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Good Vibrations: Outcome Bias in Consumer Demand

Jan van Ours[1]

1 Erasmus University Rotterdam, Tinbergen Institute

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Jan C. van Ours*

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Abstract

Expectations about future events can be influenced by prior outcomes of similar events, even when those outcomes were partly determined by chance. When such randomness is overlooked in decision-making, outcome bias may arise. This paper investigates the presence of outcome bias in consumer demand for professional football, focusing specifically on stadium attendance in the top divisions of the "big five" European football leagues. The analysis reveals that stadium occupancy rates are influenced by the outcomes of previous matches, even when those outcomes do not accurately reflect the home team's underlying performance quality. These findings suggest that consumer demand for stadium attendance exhibits outcome bias.

Keywords: Outcome bias; professional football; stadium attendance

JEL-codes: C20, L83, M12, Z20

Conflict of interest: None.

Availability of data and materials: The data supporting the findings of this study come from various public sources (see Appendix A for details) and will be made publicly available in a single dataset.

Good Vibrations is the title of a song composed by *Brian Wilson* in 1966 and performed by *the Beach Boys.*

*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

Decisions based on expectations about future events may be influenced by earlier outcomes that were, at least in part, determined by chance. When this randomness is overlooked, outcome bias may arise. Most research on outcome bias relies on laboratory experiments, where subjects evaluate past decisions given different resulting outcomes. For example, Baron and Hershey (1988), analyzing medical decisions and monetary gambles, concluded that people often mix their evaluation of a decision with its consequences. According to Brownback and Kuhn (2019), although there is extensive experimental literature on outcome bias in economics, observational studies remain scarce.

Sports data offer a rich context for economic analysis. As argued by Kocher and Sutter (2010), the presence of explicit randomization, well-defined rules, and abundant high-quality data make sports particularly suitable for empirical research. Moreover, as Balafoutas et al. (2019) noted, sports allow for direct observation of behavior under high-stakes conditions, further enhancing their value for studying decision-making. Unsurprisingly, some of the few observational studies on outcome bias have used sports data. For instance, Lefgren et al. (2015) found that NBA coaches were more likely to change their line-up following a loss than a win, even when the loss was marginal and performance was similar. Similarly, Meier et al. (2023) documented outcome bias in professional women's basketball, college basketball, and the NFL. In another example, Gauriot and Page (2019) showed that football players who scored by narrowly missing the post received higher performance ratings and more playing time than those who hit the post and missed, even though the distinction was random. This suggests that even experts such as managers and journalists are subject to outcome bias. Kausel et al. (2019) found comparable effects in penalty shootouts, where winning teams received higher performance ratings regardless of underlying performance. Bucciol et al. (2019) documented outcome bias in Italian football, finding that managers' tactical choices (e.g., defensive vs. offensive play) were influenced by recent match outcomes.

Outcome bias may also affect betting markets, where bettors may overvalue teams that have recently won, regardless of whether those wins were deserved. In an analysis of 20 European leagues, Wheatcroft (2020) found that underperforming teams were assigned more generous odds, while overperforming teams received tighter odds, suggesting that bettors overreact to recent outcomes. Merz et al. (2021) used a "good luck" variable—defined as the difference between actual and expected goals—and found that it significantly affected betting probabilities, indicating outcome-biased behavior. Flepp et al. (2024) further concluded that such biases could distort market prices, inflating the perceived chances of overperforming teams and deflating those of underperformers.

The current paper investigates outcome bias in consumer demand, focusing on real-world behavior: professional football stadium attendance.[1] The data cover the top divisions of the five major European leagues: England, France, Germany, Italy, and Spain. This study contributes to the literature in two ways. First, it adds to the limited body of observational studies on outcome bias. Second, it explores outcome bias from a largely neglected perspective: consumer behavior in sports.

In the analysis, expected goals (xG) serve as a measure of underlying match quality. An expected goal represents the probability that a shot (or header) results in a goal, based on factors such as distance, angle, body part used, and type of attack. Aggregated xG data are used to derive expected points, which reflect team performance quality. In contrast, actual points conflate performance with randomness. A team that earns more points than expected is said to overperform, while one that earns fewer is considered to underperform.

Stadium attendance depends partly on expectations about match outcomes, which are proxied by bookmaker odds. Assuming betting markets are efficient, these odds incorporate all relevant public information. Conditional on these expectations, consumers may also respond to recent team performances and outcomes. If high-quality recent performances increase attendance more than poor ones, this reflects rational behavior. However, if in addition to this actual match outcomes also affects attendance, this would suggest outcome bias.

The empirical analysis has two components. First, there is an analysis of bookmaker efficiency: Match outcomes are regressed on bookmaker odds and prior match performance and match outcomes. The results show that bookmaker odds fully capture expectations, and recent match outcomes have no additional value. This supports the assumption of market efficiency and clarifies that any effect of past outcomes on attendance is not due to missing information in the odds. Apparently, bookmakers are not outcome biased. In the second part of the empirical analysis stadium attendance is modeled. Attendance is regressed on bookmaker odds (forward-looking expectations) and recent performance/outcomes (backward-looking indicators). The analysis shows that match expectations, as reflected in bookmaker odds, significantly influence attendance. Furthermore, high-quality recent performances by the home team increase attendance. Finally, in four of the five leagues, actual outcomes of recent matches also affect attendance, even after controlling for performance quality. This indicates the presence of outcome bias in consumer behavior. Interestingly, in the English Premier League, outcome bias does not appear to influence attendance. A likely explanation is that matches

[1] In a companion paper outcome biases in managerial decisions in professional football are investigated (Van Ours, 2025).

are frequently sold out, limiting consumers' ability to adjust attendance based on recent performance.

The remainder of the paper is structured as follows. Section 2 reviews the literature on stadium attendance and presents a simple empirical model in which outcome bias can be detected. Section 3 describes the data. Section 4 tests for the efficiency of bookmaker odds, an essential precondition for interpreting outcome effects. Section 5 presents the core analysis of stadium attendance and outcome bias. Section 6 concludes.

2 Consumer Demand for Stadium Attendance

According to Borland and MacDonald (2003) demand for stadium attendance at sporting events is like a traditional decision of consumers maximizing utility subject to a budget constraint. There are various potential determinants including economic factors such as ticket prices and travel costs, potential substitutes (other sporting events, TV), quality of the contest, quality of the home team, timing of the match and so on.

Coates et al. (2014) and Humphreys and Zhou (2015) suggested to include bookmaker odds based home win probabilities and its squared value as determinants of stadium attendance. A concave relationship between home win probability and stadium attendance would suggest that fans prefer tighter matches about certain home wins. A convex relation would suggest that fans are loss averse. Schreyer et al. (2016) concluded that uncertainty of outcomes in German professional football matches had a positive effect on game attendance of seasonal ticket holders. In an analysis of developments in stadium attendance in Dutch professional football Besters et al. (2019) found a convex relationship and thus that loss aversion dominated the preferences for uncertain outcomes. They found that match expectations which also include possible draws as outcome perform better than home win probabilities. Schreyer and Ansari (2022) provided a review of stadium attendance research stating that in European football, team quality has been the dominant measure of match quality. There are various indicators of team quality including player budgets, past winning percentages, goals scored and so on. Wills et al. (2023) presented an empirical analysis of stadium attendance demand for the men's UEFA Champions League concluding that fans were not so much interested in uncertainty of outcome or competitive intensity but in the quality of the away team.

Since football is a low scoring sport, outcomes are influenced by random events. Therefore, actual match outcomes may not be a good indicators of the performance of the two teams in a match. Expected goals are considered to be more accurate measures of performance. Mead et al. (2023) concluded from an analysis of the five European top leagues of professional football that expected goals are a superior predictor of a football team's future success in terms of goal scoring when compared to traditional statistics shots and goals in previous matches. According to Roccetti et al. (2024) expected goals are informative about the long term performance of a team. Teams that are temporary underperforming in the sense that actual goals are below expected goals later on improve their goal scoring record. Brechot and Flepp (2020) argued that shots on goal carry information signals even the shots do not turn into goals. Therefore, focusing on actual goals is not fully informative about the quality of the performance. For each shot on goal the probability that the shot will turn into a goal can be calculated taking into account the location of the shot (distance and angle to the goal), the part of the body used (foot or head) and how the shot came to be from open play, a free kick or a penalty kick.

In empirical research to explain match attendance usually some measures of recent team performance are used like winning percentage or league rank. It is here that an outcome bias may occur. It may be that consumers of sports events interpret past outcomes as an indicator of quality rather than as the result of a combination of quality and randomness. If the number of points obtained in previous matches is used as an indicator for the quality of play this ignores randomness. There could be overperformance, i.e., the quality of play is not as good as suggested by the number of points obtained. Similarly, there could be underperformance if the quality of play was better than the outcome suggests.

Forward looking match expectations are summarized using bookmaker based expected points. The underlying quality of performance in recent matches is indicated by the expected number of points in these matches based on expected goals. There is a natural positive association between expected points and points. If there are more expected points there should also be more actual points. What matters is what happens if there is a difference between the two, i.e., if there is overperformance or underperformance. If this difference has an effect then this is an indication of an outcome bias in the demand for stadium performance.

To sum up, stadium attendance is assumed to be influenced by forward looking match expectations, backward looking recent indicators of underlying performance and recent under/overperformance. If 'recent' is assumed to be equal to the previous three matches attendance at a match of home team i playing against team j in match n can be specified as:

$$A_{ijn} = A(B_{ijn}, \sum_{n=-3}^{-1} (xP_{in}), \sum_{n=-3}^{-1} (P_{in})) \tag{1}$$

where B represents the number of bookmaker points, i.e., the expected points based on bookmaker odds, xP represents the number of expected points based on expected goals and P is the number of actual points obtained. If the bookmakers points contain all information about the expected outcome of the forthcoming match, there may be an effect of expected points since this indicates strong recent performance but there should not be an effect of actual points. If there is, there is an outcome bias.

3 Data

In the analysis, data are used from the top divisions of the five main European football leagues up to season 2024/25 (details are provided in Appendix A). Match expectations can be based on bookmaker odds (Hegarty and Whelan, 2024). Sports betting markets share similarities with traditional financial markets, where participants invest money in assets with the hope of generating positive returns. In both markets, future outcomes are uncertain, there are numerous participants, and historical information about relevant events is widely accessible (Makropoulou and Markellos, 2011). In an efficient market, the price fully reflects available information. Similarly, in a sports betting market bookmakers use all available information when setting their odds. According to Sauer (1998), for example, sports betting markets offer a unique setting for economists to study models of market pricing whereby these markets are efficient if the expected returns are equal across betting opportunities.

Using bookmaker odds, the probability that home team i wins against away team j is equal to: $Prob^h_{ij} = \frac{1/O^h_{ij}}{1/O^h_{ij}+1/O^d_{ij}+1/O^a_{ij}}$. Here, O^h_{ij} are the odds for a home win, O^d_{ij} are the odds for a draw and O^a_{ij} are the odds for an away win. The probabilities of a draw and an away win are derived in a similar way. The bookmaker-expected points for the home team are equal to $B_{ij} = Prob^h_{ij} * 3 + Prob^d_{ij}$. The bookmaker based expected points are ex ante, i.e., they are expected before the match start.

To indicate the underlying quality of performance in a match, information about expected goals is used. Due to the availability of information about expected goals, the first season in the analysis is 2017/18. Expected goals are transferred into expected points – called xP. Expected goals are first transferred into a probability distribution of a discrete number of goals. Then, comparing goals scored and conceded the distribution of the number of expected points is calculated (see for a similar approach Partida et al. (2021)). The assumption is that k, the number of goals scored, follows a Poisson distribution, $P_s(k; xG_s) = \frac{(xG_s)^k e^{-xG_s}}{k!}$. Here, xG_s is the number of expected goals scored. The same holds for the distribution of expected goals conceded, $P_c(m; xG_c) = \frac{(xG_c)^m e^{-xG_c}}{m!}$, where m is the number of goals conceded and xG_c is the number of expected goals conceded. Then, the probability of a match ending in a draw is equal to $P^{\text{draw}} = \sum_{k=m=0}^{N_{max}} P_s(k; xG_s)P_c(m; xG_c)$ with N_{max} as the maximum number of goals scored (and conceded). The probability of a win is equal to $P^{\text{win}} = \sum_{k=0}^{N_{max}} (P_s(k; xG_s) \sum_{m=0}^{k-1} P_c(m; xG_c))$. Then, the number of expected points is equal to: $xP = 3 \times P^{\text{win}} + P^{\text{draw}}$. Note that the terminology "expected goals" is somewhat confusing as the expectation is not future-oriented but past-oriented. After a match is played one can calculate in hindsight based on expected goals how many goals could have been scored or conceded. A team is overperforming if the balance of goals scored and conceded is higher than the balance of expected goals scored and conceded. A team is underperforming if the balance of expected goals is superior to the balance of actual goals.

4 Match Outcomes

As indicated before, two different types of explanatory variables are used. The first one is forward looking, i.e., expected match outcomes based on bookmaker odds. The second type is backward looking. These are indicators of recent performance as measured by expected points based on expected goals and under/overperformance. Recent performance is measured over the previous three matches. To formalize the outcome of a match between two teams, ordered logit models are estimated. The results between teams i and j in match n in a particular season, Y_n, in terms of the number of points obtained by the home team (0, 1, 3) is the dependent variable and the expected number of points by the home team based on bookmaker odds is among of the right-hand side variables:

$$Prob(Y_{ijn} \leq z) = \frac{1}{1 + \exp(-(\delta_z + \beta_1 B_{ijn} + \beta_2 \sum_{n=-3}^{-1} xP_{in} + \beta_3 \sum_{n=-3}^{-1} P_{in}))}, \quad z \in \{0, 1, 3\} \tag{2}$$

where the δ_z represent threshold parameters such that $-\infty < \delta_0 < \delta_1 < \delta_3 = \infty$. Furthermore, B_n represents the bookmaker based expected number of points in the match between i and j in match n and xP and P are the number of expected points and points respectively.

The parameter estimates are shown in panel a of Table 1. In every league, the parameter estimates of the bookmaker based expected points are significantly different from zero. The effects of performance as indicated by the number of expected points in the previous three matches are all positive but not significantly different from zero. The parameter estimates of match outcomes, the number of points in the previous three matches are all insignificant with one exception. The number of points in the previous three matches in the Spanish league differs from zero at a 10%-level. Panel b of Table 1 shows that the

Table 1: **Parameter Estimates Match Outcomes (Points); Ordered Logit Models**

	England		France		Germany		Italy		Spain	
a. B points	1.63	(0.08)***	1.68	(0.10)***	1.60	(0.10)***	1.94	(0.08)***	1.80	(0.09)***
xPoints previous 3 matches	0.35	(0.35)	0.41	(0.36)	0.52	(0.40)	-0.06	(0.36)	0.43	(0.32)
Points previous 3 matches	-0.10	(0.19)	0.03	(0.19)	-0.18	(0.21)	-0.03	(0.20)	-0.31	(0.16)*
Observations	2800		2556		2229		2795		2800	
Club-seasons	160		156		144		160		160	
b. B points	1.61	(0.08)***	1.68	(0.09)***	1.56	(0.10)***	1.95	(0.09)***	1.82	(0.10)***
xPoints previous 4 matches	0.31	(0.29)	0.58	(0.33)*	0.44	(0.32)	-0.20	(0.30)	0.14	(0.28)
Points previous 4 matches	-0.09	(0.17)	-0.12	(0.17)	-0.12	(0.17)	0.06	(0.16)	-0.25	(0.15)*
Observations	2720		2478		2156		2718		2720	
Club-seasons	160		156		144		160		160	

Note: Seasons 2017/18 to 2024/25. Threshold parameters not reported. In parentheses standard errors clustered by club-season; * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

parameter estimates hardly change if recent performances and outcomes over the previous four matches are used as right-hand side variables. Clearly, the betting market is efficient and if recent points or recent expected points have a value in predicting match outcomes this is absorbed in the bookmakers odds.

5 Stadium Attendance

In the recent past, football competitions were influenced by Covid-19 restrictions. Some matches had to be played behind closed doors while in other matches a limited crowd was allowed to enter the stadium. Because of these restrictions in stadium attendance seasons 2020/21 and 2021/22 were excluded from the analysis which therefore covers five seasons.

A typical situation in stadium attendance at regular football matches is that many seats are taken by seasonal ticket holders. They have access to every regular home match and they often show up to support their favorite team. This means that fluctuations in stadium attendance are dampened. Nevertheless, stadium attendance will vary during a season because some people only visit a match every now and then. There is a natural maximum to stadium attendance equal to stadium capacity. Therefore, rather than using attendance as the dependent variable, the stadium occupancy rate is used as the dependent variable. In the analysis, for every club stadium capacity in a particular season is assumed to be equal to the highest number of attendants in that season.

In the empirical model, the occupancy rate of the stadium of home team i when playing against team j in match n of a particular season, O_{in} are assumed to be dependent on the expected points from bookmaker odds and recent match outcomes as well as expected points based on expected goals:

$$O_{ijn} = \gamma_1 B_{ijn} + \gamma_2 B_{ijn}^2 + \gamma_3 \sum_{n=-3}^{-1} xP_{in} + \gamma_4 \sum_{n=-3}^{-1} P_{in} + \gamma_5 X_n + \epsilon_{ijn} \tag{3}$$

where X_n represents a vector of control variables which includes fixed effects for season and day of the week as well as a linear and quadratic term of the match number. Day of the week may be important because weekend matches tend to be more popular than midweek matches. The seasonal fixed effects pick up variation in ticket prices across seasons. The match number may affect stadium attendance because towards the end of the season matches may be more important because of possible championships, potential qualification for European tournaments or the threat of relegation from the league. To allow for a nonlinear effect also the squared match number is included in the analysis. The γ's represent parameters to be estimated and ϵ is the error term. Because there is an upper limit to stadium occupancy rates a Tobit specification is used. The idea is that stadium attendance may increase with the number of expected goals in the previous three matches ($\gamma_3 > 0$) because this is an indicator of match quality. However, stadium attendance may also be positively associated with match outcomes ($\gamma_4 > 0$). If that is the cases this indicates that there is an outcome bias.

Panel a of Table 2 presents the parameter estimates for Tobit models with an upper limit of 95% of stadium capacity. The 95% threshold is used since for security reasons stadium capacity may slightly differ from match to match. In panels b and c the upper limit is 99% while in panel c previous outcomes in the last four matches are among the right-hand side variables. In all specifications, in all leagues bookmaker based expected points have negative and significant parameter estimates while their squared terms have significant positive parameter estimates. As indicated in the table, stadium attendances have minima at bookmaker points ranging from from 1.5 to 2.4. Since the average bookmaker points are about 1.6 in all leagues most of the observations are on the downward sloping part of the attendance-bookmaker point relationship. This suggests that attendance increases if the expected points for the home team go down, i.e. if the visiting team is stronger. Although the parameters of both bookmaker point variables are significant the magnitudes are much smaller in England than in other leagues showing that although there is variation in stadium attendance with expected points this variation is much smaller in England. No doubt this is related to the higher stadium attendance in England where there is not a lot of room for variation.

The effect of recent quality of performance as measured by the expected points in the previous three matches is positive in all leagues and significantly different from zero. The

Table 2: **Parameter Estimates Stadium Occupancy Rates; Tobit Models**

	England		France		Germany		Italy		Spain	
a. Upper limit 95%										
B points	-0.29	(0.07)***	-0.79	(0.06)***	-0.62	(0.07)***	-0.40	(0.05)***	-0.33	(0.03)***
B points-squared	0.10	(0.02)***	0.22	(0.02)***	0.20	(0.02)***	0.11	(0.02)***	0.07	(0.01)***
xPoints previous 3 matches	2.08	(0.71)***	1.85	(0.47)***	1.35	(0.56)***	2.14	(0.46)***	0.90	(0.28)***
Points previous 3 matches	0.16	(0.38)	1.18	(0.26)***	0.44	(0.32)	1.42	(0.25)***	1.40	(0.15)***
Minimum at B points	1.5		1.8		1.6		1.8		2.4	
Observations	1972		1851		1588		1894		1988	
Uncensored observations	278		1318		527		1456		1689	
Percentage uncensored	14		75		33		77		85	
b. Upper limit 99%										
B points	-0.16	(0.03)***	-0.71	(0.05)***	-0.58	(0.05)***	-0.36	(0.04)***	-0.29	(0.03)***
B points-squared	0.05	(0.01)***	0.20	(0.02)***	0.18	(0.02)***	0.09	(0.01)***	0.06	(0.01)***
xPoints previous 3 matches	0.92	(0.28)***	1.67	(0.41)***	1.17	(0.42)***	2.30	(0.42)***	0.96	(0.27)***
Points previous 3 matches	0.07	(0.15)	0.99	(0.22)***	0.44	(0.23)*	1.31	(0.22)***	1.30	(0.14)***
Minimum at B points	1.6		1.8		1.6		2.0		2.4	
Observations	1972		1851		1588		1894		1988	
Uncensored observations	866		1630		823		1688		1834	
Percentage uncensored	44		88		52		89		92	
c. Upper limit 99%										
B points	-0.16	(0.03)***	-0.70	(0.05)***	-0.56	(0.05)***	-0.34	(0.04)***	-0.28	(0.03)***
B points-squared	0.05	(0.01)***	0.19	(0.02)***	0.17	(0.02)***	0.09	(0.01)***	0.06	(0.01)***
xPoints previous 4 matches	0.81	(0.25)***	1.09	(0.35)***	1.18	(0.37)***	2.08	(0.35)***	0.90	(0.23)***
Points previous 4 matches	0.05	(0.14)	0.96	(0.20)***	0.47	(0.20)**	1.13	(0.19)***	1.18	(0.12)***
Minimum at B points	1.6		1.8		1.6		2.0		2.4	
Observations	1912		1793		1534		1835		1926	
Uncensored observations	838		1577		795		1635		1773	
Percentage uncensored	44		88		52		89		92	

Note: Seasons 2017/18 to 2019/20 and seasons 2022/23 to 2024/25. All estimates contain fixed effects for season and for day of the week, and a linear term as well as a quadratic term of match number. In parentheses standard errors clustered by club-season; * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$.

number of points in the previous three matches have significant positive effects in three of the five leagues. For the English and the German leagues there is no significant effect of the number of points which would suggest absence of outcome bias in these leagues. However, the variation in stadium attendance in both leagues is limited; to 14% in the English league and 33% in the German league.

Panel b shows parameter estimates if the upper limit of the occupancy rate is increased from 95% to 99%. This increases the variation in the occupancy rates although in the English league there is only variation in 44% of the matches with the rest being sold out. The parameter estimates in panel b are very similar to those in panel a with the exception of the number of points in the previous three matches in the German league which is now significantly different from zero at a 10% level.

Panel c shows parameter estimates if the match outcomes and the number of expected points in the previous four matches are included in the analysis. Now all parameter estimates are significantly different from zero at at least a 5%-level with one exception, the number of points in the previous four matches in the English league. This suggest that in four leagues there is outcome bias in the decisions to attend football matches except for the English league.

6 Conclusions

Consumer decisions based on past events may be subject to outcome bias when the role of randomness in those events is not sufficiently accounted for. This paper analyzes consumer demand for stadium attendance in the top divisions of the five major European professional football leagues, focusing on the presence of outcome bias.

To explain variations in football match attendance, both expectations about match outcomes and information about recent team performance can be informative. Forward-looking expectations can be proxied by bookmaker odds, which, under the assumption of an efficient betting market, reflect all available information about upcoming matches. The underlying quality of recent performances is measured using the expected number of points, derived from expected goals (xG). There is a natural positive association between expected points and actual points—teams that are expected to perform well generally do. However, discrepancies between the two are especially informative. A team may overperform, achieving more points than expected given their quality of play, or underperform, earning fewer points despite strong performances. Consumers of sports events may interpret past match outcomes as a signal of team quality, even when those outcomes partially reflect randomness. This can lead to outcome-biased decisions regarding match attendance.

The main findings of the analysis are threefold. First, match expectations, as reflected in bookmaker odds, significantly influence stadium attendance. Second, recent high-quality performances by the home team positively impact attendance. Third, actual match outcomes also affect attendance in four of the five leagues, providing evidence of outcome bias in fan behavior. Interestingly, outcome bias does not appear to influence attendance in the English Premier League. A plausible explanation is that matches are frequently sold out, constraining the responsiveness of attendance to recent outcomes and performance.

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Appendix A: Information about the data

The following data sources are used:

1. Goals, bookmaker odds and stadium attendance: football-data.co.uk; stadium capacity is defined as the largest number of attendants in a particular season. Odds are from William Hill as these are most frequently available.

2. Expected goals: fbref.com

The attendance data of Tottenham Hotspur in seasons 2018 and 2019 are ignored because they then temporary played in the Wembley stadium.

Figure A.1 shows the development of average stadium attendance. Covid-19 restrictions caused a big drop in 2021. In 2022 stadium attendances in England and France recovered to pre-Covid levels but in Germany, Italy and Spain this was not until 20223. Therefore, the analysis of stadium attendance excludes seasons 2021 and 2022.

Figure A.1: **Average Stadium Attendance in the Top Divisions of Five European Football Leagues; 2018/19-2024/25 (1000 per match)**

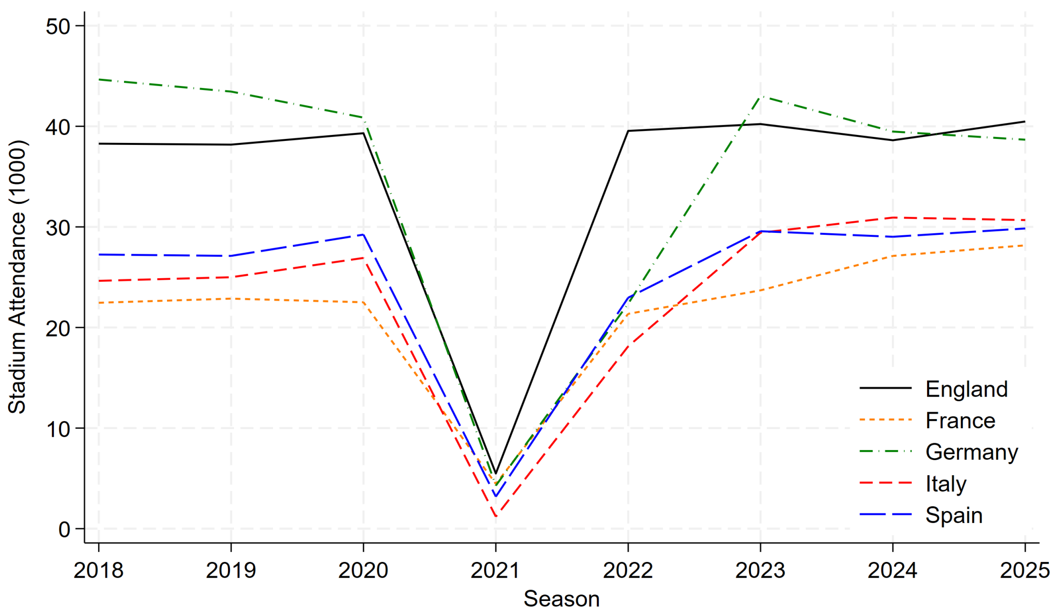

Table A.1 provides descriptives of the main variables in the two parts of the empirical analysis.

Table A.1: **Descriptives by League**

	England	France	Germany	Italy	Spain
a. Points					
Points per match	1.57	1.54	1.56	1.50	1.63
B points	1.56	1.57	1.57	1.55	1.60
xPoints previous 3 matches	4.06	4.02	4.01	4.00	3.96
Points previous 3 matches	4.07	4.03	4.06	4.06	4.00
Observations	2800	2556	2229	2795	2800
b. Stadium attendance					
Attendance (1000)	38.8	24.3	41.8	27.9	28.7
Occupancy rates (%)	0.97	0.78	0.93	0.78	0.82
B points	1.57	1.58	1.59	1.56	1.61
xPoints previous 3 matches	4.01	4.02	4.00	3.98	3.96
Points previous 3 matches	4.05	4.03	4.06	4.04	3.99
Observations	1972	1851	1588	1894	1988

Note: Panel a: seasons 2017/18 to 2024/25 (see Table 1a). Panel b: seasons 2017/18 to 2019/20 and 2022/23 to 2024/25 (see Table 2a).