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Dirty Air, Dirty Play: The Effect of Air Pollution on Sabotage in Tournaments

Christian Grund
RWTH Aachen University and
IZA@LISER

Michael Hirsch
RWTH Aachen University

IZA@LISER NETWORK
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Abstract

In this study, we examine the influence of air pollution, measured by particulate matter concentration (PM_{10} and $PM_{2.5}$), on sabotage in rank order tournaments. To achieve this, we use player-level data from German *Bundesliga* players between 2009 and 2024, which we link with hourly pollution values on the exact match location and kickoff time. This research design addresses key identification problems in estimating the effect of air pollution on non-health outcomes. Our results suggest that an increase in particulate matter concentration has a statistically significant effect on destructive efforts (i.e. competitive sabotage), measured in fouls committed by a player. If particulate matter pollution measured in PM_{10}($PM_{2.5}$) increases by 10 $\mu g/m^3$, the number of fouls committed increases by 0.6% (0.9%). We also find strong evidence that this effect is driven primarily by players from weaker teams (underdogs).

JEL classification

M5, Q53, L83, J83

Keywords

air pollution, sabotage, tournaments

Corresponding author

Michael Hirsch
michael.hirsch@hrm.rwth-aachen.de

1. Introduction

Rank order tournaments are widely used in organizations. They take the form of hiring and promotion contests, competitions for bonuses, political and marketing campaigns, or sports tournaments (Chowdhury and Gürtler 2015). The core idea of tournaments is to create incentives that increase participants' motivation, effort, and performance by linking rewards to relative rather than absolute performance (Lazear and Rosen, 1981). However, the exclusive focus on relative performance and resulting ordinal ranks also creates incentives for counterproductive or destructive behaviour by harming the outcome of competitors in order to improve one's own relative position. This is discussed under the term sabotage in the literature as for instance in the review by Chowdhury and Gürtler (2015).[1] It has been shown that a variety of personal, situational or contest attributes encourage sabotage during a tournament (Piest and Schreck 2021). These include, for example, the amount of the tournament prize spread (Garicano and Palacios-Huerta 2005; Harbring and Irlenbusch 2011), the role of rivalry (Kilduff et al. 2016) or heterogeneity between competitors (Deutscher et al. 2013). Environmental influences, in particular air pollution during a tournament, are not yet included in this list. This lack of evidence is surprising, given that the negative effects of air pollution are known to extend far beyond human health. A growing body of research shows that exposure to air pollution can impair cognitive function, increase fatigue, stress, and irritability, and alter decision-making and behaviour, for example by affecting risk-taking (Klingen and Ommeren 2020), emotions (Balleer et al. 2025), and social preferences (Ming et al. 2022). These findings suggest that air pollution may systematically influence competitors' behaviour in tournaments. Since the combination between air pollution and sabotage activities in tournaments has not yet been studied, we aim to fill this gap by addressing the following research question: What is the impact of current air pollution on sabotage activities in tournaments?

A potential link between rising air pollution and sabotage activities can be traced through several mechanisms. Particles and gases enter deep into our bodies through our breathing and trigger adverse effects (Kim et al. 2015). In particular, particulate matter can cross the blood–brain barrier and accumulating in multiple regions of the brain (Zundel et al. 2022). There, the particles trigger oxidative stress and (neuro)inflammatory processes. These processes have been shown to cause emotional changes

[1] In line with the existing literature (e.g. Chowdhury and Gürtler 2015 or Piest and Schreck 2021), this paper uses the term 'sabotage' to refer to a deliberate, costly and illegitimate act intended to harm another tournament participant. This behaviour aims to improve one's own position by reducing the performance of an opponent. In the literature, such behavior is described as a destructive effort or sabotage (often used interchangeably). For the purposes of this paper, the two terms may also be considered synonyms.

in humans and animals (Liu et al. 2021) which are linked to aggressive and impulsive behaviour (Kouchaki and Desai 2015). Furthermore, it has been proven that air pollutants impair cognitive and physical abilities (Zivin and Neidell 2012; Ebenstein et al. 2016), with these negative effects being particularly pronounced for individuals who already start from a comparatively weaker baseline (e.g. Ebenstein et al. 2016; Künn et al. 2023; Mo et al. 2023; La Nauze and Severnini 2025). In tournaments with relative performance evaluation, where differences in abilities determine the ranking, such heterogeneous impairments are of crucial importance. Weaker participants lose disproportionately more potential than their stronger competitors, thereby widening the gap between the competitors. Under these circumstances, engaging in destructive activities may appear to be an effective means of closing the arising gap.

Taking possible mechanisms together, we hypothesize that higher levels of air pollution increase sabotage activities in tournaments. In addition, if the effects are primarily caused by unequal impairments in cognitive and physical abilities among competitors, the effect should be more pronounced among weaker participants.

We test these hypotheses in a sports context. Sports data are often used for tournament issues due to their relevance and the controlled setting (e.g. Grund et al. 2013, Deutscher et al. 2013, Schneemann and Deutscher 2017 or Gürtler et al. 2023). We use data from the German soccer *Bundesliga* and focus on rule violation in terms of foul play as a proxy for sabotage activities in a tournament. Within a *Bundesliga* season, both each individual match and the entire competition can be considered a tournament. In order to investigate the linkage precisely, we take the closest possible look. Specifically, we assign hourly particulate matter data (PM_{10} and $PM_{2.5}$) collected from the German *Umweltbundesamt* to each match.

The approach described offers several key advantages. Firstly, we obtain precise information about when and where sabotage activities take place, which enables us to avoid common problems associated with measurement errors. Secondly, with a few exceptions, the matches take place outdoors, which allows us to use data from nearby measuring stations. Thirdly, and most importantly, this approach allows us to observe a player at different times and in different locations. This in turn enables us to set up our data set as a player panel and exploit the variation in air pollution and players' sabotage activities at different times and in different locations in our estimation strategy. Finally, our approach offers the significant advantage that the allocation of players to match locations and times is determined exogenously by the *Deutsche Fußball Liga* (DFL), without any influence from teams or players.

Doing this we contribute to both tournament research and the effects of air-pollution. Previous work has addressed the relation between air pollution in competitive environments on performance (Künn et al., 2023; Mo et al., 2023). However, this is the first study to focus on sabotage. Methodologically, we use a research design that specifically addresses and minimises common problems in investigating the effects of air pollution on non-health outcomes such as measurement errors, omitted variables, strategic behaviour of participants and possible habituation effects (see Levinson (2020) and Aguilar-Gomez et al. (2022)). That way, we create evidence for a previously little-studied relationship and expand the existing literature with new, reliable findings.

Using a Poisson pseudo-likelihood regression model with high-dimensional fixed effects, we demonstrate that poor air quality, as measured by particulate matter levels, at the start of a *Bundesliga* match significantly increases the number of sabotage activities measured by the amount of fouls committed. For instance, an increase in hourly pollutant levels measured in PM_{10} ($\text{PM}_{2.5}$) of $10\mu g/m^3$ leads to 0.6% (0.9%) more fouls. Taking heterogeneity between teams into account, we show that the observed relation is primarily determined by players of relatively weaker teams (underdogs). This suggests that the effects are attributable to impaired cognitive or physical functions rather than generally triggered emotions. The results have passed several robustness checks. In addition, temporal and local placebo tests show that our approach of conducting local and temporally dense investigations is essential for discovering the actual linkage between air pollution and sabotage in tournaments. Finally, we show that the results are mainly caused by high pollution levels which exceed current regulatory limits.

Overall, our work complements the existing literature branch, which deals with the influence of air pollution on non-health outcomes. While the negative effects on human health are well documented (e.g. Kampa and Castanas 2008; Kim et al. 2015), a comprehensive body of literature is currently emerging on effects that go beyond the impact on physical and mental health. Among other things, research discovered a correlation between rising air pollution and trading (Lepori 2016), voting (Bellani et al. 2024) and consumer behaviour (Keiser et al. 2018), or well-being (Balleer et al. 2025).

In addition, our work complements existing literature on air pollution and unethical or criminal behaviour. Numerous studies have already been carried out in this area. Burkhardt et al. (2019), for example, show that a 10% increase in air pollution measured in $\text{PM}_{2.5}$ leads to a 0.14% increase in violent crimes per county in the United States. Such a potential relationship is established by various works for different pollutants and regions including London (Bondy et al. 2020), Chicago (Herrnstadt et al. 2021), New York and Mexico City, (Sarmiento 2023) or Almaty (Baryshnikova et al. 2019). While studies mentioned above examine criminal and unethical behaviour at the county, dow or city level, our data set allows us to examine the impact of air pollution on illegal behaviour at a personal level. To the best of our knowledge, there exist only two other studies which investigate the impact of air pollution on such a granular level. First, Lu et al. (2018) conduct three different laboratory experiments to investigate the effect of air pollution on unethical behaviour. However, instead of actual air pollution, they use perceived air pollution. In a second study, Gong et al. (2020) investigate how the actual daily fluctuations in air pollution affect the propensity for unethical behaviour measured in cyberloafing and clock-out collision.

Finally, and most importantly, we contribute to research investigating how environmental factors, particularly air pollution, impact the behaviour of tournament competitors. For example, Mo et al. (2023) find that increasing air pollution leads to a reduction in performance in e-sports, which particularly affects weaker teams. In a soccer context, Lichter et al. (2017) find that increasing levels of ozone and particulate matter reduce soccer players' productivity by reducing the number of passes they played per game. Next to this, Künn et al. (2023) investigate the influence of air pollution on the strategic behaviour of chess players. They conclude that a $10\mu g/m^3$ increase in indoor air pollution leads to a 2.1% increase in the probability of making an erroneous move. Also in a chess setting, Klingen and Ommeren (2022) conclude that increased levels of particulate matter are associated with an increased probability of a draw. While all the studies mentioned above estimate the impact of air pollution on an ability or performance level, the impact on sabotage activities as a possible counterpart, has not been taken into account so far.

The remainder of the study is structured as follows: first, we establish the theoretical link between air pollution and sabotage activities. In section 3, we describe the data. In section 4, we outline our empirical strategy. We then present our main results in section 5 before performing some supplementary analyses in section 6. Section 7 concludes.

2. Theoretical Considerations

Two complementary channels posit a positive relation between short-term exposure to particulate matter and sabotage activities: (i) an affective pathway that alters emotions and impulse control, and (ii) an ability-impairment pathway that reduces physical and cognitive performance.

Short-term increases in particulate matter can change human emotions and behaviour, in particular by fostering more impulsive and aggressive reactions. This link is supported by numerous empirical studies by economists and psychologists (e.g. Zhang et al. 2017; Lu et al. 2018; Herrnstadt et al. 2021; Bellani et al. 2024), although the exact physiological mechanism is not fully understood (Weitekamp and Hofmann 2021).

Mechanistically, particles in the air enter the human organism through breathing. Larger particles can settle in the upper respiratory organs and promote irritation, pain and discomfort (Zaręba et al. 2024), which are directly related to aggressive and affective behaviour (Anderson and Bushman 2002; Wang et al. 2023). Smaller particles penetrate further into the body. For example, particulate matter smaller than $2.5 \mu m$ can reach the alveoli of the lungs (Kim et al. 2015). Once there, they enter the systemic circulation through gas exchange (Fu et al. 2011). Through systemic circulation, they can reach the blood-brain barrier and even cross it, eventually accumulating in various regions of the brain (Block and Calderón-Garcidueñas 2009; Ehsanifar et al. 2021a). The immune system reacts to the infiltrated particles with neuroinflammatory processes and oxidative stress (Costa et al. 2017; Ehsanifar et al. 2021b), both of which are associated with anxiety- and depression-like symptoms in humans and animals (Salim 2014).[2] Consistent with this, Ehsanifar et al. (2021b) find a link between diesel exhaust and anxious as well as depressive behaviour in mice. Zhou et al. (2021) conclude that short-term exposure to pollutants increases the risk of visiting the ambulance in an anxious state, a result supported by the meta-analysis by Liu et al. (2021).

Anxiety, in turn, favours unethical and illegal behaviour by shifting decisions toward self-interest and away from moral principles (Kouchaki and Desai 2015; Zhang et al. 2020). Conducting a meta-analysis, Lu (2020) finds a positive correlation between increasing air pollution and unethical behaviour with state anxiety as the mediating channel.

Finally, short-term exposure to particulate matter is linked to rapid changes in messenger substances that can affect behaviour within minutes (Weitekamp and Hofmann 2021). Induced inflammation can stimulate the production of stress hormones such as cortisol (glucocorticoids) (Thomson 2019; Sun et al. 2022), which are associated with more aggressive behaviour (Haller 2022).

[2] Next to this, Coccaro et al. (2016) find evidence of a directly link between an increase in markers of oxidative stress and aggression in humans.

Based on the paths described above, we formulate

Hypothesis 1: Sabotage activities increase with particulate matter levels.

Beyond affective changes, short-term exposure to pollutants can lead to cognitive and physical impairments (Shehab and Pope 2019; DeFlorio-Barker et al. 2020). First, high pollution levels can reduce physical abilities, particularly due to irritation and inflammatory reactions within the lungs and the resulting reduction in oxygen uptake (Rice et al. 2013; Int Panis et al. 2017). In line with this, reduced physical performance is found among fabric and garment workers (Chang et al. 2016; Adhvaryu et al. 2022) and among athletes (Granella 2021) when short-term pollution increases. Second, the bodily changes caused by short-term air pollution affect cognitive functions. Oxidative stress, neuroinflammation and increased stress levels are linked to reduced cognitive abilities (Block and Calderón-Garcidueñas 2009; Ehsanifar et al. 2021). Increased exposure can also lead to a drop in haemoglobin levels (Li et al. 2021), impairing oxygen supply to the brain. Based on such influences, particulate matter can impair various cognitive functions, including visual information processing speed (Saenen et al. 2016), memory (La Nauze and Severnini 2025), switching costs (Mallach et al. 2023) and functional connectivity (Gawryluk et al. 2023). In line with these arguments, Laurent et al. (2021), using a comprehensive panel data set with 302 office workers from six countries, find a correlation between rising hourly indoor particulate matter ($PM_{2.5}$) and poorer performance in various cognitive tests.[3] Complementing this, Shehab and Pope (2019) conduct two experiments: in one, subjects are exposed to particulate matter from a burning candle for one hour. In the other, participants commute along a busy road for 30 minutes. In both experiments, the authors find a deterioration in the mini mental health test.

Cognitive impairment from short-term pollution is also evident in studies of cognitively demanding tasks, such as academic tests (Ebenstein et al. 2016; Gilraine 2025), the performance of professional baseball umpires (Archsmith et al. 2018) and chess players (Klingen and Ommeren 2022; Künn et al. 2023), as well as trading behaviour of investors (Huang et al. 2020).

Previous research emphasises that the aforementioned effects of particulate matter on performance are heterogeneous. Individuals with comparatively weaker task-relevant abilities appear to suffer more from increased short-term pollution than stronger ones. Using panel data from a brain training game, La Nauze and Severnini (2025) find that the effect of days with particulate matter levels above $25\mu g/m^3$ is stronger

[3] The indoor-outdoor ratio is closely related. Normally, it ranges from 0.6 to 0.9 (Chen and Zhao 2011).

among weaker game players, potentially exacerbating inequality in cognitive performance. Similar patterns arise in competitive settings. Künn et al. (2023) use the Elo rating of chess players to proxy ex ante ability and find that the influence of indoor particulate matter on the probability of making a serious mistake is larger among weaker players. In an e-sport contest, Mo et al. (2023) find that pollution at game time magnifies the gap in performance between teams by having a larger impact on weaker teams. Finally, Chang et al. (2016) provide further evidence by showing that increasing indoor particulate matter has a particularly negative impact on the productivity of packaging employees who already perform at a lower level.

Within a tournament, ex-ante (baseline) heterogeneity is amplified, as the unequal influence on participants leads to increasing differences in their abilities. Chen (2003) concludes in his theoretical model that increasing heterogeneity increases the incentives for sabotage of weaker against relatively stronger participants (favourites). In addition, empirical findings (e.g. Balafoutas et al. 2012; Deutscher et al. 2013; Deutscher and Schneemann 2017; Kempa and Rusch 2019) also show that greater performance differences within a competition are associated with an increase in sabotage activities, especially among relatively weaker participants (underdogs).

Taken these findings together, short-term particulate exposure leads to cognitive and physical impairment. These effects are heterogeneous. Those with relatively lower task-relevant abilities tend to suffer more, which widens performance gaps. In a rank order tournament, a widening heterogeneity between participants can increase incentives for sabotage activities. Weaker participants may seek to compensate for impaired abilities through destructive actions to maintain their chances of winning and close the arising gap. This leads to

Hypothesis 2: The effect of particulate matter on sabotage activities is particularly driven by (ex ante) underdogs.

3. Tournament Setting and Data

Having developed the conceptual framework and derived our two hypotheses, we next introduce the empirical setting that allows us to test them. We begin by outlining the structure of a typical soccer *Bundesliga* season and explaining why it provides an ideal tournament environment for analysing our research question. We then present the data sources underlying our analysis.

3.1. Tournament Setting

We rely on data from professional sports, the male soccer German *Bundesliga*. The 18 clubs playing in the *Bundesliga* generate total revenues of more than €5 billion during a season.[4] In what follows, we describe both the structure of a typical *Bundesliga* season and the course of an individual match. We also explain why both the season and the match level constitute tournament structures that are well suited to our empirical setting.

A *Bundesliga* season follows the structure of a double round-robin tournament and consists of 34 match days on which 18 teams compete in a home-and-away format, resulting in a total of 306 matches. Matches are usually played from August to May and interrupted only by a winter break. The exact schedule - match dates and stadiums - is determined by the DFL.[5] In doing so, the DFL considers a range of external constraints, including local authority requirements, major events, international competition calendars, broadcasting arrangements and regional holidays.[6]

Over the course of a season, each team aims to accumulate as many points as possible. Points are awarded after each match. A match winner earns three points, a draw brings one point for each team, and the losing team receives no points. Points are aggregated in a league table that ranks all teams relative to one another. Higher rankings at the end of the season are associated with valuable rewards. The league champion receives the German championship title, top-ranked teams qualify for international

[4] More information on the financial situation of the Bundesliga can be found at *www.dfl.de*.

[5] The DFL represents the interests of German professional clubs and consists of all clubs in the first and second German Bundesliga. As such, it organizes and markets the Bundesliga and 2. Bundesliga matches, among other things. For more information, see *www.dfl.de*.

[6] For more information about match scheduling, see: *www.dfl.de*

competitions, and league position influences revenue distribution from broadcasting rights. Conversely, the lowest-ranked teams are relegated to the second division.

In this sense, the league table represents an overarching rank order tournament. Teams compete for higher relative positions and the associated rewards, while simultaneously attempting to prevent rival teams from accumulating points.

A second tournament layer emerges at the match level. A standard match lasts 90 minutes, split into two halves of 45 minutes plus additional time. Two teams compete with 11 players each (one goalkeeper and ten outfield players). During a match, a coach can substitute up to 3 (until March 2020) or 5 (from May 2020) players from these 11 players and replace them with new players. Outfield players are broadly grouped into defenders, midfielders, and forwards, each with distinct tactical responsibilities. Defenders, for example, are positioned closest to their own goal and focus on preventing scoring opportunities of the opponent. Forwards operate near the opposing goal and attempt to create and convert chances. The objective of a team is to score more goals than the opponent. All on-field actions can thus be categorised as either creating scoring opportunities or preventing them. These actions can be in accordance with the rules or violate them. The referee evaluates each action and penalises violations of the rules (foul play) accordingly.

Consequently, an individual match constitutes a rank order tournament. The outcome is determined by relative performance. The team which scores more goals wins the match and earns three points. Players therefore choose actions with the aim of maximising their team's performance and increase the probability of winning the match.

The tournament structure of both the league and individual matches provides a well-defined framework for studying how short-term pollution affects behaviour. To examine this empirically, we combine detailed information on on-field actions with high-frequency environmental data. We describe these datasets in the following section.

3.2. Data

This section provides an overview of the data used in the analysis. It presents data on player behaviour as well as air pollution and other influencing factors.

3.2.1. Match Information and Player Behaviour

We have collected data on 15 Bundesliga seasons, starting with the 2009/2010 season and ending with the 2023/2024 season. Information on the respective matches was collected by the major German sports magazine *kicker.de*. The magazine provides us with relevant information about which stadium a match took place in, on what date and at what time. This information enables us to combine the air pollution data as precisely as possible with the player behaviour data. In addition, *kicker.de* offers further match-level characteristics, including the number of spectators, the identity of the teams' coaches, and the referee assigned to each match.

As outlined above, the aim of this study is to analyse behavioural response at the most granular level feasible. Consequently, we focus on the individual player as the central unit of observation rather than restricting our analysis to team- or match-level aggregates. Information on individual player behaviour is obtained primarily from the public domain *whoscored.com* which provides rich, match-based data on player actions and performance. This includes, for example, the number of shots taken, passes completed, and the type and direction of ball actions. Among all the available variables, we use the number of fouls committed by a player as a proxy for sabotage activities in a tournament. As discussed in section 3.1, the fundamental objective of the players in a match is to score more goals than their opponents. Player actions thus either aim to create scoring opportunities or to prevent the opponent from doing so. These actions may comply with the rules of the game or violate them. When a violation occurs, the referee interrupts the play and sanctions the behaviour as a foul. Fouls are considered as illegal behaviour by a player that is punished by the referee with a ball possession (free kick) for the opposing team. We assume in line with the current literature (e.g. Garicano and Palacios-Huerta 2005; Deutscher et al. 2013; Schneemann and Deutscher 2017) that the variable is a good proxy for sabotage within a tournament. Panel A of Table 1 provides a summary of the information collected on our chosen sabotage variable. A player commits about 1 foul per match. Furthermore, the development of the variable across all seasons can be seen in Figure B3. A reduction in the number of fouls committed across the entire observation period is evident. While an average of over 34 fouls were committed in a *Bundesliga* match during the 2009/2010 season, the number fell to just over 22 fouls by the 2023/2024 season.

Also, we use a number of match and player variables as controls for our empirical investigation. Our other collected match and player data are shown in panel B and C Table 1.[7] At the match level (n=2,686), we collect information on 31 teams. Of these teams, 7 played in the 1st *Bundesliga* over the whole period. The other teams played at least one season in a lower league.[8] Kick-off time of the most matches is 3.30 p.m. on Saturday. The matches were attended by an average of 38,717 spectators.[9] In addition to the match data, information on player behaviour can be found in panel C. We observe 2,037 different players. Goalkeepers are excluded from the sample because of a different style of playing. Overall, our sample contains 71,710 observations on player-match level. On average we have 35 observations for a player. For 14 players we have more than 200 observations, only 196 observations are singletons. Most players in our sample played as a defender. In addition, an average player in our sample is 25 years old and plays 67 minutes in the course of a match. During this time, he touches the ball 43 times.

Beyond the variables obtained from our main data domains, we supplement our dataset with externally sourced variables that are used in additional estimations and to improve the precision of our estimates. First, we collected information whether an opposing team is classified as a rival. Perceived rivalry can have a significant impact on behaviour during a match (Cikara et al. 2011). For example, Kilduff et al. (2016) find that the presence of a rival leads to an increased number of cards received in the Italian soccer league. The information about whether an opponent is classified as a rival comes from the news magazine Spiegel. Based on data from a survey conducted by Spiegel, we constructed a dummy variable that takes the value 1 if a team is considered a rival.

Finally, we gather information to assess the ex ante strength of each team in a given match. To this end, we collect the betting odds for all matches under consideration from the public domain *oddsportal.com*. Based on these odds, we compute the implied win probability of each team in every match following Deutscher et al. (2013). Specifically, we sum the inverse of the odds for a win, a draw, and a loss for a given team, remove the bookmaker's margin, and thus obtain the implied probabilities of a win, draw or a loss for a team in that match.

[7] We exclude two matches because they were interrupted during play and not resumed. In addition, we lose further matches because no pollutant or meteorological measuring stations were set up in the immediate vicinity of the stadium (see section 3.2.2).

[8] We provide an overview of the teams and stadiums available for a specific season, as well as the resulting observations in Figure B1 and Figure B2.

[9] It should be noted that the matches were played without or with less spectators during the coronavirus pandemic.

Table 1: Match Information and Player Behaviour

Variable	Mean	Std. deviation	Minimum	Maximum	Obs.
Panel A: Player information – Sabotage activities					
Fouls	1.0395	1.1701	0	10	71,710
Panel B: Match information					
Stadium attendance	38.71721	20.6659	0	80.72	71,710
Away	0.5000	0.5000	0	1	71,710
Rivalry	0.1061	0.3080	0	1	71,710
Wining probability	0.3790	0.1824	0.02	0.94	71,710
Matchday					
Monday (0/1)	0.0052	0.0719	0	1	71,710
Tuesday (0/1)	0.0268	0.1616	0	1	71,710
Wednesday (0/1)	0.0307	0.1724	0	1	71,710
Thursday (0/1)	0.0008	0.0277	0	1	71,710
Friday (0/1)	0.0993	0.2991	0	1	71,710
Saturday (0/1)	0.6331	0.4820	0	1	71,710
Sunday (0/1)	0.2041	0.4031	0	1	71,710
Kick-off between					
1:00–1:59 p.m. (0/1)	0.0038	0.0615	0	1	71,710
2:00–2:59 p.m. (0/1)	0.0004	0.0190	0	1	71,710
3:00–3:59 p.m. (0/1)	0.6290	0.4831	0	1	71,710
5:00–5:59 p.m. (0/1)	0.0718	0.2582	0	1	71,710
6:00–6:59 p.m. (0/1)	0.1322	0.3387	0	1	71,710
7:00–7:59 p.m. (0/1)	0.0072	0.0845	0	1	71,710
8:00–8:59 p.m. (0/1)	0.15564	0.3625	0	1	71,710
Panel C: Player information					
Minutes	67.2662	30.3124	1	90	71,710
Age	25.6444	3.8643	16	41	71,710
Defender	0.4291	0.4949	0	1	71,710
Midfielder	0.3107	0.4628	0	1	71,710
Attacker	0.2602	0.4387	0	1	71,710
Total touches	43.4908	26.1841	0	213	71,710

Notes: Sample period: Season 2009/10 to 2023/24. A descriptive statistic of our estimation sample is described. On average, the observation period per player is 35.2037 matches. Information about match characteristics was provided by kicker.de, Spiegel and. oddsportal.com Information about player behaviour (and sabotage activities) was provided by whoscored.com.

3.2.2. Air Quality and Meteorological Conditions

In addition to the information on the number of sabotage activities per game, the information on the actual air quality at the time of the game is the second key piece of information we need.

The information on actual air quality is provided by the German Federal Environmental Agency (*Umweltbundesamt* - UBA). In cooperation with the federal states, the UBA currently operates a monitoring network of over 380 stations spread across the whole of Germany. [10] The majority of these stations provide hourly information on different prevailing pollution levels. In addition to the high temporal resolution, the UBA also provides the exact coordinates of the measuring stations. This enables a close spatial and temporal connection between the data.

As mentioned before, our work focuses on particulate matter. Particulate matter refers to small particles in the air that have a diameter of less than 10 micrometres (PM_{10}) or even less than 2.5 micrometres ($PM_{2.5}$). These particles can come from a wide range of sources, including anthropogenic sources such as traffic, bios mass burning and industrial fuel combustion or natural sources such as organic aerosols, dust storms or volcanic eruptions. In addition, particulate matter can be produced by complex chemical reactions in the atmosphere (gas-to-particle conversion) (Zhang et al. 2015).

In addition to the data on particulate matter pollution, we also received information from the UBA on three gases: ozone (O_3), sulphur dioxide (SO_2) and nitrogen dioxide (NO_2). In our study, we use the three gases as a kind of natural placebo test. Although they can cause irritation at very high concentrations, they are not known to penetrate deep into the human organism or to affect the human brain - at least not to the same extent as particulate matter (Ishihara et al. 2025). [11]

One challenge is to spatially merge the collected data on air pollution with that of player behaviour. To achieve this, we use a buffer zone approach. To this end, we first draw a radius of 20km around each stadium. We then identify all the stations within the radius and calculate the distance to the stadium as the crow flies and subsequently use the inverse distance weighting (IDW) method to interpolate a pollution level on match-time at the stadiums. When calculating an interpolated value using IDW, it is assumed that nearby stations are more important than those further away.

[10] Further information on the prescribed number, location and management of the measuring stations can be found in the 39th BimSchV.

[11] A summary statistic of the additional pollution values is provided in Table A2.

The chosen method can be seen in Figure 1. It shows the stadium "Alte Försterei", the home stadium of FC Union Berlin located in Berlin. A radius of 20 kilometres was drawn around the stadium. The stations identified within the radius are marked with blue dots. A value was then determined for 3 p.m. on 06.08.2022. The match between FC Union Berlin and Hertha BSC took place at this time on this date.

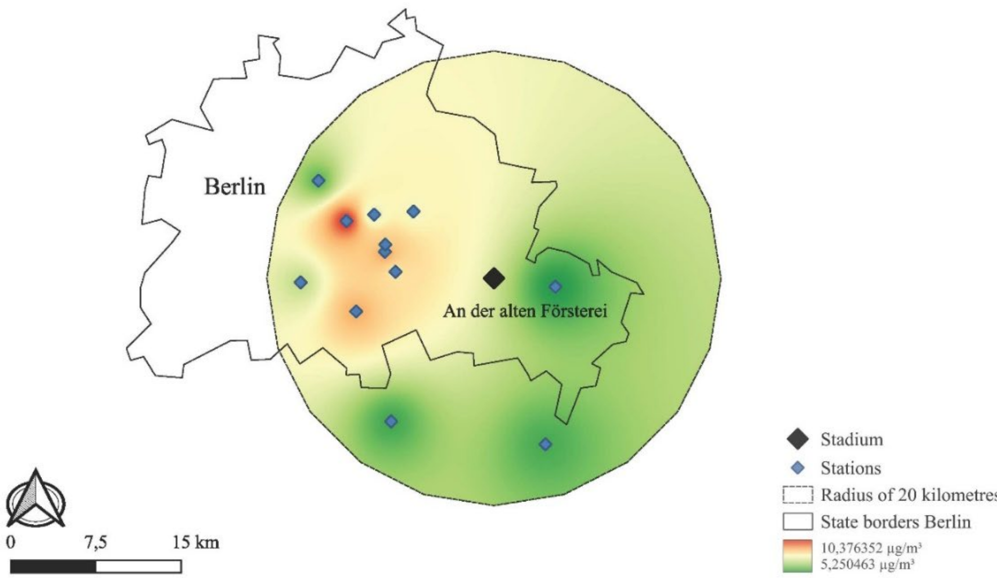

Figure 1: Application of the inverse distance weighting

Notes: Source: Authors. The application of inverse distance weighting can be seen. A radius of 20km (dashed line) is drawn around the "Alte Försterei" stadium (black diamond). All stations that measured PM_{10} at the hour of kick-off are shown (blue diamonds). The calculated value is 7.20835 $\mu g/m^3$.

The particulate matter pollution values determined at the time of kick-off are summarised in Table 2.[12] In addition, the development of the two main pollutants can be found in Figure B4. A decline in particulate matter pollution over time is evident. This applies to both $PM_{2.5}$ and PM_{10}. $PM_{2.5}$ pollution has has fallen by more than half from the 2009/2010 season ($16.0655 \mu g/m^3$) to the 2023/2024 season ($7.8306 \mu g/m^3$).

[12] It should be noted that PM_{10} and $PM_{2.5}$ are highly correlated (0.88).

Table 2: Summary Statistics on Air Pollution

Variable	Mean	Std. Deviation	Minimum	Maximum	Obs.
PM_{10} in $\mu g/m^3$	16.7941	13.1898	0.33812	170.124	71,710
$PM_{2.5}$ in $\mu g/m^3$	11.4018	10.5210	0.2678	135.8435	71,710

Notes: The data on air pollution comes from the German *Umweltbundesamt*. The pollutant load at the hour of impact is shown. All values were calculated using hourly pollution values and the buffer zone approach described above.

Finally, to investigate the relationship between air pollution and sabotage activities, it is necessary to take meteorological variables into account. Meteorological variables can influence both the prevalence of air pollution and the tendency to engage in an unethical or illegal behaviour. For example, temperature can both influence the formation of particulate matter and increase the tendency towards unethical activities. In line with this, Tiihonen et al. (2017) describe in their work that, ceteris paribus, an increase in temperatures of 2 degrees Celsius leads to a 3% increase in violent offences in Finland. In addition, higher temperatures also contribute to the formation of secondary particulate matter (Zhang et al. 2015). [13] Based on various studies, in particular those investigating the connection between meteorological conditions and criminal behaviour, we collect data for temperature, wind speed, precipitation and humidity at the time of kick-off.

The meteorological data required for this comes from the German Meteorological Service (*Deutsche Wetterdienst - DWD)*. The DWD monitors the prevailing meteorological conditions at a large number of stations on an hourly basis and also provides precise information about the location of each station. The selected variables were interpolated using the same procedure as for air pollution.

4. Empirical Strategy

Having described our dataset and its origins, in this section we will elaborate our empirical approach to estimate the impact of air pollution on sabotage activities in rank order tournaments. First, however, we discuss some of the challenges involved in estimating the impact of air pollution on a non-health outcome and explain why our chosen setting, our data collected and our estimation strategy allow us to overcome these obstacles appropriately. Finally, we present our estimation equations in this chapter.

[13] Secondary particulate matter consists of solid or liquid particles that are not emitted directly. They are formed by complex chemical reactions in the atmosphere from gaseous precursor substances.

4.1. Identification Strategy

When estimating the impact of air pollution on non-health aspects, several challenges need to be addressed. According to Graff Zivin and Neidell (2013), Levinson (2020) and Aguilar-Gomez et al. (2022), among these are (i) measurement errors, (ii) omitted variables, (iii) strategic behaviour and (iv) habituation. [14] Our identification strategy aims to tackle all these challenges simultaneously.

In order to estimate the effect of short-term air pollution on sabotage in tournaments, the actual and relevant pollution values must first be merged with the observations. This aggregation should take place at the finest possible spatial and temporal level. Only through close aggregation the temporal and spatial variation of air pollution can be correctly captured. Coarser local or temporal aggregations (e.g. on monthly, yearly or federal state level) would dilute a large part of the real variation of air pollution and lead to measurement errors and finally to a biased estimation. We demonstrate the necessity of close temporal and local control using Figure B6. We avoid this problem by focusing - as described in section 3.2.2 - on hourly pollutant levels measured in the immediate vicinity of the observation.

Next to a close monitoring to correctly record the variation, the selected data origin and the interpolation technique used are decisive to avoid measurement errors. In an ideal setting, there would be measuring devices within the stadiums that provide detailed information on pollution levels. As this is not the case, we use data from the UBA monitoring network. The UBA has a dense network of measuring stations that are set up and managed in accordance with EU directives. The guidelines provide precise information on the location and operation of the various measuring stations. We therefore assume that, due to its density and continuity, the network is suitable for interpolating the prevailing pollution at the stadium. We also assume that the interpolation method used is suitable. As described in section 3.2.2, we use the IDW to interpolate the data. Various studies have shown that the IDW is a suitable method for reliably interpolating large amounts of data (Ferreira et al. 2013). The technique leads to reliable results, especially in the context of dense measurement networks. It also appears to yield more reliable results than other interpolation methods such as ordinary or universal kriging (Vorapracha et al. 2015).

Finally, the use of compressed indices (e.g. the Air Quality Index) can lead to measurement errors within the estimate. The use of a composite index ignores the heterogeneity of the various exposure values

[14] Graff Zivin and Neidell (2013) and Levinson (2020) mainly refer to the difficulties involved in estimating the impact of air pollution on human well-being in their work. However, the concerns described there are identical to those in the study of air pollution on non-health outcomes and are therefore also highly relevant to this work (Aguilar-Gomez et al. 2022).

(Baryshnikova et al. 2019). As a result, possible drivers of effects are not clearly identified and the estimated coefficients are biased. In addition, some indices assign a higher weighting to the highest pollution value, which introduces additional noise into the estimate.[15] We therefore focus only on particulate matter that is currently considered to be the most politically relevant pollutant. However, by focussing on a single parameter, the effect of multiple stresses may be underestimated. We explore this possibility as part of our analyses and check for different types of pollutants at the same time as a robustness check.

The second challenge in the investigation is omitted variables bias. Various factors that influence the prevailing pollution levels can also have an impact on human behaviour. These include, for example, various meteorological variables as described in section 3.2.2 or geographical aspects such as the stadium where the observation takes place. To circumvent the problem of omitted variables, we use a variety of known variables from the literature that can have an impact on both the accumulation of air pollution and the tendency to engage in unethical activities. In addition, the panel structure of our player-level data allows us to account for appropriate fixed effects, such as stadium fixed effects, in our estimations. This in turn enables us to eliminate any time-constant unobserved heterogeneity resulting from omitted variable bias from our estimation. Thus, our setting enables us to eliminate time-persistent unobserved heterogeneity from our estimation, thereby addressing potential issues related to omitted variable bias.

A third challenge is that individuals can display strategic behaviour. Such behaviour can manifest itself in the form of avoidance and mitigation (Aguilar-Gomez et al. 2022). Individuals may be aversive to high exposure levels and choose their workplace and place of residence accordingly (Gruhl et al. 2025). This results in a non-randomised distribution of the persons under consideration. Strategic behaviour can also occur in a rather indirect way. Individuals often choose their place of residence and work based on characteristics such as job opportunities, local amenities or commuting costs. Such a bundle of residential characteristics may correlate strongly with the prevailing pollution levels, resulting also in a non-randomised distribution of individuals.

The challenges triggered by strategic behaviour can be almost completely avoided in our setting. Even if the place of work and residence is selected on the basis of the characteristics described above, only half of the possible observations take place at this location (stadium). The other half of the observations take

[15] See, Tan et al. (2021) for a recent survey of different methods to calculate an Air Quality Index.

place at external stadiums. In addition, the times when and where a match takes place are determined exogenously by the DFL, as described in section 3.1, and are not within the control of the respective player (Lichter et al. 2017). Therefore, avoidance and mitigation behaviour does seem to be impossible for the players within the sample and should therefore not influence our estimation.

A final potential methodological problem for empirical studies as ours is the aspect of habituation. People are able to adapt to persistent environmental stressors, so that in the long run, no clear effects on well-being or behaviour can be detected (Qin et al. 2022). To counteract these distortions, we use the approach of Levinson (2020) and Aguilar-Gomez et al. (2022) and focus on short-term, spatially high-resolution within-variations in air quality in our estimation. By exploiting differences in local pollution levels across time and space, we capture effects so that habituation processes can set in. This way, we minimise underestimation due to habituation and identify the immediate influence of air pollution on behaviour.

Considering these aspects together, we believe that we have adequately addressed the existing challenges in estimating the effect of air pollution on a non-health-outcome.

4.2. Baseline Equations

In the following section, we present our basic models. Our outcome variable, namely the number of fouls committed by player i in a stadium s at kick-off time k, is a non-negative count variable. In addition, we have a considerable proportion of 0 observations (41.03%) within our sample.[16] To adequately account for this, we use a Poisson maximum likelihood estimate with high-dimensional fixed effects.[17] This approach is in line with current literature on air pollution and crime (e.g. Bondy et al. 2020; Sarmiento 2023). For our identification we therefore exploit the variation in air pollution and the amount of sabotage activities for different individuals in different places over different periods of time. Our estimation equation can be visualised as follows:

$$\begin{aligned} Fouls_{iks} \;=\; & exp\{\beta_1 Pollution_{ks} + \beta_2 P_{ik} + \beta_3 M_{ks} + \beta_4 W_{ks} \\ & +\delta_i + \sigma_c + \lambda_r + \mu_p + \phi_{yt} + \kappa_{ms} + \varepsilon_{iks}\} \end{aligned} \tag{1}$$

[16] Figure B5 shows the distribution of the variable.

[17] We used the estimator from Correia et al. (2020). This allows for an appropriate handling of overdispersion and enables high-dimensional fixed effects to be included in the econometric model. We also estimated our baseline equation using a linear fixed effects model. The results remain constant. They are available upon request.

$Fouls_{iks}$ describes the number of fouls committed by a player in a specific match. Our variable of interest is $Pollution_{ks}$. It describes the prevailing pollution level, measured in one of the 2 variables (PM_{10} and $PM_{2.5}$), that was present in stadium s at kick-off time k. P_{ik} is a vector with various player characteristics, including his position, age, number of minutes played and number of ball touches. M_{ks} is a vector with various match characteristics. For example, whether the match was an away game for player i, how high the probability of the player's team winning was as well as a control for the kick-off time and the day of the week. W_{ks} is a vector with various metrological variables. We focus in particular on variables that can have an influence on both pollution levels and the tendency to commit a foul. As such, we include precipitation or temperature. Next to this, we control for the current humidity and wind speed at location s. All meteorological variables used by us are incorporated into our model in linear and in quadratic form.

Finally, we add a battery of fixed effects. δ_i are player fixed effects. In addition, referee-specific fixed effects (λ_r) are taken into account to reflect the individual assessment criteria of the referees. While some referees allow a more physical style of play, others penalise even minor contact or certain types of behaviour as foul play. Furthermore, we include match-pairing fixed effects (μ_p) to control for the game intensity between two teams. Next to this, we check for coach (σ_c), month-stadium (κ_{ms}) and team-season (ϕ_{yt}) fixed effects. Lastly, we cluster our standard errors at match level.

The use of player fixed effects is necessary to exclude temporally persistent characteristics (unobserved heterogeneity) from our estimation. In particular, there may be specific character traits or style of play that favour or discourage a tendency to engage in foul play. At the same time, this approach allows us to examine only the variation over time in different locations and circumvent some of the challenges mentioned in section 4.1. However, such use requires sufficient within-variation in the data. The within-variation of our sample is shown in Table A5. As can be seen, the number of fouls committed by a player varies on average by 1.09 regarding the standard deviation. Therefore, a substantial portion of the overall variation (1.17 fouls) can be attributed to the within variation. Therefore, there is sufficient variation within our sample, and our estimation strategy is appropriate to estimate the effect of air pollution on the fouls committed.

5. Results

In the following we present our results in two parts. In the first part, namely section 5.1, we demonstrate the effect of air pollution on sabotage in rank order tournaments based on our entire sample and using equation (1). In the second part, we finally examine whether, based on relative team strength, there are heterogeneous effects of air pollution on the number of fouls committed.

5.1. Baseline Results

Table 3 summarises the impact of the two types of pollutants on the number of fouls committed.[18] In columns (1) and (2) we estimate equation (1), but ignore all variables on the right-hand side except the respective pollutant levels. Both pollutant values show a significant correlation with the number of fouls committed. The coefficient in column (1) means that an increase in particulate matter pollution measured in PM_{10} of $10\mu g/m^3$ leads to an increase in the number of fouls committed in the amount of 3.5%. A somewhat larger relation is recognised for $PM_{2.5}$ (5%).

In columns (3) and (4), we add a set of various player and match covariates (e.g. minutes played, age, number of spectators, kick-off time and weekday dummies and away game). The estimated coefficients retain their statistical significance but decrease slightly in magnitude. An increase in particulate matter by $10\mu g/m^3$ results in 2.8% more fouls committed. By comparison, the estimated coefficient is quite close to that of an away game. According to the same estimated model, players commit 2.2% more fouls during an away game.

In columns (5) and (6), we add a defined set of metrological variables to our equation. As mentioned before, we use four different meteorological variables: air temperature, precipitation, humidity and wind speed at the kick-off time. All variables are included in linear and in quadratic form. The estimated coefficient hardly changes. The significant variables determined also remain unchanged.

Finally, in columns (7) and (8) we estimate our preferred specification. In this, we fully utilise the panel dimension of our sample and add various fixed effects to our estimation. On the one hand, we now use a battery of fixed effects including coach, referee, team-season, match pairing and month-stadium fixed effects. As described above, this allows us to control, for instance, for different tactical instructions by coaches, various influences within a given season, and different types of match management by referees. On the other hand -and most important-, we now also add player fixed effects to our estimation. In the following, we therefore identify the effect of air pollution on the amount of fouls committed by exploiting

[18] For simplicity, we have chosen not to report the coefficients of the control variables. Detailed information about the covariates are available upon request.

the within player variation only. However, this approach results in the loss of 394 observations, which are either singletons or those that were separated by the fixed effects used.

As we expected, the estimated coefficients become smaller. However, our two variables of interest retain their statistical relevance on a 10 and 5% level, respectively. The estimated coefficients show that an increase in particulate matter pollution measured in PM_{10} ($\mathrm{PM}_{2.5}$) of $10\mu g/m^3$ leads to an increase in fouls started of 0.64% (0.88%). The following example helps to understand these effect sizes: PM_{10} is 5.23 $\mu g/m^3$ at the 10th percentile of our sample, whereas it is $31.65\mu g/m^3$ at the 90th percentile. According to our estimates, a change from one to the other percentile leads to an increase of 1.7% more fouls per player. Alternatively, based on an average of 27.75 fouls per game, the increased particulate matter concentration content alone will result in 0.47 additional fouls during a game, ceteris paribus. [19]

Based on our results, we consider our initial hypothesis to be plausibly confirmed: The amount of sabotage activities in rank order tournament increases with particulate matter levels.

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[19] Our calculation example is based on the average number of fouls played in our sample. The fouls played by all players used (starting players and substitutes) were added up.

Table 3: Baseline Results - Fouls committed

	(a) Only pollution		(b) Add player & match covariates		(c) Add meteorological covariates		(d) Add fixed effects	
	PM_{10}	$\mathrm{PM}_{2.5}$	PM_{10}	$\mathrm{PM}_{2.5}$	PM_{10}	$\mathrm{PM}_{2.5}$	PM_{10}	$\mathrm{PM}_{2.5}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PM_{10} in 10 $\mu g/m^3$	0.0351***		0.0278***		0.0269***		0.0064*	
	(0.0049)		(0.0041)		(0.0042)		(0.0033)	
$\mathrm{PM}_{2.5}$ in 10 $\mu g/m^3$		0.0497***		0.0373***		0.0364***		0.0088**
		(0.0058)		(0.0048)		(0.0053)		(0.0042)
Pseudo R^2	0.0009	0.0011	0.0688	0.0689	0.0691	0.0692	0.1271	0.1271
Observations	71,710	71,710	71,710	71,710	71,710	71,710	71,316	71,316
Player covariates	No	No	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Match covariates	No	No	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Metro. covariates	No	No	No	No	**Yes**	**Yes**	**Yes**	**Yes**
Fixed effects	No	No	No	No	No	No	**Yes**	**Yes**

Notes: Sample period: Season 2009/10 to 2023/24. A Poisson maximum likelihood estimation was carried out to estimate the results. Standard errors are clustered at match level. $***$, $**$, and $*$ denote significance at the 1, 5, and 10 percent levels, respectively. *Player covariates* include position played, age, minutes played and ball touches. The *match covariates* include the day of the week dummies, kick-off time dummies, winning probability of the own team, number of spectators, away match and rivalry. *Metrological covariates* refer to precipitation, air temperature, wind speed and humidity. All meteorological variables enter the model in a linear and a quadratic form. Panel (d) does not include information about the player's position and the binary variable rivalry. In panel (d) the following fixed effects are estimated: player, coach, referee, team-season, month-stadium and match-pairing. Due to the use of fixed effects, 394 observations are not taken into account.

5.2. The Role of Relative Team Strength: Heterogeneity Matters

So far, our findings show that an increase in air pollution is accompanied by an increase in sabotage activities within a rank order tournament. However, it is still unclear whether this effect affects all players equally or whether it is mainly driven by players who play for the underdog. In the following section, we therefore focus on the possible heterogeneous effects of air pollution regarding the relative strength of the teams. For this aim, we use a proxy for the strength of the team in which the respective player plays. The proxy used is the winning probability of a team in a specific match which is calculated based on the betting odds of this match (Deutscher et al. 2013; Berger and Nieken 2016).

Based on the probability of winning, we construct a measure of the relative winning probability of the player's own team ($RelStr$). It is defined as the difference between the winning probability of the player's own team and that of the opposing team. Theoretically, this measure can take values in the interval $[-1,1]$. A value of -1 corresponds to a 100% probability of victory for the opposing team, while a value of $+1$ corresponds to a 100% probability of victory for the player's team. In our setting, the measure takes values between -0.91 and $+0.91$. We then transform the continuous measure ($RelStr$) into a categorical variable. Each observation is assigned to one of five groups, depending on whether the relative win probability in percent is less than -0.4 (Underdog, n=9,388), between -0.4 and -0.11 (slight underdog, n=18,095), between -0.10 and 0.10 (even, n=16,799), between 0.11 and 0.40 (slight favourite, n=18,075) and above 0.40 (favourite, n=9,353). Table 4 reports the corresponding estimation results.

In models (1) and (3), we include our created categorical variable with the favourites group as the baseline (at least a 40% higher probability of winning than the opponent) in our estimation equation. In both models, we see that slight favourites, equally strong opponents, and slight underdogs commit significantly more fouls than the favourite. However, the respective exposure coefficients remain virtually unchanged and hardly differ from the baseline effects shown in Table 3.

Table 4: Results based on Relative Team Strength - Fouls committed

	PM_{10}		$PM_{2.5}$	
	(1)	(2)	(3)	(4)
PM	0.0064*	-0.0028	0.0088**	-0.0002
	(0.0033)	(0.0073)	(0.0042)	(0.0092)
RelStr				
Baseline: Favourite				
Slight Favourite	0.0478**	0.0339	0.048**	0.0457*
	(0.0196)	(0.256)	(0.0196)	(0.0241)
Even	0.0387*	0.0185	0.039*	0.0254
	(0.227)	(0.0283)	(0.0227)	(0.0268)
Slight Underdog	0.0410*	0.0229	0.0411*	0.0303
	(0.0243)	(0.0291)	(0.0243)	(0.0278)
Underdog	0.0066	-0.0205	0.0071	-0.0221
	(0.0293)	(0.0338)	(0.0293)	(0.0325)
$RelStr \times PM$				
Baseline: $Favourite \times PM$				
Slight Favourite × PM		0.0078		0.0019
		(0.0088)		(0.0112)
Even × PM		0.0114		0.0114
		(0.0097)		(0.0117)
Slight Underdog × PM		0.0099		0.0088
		(0.009)		(0.0111)
Underdog × PM		0.0153*		0.0247**
		(0.0092)		(0.0108)
Pseudo R^2	0.1271	0.1271	0.1271	0.1272
Obs.	71,316	71,316	71,316	71,316
Player covariates	**Yes**	**Yes**	**Yes**	**Yes**
Match covariates	**Yes**	**Yes**	**Yes**	**Yes**
Metrological covariates	**Yes**	**Yes**	**Yes**	**Yes**
Fixed effects	**Yes**	**Yes**	**Yes**	**Yes**

Notes: See Table 3 for the controls and fixed effects used. The information on the probability of one's own team winning is not used in the estimate.

In models (2) and (4), we extend the estimation equation to include interaction terms between particulate matter exposure and relative team strength, so that the PM effect can differ between the strength groups. The PM coefficient in the first row now indicates the effect for clear favourites, while the interaction terms measure the deviations of the other groups from this. The results show that there is no statistically significant influence of particulate matter on the number of fouls committed by the favourite group. In addition, we find only clear underdogs experience an additional, significantly positive interaction effect, meaning that the overall effect of particulate matter is significantly greater for underdogs than for favourites.[21] Moreover, Table C1 reports the implied PM coefficients for the different strength groups. We find that only the estimated coefficient for the underdog group is statistically significant. According to this estimate, a $10\mu g/m^3$ increase in PM_{10} ($\mathrm{PM}_{2.5}$) is associated with about 1.3% (2.5%) more fouls committed by a player who played for the underdog.[22]

While this categorical specification is convenient for interpretation, a potential limitation is that the estimated effects may depend on the specific cut-off points used to define the strength groups (±10 and ±40 percentage points). To examine whether our findings are robust to alternative definitions of relative team strength, we therefore re-estimate the same model using (i) an alternative grouping into five categories that each contain approximately the same number of observations and (ii) a specification in which relative team strength enters as a continuous variable that is interacted with particulate matter exposure. The results of these robustness checks are presented in Table C3 and Table C7. Previous findings appear to be confirmed. The effect of particulate matter on the number of fouls committed is particularly driven by players from weaker teams, while no statistically significant influence can be detected among favourites.

Next to this, another limitation of our approach used so far is that when using betting odds, we assume that air-quality forecasts are not priced into them. A violation of this assumption could lead to an endogeneity problem. To address this concern, we conducted two additional checks using other proxies for the relative strength of a team. First, we use team's market values. The market values are collected from the public domain source *transfermarkt.de*. They reflect the average market value of a team over a season and represent a long-term, relative assessment of the players' expected quality. They can be regarded as exogenous with respect to air-quality forecasts. However, unlike betting odds, they could not account for short-term shocks (e.g., player injuries or strong/weak performance in recent matches) that may influence a particular game. Therefore, we also use the Elo rating derived from *clubelo.com* to control for differences regarding the relative strength between the two teams. Elo is a dynamic measure of team strength calculated from actual match results and therefore reacts much more quickly to

[21] Table C2 provides an overview of the Wald test investigating whether the PM effects differ significantly across strength groups.

[22] Because we estimate the models using the high-dimensional fixed-effects Poisson estimator of Correia et al. (2020), the numerous fixed effects are not stored as coefficients and Stata's margins command will not lead to consistent results. Therefore, these are not reported.

fluctuations in abilities than market values. We repeated our described procedure for both variables. The results are shown in Table C8 and Table C10. The estimated coefficients reconfirm the previously estimated effect.

Taken together, the results reveal that the effect of particulate matter on the number of sabotage activities is predominantly driven by players from the underdog teams, which is in line with our second hypothesis. Relatively weaker participants suffer more from particulate matter exposure than relatively stronger participants. This leads to a growing performance gap between participants. Weaker participants try to compensate for this gap through sabotage.

With regard to the underlying mechanism, we interpret our findings as follows. We consider it implausible that purely emotional influences caused by particulate matter can fully explain the observed results. If particulate matter primarily affected mood or affective states (e.g. aggression triggered by anxiety), we would expect to see similar behavioural changes in all participants, regardless of their relative strength in the competition. Our results, however, suggest that the increasing performance gap between participants is central to the effects found. Exposure to particulate matter leads to cognitive and/or physical impairments that relatively weaker participants are less able to compensate for. This widens the performance gap between strong and weak participants, and the weaker ones try to close this gap through increased sabotage activities (foul play). At the same time, our findings do not entirely support the conclusion that particulate matter has no emotional impact at all. It is conceivable that emotional and performance-related channels work together. Particulate matter could increase aggression and the general willingness to engage in sabotage activities among all players. However, since it simultaneously impairs performance and widens the gap between stronger and weaker participants, underdogs feel a particularly strong incentive to reduce the discrepancy through foul play, while from the favourites' point of view, the growing gap reduces the need for foul play, as their chances of winning are already improved by their superior performance. However, since we find no effect of particulate matter pollution on the number of fouls committed in the group of equally strong teams (Even group), we suspect that cognitive and physical impairments - largely unrelated to emotional distress - are primarily responsible for the observed effects.

6. Supplementary Analysis

In order to verify and better assess the results obtained so far, we carry out some supplemental analyses and robustness checks in the following section. Among other things, we focus on the complexity of the game facets, spatial-temporal granularity, other pollutants and non-linearity.

6.1. Match Complexity

First, we check whether our empirical strategy can fully capture the complexity of the game. One initial concern is that we have not fully taken into account the complex structure of a team sport in our analysis. It is possible that a sabotage action performed by one player may be triggered by teammates. Such spillover effects may not have been adequately captured due to the strong focus on the individual player level. In order to control for these possible interaction effects, we re-estimate the relation between particulate matter on the team and the match level (models (1) to (4) of Table 5). The results are robust to the baseline estimation on the individual level above.

Another concern relates to the role of the referee. Refereeing decisions can have a substantial impact on the course of a match and may themselves be subject to systematic distortions. For instance, if the referee's perception and judgement are impaired by ambient air pollution (Archsmith et al. 2018). To ensure that our results are not attributable to particulate matter-induced impairment of the referees, we apply a sample restriction. Based on the referee ratings awarded by the renowned German sports magazine *kicker.de*, we limited our sample to referees whose performance in a certain match was rated as satisfactory to very good (1 to 3 on a five point scale) which applies to 61% of our observations. This allows us to ensure that our sample does not include any observations from matches in which serious mistakes were made by the referee or in which the referee performed poorly. The results obtained from our subsample analysis are shown in column (5) and (6) in Table 5. As can be seen, the significant positive effect on the number of fouls committed remains.

Based on the results obtained, we find no evidence that the correlation between particulate matter and the number of fouls committed is systematically distorted by particulate matter-induced influence on the referee nor by a failure to take into account interaction effects between individual players.

Table 5: Air Pollution and Match Complexity

	Team-level		*Match-level*		*Referee Performance*	
	PM_{10}	$PM_{2.5}$	PM_{10}	$PM_{2.5}$	PM_{10}	$PM_{2.5}$
	(1)	(2)	(3)	(4)	(5)	(6)
	0.0071**	0.0106**	0.0072**	0.01094**	0.0105**	0.0102*
	(0.0034)	(0.0044)	(0.0033)	(0.0054)	(0.0048)	(0.006)
Pseudo R^2	0.1167	0.1167	0.1597	0.1596	0.1333	0.1333
Obs.	5,351	5,351	2,513	2,513	43,332	43,332
Match covariates	Yes	Yes	Yes	Yes	Yes	Yes
Metro. covariates	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: See Table 3 for the controls and fixed effects used in model (1) and (2). We used a subjective rating system from *kicker* to exclude referees from our sample whose performance was not at least 'satisfactory'. The models (3) - (6) include the following match controls: Number of spectators, day of the week and the kick-off time. The team-level model also controls for the probability of a team winning. The weather controls are the same as in the baseline model. The following fixed-effects are used for the team-level model: team, coach, referee, season, month×stadium and match-pairing. The match-level model contains: referee, season, month×stadium and match-pairing fixed effects. We lose 21 (173) observations on team-level (match-level) that are either singletons or separated by a fixed effect.

6.2. Placebo Test

In addition, to further validate our findings and highlight the importance of our spatial and temporal granular approach, we conducted a total of five placebo tests, four temporal and one spatial. If we link the dependent variable, in this case the number of fouls committed, with a randomly assigned and therefore falsified air pollution value, we should not be able to detect any measurable systematic effect. Otherwise, there would be reason to suspect that our main results were based on measurement errors or incorrect assignments. For the temporal placebos, we re-estimated equation (1), but replaced the actual pollutant exposure with measurements recorded one year or one month before or after the respective kick-off time. We applied the same procedure to all meteorological control variables. The results of these four re-estimations are documented in Table 6: none of the estimated pollutant coefficients show statistical significance. Furthermore, some of the coefficients determined have a negative sign. In addition, we conducted a spatial placebo test. Here, we replaced the measured air pollution at the match stadium with the values recorded at the same time at the visiting team's stadium. In this scenario, too, the correlation with the number of fouls remains statistically insignificant.

The consistent absence of effects in all placebo configurations confirms that our main results are not driven by misattributed environmental measurements or other distortions. At the same time, the test underscores the need to link air quality data as precisely as possible to observations in terms of space and time in order to minimise measurement errors and to demonstrate credible links between sabotage activities and rising pollutant levels.

6.3. Other Pollutants

Further, we check for the influence of other pollutants. On the one hand, this serves as an additional natural placebo test. Since we assume that the effects found are mainly caused by deep infiltration of the human organism and a resulting effect on the human brain, we should not detect any effects from other types of pollutants. On the other hand, this serves as a possible control to check whether focusing on one pollutant leads to possible joint effects being underestimated (Baryshnikova et al. 2019).

In a first step, we estimate the isolated influence of various pollutants on the number of fouls committed. The results are shown in panel (b) of Table 6. We find no significant effect for O_3, SO_2 or NO_2. The fact that no effect is found for O_3 is surprising given that various studies have established a link between rising ozone levels and reduced serotonin levels, which in turn can lead to more impulsive and aggressive behaviour (Burkhardt et al. 2019). However, it once again supports the assumption that cognitive or physical impairment is the cause of the effects found and not generally more aggressive behaviour.

In a second step, we include most of the pollutants in our equation. Only PM_{10} is not taken into account due to its high correlation with $PM_{2.5}$. The results can be seen in column (4). The influence of all pollutants leads to a significant reduction in the number of our observations. Only those player observations can now be taken into account in which all four pollutants and the selected meteorological variables were measured within a 20km radius. Nevertheless, the results obtained can be confirmed. We only find a statistically significant correlation between particulate matter measured in $PM_{2.5}$ and the number of fouls committed. We do not find such a correlation for any of the other pollution values. The estimated coefficient in the joint estimation is also higher than that of our baseline model.

6.4. Different Radii

Next to this, we examine the influence of our chosen buffer zone approach. In our baseline analysis, we included all stations located within a 20km radius of the stadium in our estimate. We consider the set radius to be a good compromise. Larger radii would possibly not correctly consider the prevailing local pollution, as the distance of the stations to the stadium is too far. However, a closer radius would reduce the size of our sample. In addition, a smaller radius could mean that important sources of particulate matter, such as major roads, are not taken into account.

To check the influence of the selected radius, we execute equation (1) again. However, we now only use data on air pollution that we have interpolated from stations within a radius of 5, 10, 15 or 50km around the stadium. Next to this, we have not further adjusted the radius for the meteorological variables in the estimates. Especially for smaller radii, the overlap between weather and pollutant stations is very small and would further burden our sample size. The results are shown in panel (c) of Table 6. Essentially, we can conclude that our results are stable regardless of the radius selected. Increasing particulate matter levels lead to more fouls being committed. Only for $PM_{2.5}$ and the control for a radius of 5km we do no longer find a statistically significant correlation. However, it should be noted that our sample size is also reduced by about half the number of observations compared to the baseline model (38,271 versus 71,316).[23]

[23] We performed the estimation for 10, 15, 20 and 50 kilometres once again using only the observations that are included in the 5km radius sample. We did not find any significant results. Accordingly, the effects that were not found may be due to an insufficient sample size.

Table 6: Placebo Test, Other Pollutants and Different Radii

Panel (a): Placebo test					
	Time placebo (t_{+360}) (1)	Time placebo (t_{-360}) (2)	Time placebo (t_{+30}) (3)	Time placebo (t_{-30}) (4)	Local Stadium Swap (5)
PM_{10} pollution ($\mu g/m^3$)	-0.0026	0.0022	-0.0017	-0.0025	0.0054
	(0.0038)	(0.0033)	(0.0033)	(0.0033)	(0.0042)
Pseudo R^2	0.1261	0.1270	0.1271	0.1271	0.1288
Observations	64,454	70,177	70,995	70,807	49,564
$PM_{2.5}$ pollution ($\mu g/m^3$)	-0.0067	0.0033	0.0033	-0.0025	0.0044
	(0.0048)	(0.0043)	(0.0045)	(0.0033)	(0.0065)
Pseudo R^2	0.1262	0.1271	0.1271	0.1271	0.1293
Observations	64,817	67,109	71,003	70,807	43,172
Panel (b): Other pollutants					
	SO_2 (1)	NO_2 (2)	O_3 (3)	All together (4)	
SO_2	0.0105			0.0065	
	(0.0105)			(0.0105)	
NO_2		0.0035		0.0026	
		(0.0033)		(0.0041)	
O_3			-0.0028	-0.000007	
			(0.0027)	(0.0034)	
$PM_{2.5}$				0.0145***	
				(0.0052)	
Pseudo R^2	0.1307	0.1271	0.1275	0.1315	
Observations	48,137	71,316	70,310	47,257	
Panel (c): Different radii					
	5 kilometres (1)	10 kilometres (2)	15 kilometres (3)	Baseline (4)	50 kilometres (5)
PM_{10} pollution ($\mu g/m^3$)	0.008*	0.0057*	0.0062*	0.0064*	0.0062*
	(0.0044)	(0.0034)	(0.0033)	(0.0033)	(0.0033)
Pseudo R^2	0.1303	0.1267	0.1267	0.1271	0.1272
Observations	37,179	65,517	67,929	71,316	71,316
$PM_{2.5}$ pollution ($\mu g/m^3$)	0.0074	0.0083*	0.0093**	0.0088**	0.0086**
	(0.0057)	(0.0045)	(0.0045)	(0.0042)	(0.0043)
Pseudo R^2	0.1315	0.1270	0.1270	0.1271	0.1272
Observations	38,271	65,670	66,034	71,316	71,316

Notes: See notes in Table 3.

6.5. Dose Response Function

In addition, we check whether the relationship between particulate matter concentration and the number of fouls committed is non-linear. To this end, we categorize the continuous exposure variable into five groups, whose threshold values are based on the applicable daily limits. The German environmental authority (*Umweltbundesamt*) states that the PM_{10} concentration should not exceed 50 $\mu g/m^3$. We therefore classified all particulate matter values above 50 $\mu g/m^3$ in the highest group. As there is currently no binding daily limit value for $\mathrm{PM}_{2.5}$ at federal level, we used the annual limit value of 25 $\mu g/m^3$ for our highest category.[24]

The results are shown in Table 7. They prove that the negative effect is almost entirely due to observations above the limits - for both $\mathrm{PM}_{2.5}$ and PM_{10}. In particular, concentrations above 25 ($\mu g/m^3$) ($\mathrm{PM}_{2.5}$) and 50 ($\mu g/m^3$) (PM_{10}) drive the effects found. We find a negative, albeit not statistically significant, effect for lower pollution levels. Furthermore, we do not find a steady linear correlation for PM_{10} and for $\mathrm{PM}_{2.5}$.

Table 7: Particulate Matter and Sabotage: Non-linear Models

	PM_{10} (1)		$\mathrm{PM}_{2.5}$ (2)
Baseline Group: <10 $\mu g/m^3$		*Baseline Group:* <5 $\mu g/m^3$	
10 < 20 $\mu g/m^3$	-0.034	5 < 10 $\mu g/m^3$	0.0312
	(0.1046)		(0.1118)
20 < 30 $\mu g/m^3$	-0.0169	10 < 15 $\mu g/m^3$	-0.3244**
	(0.0134)		(0.1388)
30 < 50 $\mu g/m^3$	0.0243	15 < 25 $\mu g/m^3$	-0.0368
	(0.0158)		(0.1381)
>50 $\mu g/m^3$	0.0679***	>25 $\mu g/m^3$	0.3412**
	(0.0239)		(0.1717)
Pseudo R^2	0.1271		0.1272
Obs.	71,316		71,316

Notes: See notes in Table 3.

[24] The legal limits differ from the stricter recommendations of the WHO. An adjustment of the EU limits is planned for 2030.

6.6. Yellow Card Received

Finally, we use the information about whether a player has received at least one yellow card in a game as an alternative measure of sabotage in a competition.[25] Since this is a binary variable (1=player received at least one yellow card) we adjust our estimation strategy accordingly and apply a binary probit model. Since the use of a probit model does not allow time-persistent characteristics to be excluded from the estimation, we follow a correlated random effects approach and the recommendations of Mundlak (1978) by including the means of the explanatory variables in the estimation. In this way, we can at least control for unobserved heterogeneity.[26]

Table 8: Air Pollution and Yellow Card Received

Variable	PM_{10} (1)	$PM_{2.5}$ (2)
PM	0.0088*	0.0088
	(0.0053)	(0.0069)
Average marginal effect	0.0018*	0.0018)
	(0.0011)	(0.0014)
Mean PM	0.0382	0.05817
	(0.0479)	(0.0628)
Average marginal effect	0.0079	0.0120
	(0.0099)	(0.0120)
Obs.	71,710	71,710
Player covariates	Yes	Yes
Match covariates	Yes	Yes
Metrological covariates	Yes	Yes
Fixed effects	Month, Season, Stadium and Referee	Month, Season, Stadium and Referee

Notes: See Table 3 for the controls and fixed effects used in model (1) and (2). No match pairing fixed effects and referee fixed effects are included in the models. Instead, we used our rivalry control. The figure shows the coefficients and average marginal effects of random-effects probit regression. The standard errors are clustered on player level.

[25] Serious fouls or offences are punished with a yellow card. They are a disciplinary measure for cautionable behaviour, such as hard foul play, time wasting, protesting, unsportsmanlike behaviour or repeated violations of the rules of the game. If a player receives two yellow cards, he is sent off and cannot be replaced by a teammate. A summary statistic of the variable can be seen in Table A5.

[26] In addition, due to the considerable computational effort involved, we excluded match-pairing fixed effects from our estimation compared to our baseline equation. Instead, we use our rivalry dummy variable. For the same reasons, we also exclude the fixed effects for month-stadium, and team-season, and remove the coach fixed effect. Our estimate is now based on the most relevant fixed effects for: stadium, month, season, and referee. The results obtained should therefore be interpreted with caution.

The results are shown in Table 8. We find only a statistically significant relationship between current particulate matter pollution measured in PM_{10} and the probability of receiving a yellow card. However, for $PM_{2.5}$ the estimated coefficients is statistically insignificant but suggest a positive correlation between particulate matter and receiving a yellow card.[27]

One possible interpretation of the results is that increased particulate matter pollution leads to more fouls during a game. However, the quantitative increase is not so large at the individual level that referees are significantly more likely to issue a warning (yellow card) in a game. Furthermore, there is no indication that the severity, i.e., the quality of the fouls committed, has increased. The additional fouls committed are not harder and are not punished more severely. This would be consistent with our thesis that fouls are due to cognitive and physical impairments and not to a general increase in aggression. Significantly more aggressive behaviour would have to be reflected in a clear increased number of yellow cards.

7. Discussion and Conclusion

In this paper, we examine whether short-term fluctuations in particulate matter pollution influence the extent of sabotage activities in rank order tournaments. We link hourly information on local particulate matter concentration and weather with individual behavioural data from soccer players in the German *Bundesliga* over 15 years.

In addition to circumventing key challenges in investigating the effects of air pollution on non-health-related outcomes, our empirical approach offers several advantages. First, we can structure our data set as a panel data set at player level. This allows us to estimate the short-term effect of particulate matter on individual behaviour in detail. Second, the observations are determined exogenously by the match schedule set by the DFL. Individual players have no influence on when, where and at what kick-off time they enter the competition. Third, using various appropriated fixed effects our identification relies on the variation in pollutant exposure to which the same individual is exposed across different locations and times.

[27] One possible bias in our estimation could arise from the fact that our dependent variables are so called *"rare event"* variables. In this sense, of all observations in our sample, only 13.5% of observations show a 1 for yellow cards. This could lead to distorted coefficients, among other things. In their model simulation, however, Woo et al. (2023) conclude that such biases are more likely to occur in smaller samples under 500 observations. Since the size of our sample in the preferred baseline estimates is not less than 70,000 observations, we assume that we do not have to worry about such biases when checking if a player received a yellow card.

Using a conservative approach, we conclude that there is a link between particulate matter pollution and the occurrence of sabotage activities in the context of a tournament. A 10 $\mu g/m^3$ increase in air pollution measured in PM_{10} ($PM_{2.5}$) is associated with an increase of approximately 0.7% (0.9%) additional fouls per player in a soccer match. In line with our theoretical considerations, this effect is particularly evident among players from weaker teams (underdogs), who appear to react more strongly to environmental stressors. With regard to the underlying mechanism which drives our results, we have formulated two central arguments in our theoretical derivation. First, air pollution can lead to emotional distress, which promotes aggressive behaviour. Secondly, higher levels of pollution have a greater impact on the cognitive and physical abilities of less capable participants, leading them to engage in more sabotage activities in order to compensate for competitive disadvantages. Our empirical results suggest that the second mechanism is the more relevant one. A predominantly affective response to air pollution should have led to behavioural changes in all players observed, regardless of their team's strength. However, we find that the effects are mainly driven by players from the underdogs. This in turn suggests that the cognitive or physical impairments caused by air pollution are stronger for players who played for the underdog or that the effects can be compensated more easily by players from stronger teams, while the corresponding compensation options are limited for weaker players. The resulting additional difference between the teams increases the performance heterogeneity among the participants. Ultimately, weaker participants attempt to close this gap through more sabotage activities.

Our findings expand on existing tournament research. Existing research has already identified a number of determinants that can influence whether participants conduct sabotage in a rank order tournament. However, ecological factors and air pollution in particular have not yet been considered as relevant determinants. Building on medical, biological, psychological and economic findings, we show that these dimensions should be added to the existing list. Although there are various studies that deal with tournament-related issues and the influence of ecological factors on ability or performance levels, these mainly focus on reductions in cognitive or physical abilities reductions and hardly ever on their heterogenous consequences for strategic or moral behaviour. Mo et al. (2023), for example, show that air pollution distorts strategic decision-making behaviour from weaker participants and thus increases differences between participants. Künn et al. (2023) conclude that increasing particulate matter pollution impairs the cognitive performance of chess players. Less experienced players suffer more from air pollution. According to the authors, this exacerbates existing inequalities between players. While the aforementioned research ends here, we can supplement that weaker players resort to sabotage activities in order to close the gap.

The results of this work have been found in a country where regular pollution levels are comparatively moderate. In 2023, for example, all measuring stations were below the EU limits for the daily average value of PM_{10}.[28] Against this background, it seems plausible that our findings can be transferred to various real-life contexts. Particularly relevant are situations in which competitive conditions prevail, participants are exposed to a certain level of pollution, and there are incentives or opportunities for sabotage. In such settings, the positive effects of tournament incentives could be mitigated by the additional stress and its potentially cognitively impairing effects. Furthermore, our findings can also be applied to work environments that require a high level of cognitive or physical performance. Particularly relevant here are activities whose demands are like those of professional players. These include, for example, planning, memory and decision-making (Bonetti et al. 2025). In this sense, the activities of highly skilled office workers could be particularly susceptible to negative influences.

[28] For more Information, see umweltbundesamt.de.

A Additional Data

Table A1: Description of all Variables

Variable	Description
Dependent Variables	
Foul	The number of fouls committed by a player in a given match
Yellow card	Binary variable that is equal to one if a player has received at least one yellow card in a given match
Pollution Variables	
PM_{10}	Particulate matter with a size smaller than $10\mu m$ measured in $\mu g/m^3$
$PM_{2.5}$	Particulate matter with a size smaller than $2.5\mu m$ measured in $\mu g/m^3$
SO_2	Sulphur dioxide pollution measured in $\mu g/m^3$
O_3	Ozone pollution measured $\mu g/m^3$
NO_2	Nitrogen dioxide pollution measured in $\mu g/m^3$
Player Information	
Age	Age of a player in years at the time of the respective match
Minutes	Minutes a player has played in a match (not including extra time)
Attacker	Binary variable that is equal to one if the player is regularly used as an attacker
Midfielder	Binary variable that is equal to one if a player is regularly used as a midfielder
Defender	Binary variable that is equal to one if a player is regularly used as a defender
Touches	Number of ball touches by a player during his playing time in a match
Match Information	
Winning Probability	The ex ante probability of a player's team winning
RelStr	Relative probability of winning compared to opposing team
Team market value	Market value of a player's team in a season
Elo-Rating	Elo rating of a player's team before a match
Spectators	Number of spectators measured in 1,000
Away	Binary variable that is equal to one if the match is an away match
Rival	Binary variable that is equal to one if a match ist played against a rival
Monday	Binary variable that is equal to one if a match took place on a Monday
Tuesday	Binary variable that is equal to one if a match took place on a Tuesday
Wednesday	Binary variable that is equal to one if a match took place on a Wednesday
Thursday	Binary variable that is equal to one if a match took place on a Thursday
Friday	Binary variable that is equal to one if a match took place on a Friday
Saturday	Binary variable that is equal to one if a match took place on a Saturday

Variable	Description
Sunday	Binary variable that is equal to one if a match took place on a Sunday
Kick-off: 1 p.m.	Binary variable that is equal to one if a match started between 1:00–1:59 p.m.
Kick-off: 2 p.m.	Binary variable that is equal to one if a match started between 2:00–2:59 p.m.
Kick-off: 3 p.m.	Binary variable that is equal to one if a match started between 3:00–3:59 p.m.
Kick-off: 5 p.m.	Binary variable that is equal to one if a match started between 5:00–5:59 p.m.
Kick-off: 6 p.m.	Binary variable that is equal to one if a match started between 6:00–6:59 p.m.
Kick-off: 7 p.m.	Binary variable that is equal to one if a match started between 7:00–7:59 p.m.
Kick-off: 8 p.m.	Binary variable that is equal to one if a match started between 8:00–8:59 p.m.
Referee rating	Subjective rating of the referee on a scale of 1 (very good) to 6 (poor)
Meteorological variables	
Precipitation	Amount of precipitation at the time of the match, measured in millimetres
Air temperature	Temperature at the time of the match, measured in degrees Celsius (°C)
Wind speed	Wind speed at the time of the match, measured in metres per second (m/s)
Humidity	Relative humidity at the time of the match, measured in %
Identifier used	
PlayerID	Unique identification number for each player
SeasonID	Unique identification number for the different seasons from 1 to 15
RefereeID	Unique identification number for each referee within the sample
CoachID	Unique identification number for each coach in the sample
StadiumID	Unique identification number for each stadium in the sample
Matchpairing	Unique identification number for a specific pairing of home and away team

Table A2:Additional Pollution Values

Variable	Mean	Std. Deviation	Minimum	Maximum	Obs.
NO_2 in $\mu g/m^3$	27.7581	20.1236	0.374	212.3061	71,710
O_3 in $\mu g/m^3$	55.7789	30.4242	0.307	181.0047	70,704
SO_2 in $\mu g/m^3$	2.8698	4.4803	0.08	78.5545	48,527

Notes: The data on air pollution comes from the German *Umweltbundesamt.* The pollutant load at the hour of impact is shown. All values were calculated using the buffer zone approach described above and a radius of 20km.

Table A3: Metrological Covariates

Variable	Mean	Std. Deviation	Minimum	Maximum	Obs.
Air temperature in C°	10.8437	7.4635	-13	34.4166	71,710
Precipitation in mm	0.0973	0.6487	0	23.7640	71,710
Wind speed in m/s	3.6689	2.0308	0	15.8333	71,710
Humidity in %	68.8617	19.1139	10	100	71,710

Notes: The data comes from the Deutscher Wetterdienst. The values at the kick-off time are shown. All values were calculated using the buffer zone approach (20km radius) and the Inverse Distance Weighted technique.

Table A4: Additional Covariates

Variable	Mean	Std. Deviation	Minimum	Maximum	Obs.
Market Value	189.0994	186.2725	25.15	965.15	71,710
Elo-Rating	1697.581	107.2078	1469.111	2106.159	71,710

Notes: The data on the team's market value comes from the public domain *transfermarkt.de*. The data on Elo comes from the public domain *clubelo.com*.

Table A5: Summary Statistics: Within Variation

Variable		Mean	Std. Dev.	Min	Max	Observations
Dependent Variables						
Foul	*Overall*	1.0395	1.1701	0	10	71,710
	Between		0.5705	0	4	
	Within		1.0885	-2.2105	8.8208	
Yellow Card	*Overall*	0.1354	0.3422	0	1	71,710
	Between		0.1354	0	1	
	Within		0.3325	-0.6146	1.1176	
Pollution Variables						
PM_{10}	*Overall*	16.7941	13.1900	0.3381	170.124	71,710
	Between		6.3239	1.88	91.9049	
	Within		12.7056	-30.3112	174.1837	
$PM_{2.5}$	*Overall*	11.4018	10.5210	0.2678	135.8435	71,710
	Between		5.1567	0.5788	76.2223	
	Within		10.1190	-17.3320	139.4302	

Notes: Summary statistics of the relevant variables. Sample period: 2009/2010 to 2023/2024.

B Additional Figures

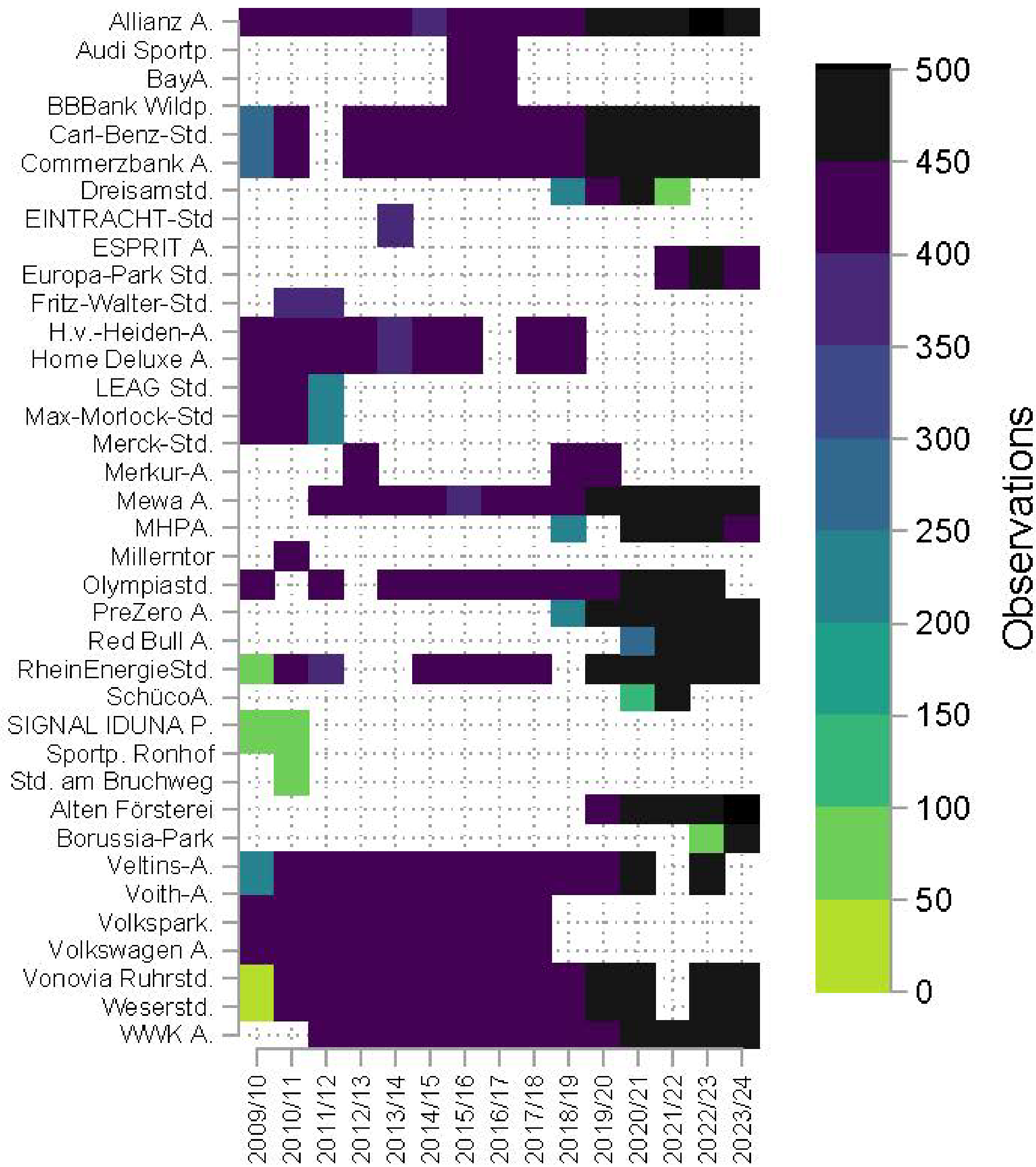

Figure B1: Number of Observations per Stadium and Season

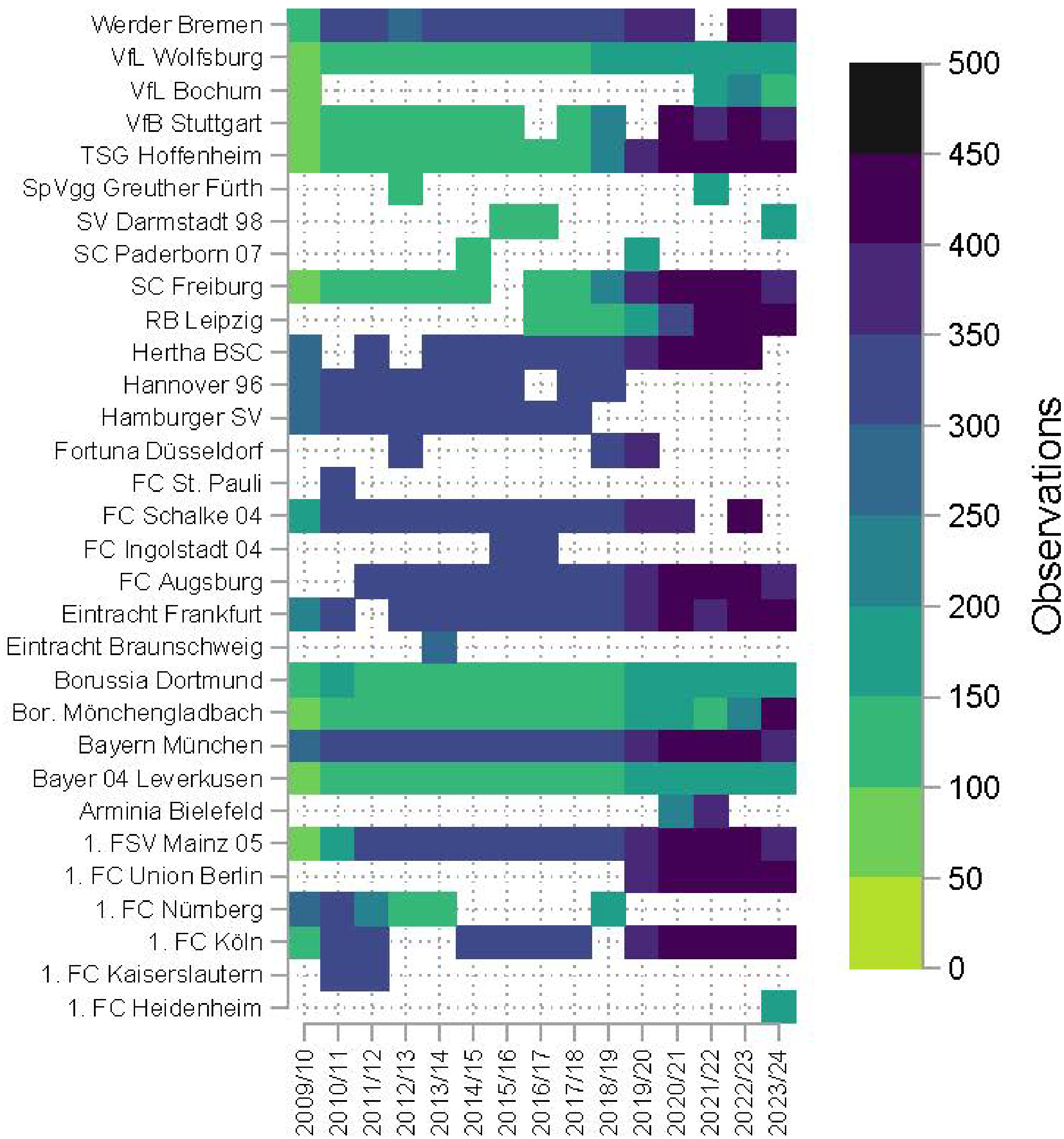

Figure B2: Number of Observations per Team and Season

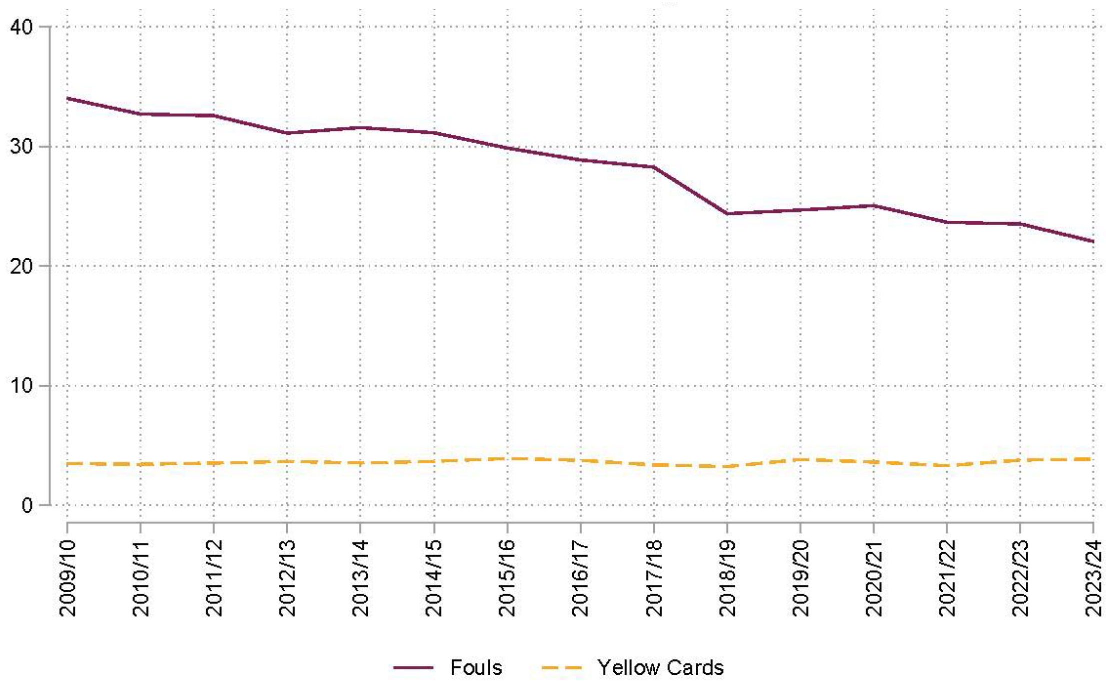

Figure B3: Fouls and Yellow Cards per Match

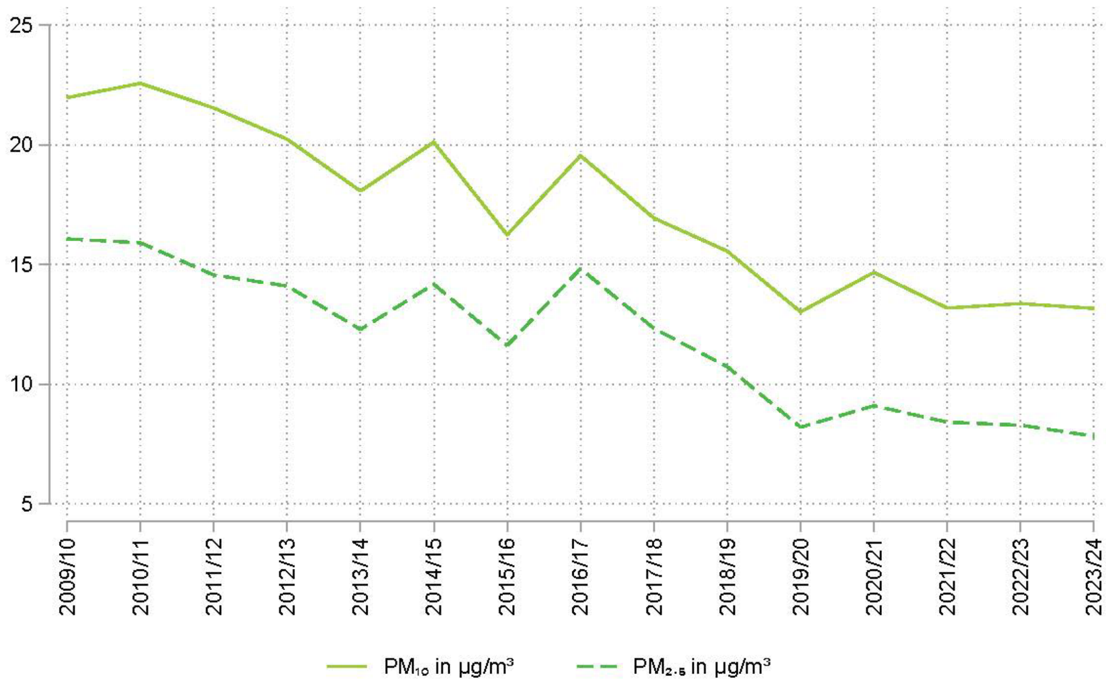

Figure B4: Particulate Matter: Trend over Seasons

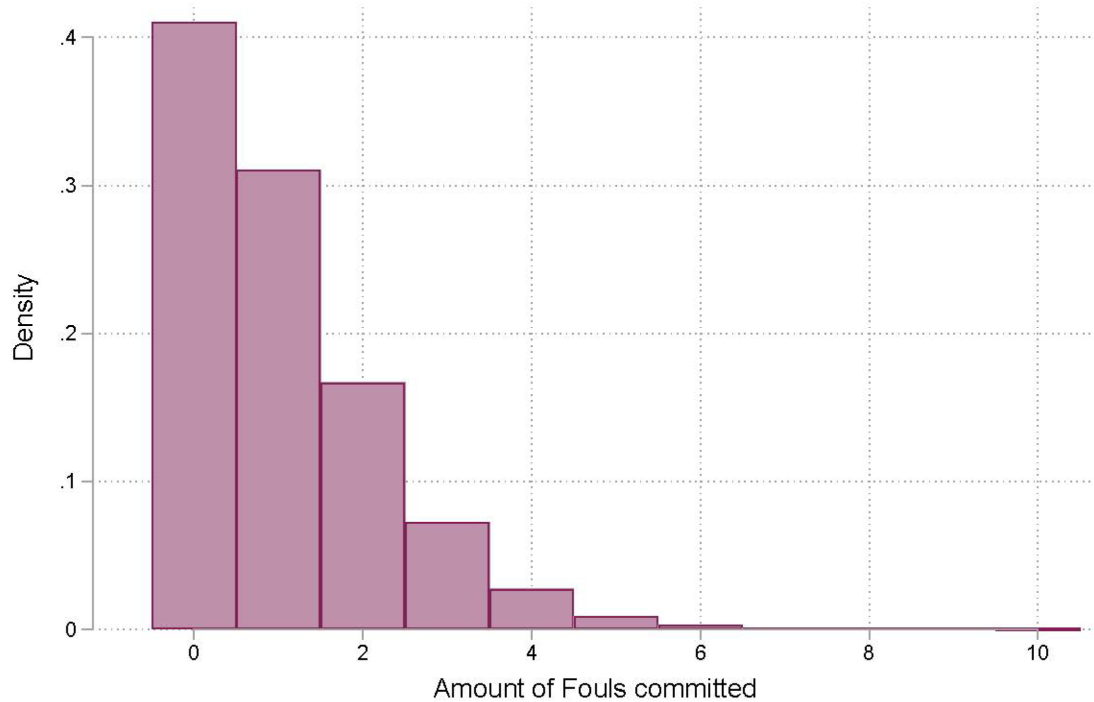

Figure B5: Histogram of Fouls committed

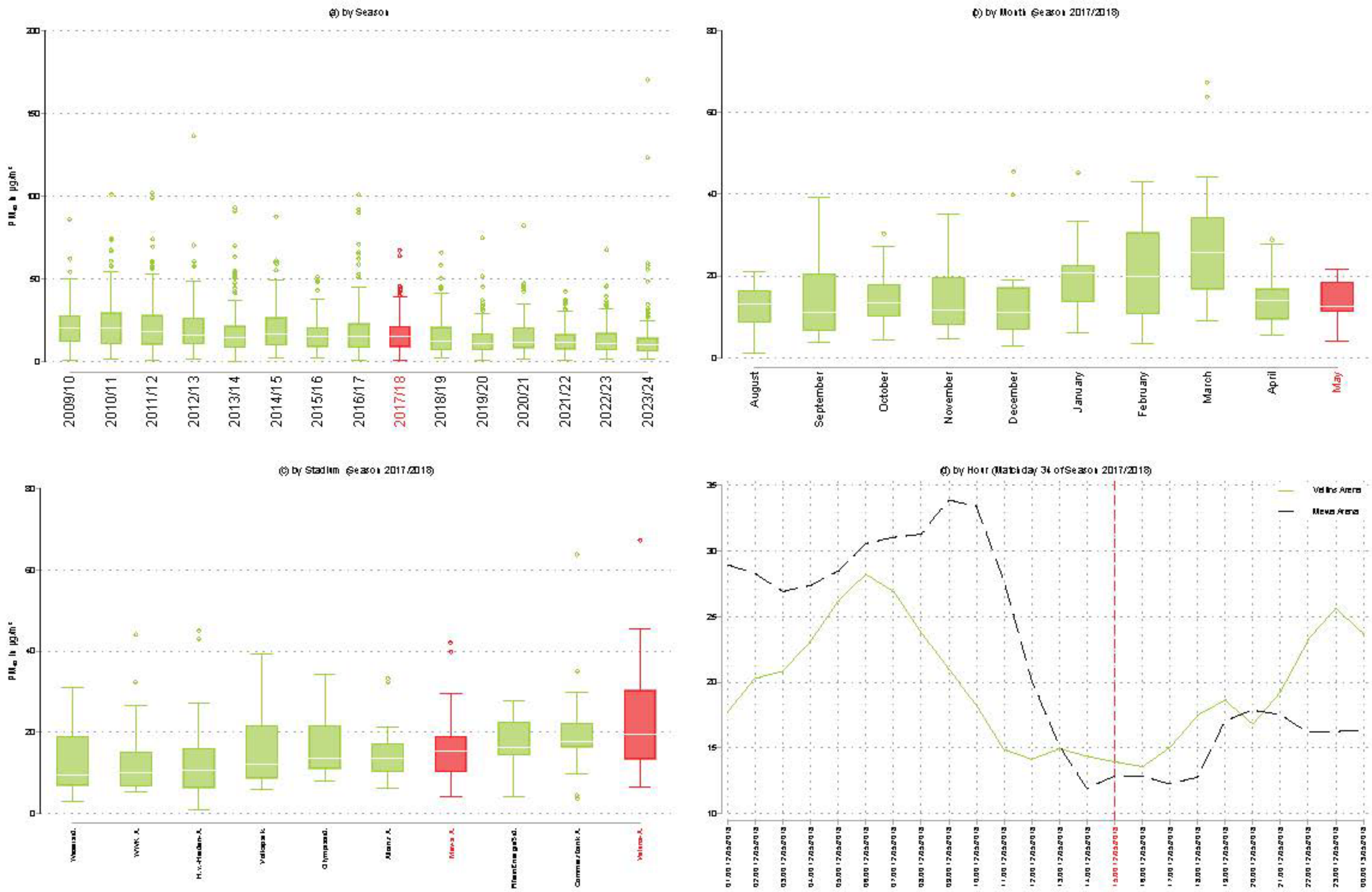

Figure B6: Temporal and local PM_{10} Variation

Notes: The information on air pollution comes from the German *Umweltbundesamt*. The values used were determined using inverse distance weighting. The graph is limited to the observations used in the estimate. Observations that are missing due to a lack of pollutant or weather measuring stations within a 20km radius were not taken into account. The values marked in red highlighted our respective zoom-ins. Panel (d) shows the final zoom-in on the 2017/18 (panel (a)) season on the 34th match day of the season (played in May panel (b)) at the two venues *(Mewa* and *Veltins Arena* - panel (c)).

Additional explanation regarding Figure B6:

Panel (a) shows the development of particulate matter pollution measured in PM_{10} across all seasons. A clear downward trend is recognisable. During the observation period, the median decreases from 20 $\mu g/m^3$ in the 2009/2010 season to 9.8576$\mu g/m^3$ in the 2023/2024 season. A similar trend can be seen for the mean value. This falls from 22.1344$\mu g/m^3$ to 13.1689$\mu g/m^3$ in the same period.

In panel (b), we zoom into one particular season and the monthly load of the 2017/2018 (marked in red in panel (a)) season is shown. A clear variation is recognisable within the season under consideration. In the winter months, particulate matter pollution increases due to meteorological conditions and the increased use of heating systems, while in the summer months particulate matter pollution decreases (Czernecki et al. 2017). Similar patterns can also be seen for other seasons. This U-shaped curve would vanish if season values were considered in our later estimate. In addition, the use of season values, especially for matches that take place at the beginning of the year, would mean that information is included in the model that was not available at the time of the observation (Schmitt 2013).

In panel (c), we also show why close local monitoring is required in addition to temporal monitoring. The particulate matter at the various stadiums in the 20017/2018 season is shown. A clear variation between the different locations is recognisable. While the average exposure at stadiums such as *Weserstadion* (Bremen) or *WWK Arena* (Augsburg) during the season remains below the WHO's recommended yearly limit of 15 $\mu g/m^3$, it is higher at *Commerzbank Arena* (Frankfurt) or *Veltins Arena* (Gelsenkirchen). Another example of the need for spatial control is the comparison of the stadiums *Commerzbank Arena* (Frankfurt) and *Mewa Arena* (Mainz). The two stadiums are only around 30km apart as the crow flies. Nevertheless, the seasonal mean load in Mainz is approximately 3.89 $\mu g/m^3$ less than in Frankfurt. If we were to use less narrowly aggregated data in our estimate, for example at the federal state or district level, we would not adequately take into account the local variation between areas and much of the local variation would vanish.

Finally, a last zoom-in can be seen in panel (d). Once again, we demonstrate why close monitoring is important. This time, we illustrate this for both local and temporal variation. Panel (d) shows the hourly particulate matter pollution in the two aforementioned stadiums *Mewa Arena* and *Veltins Arena* on the last matchday (12/05/2018) of the 2017/2018 *Bundesliga* season. Again, a clear variation is recognisable over the course of the day on different locations. While increased values are recognisable for the *Veltins*

Arena in the morning hours (6:00 a.m.), the maximum values are recognisable for the *Mewa Arena* at 10 a.m.. In addition, low values are measured for both values at kick-off hour (3:00 p.m. marked in red).

C Additional Results

Table C1: Effect of PM on the Number of Fouls committed for Different Groups – RelStr. (Baseline)

	PM_{10}	$PM_{2.5}$
	(1)	(3)
Effects for specific groups:		
Favourites	-0.0028	-0.0002
	(0.0073)	(0.0092)
Slight favourites	0.005	0.0012
	(0.0054)	(0.0071)
Even	0.0086	0.0112
	(0.0067)	(0.0079)
Slight Underdogs	0.0071	0.0087
	(0.0056)	(0.0068)
Underdogs	0.0125*	0.0245***
	(0.0075)	(0.10089)

Notes: The Table refers to the results in Table 4. It shows the estimated coefficients for each of our five subgroups. See Table 3 for the controls and fixed effects used. The information on the probability of one's own team winning is not used in the estimate.

Table C2: Comparison of the determined Coefficients (RelStr. - Baseline) – Wald Test

	PM_{10}	$\mathrm{PM}_{2.5}$
	(1)	(2)
Slight Underdog vs. Underdog	0.37	2.19
Even vs. Underdog	0.16	1.34
Slight Favourite vs Underdog	0.71	4.38**
Favourite vs. Underdog	2.79*	5.17**
Even vs. Slight Underdog	0.03	0.07
Slight Favourite vs. Slight Underdog	0.09	0.65
Favourite vs. Slight Underdog	1.22	0.63
Slight Favourite vs. Even	0.19	0.87
Favourite vs. Even	1.38	0.94
Favourite vs. Slight Favourite	0.80	0.03

Notes: The Table refers to the results in Table 4. The results shown here are from a Wald test, which determines whether the difference between the estimated coefficients of the groups is statistically significant.

Table C3: Interaction between PM and RelStr.

	PM_{10}	$PM_{2.5}$
	(1)	(2)
PM	0.0063*	0.0086**
	(0.0033)	(0.0042)
PM × RelStr	-0.0079	-0.0136*
	(0.0069)	(0.0082)
RelStr	0.0176	0.0192
	(0.0307)	(0.03)
$\chi^2 - Test$	4.82*	7.01**
Pseudo R^2	0.1271	0.1271
Obs.	71,316	71,316
Player covariates	**Yes**	**Yes**
Match covariates	**Yes**	**Yes**
Metrological covariates	**Yes**	**Yes**
Fixed effects	**Yes**	**Yes**

Notes: The results shown here come from an estimation in which we allowed PM to interact with our RelStr measure. Our RelStr measure can take on values ranging from -1 to 1, where -1 means that a player's team has a 100% probability of losing. The results indicate that the effect of PM on the number of fouls committed is stronger for weaker teams. See Table 3 for the controls and fixed effects used. The information on the probability of your own team winning is not used in the estimate. The $\chi^2 - test$ checks whether the effect of PM and $PM \times RelStr$ together is different from zero.

Table C4: Results based on Relative Team Strength - Fouls committed - Alternative Classification

	PM_{10}		$PM_{2.5}$	
	(1)	(2)	(3)	(4)
PM	0.0063*	0.0015	0.0087**	0.0037
	(0.0033)	(0.0059)	(0.0042)	0.0073
RelStr				
Baseline: Favourite: RelStr. > 0.27 n=15,293				
Slight Favourite	0.0504***	0.0435*	0.0506***	0.0492**
RelStr.: 0.27-0.7 n=14,151	(0.0146)	(0.021)	(0.0146)	(0.0195)
Even	0.0261	0.127	0.0263	0.0231
RelStr.: 0.7--0.7 n=12,761	(0.0174)	(0.0237)	(0.0174)	(0.0222)
Slight Underdog	0.0288	0.0238	0.0291	0.0218
RelStr.: -0.7--0.27 n=14,183	(0.0183)	(0.0236)	(0.0183)	(0.0221)
Underdog:	0.0157	-0.0022	0.0159	-0.0014
RelStr.: <-0.27 n=15,322	(0.0207)	(0.0244)	(0.0207)	(0.0232)
RelStr × PM				
Baseline: $Favourite \times PM$				
Slight Favourite × PM		0.0038		0.0012
		(0.0083)		(0.0105)
Even × PM		0.0076		0.0027
		(0.0094)		(0.0111)
Slight Underdog × PM		0.0028		0.0061
		(0.0083)		(0.0102)
Underdog × PM		0.0101		0.0147*
		(0.0074)		(0.0087)
Pseudo R^2	0.1272	0.1272	0.1272	0.1272
Obs.	71,316	71,316	71,316	71,316
Player covariates	**Yes**	**Yes**	**Yes**	**Yes**
Match covariates	**Yes**	**Yes**	**Yes**	**Yes**
Metrological covariates	**Yes**	**Yes**	**Yes**	**Yes**
Fixed effects	**Yes**	**Yes**	**Yes**	**Yes**

Notes: The results presented here stem from an alternative estimation where we adjusted the grouping criteria. Observations are categorized as follows: Players whose team has a winning probability exceeding 27 percent are labeled as favorites. Those with a winning probability ranging from 7 to 27 percent are considered slight favorites. Players from teams with a winning probability between -7 and 7 percent fall into the evenly matched category. Teams with a losing probability between 7 and 27 percent place their players in the slight underdog group. Lastly, players whose team has a losing probability greater than 27 percent are classified as underdogs. See Table 3 for the controls and fixed effects used. The information on the probability of one own team winning is not used in the estimate.

Table C5: Effect of PM on the Number of Fouls committed for Different Groups – RelStr. (Alternative Classification)

	PM_{10}	$PM_{2.5}$
	(1)	(3)
Effects for specific groups:		
Favourites	0.0015	0.0037
	(0.0059)	(0.0073)
Slight favourites	0.0053	0.0048
	(0.0061)	(0.0081)
Even	0.0091	0.0064
	(0.0076)	(0.0089)
Slight Underdogs	0.0043	0.0098
	(0.0061)	(0.0076)
Underdogs	0.1163*	0.0183**
	(0.0063)	(0.0074)

The Table refers to the results in Table C4. It shows the estimated coefficients for each of our five subgroups. See Table 3 for the controls and fixed effects used. The information on the probability of one's own team winning is not used in the estimate.

Table C6: Comparison of the determined Coefficients (RelStr.) – Wald Test (Alternative Classification)

	PM_{10}	$PM_{2.5}$
	(1)	(2)
Slight Underdog vs. Underdog	0.74	0.72
Even vs. Underdog	0.07	1.16
Slight Favourite vs Underdog	0.54	1.65
Favourite vs. Underdog	1.86	2.82*
Even vs. Slight Underdog	0.25	0.09
Slight Favourite vs. Slight Underdog	0.02	0.26
Favourite vs. Slight Underdog	0.11	0.36
Slight Favourite vs. Even	0.15	0.02
Favourite vs. Even	0.65	0.06
Favourite vs. Slight Favourite	0.22	0.01

Notes: The Table refers to the results in Table C4. The results shown here are from a Wald test, which determines whether the difference between the estimated coefficients of the groups is statistically significant.

Table C7: Results based on Relative Team Strength - Fouls committed – Market values and Elo-Rating

	Market value				Elo rating			
	PM_{10}		$PM_{2.5}$		PM_{10}		$PM_{2.5}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PM	0.0063*	0.0002	0.0087**	0.0019	0.0064*	0.00289	0.0088**	0.0076
	(0.0033)	(0.0079)	(0.0042)	(0.0103)	(0.0033)	(0.0073)	(0.0042)	(0.0086)
RelStr								
Baseline: Favourite								
Slight Favourite	-0.0035	-0.0208	-0.0035	-0.0176	0.0095	0.0084	0.0096	0.0131
	(0.0312)	(0.0355)	(0.0312)	(0.0346)	(0.018)	(0.0236)	(0.0181)	(0.0222)
Even	-0.0203	-0.0144	-0.0204	-0.0133	0.0046	-0.0078	0.005	0.0027
	(0.034)	(0.0378)	(0.0339)	(0.037)	(0.0216)	(0.0281)	(0.0216)	(0.026)
Slight Underdog	-0.02957	-0.0475	-0.0296	-0.0392	0.0037	0.0051	0.004	0.009
	(0.0348)	(0.0385)	(0.0348)	(0.0376)	(0.022)	(0.0271)	(0.022)	(0.0257)
Underdog	-0.0644	-0.0852**	-0.0644	-0.0858**	-0.01613	-0.0427	-0.0157	-0.0326
	(0.0403)	(0.043)	(0.0403)	(0.042)	(0.0273)	(0.0307)	(0.0273)	(0.0291)
RelStr × PM								
Baseline: Favourite × PM								
Slight Favourite × PM		0.0106		0.0127		0.0009		-0.0026
		(0.0095)		(0.012)		(0.0087)		(0.0108)
Even × PM		-0.0022		-0.0034		0.0073		0.0023
		(0.0096)		(0.0121)		(0.01)		(0.0116)
Slight Underdog		0.0108		0.0093		-0.0005		-0.0036
		(0.01)		(0.0123)		(0.0088)		(0.0107)
Underdog		0.01359		0.0213*		0.0151*		0.0148
		(0.0088)		(0.0114)		(0.0092)		(0.0101)
Pseudo R^2	0.1271	0.1271	0.1271	0.1271	0.1271	0.1271	0.1271	0.1271
Obs.	71,316	71,316	71,316	71,316	71,316	71,316	71,316	71,316

Notes: See Table 3 for the controls and fixed effects used. All estimates include player, game, and meteorological covariates, as well as all fixed effects from equation (1). The information on the probability of your own team winning is not used in the estimate. The market values used are taken from the public domain *transfermarkt.de*. They were converted to the 2023/24 season using the consumer price index. A team is considered an underdog if the difference in market value to its opponent is at least €200m. The other categories were selected as follows: slight underdog -€200m to -€30m, even -€30m-€30m, slight favourite €30m-€200m and favourite >€200m. The Elo-rating data comes from the public domain *clubelo.com*. The selected Elo ratings were chosen on the following differences in rating:underdog <-140, slight underdog -140–30, even -30-30, slight favourite 30-140 and favourite <140. The selected categories correspond to a distribution of 15, 40, 60, and 85 centiles.

Table C8: Effect of PM on the number of fouls committed for different groups – Market value

	PM_{10}	$PM_{2.5}$
	(1)	(3)
Effects for specific groups:		
Favourites	0.0002	0.0019
	(0.0079)	(0.0102)
Slight favourites	0.0108*	0.0145**
	(0.0055)	(0.0069)
Even	-.002	-0.0016
	(0.0057)	(0.0071)
Slight Underdogs	0.011*	0.0112
	(0.0062)	(0.0073)
Underdogs	0.0138*	0.0231**
	(0.0081)	(0.0087)

The Table refers to the results in Table C7. It shows the estimated coefficients for each of our five subgroups. See Table 3 for the controls and fixed effects used. The information on the probability of one's own team winning is not used in the estimate.

Table C9: Comparison of the determined coefficients (Market value) – Wald Test

	PM_{10}	$PM_{2.5}$
	(1)	(2)
Slight Underdog vs. Underdog	0.07	1.00
Even vs. Underdog	2.71*	4.54**
Slight Favourite vs Underdog	0.1	0.54
Favourite vs. Underdog	2.41	3.46*
Even vs. Slight Underdog	2.51	1.73
Slight Favourite vs. Slight Underdog	0.00	0.14
Favourite vs. Slight Underdog	1.2	0.58
Slight Favourite vs. Even	2.76*	2.92*
Favourite vs. Even	0.05	0.08
Favourite vs. Slight Favourite	1.25	1.11

Notes: The Table refers to the results in Table C7. The results shown here are from a Wald test, which determines whether the difference between the estimated coefficients of the groups is statistically significant.

Table C10: Effect of PM on the Number of fouls committed for Different Groups – Elo-Rating

	PM_{10}	$PM_{2.5}$
	(1)	(3)
Effects for specific groups:		
Favourites	0.0029	0.0076
	(0.0073)	(0.0086)
Slight favourites	0.0038	0.005
	(0.0051)	(0.007)
Even	0.0102	0.0099
	(0.0072)	(0.0083)
Slight Underdogs	0.0023	0.004
	(0.0055)	(0.007)
Underdogs	0.018**	0.0224***
	(0.0075)	(0.0074)

The Table refers to the results in Table C7. It shows the estimated coefficients for each of our five subgroups. See Table 3 for the controls and fixed effects used. The information on the probability of one's own team winning is not used in the estimate.

Table C11: Comparison of the determined Coefficients (Elo-Rating) – Wald test

	PM_{10}	$PM_{2.5}$
	(1)	(2)
Slight Underdog vs. Underdog	3.11*	3.09*
Even vs. Underdog	0.6	1.18
Slight Favourite vs Underdog	2.64	2.78*
Favourite vs. Underdog	2.73*	2.15
Even vs. Slight Underdog	0.85	0.33
Slight Favourite vs. Slight Underdog	0.05	0.01
Favourite vs. Slight Underdog	0.00	0.11
Slight Favourite vs. Even	0.57	0.23
Favourite vs. Even	0.54	0.04
Favourite vs. Slight Favourite	0.01	0.06

Notes: The Table refers to the results in Table C7. The results shown here are from a Wald test, which determines whether the difference between the estimated coefficients of the groups is statistically significant.

References

Adhvaryu, Achyuta, Namrata Kala, and Anant Nyshadham. 2022. “Management and Shocks to Worker Productivity.” *Journal of Political Economy* 130 (1): 1–47.

Aguilar-Gomez, Sandra, Holt Dwyer, Joshua Graff Zivin, and Matthew Neidell. 2022. “This Is Air: The "Nonhealth" Effects of Air Pollution.” *Annual Review of Resource Economics* 14 (1): 403–25.

Anderson, Craig A, and Brad J Bushman. 2002. “Human Aggression.” *Annual Review of Psychology* 53 (1): 27–51.

Archsmith, James, Anthony Heyes, and Soodeh Saberian. 2018. “Air Quality and Error Quantity: Pollution and Performance in a High-Skilled, Quality-Focused Occupation.” *Journal of the Association of Environmental and Resource Economists* 5 (4): 827–63.

Balafoutas, Loukas, Florian Lindner, and Matthias Sutter. 2012. “Sabotage in Tournaments: Evidence from a Natural Experiment.” *Kyklos* 65 (4): 425–41.

Balleer, Almut, Michael Hirsch, and Marvin Nöller. 2025. *How Are You Doing Today? Air Quality and Subjective Well-Being Across Time and Space in Germany*. Ruhr Economic Papers No. 1164. RWI - Leibniz-Institut für Wirtschaftsforschung. https://doi.org/10.4419/96973349.

Baryshnikova, Nadezhda V, Shannon F Davidson, and Dennis Wesselbaum. 2019. *Does Pollution Affect Crime? Evidence from US Cities*.

Bellani, Luna, Stefano Ceolotto, Benjamin Elsner, and Nico Pestel. 2024. “The Political Fallout of Air Pollution.” *Proceedings of the National Academy of Sciences* 121 (18): e2314428121.

Berger, J., & Nieken, P. (2016). Heterogeneous Contestants and the Intensity of Tournaments: An Empirical Investigation: An Empirical Investigation. *Journal of Sports Economics*, *17*(7), 631-660.

Block, Michelle L, and Lilian Calderón-Garcidueñas. 2009. “Air Pollution: Mechanisms of Neuroinflammation and CNS Disease.” *Trends in Neurosciences* 32 (9): 506–16.

Bondy, Malvina, Sefi Roth, and Lutz Sager. 2020. “Crime Is in the Air: The Contemporaneous Relationship Between Air Pollution and Crime.” *Journal of the Association of Environmental and Resource Economists* 7 (3): 555–85.

Bonetti, Leonardo, Torbjōrn Vestberg, Reza Jafari, et al. 2025. “Decoding the Elite Soccer Player’s Psychological Profile.” *Proceedings of the National Academy of Sciences* 122 (3): e2415126122.

Burkhardt, Jesse, Jude Bayham, Ander Wilson, et al. 2019. “The Effect of Pollution on Crime: Evidence from Data on Particulate Matter and Ozone.” *Journal of Environmental Economics and Management* 98: 102267. https://doi.org/10.1016/j.jeem.2019.102267.

Chang, Tom, Joshua Graff Zivin, Tal Gross, and Matthew Neidell. 2016. “Particulate Pollution and the Productivity of Pear Packers.” *American Economic Journal: Economic Policy* 8 (3): 141–69.

Chen, Chun, and Bin Zhao. 2011. “Review of Relationship Between Indoor and Outdoor Particles: I/o Ratio, Infiltration Factor and Penetration Factor.” *Atmospheric Environment* 45 (2): 275–88.

Chen, Kong-Pin. 2003. "Sabotage in Promotion Tournaments." *Journal of Law, Economics, and Organization* 19 (1): 119–40.

Chowdhury, Subhasish M, and Oliver Gürtler. 2015. "Sabotage in Contests: A Survey." *Public Choice* 164: 135–55.

Cikara, Mina, Matthew M Botvinick, and Susan T Fiske. 2011. "Us Versus Them: Social Identity Shapes Neural Responses to Intergroup Competition and Harm." *Psychological Science* 22 (3): 306–13.

Coccaro, Emil F, Royce Lee, and David Gozal. 2016. "Elevated Plasma Oxidative Stress Markers in Individuals with Intermittent Explosive Disorder and Correlation with Aggression in Humans." *Biological Psychiatry* 79 (2): 127–35.

Correia, Sergio, Paulo Guimarães, and Tom Zylkin. 2020. "Fast Poisson Estimation with High-Dimensional Fixed Effects." *The Stata Journal* 20 (1): 95–115.

Costa, Lucio G, Toby B Cole, Jacki Coburn, Yu-Chi Chang, Khoi Dao, and Pamela J Roqué. 2017. "Neurotoxicity of Traffic-Related Air Pollution." *Neurotoxicology* 59: 133–39.

Czernecki, Bartosz, Marek Półrolniczak, Leszek Kolendowicz, Michał Marosz, Sebastian Kendzierski, and Natalia Pilguj. 2017. "Influence of the Atmospheric Conditions on PM 10 Concentrations in Poznań, Poland." *Journal of Atmospheric Chemistry* 74: 115–39.

DeFlorio-Barker, Stephanie, Danelle T Lobdell, Susan L Stone, Tegan Boehmer, and Kristen M Rappazzo. 2020. "Acute Effects of Short-Term Exposure to Air Pollution While Being Physically Active, the Potential for Modification: A Review of the Literature." *Preventive Medicine* 139: 106195.

Deutscher, Christian, Bernd Frick, Oliver Gürtler, and Joachim Prinz. 2013. "Sabotage in Tournaments with Heterogeneous Contestants: Empirical Evidence from the Soccer Pitch." *The Scandinavian Journal of Economics* 115 (4): 1138–57.

Deutscher, Christian, Marco Sahm, Sandra Schneemann, and Hendrik Sonnabend. 2022. "Strategic Investment Decisions in Multi-Stage Contests with Heterogeneous Players." *Theory and Decision* 93 (2): 281–317.

Deutscher, Christian, and Sandra Schneemann. 2017. "The Impact of Intermediate Information on Sabotage in Tournaments with Heterogeneous Contestants." *Managerial and Decision Economics* 38 (2): 222–37.

Ebenstein, Avraham, Victor Lavy, and Sefi Roth. 2016. "The Long-Run Economic Consequences of High-Stakes Examinations: Evidence from Transitory Variation in Pollution." *American Economic Journal: Applied Economics* 8 (4): 36–65.

Ehsanifar, Mojtaba, S Banihashemian, and Masoud Ehsanifar. 2021a. "Exposure to Air Pollution Nanoparticles: Oxidative Stress and Neuroinfl Ammation." *J. ISSN* 2766: 2276.

Ehsanifar, Mojtaba, Zeinab Montazeri, Maryam Akhavan Taheri, Mehravar Rafati, Mohaddeseh Behjati, and Mohammad Karimian. 2021b. "Hippocampal Inflammation and Oxidative Stress Following Exposure to Diesel Exhaust Nanoparticles in Male and Female Mice." *Neurochemistry International* 145: 104989.

Ferreira, Susana, Alpaslan Akay, Finbarr Brereton, et al. 2013. “Life Satisfaction and Air Quality in Europe.” *Ecological Economics* 88: 1–10.

Fu, Minning, F Zheng, Xingsheng Xu, and L Niu. 2011. “Advances of Study on Monitoring and Evaluation of PM2. 5 Pollution.” *Meteorol. Disaster Reduc. Res* 34: 1–6.

Garicano, Luis, and Ignacio Palacios-Huerta. 2005. *Sabotage in Tournaments: Making the Beautiful Game a Bit Less Beautiful*.

Gawryluk, Jodie R, Daniela J Palombo, Jason Curran, Ashleigh Parker, and Chris Carlsten. 2023. “Brief Diesel Exhaust Exposure Acutely Impairs Functional Brain Connectivity in Humans: A Randomized Controlled Crossover Study.” *Environmental Health* 22 (1): 7.

Gilpatric, Scott M. 2011. “Cheating in Contests.” *Economic Inquiry* 49 (4): 1042–53.

Gilraine, Michael. 2025. “Air Filters, Pollution, and Student Achievement.” *Journal of Human Resources* 60 (5): 1469–506. https://doi.org/10.3368/jhr.0421-11642R2.

Gong, Shiyang, Jackson G Lu, John M Schaubroeck, Qian Li, Qiwei Zhou, and Xiaoye Qian. 2020. “Polluted Psyche: Is the Effect of Air Pollution on Unethical Behavior More Physiological or Psychological?” *Psychological Science* 31 (8): 1040–47.

Graff Zivin, Joshua, and Matthew Neidell. 2013. “Environment, Health, and Human Capital.” *Journal of Economic Literature* 51 (3): 689–730.

Granella, Francesco. 2021. “You Can’t Run from Air Pollution: The Effect of Fine Particulate Matter on Physical Tasks.” *Available at SSRN 3893692*.

Gruhl, Henri, Nicolas Volkhausen, Nico Pestel, and Nils aus dem Moore. 2025. “Air Pollution and the Housing Market: Evidence from Germany’s Low Emission Zones.” *Journal of Environmental Economics and Management* 132: 103161. https://doi.org/10.1016/j.jeem.2025.103161.

Grund, C., Höcker, J., & Zimmermann, S. 2013. “Incidence and consequences of risk-taking behavior in tournaments—evidence from the NBA.” *Economic Inquiry*, *51*(2), 1489-1501.

Gürtler, Oliver, Lennart Struth, and Max Thon. 2023. “Competition and Risk-Taking.” *European Economic Review* 160: 104592.

Haller, Jozsef. 2022. “Glucocorticoids and Aggression: A Tripartite Interaction.” *Neuroscience of Social Stress*, 209–43.

Harbring, C., & Irlenbusch, B. 2011. “Sabotage in tournaments: Evidence from a laboratory experiment. ” *Management Science*, *57*(4), 611-627.

Herrnstadt, Evan, Anthony Heyes, Erich Muehlegger, and Soodeh Saberian. 2021. “Air Pollution and Criminal Activity: Microgeographic Evidence from Chicago.” *American Economic Journal: Applied Economics* 13 (4): 70–100.

Huang, Jiekun, Nianhang Xu, and Honghai Yu. 2020. “Pollution and Performance: Do Investors Make Worse Trades on Hazy Days?” *Management Science* 66 (10): 4455–76.

Int Panis, Luc, Eline B Provost, Bianca Cox, et al. 2017. "Short-Term Air Pollution Exposure Decreases Lung Function: A Repeated Measures Study in Healthy Adults." *Environmental Health* 16 (1): 1–7.

Ishihara, Y., Tanaka, M., Nezu, N., Ishihara, N., Oguro, A., & Vogel, C. F. (2025). Pathways to the brain: Impact of fine particulate matter components on the central nervous system. *Antioxidants*, *14*(6), 730.

Kampa, Marilena, and Elias Castanas. 2008. "Human Health Effects of Air Pollution." *Environmental Pollution* 151 (2): 362–67.

Keiser, David, Gabriel Lade, and Ivan Rudik. 2018. "Air Pollution and Visitation at US National Parks." *Science Advances* 4 (7): eaat1613.

Kempa, Karol, and Hannes Rusch. 2019. "Dissent, Sabotage, and Leader Behaviour in Contests: Evidence from European Football." *Managerial and Decision Economics* 40 (5): 500–514.

Kilduff, Gavin J, Adam D Galinsky, Edoardo Gallo, and J James Reade. 2016. "Whatever It Takes to Win: Rivalry Increases Unethical Behavior." *Academy of Management Journal* 59 (5): 1508–34.

Kim, Ki-Hyun, Ehsanul Kabir, and Shamin Kabir. 2015. "A Review on the Human Health Impact of Airborne Particulate Matter." *Environment International* 74: 136–43. https://doi.org/10.1016/j.envint.2014.10.005.

Klingen, Joris, and Jos van Ommeren. 2020. "Urban Air Pollution and Time Losses: Evidence from Cyclists in London." *Regional Science and Urban Economics* 81: 103504.

Klingen, Joris, and Jos van Ommeren. 2022. "Risk-Taking and Air Pollution: Evidence from Chess." *Environmental and Resource Economics* 81 (1): 73–93.

Kouchaki, Maryam, and Sreedhari D Desai. 2015. "Anxious, Threatened, and Also Unethical: How Anxiety Makes Individuals Feel Threatened and Commit Unethical Acts." *Journal of Applied Psychology* 100 (2): 360.

Künn, Steffen, Juan Palacios, and Nico Pestel. 2023. "Indoor Air Quality and Strategic Decision Making." *Management Science* 69 (9): 5354–77.

La Nauze, Andrea, and Edson Severnini. 2025. "Air Pollution and Adult Cognition: Evidence from Brain Training." *Journal of the Association of Environmental and Resource Economists* 12 (1): 221–55.

Laurent, Jose Guillermo Cedeño, Piers MacNaughton, Emily Jones, et al. 2021. "Associations Between Acute Exposures to PM2. 5 and Carbon Dioxide Indoors and Cognitive Function in Office Workers: A Multicountry Longitudinal Prospective Observational Study." *Environmental Research Letters* 16 (9): 094047.

Lazear, E. P., & Rosen, S. 1981. "Rank-order tournaments as optimum labor contracts." *Journal of political Economy*, *89*(5), 841-864.

Lepori, Gabriele M. 2016. "Air Pollution and Stock Returns: Evidence from a Natural Experiment." *Journal of Empirical Finance* 35: 25–42.

Levinson, Arik. 2020. "Happiness and Air Pollution." In *Handbook on Wellbeing, Happiness and the Environment*. Edward Elgar Publishing.

Li, Zhongqi, Xiaona Li, Huan Song, et al. 2021. “Effects of Short-Term Ambient PM2. 5 Exposure on the Blood Cell Count and Hemoglobin Concentration Among 82,431 People in Eastern China.” *Science of The Total Environment* 776: 146046.

Lichter, Andreas, Nico Pestel, and Eric Sommer. 2017. “Productivity Effects of Air Pollution: Evidence from Professional Soccer.” *Labour Economics* 48: 54–66.

Liu, Kui, Chuyan Meng, Shasha Yang, and Guanglu Zhang. 2024. “Air Pollution and Individual Risk Preference: Evidence from China.” *Energy Economics* 136: 107738.

Liu, Qisijing, Wanzhou Wang, Xuelin Gu, et al. 2021. “Association Between Particulate Matter Air Pollution and Risk of Depression and Suicide: A Systematic Review and Meta-Analysis.” *Environmental Science and Pollution Research* 28: 9029–49.

Lu, Jackson G. 2020. “Air Pollution: A Systematic Review of Its Psychological, Economic, and Social Effects.” *Current Opinion in Psychology* 32: 52–65.

Lu, Jackson G, Julia J Lee, Francesca Gino, and Adam D Galinsky. 2018. “Polluted Morality: Air Pollution Predicts Criminal Activity and Unethical Behavior.” *Psychological Science* 29 (3): 340–55.

Mallach, Gary, Robin Shutt, Errol M Thomson, Frédéric Valcin, Ryan Kulka, and Scott Weichenthal. 2023. “Randomized Cross-over Study of in-Vehicle Cabin Air Filtration, Air Pollution Exposure, and Acute Changes to Heart Rate Variability, Saliva Cortisol, and Cognitive Function.” *Environmental Science & Technology* 57 (8): 3238–47.

Ming, Yaxin, Huixin Deng, and Xiaoyue Wu. 2022. “The Negative Effect of Air Pollution on People’s Pro-Environmental Behavior.” *Journal of Business Research* 142: 72–87.

Mo, Jiawei, Zenan Wu, and Ye Yuan. 2023. “Air Pollution Kills Competition: Evidence from eSports.” *Journal of Environmental Economics and Management* 122: 102886.

Mundlak, Yair. 1978. “On the Pooling of Time Series and Cross Section Data.” *Econometrica: Journal of the Econometric Society*, 69–85.

Piest, Simon, and Philipp Schreck. 2021. “Contests and Unethical Behavior in Organizations: A Review and Synthesis of the Empirical Literature.” *Management Review Quarterly* 71 (4): 679–721.

Qin, Yu, Jing Wu, and Rongjie Zhang. 2022. “Can Professional Football Players Adapt to Air Pollution? Evidence from China.” *Journal of Sports Economics* 23 (3): 277–300.

Rice, Mary B, Petter L Ljungman, Elissa H Wilker, et al. 2013. “Short-Term Exposure to Air Pollution and Lung Function in the Framingham Heart Study.” *American Journal of Respiratory and Critical Care Medicine* 188 (11): 1351–57.

Saenen, Nelly D, Eline B Provost, Mineke K Viaene, et al. 2016. “Recent Versus Chronic Exposure to Particulate Matter Air Pollution in Association with Neurobehavioral Performance in a Panel Study of Primary Schoolchildren.” *Environment International* 95: 112–19.

Salim, Samina. 2014. “Oxidative Stress and Psychological Disorders.” *Current Neuropharmacology* 12 (2): 140–47.

Sarmiento, Luis. 2023. “The Nonlinear Effects of Air Pollution on Criminal Behavior: Evidence from Mexico City and New York.” *Environmental Research: Health* 1 (2): 021001.

Schmitt, Maike. 2013. “Subjective Well-Being and Air Quality in Germany.” *Journal of Contextual Economics–Schmollers Jahrbuch* 133 (2): 275–86.

Schneemann, Sandra, and Christian Deutscher. 2017. “Intermediate Information, Loss Aversion, and Effort: Empirical Evidence.” *Economic Inquiry* 55 (4): 1759–70.

Shehab, MA, and FD Pope. 2019. “Effects of Short-Term Exposure to Particulate Matter Air Pollution on Cognitive Performance.” *Scientific Reports* 9 (1): 8237.

Sun, Ying, Guozhe Deng, Jinhui Fan, et al. 2022. “Associations of Air PM2. 5 Level with Gut Microbiota in Chinese Han Preschoolers and Effect Modification by Oxytocin Receptor Gene Polymorphism.” *Environmental Research* 214: 114123.

Tan, Xiaorui, Lijian Han, Xiaoyan Zhang, Weiqi Zhou, Weifeng Li, and Yuguo Qian. 2021. “A Review of Current Air Quality Indexes and Improvements Under the Multi-Contaminant Air Pollution Exposure.” *Journal of Environmental Management* 279: 111681. /https://doi.org/10.1016/j.jenvman.2020.111681.

Thomson, Errol M. 2019. “Air Pollution, Stress, and Allostatic Load: Linking Systemic and Central Nervous System Impacts.” *Journal of Alzheimer’s Disease* 69 (3): 597–614.

Tiihonen, Jari, Pirjo Halonen, Laura Tiihonen, Hannu Kautiainen, Markus Storvik, and James Callaway. 2017. “The Association of Ambient Temperature and Violent Crime.” *Scientific Reports* 7 (1): 6543.

Vorapracha, Phatarapon, Pongtep Phonprasert, Suparada Khanaruksombat, and Nuchanaporn Pijarn. 2015. “A Comparison of Spatial Interpolation Methods for Predicting Concentrations of Particle Pollution (PM10).” *International Journal of Chemical, Environmental and Biological Sciences* 3 (4): 302–6.

Wang, Yanfang, Lu Li, Junhao Cai, Huaifang Li, and Chenbo Wang. 2023. “Incidental Physical Pain Reduces Brain Activities Associated with Affective Social Feedback and Increases Aggression.” *Social Cognitive and Affective Neuroscience* 18 (1): nsac048.

Weitekamp, Chelsea A, and Hans A Hofmann. 2021. “Effects of Air Pollution Exposure on Social Behavior: A Synthesis and Call for Research.” *Environmental Health* 20 (1): 72.

Woo, Hyun-Soo, John P Berns, and Pol Solanelles. 2023. “How Rare Is Rare? How Common Is Common? Empirical Issues Associated with Binary Dependent Variables with Rare or Common Event Rates.” *Organizational Research Methods* 26 (4): 655–77.

Zaręba, Ł., Piszczatowska, K., Dżaman, K., Soroczynska, K., Motamedi, P., Szczepański, M. J., & Ludwig, N. (2024). The relationship between fine particle matter (PM2. 5) exposure and upper respiratory tract diseases. *Journal of personalized medicine*, *14*(1), 98.

Zhang, Hui, Yanwei Shi, Zhiqing E Zhou, Hongyu Ma, and Hanying Tang. 2020. “Good People Do Bad Things: How Anxiety Promotes Unethical Behavior Through Intuitive and Automatic Processing.” *Current Psychology* 39 (2): 720–28.

Zhang, Renyi, Gehui Wang, Song Guo, et al. 2015. "Formation of Urban Fine Particulate Matter." *Chemical Reviews* 115 (10): 3803–55.

Zhang, Xin, Xiaobo Zhang, and Xi Chen. 2017. "Happiness in the Air: How Does a Dirty Sky Affect Mental Health and Subjective Well-Being?" *Journal of Environmental Economics and Management* 85: 81–94.

Zhou, Yu-Meng, Yan-Ni Fan, Chun-Yan Yao, et al. 2021. "Association Between Short-Term Ambient Air Pollution and Outpatient Visits of Anxiety: A Hospital-Based Study in Northwestern China." *Environmental Research* 197: 111071.

Zivin, Joshua Graff, and Matthew Neidell. 2012. "The Impact of Pollution on Worker Productivity." *American Economic Review* 102 (7): 3652–73.

Zundel, Clara G., Patrick Ryan, Cole Brokamp, et al. 2022. "Air Pollution, Depressive and Anxiety Disorders, and Brain Effects: A Systematic Review." *NeuroToxicology* 93: 272–300. https://doi.org/10.1016/j.neuro.2022.10.011.