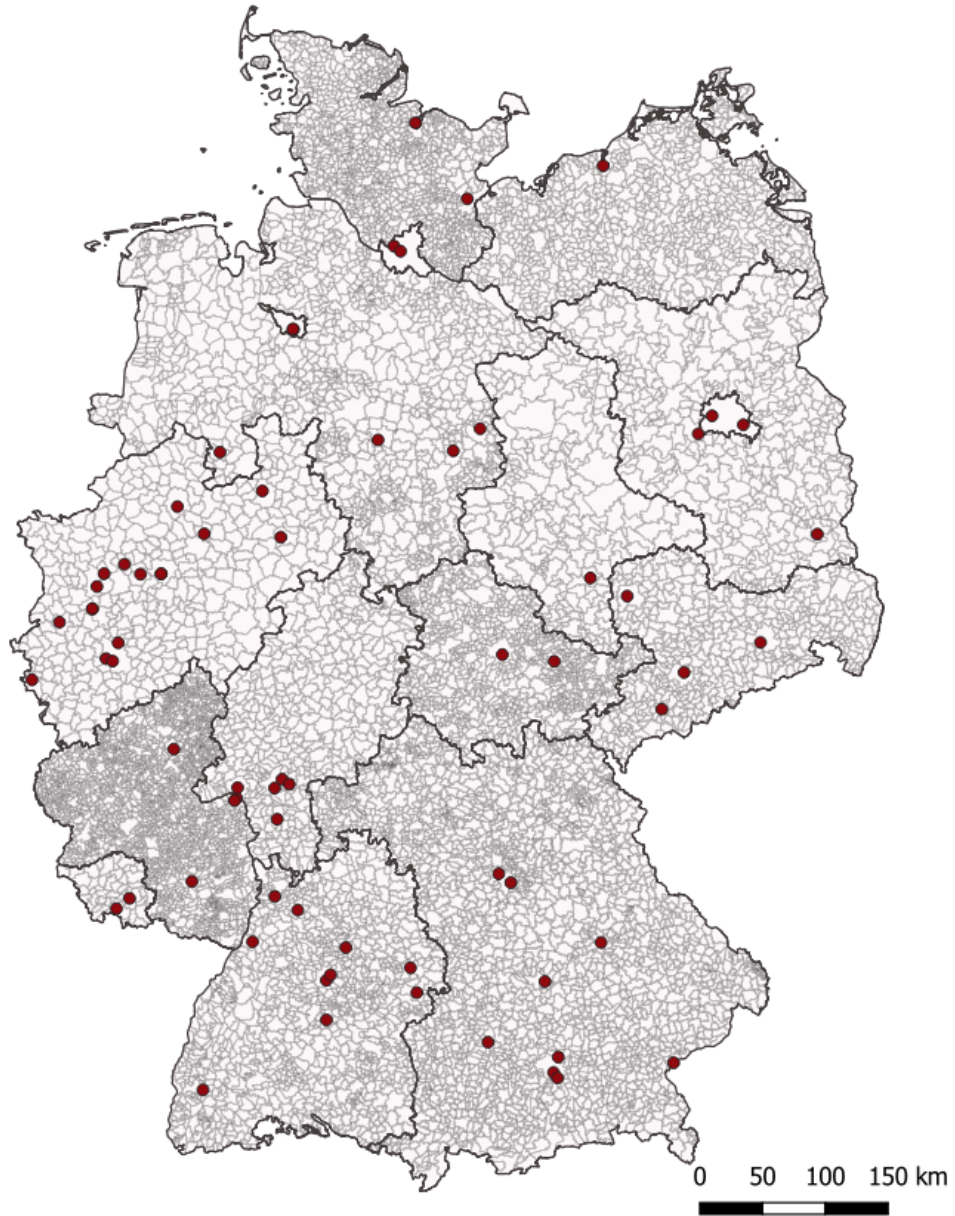
Significance levels: \*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$ .

## Appendix: Intended for Online Publication



**Figure A.1.** The types of criminal offenses

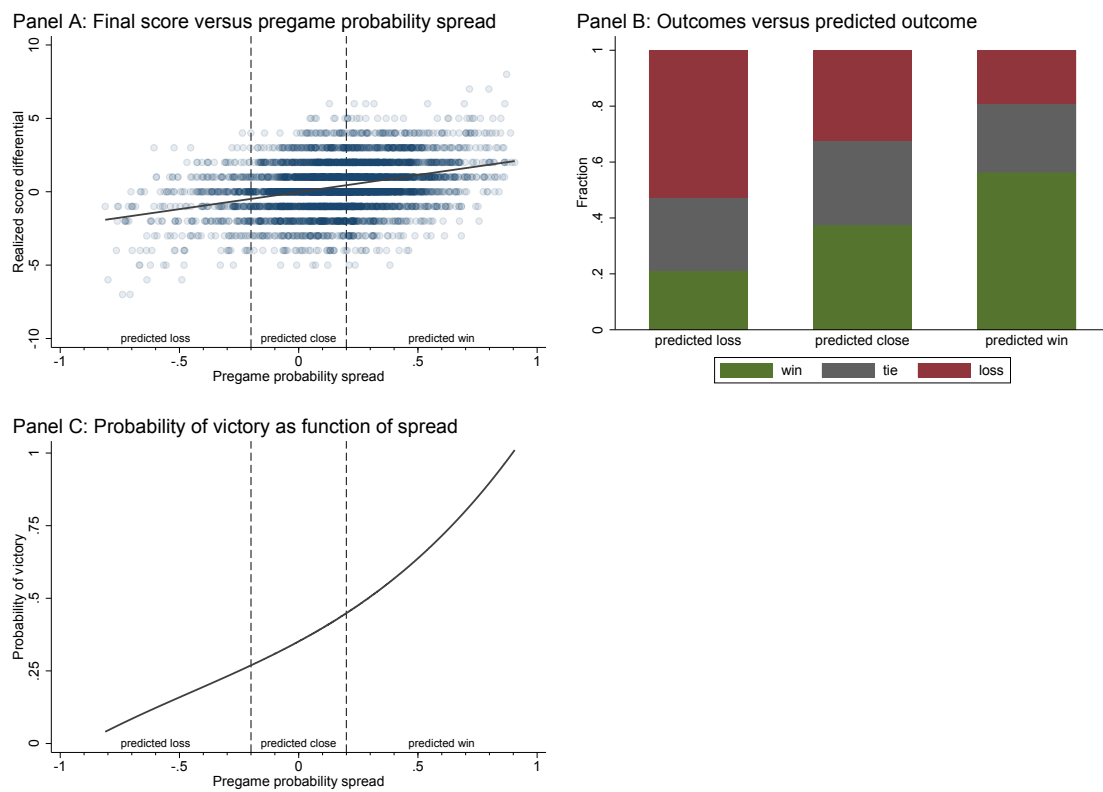
*Notes:* The figure depicts the frequency distribution of the most common criminal offenses in the Federal Republic of Germany in 2014. The most common offense type is simple willful bodily harm (224000), followed by threats (232300), and two forms of dangerous and serious bodily injury (222110 & 222010).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



**Figure A.2.** The stadiums

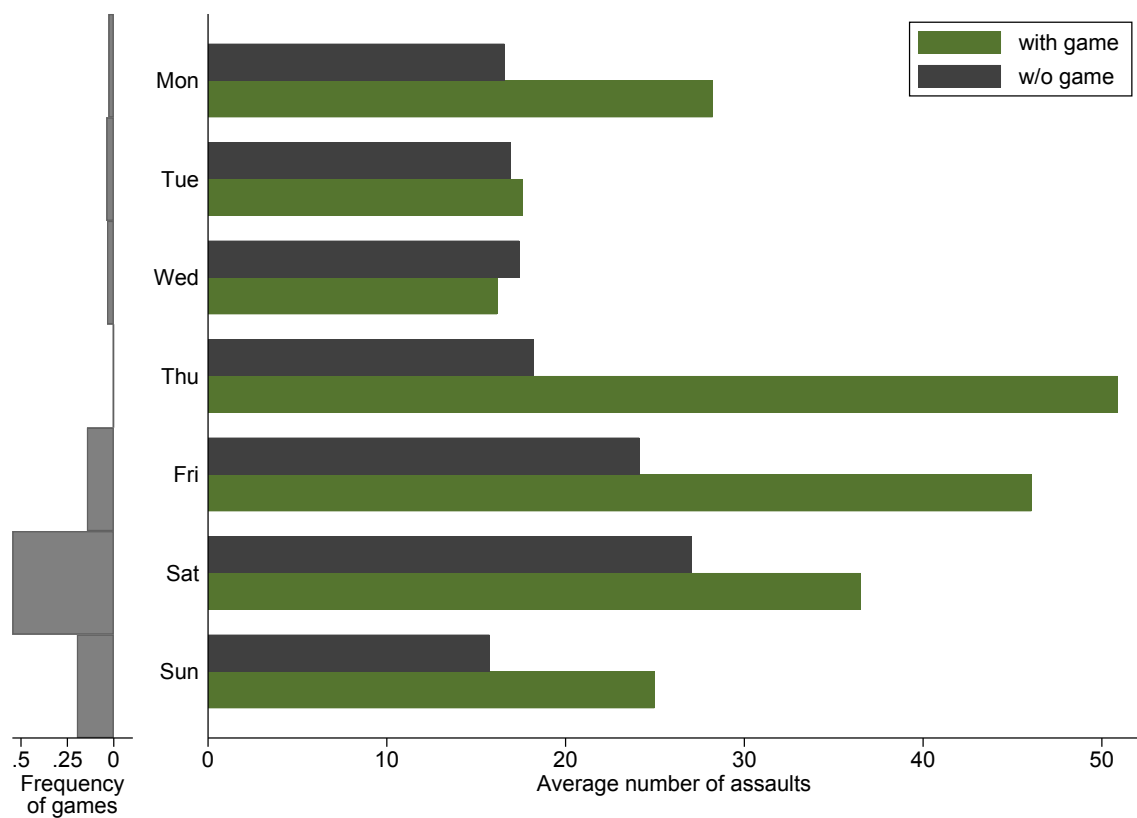
*Notes:* This map shows the stadiums used in the analysis over the seasons 2010/11 until 2014/15. The black outlines indicate federal state boundaries.

*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.** Average number of assaults on gamedays and days when 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 of the German football league system. The daily rates are shown for weeks in which a game is played and for weeks in which no game takes place.

**Table A.1.** Coding of various offenses

	(1) offense key	(2) § StGB
<b>Broadly defined assault</b>		
Simple willful bodily harm	224000	223
Negligent bodily harm	225000	229
Dangerous bodily harm	222010,222110	224
Grievous bodily harm	222020,222120	226
Brawls	222030,222130	231
<b>Resistance to enforcement officers</b>	621021,621029	113
<b>Threatening commission of serious criminal offense</b>	232300	241

*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.** 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 \(2020\)](#)