TI 2026-005/IV
Tinbergen Institute Discussion Paper

Psychological Pressure and Team Performance

Jan C. van Ours[1]

1 Erasmus University Rotterdam, Tinbergen Institute

Tinbergen Institute Amsterdam
Gustav Mahlerplein 117
1082 MS Amsterdam
The Netherlands
Tel.: +31(0)20 598 4580

Tinbergen Institute Rotterdam
Burg. Oudlaan 50
3062 PA Rotterdam
The Netherlands
Tel.: +31(0)10 408 8900

Psychological Pressure and Team Performance

Jan C. van Ours*

February 4, 2026

Abstract

Team production is increasingly important for economic outcomes, yet the factors driving team performance remain poorly understood. This paper examines the influence of psychological factors on team performance using data from the top divisions of the five major European football leagues, with a particular focus on the phenomenon of home advantage. Home advantage has been widely studied, and research has reached a point where further progress is challenging. This study offers a modest but insightful contribution by distinguishing between goals and expected goals to separate the creation of scoring opportunities from the conversion of those chances into actual goals, which reflects individual performance. The analysis shows that home teams not only generate more scoring chances but also convert them into goals more efficiently. In the absence of a stadium crowd, home advantages in goals and expected goals are substantially reduced, and the home advantage in the conversion of expected goals into actual goals is virtually absent. These findings suggest that psychological factors can be stimulating and have a positive effect on productivity, rather than workers choking under pressure and thereby decreasing their productivity.

Keywords: Home advantage, professional football, expected goals

JEL-codes: D91, L83, Z20

Conflict of interest: None.

Availability of data and materials: The data supporting the findings of this study come from various public sources and will be made available through zenodo.com.

*Erasmus School of Economics, Tinbergen Institute (Rotterdam) and ECASE (Erasmus Center for Applied Sports Economics), the Netherlands; CEPR (London). Address: Burg. Oudlaan 50, 3062 PA Rotterdam, the Netherlands; email: vanours@ese.eur.nl.

1 Introduction

Working in teams can be both stressful and stimulating. It can be stressful because team performance depends on the contribution of each individual; if one worker fails to deliver, the entire team's output may suffer. At the same time, teamwork can be stimulating: interacting with colleagues can be intrinsically rewarding, and cooperation may enhance individual productivity. Psychological factors may have positive or negative effects on teamwork as well as individual productivity. They may be stimulating and enhance productivity, but they can also create pressure that reduces productivity. Within a team, workers often have different roles. Some workers focus on the preparation of intermediate products, while others are responsible for the final stages of the production process, adding the finishing touch. Psychological pressure may affect productivity differently depending on a worker's role. Workers in preparatory roles may be less affected by psychological pressure than those in finishing roles, who might be more sensitive to such stress.

This paper studies how psychological factors influence team performance. These factors can be stimulating and enhance productivity, or they can be experienced as pressure with negative effects on productivity. The data analyzed are from professional football, where, as in other team sports, teamwork is essential.[1] The output of sports teams can be compared to production in regular workplaces where workers interact to achieve a common goal. In professional football teams, interaction is sequential, as the ball is passed from one player to the next (Katz, 2001). Ultimately, the aim of teamwork is to score goals and prevent the opponent from scoring. Although many passes are needed to score a goal, a distinction can be made between preparing and finishing. Preparing involves bringing one of the team members into a scoring position, while finishing is the conversion of an opportunity into a goal. The preparation part of the production process requires teamwork and effort, whereas the finishing part requires high-quality individual skills.

Through psychological influences, the presence of stadium crowds may affect the productivity of football teams. Stadium crowds may have a stimulating effect on a team's effort, while they may have a choking effect on more skill-related tasks. Harb-Wu and Krumer (2019), for example, analyzed biathlon, in which athletes ski and shoot rifles. The first activity is effort-related, the second is skill-related. They showed that among the most capable biathletes, home crowds induced an improvement in skiing speed but a worsening in shooting performance.

The current paper offers a modest but insightful contribution by incorporating the concept of expected goals into the analysis of home advantage in top-tier professional

[1] Palacios-Huerta (2025) provided a broad overview of studies in which sports data were used to gain insights into economic mechanisms, including the role of social pressure on performance.

football across the five major European leagues. Home advantage may originate from home teams creating more scoring opportunities, from home teams being more effective in converting opportunities into goals, or from a combination of the two. The question of whether preparation, finishing, or a combination of both drives home advantage is the main topic of this paper.

The paper is set up as follows. Section 2 presents an overview of previous studies on home advantage and recent research on the use of expected goals in the analysis of football matches. Section 3 presents the data used in the analysis, drawn from eight seasons of the top divisions in the five main European professional football leagues, and also discusses the setup of the analysis. Section 4 presents the main parameter estimates, showing that home advantages materialize both in goal preparation and in the conversion of scoring opportunities into actual goals. It is also shown that the home advantage in goal conversion is reduced substantially in the absence of stadium crowds. Section 5 concludes that there is a home advantage mainly through the presence of stadium crowds. Stadium crowds stimulate the productivity of home teams in goal preparation and do not have a choking effect on the conversion of goal opportunities into actual goals; on the contrary, psychological support appears to outweigh psychological pressure.

2 Previous Studies

2.1 Home Advantage

It is well established that, in sports matches, home teams tend to have an advantage over away teams. This advantage is often attributed to factors such as crowd support, familiarity with the home ground, and the physical fatigue experienced by away teams due to travel. The impact of stadium crowds on match outcomes has been studied by comparing games with spectators to games played behind closed doors, either due to fan misconduct or as a result of COVID-19 restrictions. Researchers have also examined matches between teams that share the same stadium, where the only variable is the size and support of the home crowd. While the findings are not always consistent, the general consensus is that crowd presence plays a significant role in home advantage, whereas factors like familiarity with the venue or travel-related fatigue appear to be less important.

Due to COVID-19 containment measures, professional football matches in many countries were played behind closed doors, that is, without the presence of a stadium crowd. These stadium closures created natural experiments on the role of crowd presence, and their consequences have been widely analyzed.

For example, Endrich and Gesche (2020) found that in German professional football, compared to matches with crowds, referees treated home teams less favorably in empty stadiums, particularly in the assignment of yellow cards. In a cross-country study, Sors et al. (2021) found a reduced home advantage during matches in the top four European football leagues played behind closed doors, but no evidence of referee bias. Similarly, Fischer and Haucap (2021) found no significant changes in referee behavior or team tactics in German football due to reduced crowd sizes. Wunderlich et al. (2021) examined COVID-related crowd restrictions across ten professional leagues, including four major European leagues. They found that while increased sanctioning of away teams disappeared in the absence of crowds, overall home advantage did not significantly decline. Scoppa (2021) used data from the top two divisions in the five major European leagues over a period of ten seasons to analyze home advantage, finding that it almost halved when matches were played in empty stadiums. Bryson et al. (2021) analyzed matches across 23 professional leagues in 17 countries. Although they observed goal-scoring effects in some countries, on average they found no effect of playing behind closed doors on final match outcomes. McCarrick et al. (2021) analyzed data from 15 leagues in 11 countries, finding that in games without fans, home teams created fewer attacking opportunities, while referee bias was reduced. Benz and Lopez (2023) reached similar conclusions across 17 leagues in 13 countries. Reade et al. (2022) analyzed multiple competitions, including the UEFA Champions League and Europa League, finding that playing behind closed doors reduced referee bias. Ferraresi and Gucciardi (2023) analyzed the top five European football leagues, focusing on the 2019/20 season. A home team, after the lockdown, when playing behind closed doors, obtained fewer points compared to what it would have obtained in the absence of the pandemic. Playing behind closed doors due to COVID-19 halved the home advantage. Cross and Uhrig (2023), focusing on the five major European leagues, found that home advantage declined, both in goals and expected goals, when matches were played without spectators. They also noted that home advantage in expected goals was smaller than that in actual goals, suggesting that part of the advantage lies in finishing efficiency, the conversion of chances into goals. Bhagwandeen et al. (2024) analyzed data from 11 leagues in 7 countries in the 2019/20 season, exploiting COVID-19-related restrictions in stadium attendance. Teams appeared to win fewer points and were less dominant when playing at home without fans. The absence of fans' influence did not affect the number of goals scored nor the number of red cards issued by referees. Leitner et al. (2023) provided an overview of earlier home advantage studies using COVID-19 restrictions as an exogenous intervention into stadium attendance. Their main conclusion was that home advantage was reduced in matches played behind closed doors, which they attributed primarily to reduced referee bias and a lack of emotional support from stadium crowds (see Wang and Qin (2023) for a similar overview of previous COVID-19-related studies). Van Ours (2024) analyzed the Dutch Eredivisie and found that home advantage disappeared in empty stadiums, while away teams received fewer yellow cards. Interestingly, when stadiums operated at one-third capacity, there were no significant effects on team performance, though the reduction in yellow cards for away teams persisted. This suggested that the absence of crowds directly affected home team performance rather than operating through changes in referee decisions.

Although the COVID-19 restrictions gave a boost to research on home advantage, non-COVID-19 studies have also provided evidence. Pettersson-Lidbom and Priks (2010), for example, exploited information from Italian football, where in 2007, because of tightened safety regulations, some matches had to be played in empty stadiums. They found that when playing in front of an audience, there was a home bias in referee decisions. Peeters and van Ours (2021) analyzed 45 seasons from four English professional football leagues, focusing on seasonal home advantage, and found that it correlated with stadium attendance. Home advantage declined over time, but this was not related to technological developments involving closer monitoring of referee decisions. In August 2013, the Argentine government allowed only home team supporters during first-division football matches. Colella et al. (2024) exploited this policy change to analyze the effects of stadium crowds, finding that visiting teams were, on average, about 20% more likely to lose without the presence of their supporters.

All in all, it is not clear whether home advantage materializes in both preparation and finishing. The presence of supportive home crowds may stimulate team performance such that goal-scoring opportunities increase. Supporting crowds can also have a positive effect on the conversion of opportunities into goals, but this is not necessarily the case. Dohmen (2008), for example, analyzing penalty kicks in the top league of German football, found that the pressure of playing in front of a home audience mattered. About a quarter of the missed penalty kicks were missed without goalkeeper interference because players choked under pressure and their shots were simply not on target.

2.2 Expected Goals

An expected goal is a metric that represents the estimated probability that a shot (including headers) results in a goal. This probability is derived from analyzing thousands of past shots and depends on factors such as the shooter's location (distance and angle to the goal), the body part used, the type of pass preceding the shot, and the nature of the attacking play (e.g., open play, set piece, or penalty). Importantly, expected goals do not account for the specific quality or skill of the players involved in a given play.

Instead, they estimate how an average player or team would be expected to perform in similar circumstances. As such, expected goals are widely considered reliable indicators of a team's underlying performance. Expected goals are based on expectations before a shot is taken, Post-shot expected goals are based on expectations after the shot is taken taking the direction of the shot to the goal line into account. Post-shot expected goals take the quality of the shot in terms of whether or not it is directed towards the goal into account.

Brechot and Flepp (2020) argued that shots on goal carry informational value, even if they do not result in actual goals. Actual goals scored or conceded are not fully reflecting team performance. In their study, they showed that recent expected goals were better predictors of future performance than recent actual goals. Similarly, Mead et al. (2023) analyzed matches from the five major European leagues and concluded that expected goals outperformed traditional metrics, such as shots and past goals, in predicting future scoring success. Roccetti et al. (2024) further supported this view, finding that expected goals were informative about long-term team performance. Teams that temporarily underperformed, that is, scored fewer goals than expected, tended to improve their goal-scoring records over time. Van Ours (2026a,b) used match results based on expected goals scored and expected goals conceded as indicators of underlying performance. Actual match results are a combination of underlying performance and randomness in converting expected goals into actual goals. If decisions are based on outcomes rather than performance, they are outcome-biased. Van Ours (2026a) found an outcome bias in consumer demand for professional football, specifically, in stadium attendance in the top divisions of the five European football leagues. Van Ours (2026b) showed that decisions to replace football managers mid-season in the top divisions of the five major European football leagues were outcome-biased.

3 Data and Set-up of the Analysis

3.1 Data

In the analysis, data are used from eight seasons of the top divisions of the five major European football leagues: English Premier League, Italian Serie A, Spanish La Liga, German Bundesliga, and French Ligue 1. During this period, many teams relegated to a lower division or were promoted to the top division. To avoid that the outcomes of the analysis are influenced by changes in sample composition in terms of teams, the analysis is based on a balanced panel. The data are from teams that were present in their respective leagues in every season from 2017/18 to 2024/25. For England, Germany, Italy, and Spain, there are eleven clubs in the balanced panel; for France, there are ten clubs (see Appendix A for details). In the analysis information is used about both expected goals and post-shot expected goals. It is not clear from the onset of the analysis if the distinction between the two indicators is relevant since the analysis is based at the level of a match and not at the level of individual shots.

Table 1: **Goals and Expected Goals; Averages per Match**

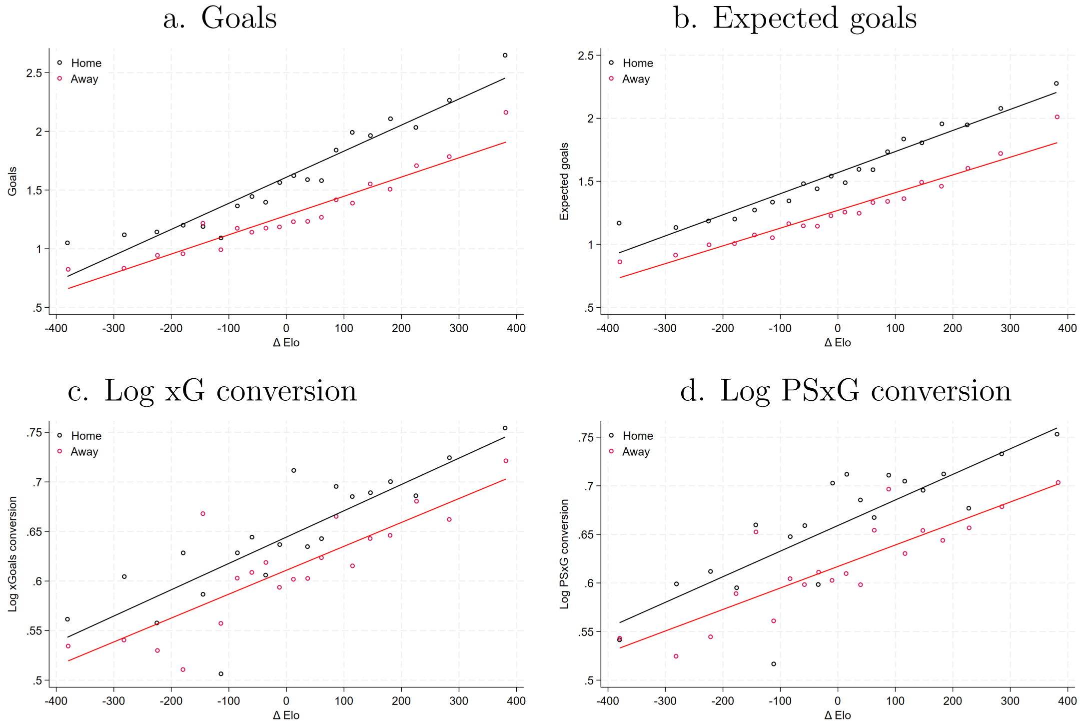
				Conversion		Log-conversion	
	G	xG	$PSxG$	G/xG	$G/PSxG$	G/xG	$G/PSxG$
a. Min-max							
Minimum	0	0.02	0	0	0	0	0
Maximum	8	7.40	7.61	25.00	50.00	3.26	3.93
Mean	1.45	1.42	1.39	1.09	1.14	0.63	0.64
b. Home-away							
Home	1.61	1.57	1.54	1.09	1.17	0.64	0.66
Away	1.28	1.27	1.25	1.08	1.12	0.61	0.64
Δ	0.33	0.30	0.29	0.01	0.05	0.03	0.02

G = Goals; xG = Expected goals; $PSxG$ = Post-shot expected goals. Log-conversion: $\log(1+G/xG)$ and $\log(1+G/PSxG)$. Based on 8,378 observations except $G/PSxG$: 8,187 observations (details in Appendix A).

Table 1 presents summary statistics of the main variables in the analysis in terms of goals and expected goals. Panel a presents minimum and maximum values of each of the variables; panel b shows averages distinguished by home and away matches. As shown in panel a, on average a teams scores 1.45 goals per match ranging from zero to a maximum of 8. The expected goals are very similar, ranging from 0.02 to 7.4 with an average of 1.42. For the post-shot expected goals the range is from 0 to 7.61 with an average of 1.39. As shown in panel b, on average, the number of goals scored by the home team is 0.33 higher than that scored by the away team. It should be noted, however, that scoring more goals in home games also implies conceding fewer goals in home games. The goal difference between home and away games is equivalent to the home advantage in terms of goals. The averages of the expected goals, shown in the second column, are again not very different from the actual goals. The home advantages are equal to 0.30 in expected goals and 0.29 in post-shot expected goals.

The fourth and fifth columns of Table 1 show the conversion rates of expected goals and post-shot expected goals into actual goals. The averages of 1.09 and 1.14 for both conversion rates. However, because small numbers expected goal sometimes lead to one or more actual goals the maximum of the conversion rates is very high: 25 for G/xG and 50 for $G/PSxG$. To reduce the effects of these outliers in the analysis log-transformations are used: $\log(1 + G/xG)$ and $\log(1 + G/PSxG)$. The maximum of these log-conversion rates are equal to 3.26 and 3.93.[2] As shown in Table 1 panel b, the log goal conversion rates are higher in home matches than in away matches.

Figure 1: **Goal Scoring by Δ Elo; Home and Away Matches**



The binscatter-plots in Figure 1 show the relationship between various goals scoring metrics and the difference in Elo-ratings between the two teams. Panel a shows this relationship for goals scored and clearly conditional on the difference in Elo-ratings more goals are scored by the home team. Panel b shows that the same holds for expected goals. Panels c and d show that although there is a lot of variation in the log-conversion rates, on average they are are higher in home games than in away games.

Playing behind closed doors may affect performance of home teams because of the absence of encouraging support of the home crowd. Playing behind closed doors may also affect the performance of away teams because the hostile stadium attendants are not present and they may therefore be more able to focus on their main task, scoring goals.

In the analysis, the focus is on the conversion rates of (post-shot) expected goals into actual goals. On average, over a season and across all teams, the numbers of (post-shot) expected goals are approximately the same as the number of actual goals; i.e., the conversion rates are about one.[3] The main question in this paper is whether the

[2]The main reason for using the log-transformation is to reduce the influence of outliers. Because for some of the matches the number of post-shot expected goals is equal to zero for the second log-conversion indicator the number of observations is lower; 8,187 instead of 8,378.

[3]Note that if the average number of goals is equal to the average number of expected goals over a

conversion rates are significantly higher in home matches than in away matches, taking into account differences in strength between the teams. If so, this would imply that home teams are more efficient in converting goal opportunities into actual goals, i.e., teams have higher finishing ability when playing at home. A related question is to what extent a potential home advantage is related to the presence of a stadium crowd.

3.2 Set-up of the Analysis

The conversion of expected goals into actual goals may be influenced by the presence of a stadium crowd. A stadium crowd may affect the performance of the home team as well as the performance of the away team. Most likely the presence of a stadium crowd has a stimulating effect on the performance of the home team and a negative effect on the performance of an away team. This also implies that when matches are played behind closed door, the home advantage for home teams is reduced while the away disadvantage for away teams is also reduced. To investigate whether the presence of a stadium audience matters for the magnitude of home advantage, a distinction is made between H_{Att} (home advantage with a stadium crowd) and H_{BCD} (home advantage when a match is played behind closed doors). In the empirical analysis of match outcomes between club i and club j in match t in season s the following equation is used:

$$Y_{ijt} = \alpha_{is} + \alpha_{js} + \beta_1 H_{i,Att} + \beta_2 H_{i,BCD} + \gamma \Delta E_{ijt} + \varepsilon_{ijt} \tag{1}$$

where Y represents a variety of dependent variables: number of goals, number of expected goals, number of post-shot expected goals and three goal conversion indicators. To account for differences in strength between teams across seasons, fixed effects for home and away clubs × seasons (α_{is} and α_{js}) are included. The average differences in strength between teams in season s are captured by the team fixed effects. To account for variation in strength within a season, the differences in Elo ratings between the two teams at the start of match t, ΔE_{ijt}, are included.[4] Finally, ε_{ijt} represents the error terms. Equation (1) is specified alternatively as a Poisson model (for goals), a linear model (for expected

season ($\overline{G} = \overline{xG}$), it is not necessarily the case that the conversion rates at the match level are equal to one, since $\frac{1}{n}\sum_{i=1}^{n} \frac{G_i}{xG_i} \geq \frac{\overline{G}}{\overline{xG}}$, where n is the number of matches in the league under investigation.

[4] Elo-ratings were originally used to indicate the relative strength of chess players (Elo, 1978) but nowadays they are used in many sports to indicate the strength of an athlete or team. Updating of Elo-ratings is mechanical. After two teams have played against each other, their Elo-ratings are adjusted depending on the outcome of the match. Winning increases a team's rating, while losing decreases it. Teams with a history of good results have higher Elo-ratings, while those with poor results have lower ones. Hvattum and Arntzen (2010) for example concluded that using Elo-ratings as a measure of team strength is justified.

goals), and Tobit models (for post-shot expected goals and the two goal conversion rates). Every match is included in the analysis twice: once for team i playing at home and once for team j playing away. Because the results of every match are used twice, standard errors are clustered by match.

4 Parameter Estimates

4.1 Baseline results

Table 2 shows the parameter estimates; in panel a there is only one variable representing home advantage; in panel b there are separate variables for home advantage depending on whether or not there was stadium attendance.

Table 2: **Parameter Estimates Goals Scoring**

	(1) G	(2) xG	(3) PSxG	(4) G/xG	(5) G/PSxG	(6) PSxG/xG
a. One home advantage						
H	0.329***	0.300***	0.288***	0.062***	0.068***	0.011*
	(0.025)	(0.017)	(0.020)	(0.013)	(0.012)	(0.006)
ΔELO/1000	1.316***	1.058***	1.105***	0.309***	0.309***	0.063***
	(0.098)	(0.062)	(0.075)	(0.051)	(0.050)	(0.025)
b. Two home advantages						
Home-Attendance	0.359***	0.333***	0.322***	0.067***	0.073***	0.013*
	(0.027)	(0.018)	(0.021)	(0.013)	(0.013)	(0.007)
Home-BCD	0.158***	0.111***	0.091*	0.031	0.038	−0.001
	(0.058)	(0.042)	(0.048)	(0.030)	(0.031)	(0.014)
ΔELO/1000	1.317***	1.058***	1.106***	0.309***	0.309***	0.063***
	(0.098)	(0.062)	(0.075)	(0.051)	(0.050)	(0.025)
Observations	8,378	8,378	8,378	8,378	8,187	8,378

Note: Columns (4) to (6): log-conversion. All estimates contain fixed effects for club × season. Goals: Poisson model (presented: average marginal effects); xG: linear model; PSxG and Goal conversion rates: Tobit models. In parentheses standard errors (clustered by match); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

From panel a of Table 2, it is clear that there are significant positive effects of matches played at home; for every metric there are clear home advantages, statistically significant at a 1% level. The differences in Elo-ratings also have significant positive effects on each of the goal scoring metrics. Clearly, relatively stronger teams are likely to score more goals, expected goals and post-shot expected goals against relatively weaker teams. These relatively stronger teams also have higher goal conversion rates. The parameter estimates for the two goal conversion rates are not very different from each other. The effects of the differences in ELO-rating are the same while the effect of home advantage is slightly larger though not significantly different for the goal conversion of post-shot expected goals. In column (6) of Table 2, the parameter estimates for an alternative log conversion indicator are shown, $\log(1 + PSxG/xG)$. The effect of home advantage is positive though significant only at a 10%-level. The conversion of expected goals into post-shot expected goals is somewhat higher in home matches. Apparently, there is a small increase in potential accuracy in home matches; they are more likely to be on target in home matches than in away matches. Other than that, it is not clear what can be learned from the distinction between expected goals and post-shot expected goals.

In panel b home advantage is split-up in two terms; one for matches with a stadium crowd and one for matches played behind closed doors. The home advantage in a stadium with crowd attendance is significant for all metrics. The home advantage in empty stadiums is significant for goals and expected goals and at a 10%-level for post-shot expected goals. For the goal conversion indicators the home advantage effect for empty stadiums is imprecisely estimated; they are not significantly different from the parameter estimates for the home advantage effect in full stadiums but also not significantly different from zero. The latter suggests that there is no longer a home advantage in the conversion rates from expected goals and post-shot expected goals into actual goals.

The main conclusion from Table 2 is that in stadiums with attendance there are clear home advantages for goals, expected goals, post-shot expected goals and the conversion of (post-shot) expected goals into actual goals. In empty stadiums, the home advantages are much smaller or almost absent. For the goal-conversion indicators there is not a lot of difference between expected goals and post-shot expected goals. The distinction between post-shot expected goals and expected goals does not provide new information about the goal-scoring processes and how these are affected by home advantages and differences in strength between two teams.

4.2 Parameter estimates by league

To investigate the heterogeneity of the main findings across the five leagues, Table 3 shows the parameter estimates for the two log-conversion rates of expected goals and post-shot expected goals separately for each league.

Panel a shows that for the first goal conversion indicator the home advantage effects in the presence of stadium crowds are all positive and significantly different from zero except for Italy. Whereas the home advantages in four countries are all insignificantly different from zero when matches are played behind closed doors in Italy this effect is significantly positive. The effects of differences in strength during the seasons are positive and significant except for the German league. Perhaps, for the German league the differences in strength are picked up by the club-season fixed effects. All in all, in every league there are significant home advantage effects in turning scoring opportunities into actual goals.

Panel b of Table 3 shows the parameter estimates for the second goal-conversion indicator: from post-shot expected goals to expected goals. These parameter estimates are very similar to those in panel a. This, again, indicates that working with post-shot expected goals instead of expected goals does not lead to new insights in the goal scoring process and how this is affected by home advantages and differences in strength between two teams.

Table 3: **Parameter Estimates by League**

	(1) England	(2) France	(3) Germany	(4) Italy	(5) Spain	(6) Total
a. $\log(1+G/xG)$						
Home-Attendance	0.088***	0.065**	0.060**	0.039	0.088***	0.067***
	(0.031)	(0.032)	(0.027)	(0.031)	(0.031)	(0.013)
Home-BCD	−0.047	−0.101	0.014	0.146**	0.071	0.031
	(0.072)	(0.079)	(0.056)	(0.062)	(0.073)	(0.030)
ΔELO/1000	0.230**	0.251**	0.085	0.427***	0.631***	0.309***
	(0.111)	(0.120)	(0.102)	(0.117)	(0.125)	(0.051)
Observations	1,760	1,366	1,760	1,758	1,734	8,378
b. $\log(1+G/PSxG)$						
Home-Attendance	0.109***	0.079**	0.050*	0.037	0.097***	0.073***
	(0.029)	(0.032)	(0.026)	(0.030)	(0.030)	(0.013)
Home-BCD	−0.015	−0.095	0.027	0.165**	0.033	0.038
	(0.070)	(0.085)	(0.055)	(0.065)	(0.075)	(0.031)
ΔELO/1000	0.244**	0.322***	0.188*	0.359***	0.489***	0.309***
	(0.108)	(0.120)	(0.101)	(0.112)	(0.122)	(0.050)
Observations	1,712	1,341	1,720	1,729	1,685	8,187

Note: Tobit models. All estimates contain fixed effects for club × season; in parentheses standard errors (clustered by match); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.3 Additional sensitivity analysis

To investigate the robustness of the main findings some sensitivity analysis is done of which the parameter estimates are shown in Appendix B. The first sensitivity analysis is on the log-transformations of the conversion rates. As an alternative inverse hyperbolic sine transformations are used: $\log(y + \sqrt{y^2 + 1})$ with $y = G/xG$ and $y = G/PSxG$. Table B.1 shows the parameter estimates. Although the magnitudes of the parameter estimates are different the main findings are very similar to those presented in Table 3. Tables B.2 and B.3 show parameter estimates if instead of a balanced sample information about all clubs in all seasons is used. The parameter estimates are again very similar to the ones presented in Tables 2 and 3. Clearly, using a balanced sample in the main analysis does not introduce a bias.

5 Conclusions

From an economic perspective, it is valuable to study how team performance in a production process is influenced by psychological factors that are not directly related to the technical or physical aspects of production. Sports data offer a unique and compelling opportunity for such research, as both individual productivity and team performance are measured accurately and recorded frequently.

In many sports, including professional football, home teams often demonstrate a consistent performance advantage. This home advantage is difficult to fully explain through physical or tactical factors alone, suggesting the presence of a significant psychological component. The presence of a passionate and vocal home crowd appears to positively influence the performance of home players relative to their opponents.

This paper contributes to the understanding of psychological effects on team performance by focusing on two key components of the football production process: the creation of goal-scoring opportunities and the successful conversion of those opportunities into goals. By considering both components, it becomes possible to assess the impact of the home environment on both the preparatory and execution stages of the team production process aimed at goal scoring. The main finding is that productivity in both parts of the production process is higher in home matches. Home teams not only create more goal-scoring opportunities but are also more effective in converting those chances into actual goals. In the absence of stadium crowds, home advantage in expected goals is strongly reduced, i.e., without the stimulating effects of stadium crowds on teamwork, goal-scoring opportunities decline. This also holds for the second part of the production process, where the individual productivity of converting goal opportunities into actual goals is also strongly reduced.

The presence of stadium crowds can be stressful, and players may choke when performing high-skilled activities. Nevertheless, the positive effects of psychological support on productivity in both teamwork and finishing skills dominate. The support of the home crowd does not appear to have a choking effect on the performance of the home team. On the contrary, the home advantage is substantially smaller and often absent when a match is played behind closed doors. When psychological pressure comes from a supportive environment, it seems to enhance the productivity of individual players with different roles within the team. In this way, psychological pressure stimulates home team performance.

Professional football players in home teams who feel the support of the home crowd tend to be more productive than players from away teams, who lack this support. Stadium crowds closely monitor the performance of players, much like managers monitor their workers, though the latter likely occurs with less precision.

The implications for team production processes outside professional football are significant. Regardless of whether workers are engaged in preparatory or finishing tasks, psychological pressure and support appear to have an impact. Psychological pressure does not seem to have a choking effect on workers who are closely monitored. Workers who feel supported and encouraged by their managers may achieve higher productivity than those who lack such support.

References

Benz, L. S. and M. J. Lopez (2023). Estimating the change in soccer's home advantage during the Covid-19 pandemic using bivariate Poisson regression. *AStA Advances in Statistical Analysis 107*(1-2), 205–232.

Bhagwandeen, B., A. Mohammed, and I. Dialsingh (2024). Investigating the influence of fans on home advantage outcomes in association football across Europe. *Soccer & Society 25*(8), 1093–1109.

Brechot, M. and R. Flepp (2020). Dealing with randomness in match outcomes: How to rethink performance evaluation in European club football using expected goals. *Journal of Sports Economics 21*(4), 335–362.

Bryson, A., P. Dolton, J. J. Reade, D. Schreyer, and C. Singleton (2021). Causal effects of an absent crowd on performances and refereeing decisions during Covid-19. *Economics Letters 198*, 109664.

Colella, F., P. S. Dalton, and G. Giusti (2024). Moral support and performance. *Management Science 70*(7), 4614–4628.

Cross, J. and R. Uhrig (2023). Do fans impact sports outcomes? A Covid-19 natural experiment. *Journal of Sports Economics 24*(1), 3–27.

Dohmen, T. J. (2008). Do professionals choke under pressure? *Journal of Economic Behavior & Organization 65*(3), 636–653.

Elo, A. E. (1978). *The Rating of Chessplayers, Past and Present.* London Batsford.

Endrich, M. and T. Gesche (2020). Home-bias in referee decisions: Evidence from "ghost matches" during the Covid19-pandemic. *Economics Letters 197*, 109621.

Ferraresi, M. and G. Gucciardi (2023). Team performance and the perception of being observed: Experimental evidence from top-level professional football. *German Economic Review 24*(1), 1–31.

Fischer, K. and J. Haucap (2021). Does crowd support drive the home advantage in professional football? Evidence from German ghost games during the Covid-19 Pandemic. *Journal of Sports Economics 22*(8), 982–1008.

Harb-Wu, K. and A. Krumer (2019). Choking under pressure in front of a supportive audience: Evidence from professional biathlon. *Journal of Economic Behavior & Organization 166*, 246–262.

Hvattum, L. and H. Arntzen (2010). Using ELO ratings for match result prediction in association football. *International Journal of Forecasting 26*(3), 460–470.

Katz, N. (2001). Sports teams as a model for workplace teams: Lessons and liabilities. *Academy of Management Perspectives 15*(3), 56–67.

Leitner, M. C., F. Daumann, F. Follert, and F. Richlan (2023). The cauldron has cooled down: A systematic literature review on home advantage in football during the COVID-19 pandemic from a socio-economic and psychological perspective. *Management Review Quarterly 73*, 605–633.

McCarrick, D., M. Bilalic, N. Neave, and S. Wolfson (2021). Home advantage during the COVID-19 pandemic: Analyses of European football leagues. *Psychology of Sport and Exercise 56*, 102013.

Mead, J., A. O'Hare, and P. McMenemy (2023). Expected goals in football: Improving model performance and demonstrating value. *PLoS ONE 18*(4), e0282295.

Palacios-Huerta, I. (2025). The beautiful dataset. *Journal of Economic Literature 63*(4), 1363–1423.

Peeters, T. and J. C. van Ours (2021). Seasonal home advantage in English professional football; 1974–2018. *De Economist 169*(1), 107–126.

Pettersson-Lidbom, P. and M. Priks (2010). Behavior under social pressure: Empty Italian stadiums and referee bias. *Economics Letters 108*(2), 212–214.

Reade, J. J., D. Schreyer, and C. Singleton (2022). Eliminating supportive crowds reduces referee bias. *Economic Inquiry 60*(3), 1416–1436.

Roccetti, M., F. Berveglieri, and G. Cappiello (2024). Football data analysis: The predictive power of expected goals (xG). *GAME-ON 2024*, 20–24.

Scoppa, V. (2021). Social pressure in the stadiums: Do agents change behavior without crowd support? *Journal of Economic Psychology 82*, 102344.

Sors, F., M. Grassi, T. Agostini, and M. Murgia (2021). The sound of silence in association football: Home advantage and referee bias decrease in matches played without spectators. *European Journal of Sport Science 21*(12), 1597–1605.

Van Ours, J. C. (2024). They didn't know what they got till the crowd was gone. *Economics Letters 236*, 111615.

Van Ours, J. C. (2026a). Good vibrations: Outcome bias in consumer demand. *Applied Economics Letters*, forthcoming.

Van Ours, J. C. (2026b). Outcome bias in managerial decisions. *Journal of Economic Psychology 112*, 102872.

Wang, S. and Y. Qin (2023). The impact of crowd effects on home advantage of football matches during the COVID-19 pandemic – A systematic review. *PLOS ONE 18*(11), e0289899.

Wunderlich, F., M. Weigelt, R. Rein, and D. Memmert (2021). How does spectator presence affect football? Home advantage remains in European top-class football matches played without spectators during the Covid-19 pandemic. *PLOS ONE 16*(3), e0248590.

Appendix A: Details on the Data

The analysis covers eight seasons, from 2017/18 to 2024/25, based on the availability of expected goals data. The following data sources are used:

- Match-level goals: football-data.co.uk.
- (Post-shot) expected goals: aggregating individual shots to match level: fbref.com.
- Elo-ratings: elofootball.com.

The analysis is based on a balanced panel, i.e., a data sample of clubs that were present in their league in every season from 2017/18 to 2024/25. Table A.1 provides an overview of the clubs in the balanced panel.

Table A.1: **Clubs Balanced Panel**

England	France	Germany	Italy	Spain
Arsenal	Lille	Augsburg	Atalanta	Ath Bilbao
Brighton	Lyon	Bayern Munich	Bologna	Ath Madrid
Chelsea	Marseille	Dortmund	Fiorentina	Barcelona
Crystal Palace	Monaco	Ein Frankfurt	Inter	Betis
Everton	Montpellier	Freiburg	Juventus	Celta
Liverpool	Nantes	Hoffenheim	Lazio	Getafe
Man City	Nice	Leverkusen	Milan	Real Madrid
Man United	Paris SG	M'gladbach	Napoli	Sevilla
Newcastle	Rennes	Mainz	Roma	Sociedad
Tottenham	Strasbourg	RB Leipzig	Torino	Valencia
West Ham		Wolfsburg	Udinese	Villarreal

Table A.2 shows match attendance by season and league. In particular in season 2020/21 many matches were played behind closed doors. In the balanced sample of 11 teams there are 11 teams $\times$ 10 opponents $\times$ Home/Away $\times$ 8 seasons = 1,760 observations. This is the case for England and Germany. Due to missing observations on Elo-ratings, in Italy the number of observations is 1,758 and in Spain it is 1,734. In France with a balanced panel of 10 teams, the number of observations could have been 10 teams $\times$ 9 opponents $\times$ Home/Away $\times$ 8 seasons = 1,440. However, due to missing Elo-ratings and missing matches because the Covid-19 season 2019/20 was ended prematurely the actual number of observations is 1,366. Table A.3 provides further descriptives.

Table A.2: **Observations and Stadium Crowds**

Season	Attendance	BCD	All	League	Attendance	BCD	All
2018	1,052	0	1,052	England	1,510	250	1,760
2019	1,052	0	1,052	France	1,188	178	1,366
2020	762	244	1,006	Germany	1,490	270	1,760
2021	76	974	1,050	Italy	1,484	274	1,758
2022	1,026	26	1,052	Spain	1,462	272	1,734
2023	1,052	0	1,052				
2024	1,056	0	1,056				
2025	1,058	0	1,058				
Total	7,134	1,244	8,378	Total	7,134	1,244	8,378

Note: Attendance = with stadium crowds; BCD = Behind Closed Doors

Table A.3: **Descriptives by League**

		Mean	St Dev	Min	Max
a. England	Goals	1.45	1.29	0	7
	xG	1.39	0.85	0.0	7.4
	$PSxG$	1.39	1.05	0.0	6.7
	$\Delta E/100$	0.00	2.07	-4.9	4.9
b. France	Goals	1.42	1.19	0	7
	xG	1.42	0.82	0.0	5.0
	$PSxG$	1.40	0.98	0.0	5.8
	$\Delta E/100$	0.00	1.88	-5.9	5.9
c. Germany	Goals	1.65	1.35	0	8
	xG	1.57	0.91	0.0	6.6
	$PSxG$	1.56	1.12	0.0	7.6
	$\Delta E/100$	0.00	1.94	-5.9	5.9
d. Italy	Goals	1.36	1.18	0	7
	xG	1.33	0.76	0.1	5.6
	$PSxG$	1.31	0.93	0.0	7.4
	$\Delta E/100$	0.00	1.77	-5.3	5.3
e. Spain	Goals	1.32	1.19	0	7
	xG	1.33	0.81	0.0	5.1
	$PSxG$	1.32	0.97	0.0	5.8
	$\Delta E/100$	0.00	1.81	-5.4	5.4

Appendix B: Additional Estimates

This appendix presents additional parameter estimates to illustrate the robustness of the main findings. These additional estimates are briefly discussed in Section 4.3. Table B.1 uses the inverse hyperbolic sine as an alternative transformation to reduce the effects of outliers.

Table B.1: **Parameter Estimates by League; Alternative Conversion Rates**

	(1) England	(2) France	(3) Germany	(4) Italy	(5) Spain	(6) Total
a. IHS(G/xG)						
Home-Attendance	0.113***	0.083**	0.076**	0.048	0.112***	0.086***
	(0.040)	(0.041)	(0.036)	(0.040)	(0.040)	(0.018)
Home-BCD	−0.060	−0.132	0.018	0.193**	0.093	0.041
	(0.093)	(0.103)	(0.074)	(0.080)	(0.096)	(0.040)
ΔELO/1000	0.292**	0.318**	0.102	0.554***	0.825***	0.397***
	(0.144)	(0.158)	(0.134)	(0.153)	(0.164)	(0.067)
Observations	1,760	1,366	1,760	1,758	1,734	8,378
b. IHS(G/PSxG)						
Home-Attendance	0.140***	0.100**	0.063*	0.047	0.123***	0.093***
	(0.038)	(0.042)	(0.034)	(0.039)	(0.039)	(0.017)
Home-BCD	−0.022	−0.120	0.040	0.214**	0.043	0.050
	(0.091)	(0.110)	(0.072)	(0.084)	(0.096)	(0.040)
ΔELO/1000	0.314**	0.414***	0.237*	0.463***	0.633***	0.397***
	(0.140)	(0.156)	(0.130)	(0.145)	(0.158)	(0.065)
Observations	1,712	1,341	1,720	1,729	1,685	8,187

Note: IHS = Inverse Hyperbolic Sine. Tobit models. All estimates contain fixed effects for club × season; in parentheses standard errors (clustered by match); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Tables B.2 and B.3 show parameter estimates in the sample includes all clubs in all seasons rather than a balanced sample of teams.

Table B.2: **Parameter Estimates Goals Scoring – All Clubs in All Seasons**

	(1) G	(2) xG	(3) PSxG	(4) G/xG	(5) G/PSxG	(6) PSxG/xG
Home-Attendance	0.301***	0.307***	0.283***	0.056***	0.057***	0.008**
	(0.014)	(0.010)	(0.012)	(0.008)	(0.008)	(0.004)
Home-BCD	0.151***	0.151***	0.140***	0.012	0.010	−0.002
	(0.032)	(0.021)	(0.025)	(0.017)	(0.017)	(0.008)
ΔELO/1000	1.523***	1.216***	1.212***	0.357***	0.340***	0.062***
	(0.052)	(0.031)	(0.038)	(0.028)	(0.028)	(0.013)
Observations	28,536	28,536	28,536	28,536	27,769	28,536

Note: Columns (4) to (6): log-conversion. All estimates contain fixed effects for club × season. Goals: Poisson model (presented: average marginal effects); xG: linear model; PSxG and Goal conversion: Tobit models. In parentheses standard errors (clustered by match); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: **Parameter Estimates by League – All Clubs in All Seasons**

	(1) England	(2) France	(3) Germany	(4) Italy	(5) Spain	(6) Total
a. $\log(1 + G/xG)$						
Home-Attendance	0.055***	0.051***	0.057***	0.039**	0.082***	0.056***
	(0.017)	(0.017)	(0.017)	(0.016)	(0.017)	(0.008)
Home-BCD	−0.021	−0.086**	0.014	0.081**	0.034	0.012
	(0.037)	(0.043)	(0.035)	(0.033)	(0.038)	(0.017)
ΔELO/1000	0.305***	0.328***	0.222***	0.414***	0.494***	0.357***
	(0.060)	(0.068)	(0.062)	(0.055)	(0.065)	(0.028)
Observations	6,074	5,464	4,884	6,064	6,050	28,536
a. $\log(1 + G/PSxG)$						
Home-Attendance	0.062***	0.044**	0.060***	0.033**	0.091***	0.057***
	(0.017)	(0.017)	(0.017)	(0.016)	(0.017)	(0.008)
Home-BCD	0.000	−0.087**	−0.010	0.084**	0.025	0.010
	(0.038)	(0.043)	(0.036)	(0.034)	(0.038)	(0.017)
ΔELO/1000	0.321***	0.313***	0.245***	0.425***	0.364***	0.340***
	(0.060)	(0.069)	(0.062)	(0.055)	(0.064)	(0.028)
Observations	5,899	5,312	4,764	5,923	5,871	27,769

Note: Tobit models. All estimates contain fixed effects for club × season; in parentheses standard errors (clustered by match); * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$