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Risk-Taking and Air Pollution: Evidence from Chess

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Abstract

Medical research suggests that particulate matter (PM) increases stress hormones, therefore increasing the feeling of stress, which has been hypothesised to induce individuals to take less risk. To examine this, we study whether PM_{10} increases the probability of drawing in chess games using information from the Dutch club competition. We provide evidence of a reasonably strong effect: A 10μg increase in PM_{10} (33.6% of mean concentration) leads to a 5.6% increase in draws. We examine a range of explanations for these findings. Our preferred interpretation is that air pollution causes individuals to take less risk.

Keywords Air pollution · Particulate matter · Decision-making · Risk-taking

JEL Classification D81 · I18 · J24 · Q53

1 Introduction

Particulate matter (PM) is found to increase stress hormones and blood pressure, therefore increasing the feeling of stress, which has been hypothesised to induce individuals to take less risk (Duflo and Banerjee 2011).[1] To examine this, we study the effect of PM_{10} on risk outcomes of the game of chess, i.e. the probability to make a draw in a quasi-experimental setting.

The literature mainly focuses on long-term health effects of exposure to PM (i.e. PM_{10} and $PM_{2.5}$) and other air pollution (see e.g. Chappie and Lave 1982 and Beach and Hanlon

[1] Duflo and Banerjee (2011) observe that poorer individuals have more stress and make less risky investment decisions.

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2018). In contrast, we focus on the immediate effect of air pollution, for which there is growing attention (Graff Zivin and Neidell 2018). Recently, it has been shown that pollution also has an immediate detrimental effect on physical health and therefore on economic and social activities which depend on physical health (e.g. labour productivity, cycling to work).[2]

It is less well-known that the immediate effects of PM reach beyons health concerns and are widespread. PM affects cognitive ability, and therefore reasoned judgement and decision-making (see e.g. Hamanaka and Mutlu 2018). Medical studies show that PM increases stress hormones (such as cortisol) as well as blood pressure (Li et al. 2017; Barbosa et al. 2012). In other contexts, PM negatively affects important activities which require cognitive performance, including educational achievement (Ebenstein et al. 2016), high skill work (Kahn and Li 2019) and investment decisions (Huang et al. 2017). Traders on Wall Street have lower returns on days with higher PM concentrations (Heyes et al. 2016), while baseball referees underperform given higher levels of PM (Archsmith et al. 2018). Künn et al. (2019) find that chess players make more meaningful errors due to PM, especially when under time pressure.

Several recent studies show individuals' decision-making effects of PM that point at the possibility that PM reduces risk-taking (Lu 2019; Chew et al. 2019). For example, Heyes et al. (2016) argue that one possible interpretation of their findings for lower returns for Wall Street traders is that PM induces these traders to take less risk.[3] This is in line with papers on PM and crime that suggest that anxiety increases with PM (Herrnstadt et al. 2016; Burkhardt et al. 2019). There is also evidence that daily higher PM levels increase the probability of buying health insurance (Chang et al. 2018), and reduce the sales of lottery tickets (Bondy et al. 2019).[4]

These studies estimate PM effects that are likely the result of several behavioural factors (notably skills, discounting, and risk-taking). It is still unclear which behavioural mechanisms underlie previous findings. More specifically, we do not know whether PM directly affects risk attitude. In contrast to existing studies, we study the effect of PM_{10} on an indicator of risk-taking using the game of chess. Thereby, we can provide field evidence on the often stated hypothesis that PM air pollution induces individuals to take less risk, and thereby reduces the expected pay-offs of the strongest player.

Risk-taking is essential to the game of chess. Another advantage of focusing on chess is that it offers a direct measure of risk outcomes: the variance of game outcomes reflects risk-taking, as many games end in a draw. Furthermore, the time horizon of a chess game is short (a few hours), so estimates are not affected by the effects of PM on discount rates

[2] Graff Zivin and Neidell (2012) show that agricultural workers are less productive on days with high ozone levels. Lichter et al. (2017) identify a small effect of PM on some productivity indicators of professional players in football. Chang et al. (2016), Chang et al. (2019) study productivity of pear packers and call centre employees and find adverse effects of PM pollution on productivity. Klingen and van Ommeren (2020) show that ozone reduces cycling speed.

[3] An alternative explanation is that these traders lose or adapt their discount rate. PM increases car accidents (Sager 2019) as well as crime (Bondy et al. 2019), but these results are shown to be unlikely due to higher levels of risk-taking.

[4] The benefits of health insurance and lottery gains are in the future, so an alternative explanation is that PM affects the discount rate. Projections bias may also play a role. Projection bias is the tendency for individuals to exaggerate the degree to which their future tastes will resemble current tastes, which is likely affected by pollution.

or projection bias (Heyes et al. 2016; Bondy et al. 2019). Consequently, the effect of PM on risk-taking can be examined by analysing its effect on the probability of making a draw.[5]

The ideal experimental setup to estimate the causal effect of pollution on the probability to make a draw is to examine the outcome of games of players that are randomly assigned to play against each other at different locations with different levels of pollution. We come close to that set up by analysing games played in the Dutch team club competitions, where teams belonging to the same league play at different locations and all teams play each other (as is common in most national team sports competitions).[6] Ideally, one would also analyse the exact chess moves for each game. We only observe moves for a small subsample from the highest league. Since the effect we are studying is rather subtle, we mainly concentrate on the full sample.

All games take place at the same time (on Saturdays at 1 pm), and are scheduled in advance, so that our results are *not* driven by any extensive margin decisions (i.e. the decision to play), as would for example be the case for online chess games. Because pollution levels do not vary randomly over time and space, we control for time-specific as well as location-specific unobserved factors using a two-way fixed-effects strategy.[7]

In our estimation approach, we pay special attention to measurement error in PM_{10} due to the distance between the pollution monitor and the chess location. Measurement error in pollution levels usually causes attenuation bias. One way to deal with this is to use instrumental variables, which is the preferred strategy in the literature. In particular, it is common to use temperature inversion as an instrument (Jans et al. 2018). Although this strategy is attractive, there are also disadvantages with its use.[8] We follow a different route. We focus on chess locations close to PM_{10} monitoring stations. Furthermore, we will show how the PM_{10} effects decrease with distance to the pollution monitor.

There may be alternative explanations of our finding of increased draws due to PM_{10}. Most notably, one may think that because PM_{10} negatively affects the cognitive performance of chess players, this would increase the probability of making a draw. We show that this alternative hypothesis does not explain our findings by demonstrating that weaker players make fewer, and not more, draws. We will further show that reduced cognitive performance can only induce a negligible downward bias. Furthermore, as shown by Künn et al. (2019), PM seems to only increase meaningful errors (i.e. blunders), which make draws even *less* likely. Another possible explanation is increased fatigue due to PM_{10}, which may induce players to offer or accept draws earlier in the game. We cannot completely rule out this explanation, but we note that players can also end games earlier by resignation, which is very common in chess. Therefore, a preference for shorter games does not imply more draws, as it is plausible that both resignations and draw-offerings increase. Overall, our preferred interpretation for finding more draws is, therefore, a reduction in risk-taking.

[5] We will discuss alternative explanations for finding an increased number of draws due to PM, such as the length of a game or reduced cognitive performance.

[6] For that reason, we concentrate on the Dutch national competition, but ignore information from other countries (e.g. Germany, UK), where players tend to play at the same location, hence there is little or no spatial variation in those contexts.

[7] The probability of a draw depends on the strength of the players. Therefore, we improve the efficiency of our estimates by controlling for the so called Elo rating, which is a very accurate measures of a player's strength at the time of playing (Regan and Haworth 2011).

[8] It is plausible that the instrument affects a range of pollutions, and not only PM, so it is difficult to interpret the IV estimate as a causal estimate of PM. In addition, confidence intervals of the IV estimates are much larger (and tend not to differ from OLS estimates using Hausman tests).

In conclusion, we will provide evidence that PM_{10} reduces risk-taking.[9] A 10μg increase in PM_{10} (33.6% of mean concentration) leads to a 5.6% increase in draws. We do not find any effect of PM_{10} when measured at the location of the visiting club, or of PM_{10} on previous days, which implies that the PM_{10} effect is immediate. This finding supports and complements other studies showing the effect of pollution on decision taking, but which cannot distinguish between several explanations to explain their findings (Heyes et al. 2016; Bondy et al. 2019).

This paper proceeds as follows. Section 2 explains the methods employed. Section 3 describes the data and descriptive statistics. Section 4 presents results. Section 5 concludes.

2 Empirical method

2.1 Identification

Chess is a zero-sum perfect information game between two players with three possible outcomes: either one of the players wins, or there is a draw. In chess, the players' moves are strongly related to level of risk they take (these determinants are discussed later on). For example, players choose between safe and risky openings, which affects the probability of a draw. Players can also choose risky moves, i.e. moves that reduce the probability of a draw.[10]

Throughout the paper, we will assume that the expected utility of each chess match is equal to the expected outcome of the game, plus a constant for playing the game itself. Because air pollution affects both players to the same extent, we further assume that PM_{10} has a symmetric effect on the players, regardless of their ability. These assumptions seem reasonable given that we consider chess matches in the national competition, where player's abilities and the stakes of the game are comparable.

In the (financial and economics) literature on risk-taking, a common measure of risk-taking outcomes is the standard deviation (e.g. the standard deviation of the return of a portfolio), and therefore the outcome variance. The variance of chess outcomes is a one-to-one linear negative function of the proportion of draws.[11] Let D_{ict} be a dummy indicator of whether a game i in location c on day t ends in a draw. The level of PM_{10} in location c on day t is denoted by PM_{ct}. We aim to estimate the causal effect of PM_{ct} on D_{ict}. Because draws are common (32% in our sample) we use a linear probability model.[12]

The first main econometric issue when aiming to estimate a causal effect of PM_{10} on the probability of a draw, is that PM_{10} does not randomly vary over time, but there are strong time trends in levels of PM_{10} (as air pollution tends to decrease over this time).

[9] We use a daily measure of PM_{10} rather than a measure of $PM_{2.5}$ observed during the game. $PM_{2.5}$ may be a slightly better measure from a theoretical point of view as it is roughly 1/30 of the diameter of a human hair, and may go through walls. However, data on $PM_{2.5}$ is not sufficiently available in our context and time window. At the same time outside and inside concentration levels are usually very similar for both measures, with a correlation between PM_{10} and $PM_{2.5}$ of 0.90 for days and locations with both data available.

[10] Players are often categorised as those with a high risk attitude (e.g., the 1985-2000 world champion Kasparov) or with a less risky attitude (e.g., the 1963-1969 world champion Petrosian).

[11] The outcome variance is equal to (1 - proportion of draws)/4.

[12] The estimates results hardly change when estimating using similar specifications with a logit model.

Furthermore, PM_{10} is not randomly allocated across space but is concentrated in certain cities. It is also possible that certain cities attract players with different propensities of making a draw.

The ideal way to address these issues is to compare outcome of games of players that are randomly allocated to other players at different locations for different time periods. By using the universe of chess games of a national competition for longer periods, combined with a day and location fixed effect regression design, we approach this ideal setup. In the national competition, players play half of all games at their home location and the other half at another location. Hence, in essence, we use variation in PM_{10} at different locations within the same day. For reasons of efficiency, we include two game-specific control variables: the difference in Elo rating between the players, as well as the average rating of the players.[13] We will control for weather conditions that potentially confound the effect of PM, as studies such as Wang (2017) and Heyes and Saberian (2019) show that temperature has an effect on decision making.

Consequently, we will estimate the following two-way fixed-effects regression:

$$D_{ict} = \alpha_c + \alpha_t + \beta \cdot PM_{ct} + \gamma \cdot \mathbf{X}_{ict} + \delta \cdot z_{ct} + \varepsilon_{ict}, \quad (1)$$

where α_c and α_t denote location and day fixed effects. Here, $\mathbf{X}_{ict}$ denotes control variables that capture players' strength and z_{ct} denotes (time-varying) location-specific control variables, such as weather conditions. For weather we include dummies representing bins for each of the variables, to fully capture non-linearities. For temperature we include 30 dummies, one for each degree Celsius of the average daily temperature. For rain we include a 40 dummies for each mm of rainfall. For atmospheric pressure we include 8 dummies, each covering a 10 hPa bin. For solar radiation we include 14 dummies, each representing an increment of 200 mW. We have also estimated the effect of several other weather specifications, these yield very similar results (see Table 5 in Appendix B).

We have not yet been specific about the type of location fixed effects used. To elaborate on this, we use three types of location fixed effects. We use one for the club of the home player, one for the club of the visitor player, and one for the PM_{10} monitor. In the analysis, we will cluster the standard errors at the level of the PM_{10} monitor as well as day t.

One of the strengths of the design is that we will see that inclusion of the location fixed effects as well as the weather control variables does not affect the results, which makes it more plausible that the variation in PM_{10} is exogenous.[14] This also makes sense, as the Netherlands is a geographically small country, hence the distance between these locations is small (the average distance is only 70km, where we weigh by number of games per location).[15] Hence, by including day fixed effects, we already almost perfectly control for differences in *weather* conditions (e.g. differences in temperature and sunshine are negligible).

We note that the many fixed effects that we include absorb a large part variation in PM_{10} levels. However, weather conditions like wind direction and humidity still affect the PM_{10} concentrations over time per location, and over space within a day. At the same time, the

[13] This specification implies that we control for the rating of the strongest player and the rating of the weakest player, where we allow the effects of these variables to differ.

[14] Because our results also hold using only one-way time fixed effect, we do not have the issue that two-way fixed effects models have difficulties addressing heterogeneity of estimates, resulting in inconsistent estimates (de Chaisemartin and d'Haultfoeuille 2020).

[15] For example, the distance between Amsterdam and Rotterdam, the two largest cities of the Netherlands, is only 65 km, whereas a number of cities, such as the Hague, Delft and Leiden, are located in between.

indoor climate inside chess clubs is arguably stable. In addition, because we observe a sample that spans over more decade of data, abatement of air pollution for chess clubs at locations closer to industrial areas provides us with plenty of identifying variation.

The second econometric issue is that PM_{10} reduces the ability of players to play well, resulting in more mistakes (Ebenstein et al. 2016; Künn et al. 2019). This does *not* imply that this will induce more draws. An important feature of chess, for which we will provide ample evidence, is that the probability of making a draw is a *non-decreasing* function of players' ability level. More precisely, we show that the probability to make a draw does *not* depend on the level of the player, except for very strong players (who are rare in our dataset) who make more draws.[16] Hence, the effect of PM_{10} on the probability of draws through its effect on ability is negligible in our sample. Furthermore, we will demonstrate that even if we assume that PM_{10} has (unreasonably) large effects on the ability of both players (i.e. an unreasonable large drop in their Elo ratings), then this assumption cannot explain our findings.

The third econometric issue is measurement error, as the spatial density of PM_{10} monitor stations is usually rather low, which causes attenuation bias. To avoid this, we use to our advantage that in the Netherlands many chess clubs, and in particular large clubs with many players, are located in larger cities which have several monitoring stations. Subsequently, we will focus on chess games within a maximum distance of 5 km of a monitoring station, so the average distance between the chess location and the monitoring station is small and slightly more than 2 km. In our sensitivity analysis, we will show that increasing the maximum distance indeed results in lower, but still statistically significant, estimates, whereas reducing the maximum distance results in somewhat higher point estimates but larger confidence intervals.[17]

The fourth econometric issue is whether the effect of PM_{10} is dynamic. The medical literature shows convincingly an effect of PM, but does not answer the question whether the effect of PM_{10} is immediate or also comes with a delay (Li et al. 2017).[18] The latter is theoretically possible, because PM remains in the blood circulation. For that reason, we will also measure PM_{10} on the day before the match, as well as at the location of the visiting club. The idea of the latter PM_{10} measure is that chess players typically live close to their club, and hence visitor players might be treated in the night or morning before travelling to the game. As a placebo check, we will additionally examine the effects of PM_{10} measured on the day after the game.

[16] This makes sense. Stronger players are better able to calculate the consequences of their moves, and therefore have more control over the game outcome.

[17] It is not an issue that we do not measure PM_{10} inside buildings, as environmental policies use information from outside monitoring stations, so the preferred measures, from a policy point of view, is the measure used by us.

[18] In this study, participants are treated with PM for a number of days, but dynamic treatment effects are not investigated.

3 Data

We observe the universe of outcomes of (classical) chess games for the Dutch national team competition from 2002 until 2018, played at locations as shown on the map in Fig. 1.[19] Each year, there are about 15 different leagues, in which between 8 and 10 teams compete. For games played in the highest league, we also observe the moves of the full game. Teams have 8 or 10 players and play either at home or away (similar to, for example, soccer). Although chess players play for a team, individual chess outcomes are relevant for players, as the outcome influences their Elo-rating. A competition year contains 9 rounds, played on Saturday afternoons (from September until May). Typically, there is one month between two consecutive rounds. In a round, each player plays one game (a game takes about 4 hours).[20]

To reduce measurement error in PM_{10} measurements, we focus on games within 5km of a PM_{10} station (we come back to this in the sensitivity analysis). Furthermore, we exclude a limited number of games further than 50km of a weather station. We also make another selection, which is not essential, but improves interpretation. To reduce correlation between PM_{10} observations measured at the home club and the visitors club, we concentrate on games with a minimum distance between home location and visitors location of 20km. We also require the presence of a PM_{10} station within 20km of the visitor club's location. Given these restrictions, the average distance to the PM_{10} monitor is slightly above 2 km, hence the distance to the nearest weather station is small and about 11 km.[21] The share of draws is 0.32. The average PM_{10} level is about 30 μg/m^3. Given these restrictions, we have almost 20k games played by 3,326 players at 81 different locations (see Table 1). We do not always observe weather conditions. When we focus on games for which we observe weather conditions, we observe more than 17,000 games for more than 1,000 clusters, defined as unique PM_{10} location-day observations.

For each player, we observe the so called Elo rating at the time of playing, which is an accurate numerical representation of a player's strength (Regan and Haworth 2011). The average rating is about 2100, with a standard deviation of 157. Almost all players have a rating between 1800 and 2400. In Fig. 4a in the Appendix, we provide the rating distribution. Taking risks may be perceived differently by two players who play a game depending on the difference in strength. Figure 6 shows a histogram of the (absolute) difference in rating as well as the probability that the player with the highest rating will win, draw, or lose. The difference in ratings is usually less than 300 points (less than two standard deviations), and up to that level, the weaker player still has a reasonably high chance of winning the game.

We use daily PM_{10} measured at 63 locations provided by Netherlands National Institute for Public Health and the Environment (2019), see Fig. 1. In addition we use daily weather

[19] The Dutch league follows the rules of the World Chess Federation FIDE: players receive 90 minutes for the first 40 moves, and an additional 30 minutes for the rest of the game. For each move played, the player receives an additional 30 seconds. A player who exceeds the time limit loses the game.

[20] When chess clubs have several teams in the national competition, and the team plays at home, then all games are played at the same location.

[21] The correlation between PM_{10} measurement stations for a sample with the same average distance as our main sample, is about 0.77, suggesting that attenuation bias will be about 40%. Here we use the formula $1 - \rho^2 = 1 - 0.77^2 = 0.40$, derived from Cameron and Trivedi (2005), where ρ is the correlation between PM_{10} at the measured location and PM_{10} at the chess location.

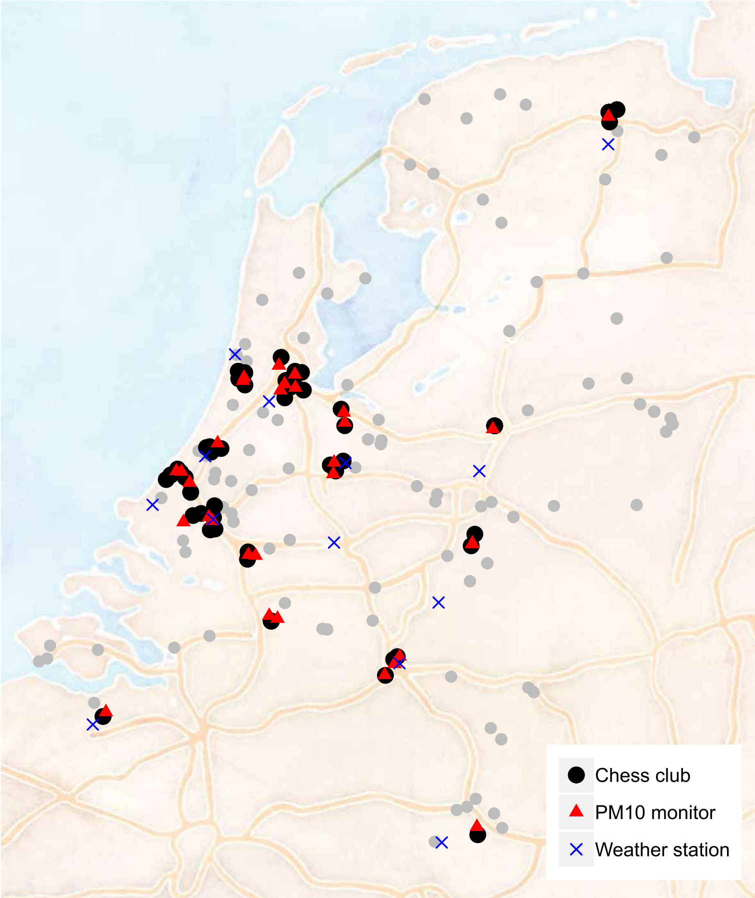


Fig. 1 Locations of chess clubs, weather stations and PM_{10} monitoring stations. *Notes:* Greyed out chess locations are excluded because of a too large distance to PM_{10} or weather monitoring stations. Some of these locations are used for sensitivity analyses

observations from Royal Netherlands Meteorological Institute (2019), which include temperature, solar radiation, rain and atmospheric pressure.

4 Results

4.1 Main results

We show in Table 2 the estimated effects of PM_{10} on draws for a range of specifications based on equation (1). In specification (1), we show the effect when we control for day fixed effects, the average rating (per game) and the difference between the rating of the players. We find a positive effect of PM. The point estimate is equal to 0.015 (with a standard error

Table 1 Descriptive statistics of main variables

Statistic	N	Mean	St. Dev.	Min	Max
Draw	4415	0.32	0.47	0.00	1.00
Mean rating game (100 points)	4415	21.06	1.56	16.80	26.26
Abs. rating difference game (100 points)	4415	1.11	0.94	0.01	8.08
Distance to PM monitor (km)	4415	2.33	1.03	0.27	4.96
Distance to weather station (km)	4415	10.86	6.95	0.65	36.77
Distance between home and visitors (km)	4415	68.75	43.06	20.22	266.54
PM_{10} (10 μg/m^3)	4415	2.91	1.41	0.57	13.77
Temperature (Celsius)	3897	7.71	4.72	−7.80	20.10
Radiation (Watt/m^2)	3897	0.68	0.54	0.02	2.32
Rainfall (mm per day)	17,713	2.22	4.58	0	40.40
Air Pressure (1000 hPa)	3887	1.02	0.01	0.98	1.04

Table 2 Main regression results

	Draw					
	(1)	(2)	(3)	(4)	(5)	(6)
PM_{10}	0.0145***	0.0179***	0.0182***	0.0206***		0.0190***
	(0.0046)	(0.0051)	(0.0052)	(0.0053)		(0.0063)
PM_{10} (visitors)			−0.0033	−0.0052		−0.0028
			(0.0048)	(0.0051)		(0.0066)
PM_{10} lag					0.0141**	0.0047
					(0.0062)	(0.0071)
PM_{10} lag (visitors)					−0.0049	−0.0025
					(0.0061)	(0.0075)
PM_{10} lead						−0.0004
						(0.0074)
PM_{10} lead (visitors)						−0.0024
						(0.0073)
Mean rating (100 points)	0.0089***	0.0081***	0.0082***	0.0107***	0.0107***	0.0108***
	(0.0022)	(0.0027)	(0.0027)	(0.0029)	(0.0029)	(0.0029)
Abs. diff. rating (100 points)	−0.0492***	−0.0510***	−0.0510***	−0.0490***	−0.0489***	−0.0490***
	(0.0031)	(0.0032)	(0.0032)	(0.0035)	(0.0035)	(0.0035)
Loc. & club FE		Yes	Yes	Yes	Yes	Yes
Weather dummies				Yes	Yes	Yes
Time FE	Day	Day	Day	Day	Day	Day
Clusters	1138	1138	1138	1043	1042	1042
Observations	19,804	19,804	19,804	17,513	17,496	17,496
R^2	0.0173	0.0382	0.0382	0.0440	0.0436	0.0440

PM_{10} variables are rescaled to 10μg/m^3. Location fixed effects are at the level of a monitoring station. Club fixed effects contain separate controls for playing at home or as visitor. Weather dummies contain: temperature (1 °C indicators), rain (1 mm indicators), atmospheric pressure (10 hPa indicators), and solar radiation (200 mW indicators). Robust standard errors in parentheses are clustered at the level of day×monitoring station.

***,**,*Indicate significance at 1%, 5%, and 10%

of 0.005), which implies that one standard deviation increase in PM_{10} increases the probability of a draw with 2.4 percentage points. Furthermore, we find a weak (but positive) effect of the mean rating (later on we will see that this effect is entirely due to the games with higher ratings), whereas we find a rather strong effect of the difference in rating.

One criticism of this specification is that it does not control for unobserved characteristics. We deal with this in specification (2), which is our preferred specification, where we include PM_{10} locations and club fixed effects. The results become somehow more pronounced.[22] We have additionally estimated models with player fixed effects rather than rating controls (see Table 6 in Appendix B). The results are statistically the same and the point estimates hardly different, which indicates that our rating controls and club fixed effects sufficiently control for player characteristics. As expected, including player fixed effects increases the standard errors due to fewer degrees of freedom.

Another criticism is that our approach may provide an underestimate of the overall effect of PM, because visitors are treated for a shorter period (i.e. only during the game) than home players, who are treated before they arrive, because they tend to live locally. In line with that, we find a slightly stronger effect when we control for PM_{10} at the visitor's location, see specification (3).[23]

In specification (4) we also control for weather conditions. As the Netherlands is small, it appears that these additional control variables do not have any effect on the estimated effect of PM. In the last two specifications, we further investigate the effect of PM_{10} on the previous day, as well as on the next day. In specification (5), we find a small positive effect of lagged PM_{10} (about half), but no effect for lagged visitors PM_{10} when we do not control for PM_{10} on the day itself. In specification (6) we show that this lagged PM_{10} effect is spurious (and entirely due to positive autocorrelation of PM). Specification (6) includes two additional placebo variables, PM_{10} and visitor PM_{10} on the next day, which are both highly statistically insignificant.

One may argue that our results are driven by reduced cognitive ability and not by reduced risk-taking. This could be the case if PM_{10} reduces the playing strength of chess players (which is very plausible) and the probability of a draw depends on players' strength. To examine the latter, we first show in Fig. 4b in the Appendix the probability of a draw as a function of the players' rating. It clearly shows that the probability of a draw does *not* depend on the rating level, except for low (below 1800) and high ratings (above 2350), which occur infrequent in our data (in less than 14% of the data). This figure is slightly misleading as it ignores that the players' probability of a draw does not only depend on the player's rating, but also on the opponent's rating (and the opponents' ratings are positively correlated). We therefore show Fig. 5 in the Appendix, where we show the effect of the rating on the probability of a draw, while controlling for the difference in rating between opponents. This figure confirms the previous message and even shows that there is only an effect of rating for players with a rating above 2350, which occur seldom in our data (less than 9 percent). Hence, our estimates may be slight underestimates. Notice however, that the effect of mean rating is very small, implying that even if the stronger player would play much weaker, the underestimate is still negligible.

[22] We have also estimated models with different restrictions on the distance between home and visitors team locations. The results are not sensitive to that.

[23] Consistent with this reasoning, the point estimate of visitor's PM_{10} is negative (but not statistically significant).

For policies that aim to reduce PM_{10} levels, an important question is whether the marginal effect of PM_{10} is constant, as implied by the linear specification.[24] We investigate this in several ways. An analysis using dummy indicators, as shown in Fig. 2, finds no evident non-linear response, as one can draw many linear response curves through the confidence intervals. Linearity is further confirmed by an analysis using polynomials, see Table 7 in Appendix B. These estimates imply that the marginal effect is constant (i.e. the quadratic term is highly insignificant, whereas the linear term remains statistically significant). Hence, we do not reject linearity.

In conclusion, we find robust evidence of the effect of PM_{10} for a range of specifications, whereas placebo tests confirm that these results are unlikely by chance. Furthermore, we have demonstrated that this effect captures a reduction in risk-taking and cannot be explained by the alternative hypothesis that players make more draws because of weaker play. If anything, our estimates are underestimates of the true effect.

4.2 Sensitivity analysis

4.2.1 Distance to the PM_{10} monitor

We perform several other analyses to examine the robustness of our results to measurement error induced by the distance between the chess location and PM_{10} monitor. In particular, we have examined how the results in Table 2 change when we depart from 5km as maximum distance between chess location and PM_{10} monitor stations. The 5km maximum distance implies an average distance of about 2.3km, see Fig. 3. It shows that the PM_{10} point estimate becomes smaller if we increase the maximally allowed distance, and therefore the average distance. Conversely, the coefficient increases if we reduce the maximum distance, but the confidence interval also increases because of the reduction in observations. Hence, our preferred specification is a conservative estimate of the effect of PM_{10} on risk-taking.

4.2.2 Other pollutants

There is no medical literature that suggests that other air pollutants affect risk taking. Nevertheless, there may be omitted variable bias in our main analysis when other pollutants that correlate with PM_{10} reduce risk taking. Therefore, we perform an additional regression where we explore the effect of $PM_{2.5}$, NO_x and O_3 on draws. We have some observations for these pollutants, but given the time window of our analysis (dating back to the early 00's), data availability is limited. This means that for a co-pollutant check we have to rely on a much smaller data set that contains a shorter period and fewer measurement stations. Table 8 in Appendix B shows the results of these analyses and indicates that the results for $PM_{2.5}$ appears to be very similar to our main finding. Furthermore, we find no evidence that NO_x and O_3 affects the probability of draws in chess.

4.2.3 Heterogeneity

[24] On theoretical grounds, one may expect a convex function, for example as PM_{10} has to surpass a certain threshold, or a concave function, for example because a saturation level of PM_{10} kicks in.

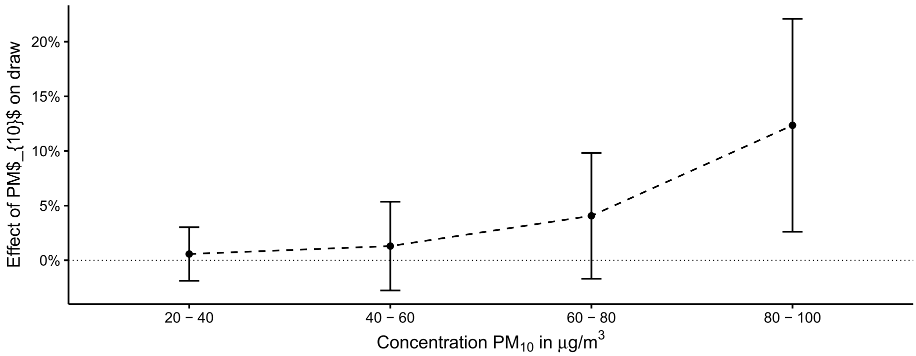


Fig. 2 Estimation results with PM_{10} dummies. *Notes:* Controls in this analysis are identical to those in specification (2) of Table 2, and < $20\mu g/m^3$ is used reference category. Error bars indicate robust 95% confidence intervals

One relevant sensitivity analysis is to distinguish between the effects of different rating levels. In Table 3, using our preferred specification, it is shown that the point estimates are positive when we distinguish between three rating subgroups (see the first three specifications), but we do not have enough power to distinguish between the PM_{10} effect of these subgroups. These estimates also confirm that, except for the subgroup of strongest players, there is no effect mean rating, and therefore of players' strength, on the probability to make a draw. Consequently, one may argue that the estimates based on samples excluding the strongest players subgroup are more accurate if one is interested in the effect of PM_{10} on risk outcomes. If one accepts this view, then the estimated effect in Table 2 is a slight underestimate of the effective PM_{10} on risk-taking. We come to the same conclusion if we do not control for visitors PM_{10} (see the last three specifications).

Another form of heterogeneity that may be interesting to examine, is whether the effect of the PM_{10} varies between players, because PM_{10} exacerbates existing stress levels. We cannot directly test this. However, it may be the case that stress levels are related to the difference in ratings between players. Additional analysis indicates that the marginal effects of PM_{10} does not depend on the Elo rating difference.[25]

4.2.4 Other dependent variables

In Table 4 we perform consistency checks by analysing the effect of PM_{10} on the probability that the stronger player wins and on the probability that the weaker player wins using linear probability models.[26] Given the reasonable assumption that players maximize expected outcome (and hence their rating) the stronger players win *less* due to PM_{10} (because the stronger player reduces the outcome variance by taking *less* risk, which comes

[25] We have also estimated logit models using the same specification. The average marginal effects are almost identical to those in the linear model. Because the difference in Elo ratings between players strongly reduces the probability of a draw, the relative effect of PM_{10} becomes stronger when the absolute difference in Elo ratings increases.

[26] We have also estimated a multinomial logit models with three outcomes (stronger player wins, draw, weaker player wins). Results are almost identical to the results in Table 4.

Fig. 3 Sensitivity to distance between chess game and air quality monitoring station (error bars indicate 95% confidence intervals)

Table 3 Regression results using Elo subsamples

	Draw					
	(1)	(2)	(3)	(4)	(5)	(6)
PM_{10}	0.0132	0.0266***	0.0100	0.0132	0.0255***	0.0101
	(0.0115)	(0.0081)	(0.0096)	(0.0115)	(0.0081)	(0.0097)
PM_{10} (visitors)	0.0006	−0.0149*	0.0042			
	(0.0095)	(0.0082)	(0.0114)			
Mean rating (100 points)	−0.0023	0.0049	0.0419***	−0.0023	0.0046	0.0419***
	(0.0128)	(0.0103)	(0.0111)	(0.0128)	(0.0103)	(0.0111)
Abs. diff. rating (100 points)	−0.0414***	−0.0460***	−0.0698***	−0.0415***	−0.0460***	−0.0697***
	(0.0067)	(0.0058)	(0.0081)	(0.0067)	(0.0058)	(0.0081)
Loc. & Club FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Weather dummies	Yes	Yes	Yes	Yes	Yes	Yes
ELO subsample	< 2000	2000-2200	> 2200	< 2000	2000-2200	> 2200
Clusters	883	1009	760	883	1009	760
Observations	4,942	8,191	4,322	4,942	8,191	4,322
R^2	0.1000	0.0680	0.1118	0.1000	0.0677	0.1117

PM_{10} rescaled to $10\mu g/m^3$. Location fixed effects are at the level of a monitoring station. Club fixed effects contain separate controls for playing at home or as visitor. Robust standard errors are clustered at the day× monitoring station.

***,**,*Indicate significance at 1%, 5%, and 10%

at the cost of having fewer wins). Additionally, the weaker player cannot win *more* due to PM_{10} (because a draw exceeds the expected outcome for this player). This assumption also implies that the stronger player's effect on the probability of winning must be stronger than the weaker player's effect on the probability of winning in absolute value, i.e. increased

Table 4 Regression results for game outcomes

	Draw (1)	Stronger wins (2)	Weaker wins (3)	Home wins (4)	Away wins (5)
PM_{10}	0.0183***	-0.0118***	-0.0062	-0.0172***	-0.0011
	(0.0050)	(0.0044)	(0.0040)	(0.0056)	(0.0061)
Mean rating (100 points)	0.0081***	0.0000	-0.0080***	-0.0111***	0.0030
	(0.0027)	(0.0028)	(0.0022)	(0.0028)	(0.0028)
Abs. diff. rating (100 points)	-0.0507***	0.1265***	-0.0732***	0.0407***	0.0100**
	(0.0033)	(0.0036)	(0.0026)	(0.0044)	(0.0041)
Loc. & Club FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
Clusters	1137	1137	1137	1137	1137
Observations	19,763	19,763	19,763	19,763	19,763
R^2	0.0378	0.0797	0.0551	0.0405	0.0327

***,**,*Indicate significance at 1%, 5%, and 10%

number of draws should mainly come at the cost of the strongest player's wins (otherwise taking less risk as the stronger player would be a dominant strategy i.e. less risk and more wins).[27] Columns (2) and (3) confirm these predictions and support our claim that PM_{10} induces less risk-taking. It suggests that people are willing to trade off a lower expected pay-off with a safer approach, in line with Duflo and Banerjee (2011). It thus appears that players take less risk than what they would prefer without PM.

In columns (4) and (5) we test whether there is a difference of the PM_{10} effect for home and visiting players. It appears that home players are affected more strongly by PM_{10} pollution. This makes sense and suggests that PM_{10} exposure prior to the game (but on the same day) has a detrimental effect in addition to the exposure during the game itself.

Finally, for games played in the highest league (about 10 percent of our sample), we know the moves. This offers alternative ways of doing a sensitivity analysis, because if PM_{10} induces players to make more draws, then it must be true that they either play less risky moves or they are more likely to agree to a draw (which nullifies the risk of losing), which will result in shorter games (i.e. games with less moves), given higher levels of PM. We find evidence of both mechanisms.[28] However, the results are not robust with respect to specification (e.g. controlling for weather) and sample selection, which is not surprising given that we have a small subsample. Most importantly, for all specifications, we either

[27] Conversely, the weaker player should not win more often due to PM. It is however possible that there is *no* effect on the number of wins of weaker player, as increased draws are *favourable* for the weaker player.

[28] We have classified risky play using several measures distinguishing between opening risk, where risk is based on the opening's share of draws, opposite castling, and white plays G4 in the opening. We also demonstrate that these measures are valid measures of risk-taking as they are strongly related to the probability of making a draw. Results can be received upon request.

find no effect (due to large standard errors), or we find statistically significant results that support that PM_{10} reduces risk-taking.

5 Conclusion

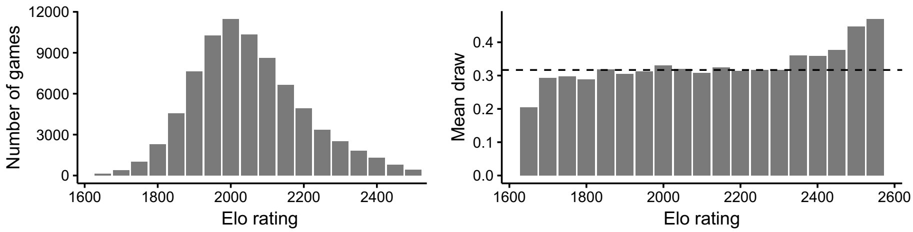
Air pollution has been shown to affect cognitive ability and is hypothesized to decrease an individual's risk-taking. This hypothesis emerged from earlier literature that finds detrimental effects of particulate matter on composite decision outcomes (e.g. stock market returns in Heyes et al. 2016). Because it is unclear which mechanism drives these results, in this paper, we focus specifically on risk-taking using the game of chess as a natural experiment.

We estimate the effect of PM_{10} on the probability that chess players make a draw, which directly reflects the variance of game outcomes, and is a clean indicator for risk-taking. We use information from the Dutch national team league, where games are played at the same time in different locations. This setting comes close to the ideal experimental setup, as air pollution levels vary over time and space.

Our results show that PM_{10} induces chess players to make more draws. We find that A 10μg increase in PM_{10} (33.6% of mean concentration) leads to a 5.6% increase in draws. We do not find any effect of PM_{10} when measured at the location of the visiting club, or of effects of PM_{10} on previous days, which implies that the PM_{10} effect is immediate. Our results demonstrate that air pollution reduces risk-taking.

Additional descriptives

See Figs. 4, 5, 6.



(a) Histogram of Elo rating. (b) Draw as a function of rating.

Fig. 4 Frequency of Elo rating and draw per rating

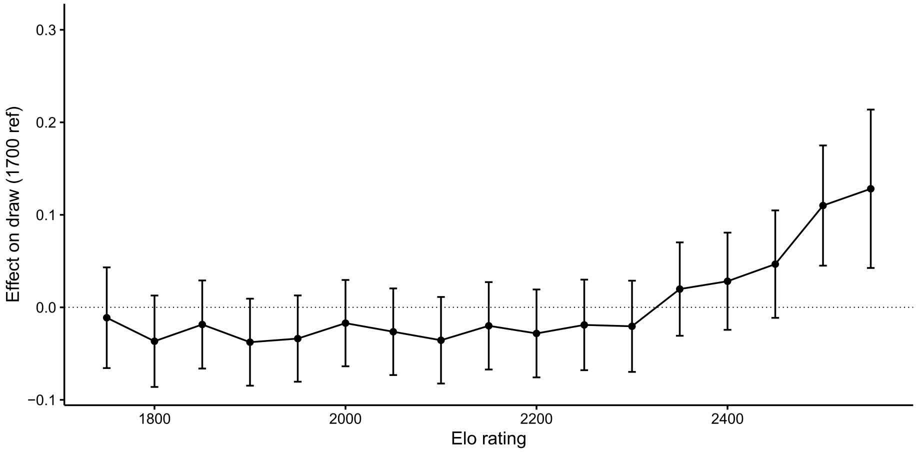
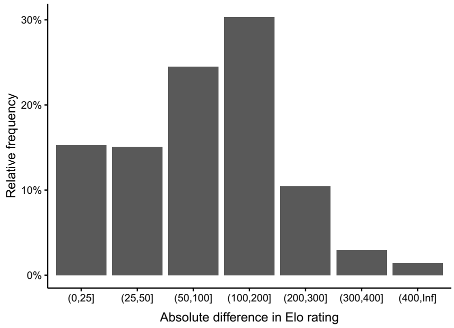
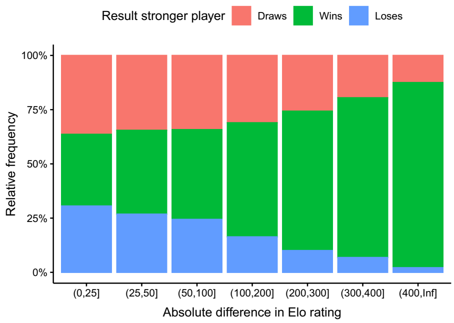


Fig. 5 Effect of players strength (mean rating per game) on draw, conditional on difference in rating



(a) Histogram of difference in rating



(b) Results player with highest rating

Fig. 6 Histogram difference in rating and results stronger player

Additional results

See Tables 5, 6, 7.

Table 5 Regression results with various specifications for weather controls

	Draw					
	(1)	(2)	(3)	(4)	(5)	(6)
PM_{10}	0.0179***	0.0202***	0.0189***	0.0185***	0.0185***	0.0188***
	(0.0051)	(0.0053)	(0.0052)	(0.0052)	(0.0052)	(0.0052)
Temperature			−0.0022	0.0017	0.0012	−0.0026
			(0.0065)	(0.0077)	(0.0078)	(0.0065)
Rain			−0.0003	−0.0003	−0.0003	−0.0002
			(0.0018)	(0.0018)	(0.0018)	(0.0018)
Atmospheric pressure			0.0011	0.0007	0.0008	0.0012
			(0.0048)	(0.0048)	(0.0048)	(0.0048)
Solar radiation			0.0606**	0.1125**	0.1504*	0.1116
			(0.0308)	(0.0560)	(0.0878)	(0.0812)
$(\text{Solar radiation})^2$					−0.0229	−0.0284
					(0.0453)	(0.0441)
Solar radiation $\times$ temperature				−0.0060	−0.0057	
				(0.0057)	(0.0058)	
Loc. & club FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather dummies		Yes				
Time FE	Day	Day	Day	Day	Day	Day
Clusters	1138	1043	1043	1043	1043	1043
Observations	19,804	17,513	17,513	17,513	17,513	17,513
R^2	0.0382	0.0439	0.0396	0.0396	0.0396	0.0396

PM_{10} variables are rescaled to $10\mu g/m^3$. Location fixed effects are at the level of a monitoring station. Club fixed effects contain separate controls for playing at home or as visitor. Rating controls are as previous specifications (e.g. Table 2). Weather dummies contain: temperature (1 °C indicators), rain (1 mm indicators), atmospheric pressure (10 hPa indicators), and solar radiation (200 mW indicators). Robust standard errors in parentheses are clustered at the level of day×monitoring station.

***,**,*Indicate significance at 1%, 5%, and 10%

Table 6 Regression results with player fixed effects

	Draw					
	(1)	(2)	(3)	(4)	(5)	(6)
PM_{10}	0.0145***	0.0165**	0.0165**	0.0224***		0.0249***
	(0.0046)	(0.0068)	(0.0068)	(0.0070)		(0.0083)
PM_{10} (visitors)			0.0001	−0.0012		−0.0000
			(0.0061)	(0.0068)		(0.0090)
PM_{10} lag					0.0109	0.0002
					(0.0078)	(0.0087)
PM_{10} lag (visitors)					−0.0044	−0.0071
					(0.0076)	(0.0094)
PM_{10} lead						−0.0075
						(0.0099)
PM_{10} lead (visitors)						0.0072
						(0.0095)
Mean rating (100 points)	0.0089***	−0.0049	−0.0049	−0.0050	−0.0056	−0.0057
	(0.0022)	(0.0121)	(0.0121)	(0.0136)	(0.0136)	(0.0136)
Abs. diff. rating (100 points)	−0.0492***	−0.0546***	−0.0546***	−0.0533***	−0.0535***	−0.0534***
	(0.0031)	(0.0056)	(0.0056)	(0.0062)	(0.0062)	(0.0062)
Player FE		Yes	Yes	Yes	Yes	Yes
Weather dummies				Yes	Yes	Yes
Time FE	Day	Day	Day	Day	Day	Day
Clusters	1138	1138	1138	1043	1042	1042
Observations	19,804	19,804	19,804	17,513	17,496	17,496
R^2	0.0173	0.3687	0.3687	0.3984	0.3980	0.3985

PM_{10} variables are rescaled to $10\mu g/m^3$. Player fixed effects are separated for black and white, i.e. each player has its own dummy for playing with black or playing with white. Weather dummies contain: temperature (1 °C indicators), rain (1 mm indicators), atmospheric pressure (10 hPa indicators), and solar radiation (200 mW indicators). Robust standard errors in parentheses are clustered at the level of day×monitoring station.

***,**,*Indicate significance at 1%, 5%, and 10%

Table 7 Regression results with higher order polynomial terms

	Draw		
	(1)	(2)	(3)
PM_{10}	0.0179***	0.0242**	0.0181
	(0.0051)	(0.0116)	(0.0253)
$(PM_{10})^2$		−0.0006	0.0006
		(0.0009)	(0.0046)
$(PM_{10})^3$			−0.0001
			(0.0002)
Mean rating (100 points)	0.0081***	0.0081***	0.0081***
	(0.0027)	(0.0027)	(0.0027)
Abs. diff. rating (100 points)	−0.0510***	−0.0510***	−0.0510***
	(0.0032)	(0.0032)	(0.0032)
Loc. & team FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Clusters	1138	1138	1138
Observations	19,804	19,804	19,804
R^2	0.0382	0.0382	0.0382

PM_{10} variables are rescaled to $10\mu g/m^3$. Column (1) is a copy of our preferred specification (column (2) of Table 2) and is included as a referenceLocation fixed effects are at the level of a monitoring station. Club fixed effects contain separate controls for playing at home or as visitor. Robust standard errors in parentheses are clustered at the level of daymonitoring station.

***,**,*Indicate significance at 1%, 5%, and 10%

Table 8 Regression results with co-pollutants

	Draw				
	(1)	(2)	(3)	(4)	(5)
PM_{10}	0.0179***				0.0141*
	(0.0051)				(0.0073)
$PM_{2.5}$		0.0141**			
		(0.0067)			
NO_x			0.0006		0.0002
			(0.0005)		(0.0008)
O_3				0.0007	0.0009
				(0.0014)	(0.0017)
Mean rating (100 points)	0.0081***	0.0225	0.0002	−0.0026	−0.0021
	(0.0027)	(0.0242)	(0.0055)	(0.0066)	(0.0067)
Abs. diff. rating (100 points)	−0.0510***	−0.0458**	−0.0583***	−0.0627***	−0.0623***
	(0.0032)	(0.0221)	(0.0065)	(0.0088)	(0.0090)
Loc. & club FE	Yes	Yes	Yes	Yes	Yes
Time FE	Day	Day	Day	Day	Day
Clusters	1138	35	291	193	191
Observations	19,804	506	4,726	3,270	3,252
R^2	0.0382	0.1348	0.0624	0.0797	0.0793

PM variables are rescaled to $10\mu g/m^3$. Column (1) is a copy of our preferred specification (column (2) of Table 2) and is included as a reference. Location fixed effects are at the level of a monitoring station. Club fixed effects contain separate controls for playing at home or as visitor. Robust standard errors in parentheses are clustered at the level of day×monitoring station.

***,**,*Indicate significance at 1%, 5%, and 10%

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